The Pre-FOMC Announcement Drift: A Pumping Explanation[*]

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Abstract

We provide a theoretical, cross-pumping explanation for the upward drift in equity prices before FOMC announcements. The novel insight emerging from our model is that managers holding high beta stocks have incentives to pump stocks other than the ones they hold. Studying five-minute order imbalances and returns, we find that the order imbalance for the market and for portfolios of mid- and high- beta stocks explains the drift for the market, beta, size, and size-BM portfolios, and for two major stock ETFs. Stock-level tests highlight the important role of beta in the drift. Our results are consistent with the model's predictions, and suggest that cross-pumping provides a partial explanation for the pre-FOMC announcement drift.

1. Introduction

The Federal Open Market Committee (FOMC) of the US Fed meets eight times a year to set US interest rate policy, and these meetings are closely watched. Between September 1994 and March 2011, the outcome has been announced at around 2:15 PM EST. Lucca and Moench (2015) uncover an upward drift of 0.49% in the S&P 500 index over the 24-hour period before the FOMC announcement. This pre-FOMC announcement drift cannot be explained by risk, illiquidity, or persistent good news associated with policy changes. Panel A of Figure 1 shows a 0.48% pre-announcement aggregate value-weighted return and a smaller 0.36% equally-weighted return over a slightly longer 1994-2014 sample period, while Panel B shows value-weighted buying pressure across all stocks, although the equally-weighted curve suggests selling of small stocks.

In this paper, we link the results in the two panels by offering an explanation for the drift based on strategic investor buying of targeted stocks. This is presented in the form of a simple model. The model involves a market-maker, an informed investor, noise traders, and a long-only uninformed fund manager, and extends Bhattacharyya and Nanda (2013) to a multi-security economy with optimization over the fund's prior holdings. The informed investor maximizes the long-term profit taking advantage of his private knowledge about asset payoffs. Unlike the informed investor, the manager is compensated on short-term as well as long-term performance. The market maker sets asset prices given the aggregate order flow. We assume that a factor structure governs asset payoffs, as is likely on days with important economy-wide news, such as FOMC rate announcements. With a simplifying assumption about noise trading, the model makes three sharp predictions. First, asset returns on FOMC days will be explained by the marketwide order imbalance and the asset's own imbalance, and the slope coefficient on the marketwide imbalance will increase with the asset's beta, while that on the own imbalance will be constant across assets. Second, if the market maker and the informed investor underestimate her holdings of some assets, the manager has incentives to buy those with highest betas. We argue that this additional assumption is plausible in a large economy with numerous securities available for investment. Third, under the same additional assumption and strong enough short termism, buying high beta assets that the manager is not believed to own, and indeed does not own, can generate larger profits than buying low beta assets.

The intuition is as follows. The factor structure on announcement days implies that factor returns will be transmitted to individual stocks more strongly. This creates incentives for the manager to first hold high beta assets (before the announcement day) and then broadly drive up asset prices on the announcement day, thereby giving the value of her existing holdings a boost that is proportional to the beta. This strategy positively influences the prices because the market maker cannot distinguish informed and uninformed (noise) trading as in Kyle (1985). Further, on the announcement day, the manager's profits from buying high beta assets will exceed those from buying low beta assets, because the price impact is larger for assets with higher betas. This, in turn, gives rise to our prediction regarding the explanatory power for the drift of order flow both for the entire market and for high beta assets.[1]

Our second contribution is to evaluate these predictions in the data. We compile high-frequency (five-minute) returns and order imbalances (to capture net buying pressure) for NYSE, AMEX and NASDAQ stocks. The pre-announcement market is characterized by low volume, positive order imbalance, and large price impact. This is possible if some traders buy stocks while

[1] Assuming a factor structure in payoffs is uncontroversial. There is an emerging 'betting on beta' literature suggesting that long-only managers have incentives to buy high beta stocks (e.g. Frazzini and Pedersen, 2014). Recent evidence of portfolio pumping comes from Hu et al. (2014). We add to these strands of research by exploring the role of cross-pumping, i.e. trades by investors designed to drive up the prices of stocks they do not own.

most others wait for important macroeconomic news. Such a quiet market helps uninformed strategic traders such as the fund manager in our model disguise themselves as being informed.

As test assets, we choose portfolios formed on beta, size, and BM, the market portfolio and two prominent ETFs (SPY and QQQ). Most portfolios exhibit statistically and economically significant drift, e.g. 0.71% for the highest beta decile. In the pre-FOMC period, most portfolios are also subject to stronger buying pressure, which increases with portfolio beta. This is consistent with the model's second prediction that there will be stronger buying pressure for high beta stocks.

We then regress the return for each portfolio on the marketwide and portfolio (i.e. own) imbalances. Consistent with the model's first prediction, the marketwide and own order imbalances together explain the drift for each portfolio. Looking separately at the explanatory power of these two regressors, we find that the own imbalance cannot entirely explain the drift while the aggregate imbalance does. The regression R^2 tends to increases with beta, also consistent with the model's predictions.

To explore the underlying channel further, we construct order imbalances for beta tercile portfolios and relate the drift for the test portfolios to the order imbalance for the low, mid and high beta portfolios. If the drift has its origins in the purchases of high beta stocks, we expect the high beta imbalance to be most influential in explaining the drift. This turns out to be the case. In addition, we find that the mid beta imbalance can also explain the drift. By contrast, the low beta imbalance cannot eliminate the drift. The success of the imbalances for the mid beta stocks in explaining the drift is consistent with the cross-pumping implied by the model, because fund managers would hold high beta stocks and yet buy other stocks to boost their values.

We examine the robustness of these results. First, we split trades into small, medium and large, following Lee and Radhakrishnan (2000) and Barber et al. (2009). Imbalances comprising medium trades, and to a lesser extent, small trades, are able to explain the drift on all the test assets. Given the trade fragmentation that characterizes much of our sample period, the success of medium and small trade imbalances is consistent with institutional investors being important contributors to the drift. Second, we confirm that beta is the only characteristic that explains the cross section of the drift for individual stocks. Specifically, panel regressions controlling for characteristics that are known to spread returns, such as size, the book-to-market ratio, momentum, and more provide evidence of the strong explanatory power for beta. Finally, we document wide cross-sectional dispersion in beta, an important premise for the betting on beta strategy to work.

The idea of cross-pumping builds on the recent theoretical literature on pumping. Bhattacharyya and Nanda (2013) show that a fund manager has an incentive to pump her holding when she is compensated on the short-term fund value, even though it hurts long-term performance. Pasquariello and Wang (2017) propose and test a theory of "pumping by disclosing," in which a speculator optimally discloses a mixture of her private information and position to induce the market maker to revise the price in the direction of her position. We extend the scope of trading to multiple correlated securities endowing the fund manager with no private information to disclose.

We aim to explain the pre-announcement drift in a quiet market with no apparent public news. Ai and Bansal (2017) provide conditions for the existence of a positive announcement premium and a pre-announcement drift under non-expected utility. A critical condition for the pre-announcement drift is that investors receive exogenous informative signals prior to announcements. In our model, as a "signal" the market maker privately receives a noisy aggregation of endogenous order flows from optimizing agents.

Two recent papers study the effects of FOMC announcements empirically. Bernile et al. (2016) find that imbalances for S&P and NASDAQ futures contracts and ETFs in the 10-20 minutes before FOMC and other macro announcements are positively correlated with the nature of the news, consistent with information leaks. However, leaks cannot explain the entire pre-FOMC drift since the news is provided to news agencies only 30 minutes prior to its official release. Cieslak et al. (2014) suggest that the drift is part of a broader Fed cycle, with the equity premium over the past 20 years arising in weeks 0, 2, 4 and 6 of roughly a six-seven week Fed cycle (week 0 starts the day before an FOMC meeting). The paper provides suggestive evidence that the returns are driven by risks associated with information arrival and decision making at the Fed, which also follow a two-week cycle. The cyclical pattern is stronger for high beta portfolios. In contrast, our analysis of the FOMC window studies the patterns in, and importance of, order imbalance and provides support for a cross-pumping explanation.

Frazzini and Pedersen (2014) suggest that high beta stocks have low alphas because constrained institutional investors bid up their prices to bet on beta. They show that a strategy that is long leveraged low-beta assets and short high-beta assets yields a significantly positive alpha. Christoffersen and Simutin (2015) document that defined-contribution pension funds shift exposure from low beta stocks to high beta stocks with low idiosyncratic volatility to beat market benchmarks while minimizing tracking error. Our analysis suggests that the pre-FOMC announcement period is a prime opportunity for constrained investors both to bet on beta and in particular, via cross-pumping, to strategically enhance the returns to high beta bets.

We do not view our 'order imbalance explains the drift' results as being a 'dog bites man' story. If direct buying pressure were driving the drift, own order imbalance would explain the drift on each portfolio. But own order imbalance fails to explain the drift on several portfolios, and it is specific imbalances that explain the drift for all portfolios.

The rest of the paper proceeds as follows. The next section develops our hypotheses. Section 3 establishes our main results on the drift and trading activity. Section 4 demonstrates the robustness of our result. Section 5 concludes.

2. Betting on Beta for Cross-pumping

2.1. Motivating Evidence

Before turning to our theoretical predictions, we provide brief empirical motivation. First note that the Federal Funds Rate affects the short end of the yield curve and thereby alters firms' cost of debt and investors' savings behavior. FOMC rate decision announcements thus release public information of a 'systematic' nature, i.e. with implications for the entire stock market.[2]

We characterize trading activity surrounding FOMC announcements by calculating, at the five-minute frequency within a five-day window centered on the FOMC announcement day, the value-weighted share turnover across domestic NYSE, AMEX and NASDAQ stocks.[3] Mean turnover drops from 0.0082% per five minutes on day -2 and 0.0085% on day -1 to 0.0079% on day 0 before the announcement (we do not tabulate these statistics to save space). Following the announcement, there is a sharp rise in turnover to 0.0125% per five minutes for the rest of day 0, and turnover remains elevated on day +1 (0.0094%) and even on day +2 (0.0091%). These patterns in stock turnover are consistent with Lucca and Moench's (2015) finding of a drop in e-mini futures volume before the announcement and a pick-up thereafter. The drop in trading activity is consistent with investors with discretion staying out of the market while waiting for the news, and provides the empirical backdrop for our theoretical hypothesis that some investors (who are betting on beta) exert buying pressure as other investors withdraw from the market.

[2] Such effects are documented in, for example, Savor and Wilson (2013).
[3] Details on the sample and data are provided in Section 3 and the appendix.

As a measure of such buying pressure, the second panel of Figure 1 shows the mean cumulative five-minute value- and equally-weighted signed share turnover, or ASTOV.[4] Indicative of net buying pressure for big stocks, the blue value-weighted ASTOV series rises steadily between day -2 and day +2. The pattern in the value-weighted series resembles that in the cumulative excess return in the first panel, though the return series is noisier. In contrast to value-weighted ASTOV, the steady decline in equally-weighted ASTOV (shown in pink) on day -1 implies selling pressure for small stocks. While the pink line flattens on day 0 and days +1 and +2, we never see aggressive buying pressure when stocks are equally-weighted. Thus, the pre-FOMC announcement drift appears to be, for the most part, a large stock phenomenon. In untabulated analysis, we examine the five-minute aggregate order imbalance. With value-weighting, there is buying pressure throughout the five-day window, but it picks up on day -1 and on day 0 before the announcement, and surges post-announcement.

In a quiet market, we expect transactions that do occur to move prices to a greater extent, notably because there is a higher likelihood of their being placed by informed investors. We examine the sensitivity of price to order imbalance by estimating 'price impact' regressions of the five-minute return on the contemporaneous order imbalance. The results (untabulated) show that the price impact of trades (positive throughout) increases significantly in the pre-FOMC window.[5] Thus, investors placing trades move prices more aggressively in the pre-FOMC period. This result points to the potential success of cross-pumping strategies in this window.

In Figure 2, we plot the average cumulative intraday return for selected value-weighted beta-decile portfolios over the three days centered on the FOMC announcement, deferring the

[4] The details are in Appendix A.2. Briefly, the difference between the volume of trades classified as buys and sells in a five-minute interval is scaled by the number of shares outstanding and then aggregated across stocks.
[5] We provide selected price impact coefficients in Table 2.

details on variable construction until the next section. The pre-announcement cumulative returns of the beta portfolios generally line up with their decile ranks. The shapes of the graphs for mid- to high-beta portfolios are similar to that for the S&P 500 index in Lucca and Moench's (2015) Figure 1, except that opening returns are more pronounced for our portfolios of individual stocks. It is evident that the returns are larger for higher beta stocks. That is, beta "works" in the FOMC announcement window, a fact also pointed out by Cieslak et al. (2016). This is somewhat surprising given the well-known failure of beta to explain the cross section of stock returns in tests of the Capital Asset Pricing Model. However, this is not an issue in correlated markets prior to the FOMC announcement.

Betting on beta for (cross) pumping. The positive relation between return and beta in the pre-FOMC period creates an incentive for investors to bet on beta and engage in direct or indirect pumping. In both cases, investors build a position in high beta stocks before FOMC announcement days. With direct pumping, the investors buy the high beta stocks they already hold in order to boost their prices on the announcement day. While it provides the most direct route to gains, the high beta stocks that investors hold may be costly to trade in the quiet pre-announcement market. Moreover, aggressively buying stocks already held runs the risk of detection and prosecution for market manipulation. Both these concerns can be mitigated with indirect pumping, or what we call *cross-pumping*. Under this pumping technique, investors buy other stocks, say big, mid-beta stocks, to push up the market and hence the value of their high-beta holdings proportionally. Big stocks tend to be more liquid and can allow investors to camouflage their real trading motives.[6]

[6] Buying illiquid stocks can increase prices rapidly but will not directly benefit investors if they do not hold these stocks (institutions are unlikely to have large positions in illiquid stocks). Moreover, the impact of these price changes on the broader market will be limited since illiquid stocks are not widely followed.

Cross-pumping can work in the pre-announcement period, given the positive relation between beta and return in Figure 2.

We will now formalize these mechanisms in a model with strategic trading.

2.2. A Model of Betting on Beta for Cross-pumping

This section presents a formal model of strategic trading with short termism in correlated markets. Our claim has two parts, one that depends only on the factor structure that an intraday macroeconomic announcement induces, and the other that builds on it: betting on beta for pumping. The factor structure produces beta, and creates an environment where investors can take advantage of the predictable price movements that they are able to create.

The model is set up in a multiple-security economy populated by a market maker and three types of traders: a fund manager (pumper), an informed trader, and noise traders. All optimizing traders are assumed to be risk-neutral. There are three dates, $t = 0$, 1, and 2. K risky stocks and a risk-free bond are traded in the market. At $t = 2$, the stocks pay a vector of normally distributed random payoffs, $v \sim N(\mu, \Sigma_v)$, where μ is a K by 1 mean vector and Σ_v is a K by K symmetric positive-definite variance-covariance matrix. The prices of the stocks are denoted by the vector P_t, $t = 0$, 1. Given the risk-neutrality of all the relevant agents, we set

$$P_0 = E[v] = \mu \tag{1}$$

by convention. For simplicity, we normalize the interest rate on the bond to zero.

An uninformed manager oversees a fund. At $t = 0$, the fund receives capital, $I_0 > 0$, and the manager purchases equities by taking positions, $z \geq 0$. The positivity of z reflects the short-selling restriction that some institutions such as mutual funds face. At $t = 1$, the manager places an additional, proprietary trade, x. At each point in time, she cares about both the interim profit at $t = 1$ and the terminal profit at $t = 2$. Specifically, following Bhattacharyya and Nanda (2013), we assume that she maximizes W, the expected weighted average of the interim profit, $z'(P_1 - P_0)$, and the terminal profit, $z'(v - P_0) + x'(v - P_1)$, with weights γ and $1 - \gamma$, $0 \leq \gamma \leq 1$, respectively:

$$W = I_0 + \gamma z'(P_1 - P_0) + (1-\gamma)[z'(v - P_0) + x'(v - P_1)]. \tag{2}$$

The parameter γ represents the degree of short termism. The manager receives no private information about the payoffs at any point.

At $t = 1$, the informed trader receives perfect information about the dividends and places a market order, ξ. Noise traders submit a normally-distributed random order $u \sim N(0, \Sigma_u)$, where Σ_u is a K by K symmetric positive-definite matrix. The market maker receives the net order flow,

$$y = x + \xi + u, \tag{3}$$

and sets the price as the expected payoff conditional on it,

$$P_1 = E[v \mid y]. \tag{4}$$

As usual in a Kyle model, this can be viewed as a competitive zero-profit condition. Assuming the normality of y, the date-1 price in (4) is given by linear projection,

$$P_1 = P_0 + \Lambda(y - \bar{y}), \tag{5}$$

where Λ is a matrix version of Kyle's lambda and $\bar{y}$ is the prior mean of the order flow before the market maker receives it, both to be determined in equilibrium.

At $t = 0$, the fund manager maximizes the expected value of her objective function in (2) over z. She faces a short-selling restriction, $z \geq 0$, and a capital constraint such that the fund's stock investment is no more than fraction h of its total net assets, I_0:

$$\begin{aligned} &\max_z E_0[W] \\ &\text{s.t. } P_0'z \leq h \cdot I_0, \\ &\qquad z \geq 0, \end{aligned} \tag{6}$$

where $E_0[\cdot]$ denotes the conditional expectation given her information set at time 0. The case of $h < 1$ represents a fund that holds fraction $1 - h$ in the bond. Mutual funds typically do so to meet redemption needs, and insurance companies to pay claims (Frazzini and Pedersen (2014)). z is not observable to the market maker or the informed trader. They conjecture that it is constant at $\bar{z}$.

For simplicity, we now make assumptions about two key quantities, the payoffs and noise trading.

Assumption 1: (Factor structure in payoffs) The payoffs have the following factor structure:

$$v = v_0 \mathbf{1} + \delta v_M + \varepsilon, \tag{7}$$

where $v_0 > 0$ is a constant mean scalar, $\mathbf{1}$ is a K by 1 vector of ones, $v_M \sim N(0, \sigma_{vM}^2)$ is the common factor, δ is a K by 1 vector of positive factor loadings, and $\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$ is a K by 1 vector of uncorrelated idiosyncratic noise.

In our context, we can think of v_M as a common interest-rate factor affecting the whole stock market. The next assumption implies that market prices inherit the properties of payoffs.

Assumption 2: (Independently and identically distributed noise trading) Noise trading is uncorrelated across the stocks and has a common variance, σ_u^2, i.e., $\Sigma_u = \sigma_u^2 I$.

With the linear price P_1 in (5), the manager's weighted profit in (2) is concave quadratic in demand, x. Moreover, the informed trader's problem is standard. Therefore, the standard procedure as in Kyle (1985), suitably adjusted for a multiple-security economy and short termism, gives a unique equilibrium at date 1.

Theorem 1: (Equilibrium at date 1) Under Assumptions 1 and 2, there exists a unique equilibrium at date 1 with the fund manager's demand

$$x = \frac{1}{2}\frac{\gamma}{1-\gamma}(z+\overline{z}), \tag{8}$$

the informed trader's demand

$$\xi = \frac{1}{2}\Lambda^{-1}(v - P_0), \tag{9}$$

and the price vector in (5) with a symmetric price-impact coefficient matrix

$$\Lambda = \frac{1}{2\sigma_u}\Sigma_v^{1/2} \tag{10}$$

whose elements all are positive and expected order flow

$$\overline{y} = \frac{\gamma}{1-\gamma}\overline{z}. \tag{11}$$

Proof: All proofs are given in Appendix A.1. ■

As in Bhattacharyya and Nanda (2013), the equilibrium demand *x* in (8) exhibits pumping; i.e., the manager trades in the same direction as the existing position, *z*.

Equation (7) from Assumption 1 implies that δ contains the unstandardized coefficients of the first principal component of dividends, and under Assumption 2, that of asset prices as well, through Equation (10). Moreover, it represents the only principal component whose coefficients all are positive, i.e., with no short position.[7] Therefore, we define the aggregate market portfolio by the vector of shares held in assets, δ. Since the vector of dollar returns is $P_1 - P_0$, the dollar return on the market is given by $(P_1 - P_0)'\delta$. So, define the vector of market betas as the slope coefficient in a regression of the former on the latter,

[7] All the other principal components have coefficients orthogonal to δ, and therefore must contain at least one negative coefficient. This is a part of the mathematical result known as the Perron-Frobenius theorem.

$$\beta = \frac{Cov(P_1 - P_0, (P_1 - P_0)'\delta)}{Var((P_1 - P_0)'\delta)}. \quad (12)$$

Lemma 1: (Market beta) Under Assumption 1, the vector of market betas is proportional to the vector of factor loadings, δ.

Since the date 0 price is identical across assets under Assumption 1, this lemma and the following propositions also hold for beta with respect to the percentage return, rather than the dollar return, as well. With the factor structure in Assumption 1, the linearity of the price function gives us a sharp prediction about the relation between return and trade in a regression framework.

Proposition 1: (Regressing the drift on order flows) Under Assumptions 1 and 2, the drift of an asset is a positive linear combination of the common aggregate order flow and the asset's own order flow. In a multiple regression of the drift on the two order flows with an intercept, the slope coefficient on the aggregate order flow is proportional to the asset's beta, while the slope coefficient on the asset's own order flow is identical across the assets. The R-squared of the multiple regression is 1. In a simple regression of the drift on the aggregate order flow with an intercept, the slope coefficient on the aggregate order flow is again proportional to the asset's beta. Moreover, the R-squared of the simple regression increases with beta.

Given the optimal strategy at date 1, we can step back in time and dynamically solve for the problem at date 0.

Proposition 2: (Betting on beta) Under Assumptions 1 and 2, for sufficiently small $\bar{z}$, the fund manager will invest all capital in the stock with the highest beta at time 0.

This is so because short termism ($\gamma > 0$) makes the value function at time 0 convex quadratic in the equity position, z, centered at the market maker's prior, $\bar{z}$. Moreover, the value function increases in the betas of invested stocks. For $\bar{z}$ small enough, this implies that the manager will allocate all capital to the stock with the highest beta. In reality, no fund follows such an extreme strategy. It is straightforward to impose more realistic restrictions such as minimizing tracking error at the cost of complexity, but this is beyond the scope of our analysis.

In equilibrium, the fund manager's expected wealth is given by (substitute the expected order flow (32) into the maximized wealth (29) in the appendix)

$$\begin{aligned} E_1[W] &= I_0 - (1-\gamma)\left(x - \frac{\gamma}{1-\gamma} z\right)' \Lambda \left(x - \frac{\gamma}{1-\gamma}\bar{z}\right) \\ &= I_0 - (1-\gamma)\left(x - \frac{1}{2}\frac{\gamma}{1-\gamma}(z+\bar{z})\right)' \Lambda \left(x - \frac{1}{2}\frac{\gamma}{1-\gamma}(z+\bar{z})\right) \\ &\quad + \frac{1}{4}\frac{\gamma^2}{1-\gamma}(z-\bar{z})' \Lambda (z-\bar{z}). \end{aligned} \tag{13}$$

Since Λ is positive definite, the quadratic form in the second line of (13) is weakly negative. Therefore, zeroing it out given z maximizes the expected wealth and confirms the solution, $x = \frac{1}{2}\frac{\gamma}{1-\gamma}(z+\bar{z})$, in (8). With a plan to place that optimal order at time 1, dynamically stepping back to time 0 and building a position $z = \bar{z}$ (as the market maker and the informed trader expect) will also nullify the last line of (13) and earn just zero expected profit, so that the expected terminal wealth equals the initial wealth, I_0. This is the benchmark case. On the other hand, building an initial position $z \neq \bar{z}$ and subsequently placing the optimal order will earn the maximal positive profit that equals the last term of (13). However, this runs the risk of detection and prosecution because x directly pumps the preexisting position, z. If the manager is afraid of such unmodeled risk, she may place a suboptimal order that buys stocks not held in z, dubbed *cross-pumping*:

Definition 1: (Cross-pumping) Cross-pumping is an order x that buys stocks not held in the preexisting position, z, in correlated markets.

When the manager builds a position $z \neq \bar{z}$ at time 0, she outwits the market maker and the informed trader. She can further go against their expectations by purchasing the stocks that she does not hold at time 1. Such cross-pumping is suboptimal, but can still be profitable in correlated markets such as those prior to the FOMC announcement. Somewhat surprisingly, when the market maker underestimates the manager's existing position, the manager can *always* find a profitable cross-pumping strategy as the next proposition states.

Proposition 3: (Cross-pumping) Consider a preexisting long position z that does not hold at least one stock. For sufficiently small $\bar{z}$, there exist multiple profitable cross-pumping strategies x that buy only those stocks not held by z. Moreover, under strong enough short termism, a high beta strategy earns a larger profit than a comparable low beta strategy with an equal sum of squared shares traded.

Theorem 1 and Proposition 1 require only the factor structure in payoffs and uncorrelated noise trading in Assumptions 1 and 2, while Propositions 2 and 3 additionally assume the common prior belief that the fund's holdings, $\bar{z}$, is small. This latter assumption can be interpreted as the underestimation of preexisting holdings amenable to pumping. Since Proposition 2 predicts that the manager will invest all capital in the highest beta stock for sufficiently small $\bar{z}$, the extreme belief that $\bar{z} = 0$ is actually correct for all stocks but the one with the highest beta. This has a pricing implication; Equation (5) implies that order flow y must exceed expectations $\bar{y}$ to positively influence the prices, which is a general feature of a Kyle model. Small $\bar{z}$, and hence $\bar{y}$ in (11), allows this to happen on average. What is special in positively correlated markets is that underestimation of the pumping motive for just one stock results in price appreciation for all stocks. The next two sections provide empirical evidence consistent with this explanation.

3. Results

3.1. Data

We collect 163 FOMC meeting dates from the FOMC website and study the period, September 1994–December 2014. While data on FOMC meeting dates go back to the 1950s, rate decisions have explicitly been announced at approximately 2:15 pm EST since September 1994; before 1994, policy decisions could only be inferred from the open market operations that followed the meetings.

Two of our propositions relate to beta. To examine their implications, we form beta-sorted decile portfolios and six size-beta sorted portfolios, where beta is estimated from the previous six months of daily returns skipping a month. Here, size is meant to measure tradability. We also employ the six Fama-French portfolios sorted by size and BM, as these characteristics form widely-followed investment styles. Finally, we include two major exchange-traded funds, SPY (which tracks the S&P 500) and QQQ (which tracks NASDAQ). These ETFs provide affordable broad market exposure to institutional and individual investors.

We process intraday data off the TAQ database for five-day intervals centered on the FOMC announcements during the 1994-2014 sample period, and collect data for domestic ordinary common stocks trading on the NYSE, AMEX and NASDAQ. ETF data begin in September 1994 for SPY and in March 1999 for QQQ. Appendix A.2 has details about variable construction and screens. We use only quotes and trades that meet no-arbitrage and eligibility conditions, and calculate the five-minute mid-quote return, volume, and order imbalance at the stock level. The return is based on the last NBBO-eligible quote posted in each five-minute interval. The return over the first interval (ending at 9:35 am) includes the overnight return from 4:00 pm on the previous day. We opt to include the overnight return to be consistent with Lucca and Moench (2015). Trades are signed using the Lee-Ready (1991) algorithm.

3.2. Measuring the Drift

Table 1 quantifies and decomposes the drift for several portfolios of interest, via the following regression:

$$R_{it} = a_i + b_{1i}PRE_t + b_{2i}INI_t + b_{3i}INI_t \times PRE_t + \varepsilon_{it}, \quad (14)$$

where R_{it} is the excess return on asset i in five-minute period t, PRE_t and INI_t are dummy variables defined below, a_i is the intercept (shown as "Const"), b_{1i}, b_{2i}, and b_{3i} are slope coefficients, and ε_{it} is the residual. PRE_t is one in the period between 9:30 am and 2:00 pm on FOMC announcement days and zero otherwise, and INI_t is one for the first five-minute interval in a day and zero otherwise. The model is estimated for the value-weighted market portfolio, ten beta-sorted portfolios, six size-beta sorted portfolios, six size-BM sorted portfolios, and the SPY and QQQ ETFs.

The estimated coefficient on *PRE* in the table is positive and significant for all but a few low-beta portfolios, implying that most portfolios have a significant pre-FOMC drift. The coefficient on the interaction of *INI* and *PRE* is positive and significant for the high beta portfolios. Thus, high beta stocks experience additional large returns at the open on FOMC news days. The third to last column, labeled "Close-2pm drift," shows the average return from the close on the day before the announcement to 2:00 pm on the announcement day.[8] As shown in the first row of the table, the close-to-2 pm drift for the value-weighted market portfolio is 0.342% over the same sample period as Lucca and Moench (2015). This is close to the 0.335% figure in the "Close-to-2 pm" column in their Table II. Thus, using individual stocks on the NYSE, AMEX, and NASDAQ,

[8] Lucca and Moench (2015) include overnight returns in the drift. In the same spirit, we include the overnight return in the first five-minute period, which is captured by the INI coefficient. Thus, the average return from the market close on the day before the announcement to 9:35am on the announcement day is PRE + INI + INI×PRE + Const. The average return in each of the 53 five-minute periods from 9:35am to 2:00pm on the announcement day is PRE + Const. The close-to-2pm return compounds the former once and the latter 53 times.

we have effectively replicated their result based on the intraday S&P 500 cash index. The rest of our analysis focuses on the full 1994-2014 sample period. The close-to-2pm drift is 0.71% for the highest beta decile, compared to 0.01% for the lowest beta decile. Our goal is to explain the large spread in the drift, which points to the strong profitability of a cross-pumping / betting-on-beta strategy on FOMC announcement days.

3.3. Drift and Trading Activity

The mean turnover (*TOV*) for the portfolios is shown in the last column of Table 1. *TOV* tends to increase in beta, and more so for mid to high beta portfolios, indicating active trading of higher beta stocks. Turnover for the highest beta decile, 172.9 millionths of shares outstanding per five minutes, is the largest of all the portfolios. The second to last column of Table 1 shows the average order imbalance (*STOV* for "signed turnover") during the pre-announcement window. Like the drift, *STOV* increases almost monotonically with beta except for the lowest decile. While positive throughout, *STOV* for the bottom four beta-sorted portfolios is half or less that for the top three deciles and jumps appreciably for the highest beta portfolio. This heavy buying of high beta stocks suggests that investors are pumping high beta stocks especially aggressively (Proposition 3).[9]

To demonstrate this point visually, Figure 3 plots the mean imbalance and the average return for the beta-sorted decile portfolios during several windows of interest. The panels share common axes to facilitate comparison. To match the horizon of *STOV* in the pre-announcement window, the average return is calculated as the five-minute return that compounds to the "Close-

[9] Interestingly, the STOV column shows that the two ETFs, SPY in particular, are strongly bought. However, according to untabulated analysis, the t-statistics for the mean STOV, 5.5 for SPY and an insignificant 1.45 for QQQ, are appreciably lower than those for high beta or big stock STOV, which are on the order of 17 to 30, suggestive of high volatility in ETF trades. The time-series standard deviation of STOV for the two ETF is at least six times as large as that of the big growth portfolio. The STOV column in Table 3 shows that the order imbalances of the ETFs cannot explain their own drifts.

2pm drift" in Table 1 over the 54 five-minute periods constituting this window. Panel A confirms the near-monotonic relation between beta and return or imbalance in the pre-announcement window, and the close association between the two lines is evident.

In the post-announcement period (Panel B), high beta stocks are even more strongly bought than in the pre-announcement period, despite their slightly negative returns. However, except for decile 1, none of these returns is significantly different from zero (these results are not tabulated). Since these returns are five-minute averages, the small negative cumulative return in the 1¾ hour post-announcement window does not offset the huge cumulative gain in the 4½ hour pre-announcement window, as already seen in Figure 2. Thus, betting-on-beta investors do not necessarily have to sell their holdings immediately after the announcement for their positions to be profitable.

Panel C shows that, on the day prior to the announcement, the lowest beta stocks are sold (untabulated, *STOV* = -0.0041, t = -8.5), while high beta stocks are bought. On the day after the announcement (Panel D), returns and imbalances are similar across deciles. Thus, in contrast to Panel A, the remaining three panels show that the relation between average return and beta is flat or even negative, which is consistent with existing tests of the CAPM. Figure 2, discussed above, is consistent with these observations.

3.4. Explaining the Cross Section of Drifts

To examine the empirical implications of Proposition 1, we regress each asset's return on the value-weighted aggregate order imbalance, *ASTOV*, and the asset's own order imbalance, *STOV*, along with a constant interacted with the two dummy variables, *PRE* and *INI*:

$$R_{it} = a_i + b_{1i}PRE_t + b_{2i}INI_t + b_{3i}INI_t{\times}PRE_t$$
$$+ b_{4i}ASTOV_t + b_{5i}PRE_t{\times}ASTOV_t + b_{6i}INI_t{\times}ASTOV_t + b_{7i}INI_t{\times}PRE_t{\times}ASTOV_t \qquad (15)$$
$$+ b_{8i}STOV_t + b_{9i}PRE_t{\times}STOV_t + b_{10i}INI_t{\times}STOV_t + b_{11i}INI_t{\times}PRE_t{\times}STOV_t + \varepsilon_{it}.$$

Here, *ASTOV* and *STOV* are proxies for $\delta' y$ and y_k, respectively, in the proposition. For simplicity, Table 2 reports only the coefficient estimates of interest. Starting with the beta decile portfolios, the first column shows that the *PRE*×*ASTOV* coefficient is significant for almost every beta portfolio. The coefficient roughly increases with the portfolio's beta ranking, although the lowest beta decile has a slightly larger coefficient than the second decile. In the second column, the *PRE*×*STOV* coefficient exhibits no clear pattern and significance is much more muted, although it tends to be larger for the high beta portfolios. These patterns in the pre-announcement window are consistent with the prediction of Proposition 1.

The slope coefficients display similar patterns for the other portfolios in Table 2: positive and significant for *ASTOV* and insignificant for *STOV*. In the size-beta portfolios, we see confirmation of the result that the coefficient on *ASTOV* is larger for high beta stocks. In the size-BM portfolios, the *ASTOV* coefficient is lower for value than growth firms. There is no clear pattern in the coefficient on *ASTOV* as firm size varies.

The significance of *ASTOV* and, to a lesser extent, of *STOV* raises the possibility that these regressors are sufficient to explain the cross section of drifts. This possibility is confirmed in the columns for the *PRE* and *INI*×*PRE* coefficients, all of which are insignificant or significantly negative.[10] As a result, the close-to-2pm drift (calculated using, in addition, the untabulated estimates of the intercept and the *INI* coefficient) is negative for all the assets. Consistent with

[10] A negative coefficient on *PRE* or *INI*×*PRE* means that the drift actually is smaller than fit by the two imbalance measures, given the positive level of *ASTOV* with its positive loading and, to some degree, *STOV*.

Proposition 1, the adjusted R-squared generally increases in beta, although it becomes flat in the mid- to high-beta range. However, contrary to the proposition's prediction, the adjusted R-squared (in the 4% – 15% range) is well below 1, suggesting that these regressions leave substantial return variation unexplained.

3.5. The Aggregate Order Imbalance Explains the Drift

The previous section shows that each asset's drift is explained by its own order imbalance and the aggregate order imbalance. To see which imbalance plays a more important role, we run the following simple regression for each asset,

$$R_{it} = a_i + b_{1i}PRE_t + b_{2i}INI_t + b_{3i}INI_t \times PRE_t + b_{4i}X_t + b_{5i}PRE_t \times X_t + b_{6i}INI_t \times X_t + b_{7i}INI_t \times PRE_t \times X_t + \varepsilon_{it}, \quad (16)$$

where X_t is an order imbalance variable. According to Proposition 1, when X_t is *ASTOV*, its loading during the pre-announcement window (i.e., on $PRE_t \times X_t$) should increase in beta. To save space, we do not tabulate this coefficient but report that this is roughly true, and that the coefficient estimates are similar to the *PRE*×*ASTOV* coefficients in Table 2. Table 3 presents the drift-related coefficients, *PRE* and *INI*×*PRE*. Insignificant or negative values of these two coefficients imply that the pre-announcement drift is not significantly larger than during other periods.

Panel A shows the estimated *PRE* coefficient for R_{it} listed in rows and X_t in columns. In the first column, X_t is the portfolio's own *STOV*. We see that the *PRE* coefficient remains significantly positive—and thus the pre-FOMC drift excluding the initial five-minute period is significantly higher than other periods—for five of the ten beta portfolios, three of the six size-beta-sorted portfolios, two of the six size-BM-sorted portfolios, and both the ETFs. Panel B reports the estimated *INI*×*PRE* coefficient in the same format. Since there are 54 five-minute trading periods prior to the FOMC announcement (9:30am-2:00pm) and *INI* takes the value of one only in the initial period, the $INI \times PRE$ coefficient is estimated with one fifty-fourth as many observations as the PRE coefficient.[11] As a result, the t-statistics in Panel B are generally lower than in Panel A. Nevertheless, the coefficient on the interaction term is significantly positive for a few assets. Altogether, the drift for many portfolios cannot be explained by their own order imbalance.

In column 2 of Panels A and B, X_t is the aggregate order imbalance, *ASTOV*. The presence of *ASTOV* makes both the PRE and $INI \times PRE$ coefficients insignificant or negative.[12] Thus, the drift for every portfolio is explained by the market-wide imbalance alone. The contrasting success of aggregate and portfolio imbalances in explaining portfolio-level drift casts doubt on a mechanical explanation for the drift, wherein buying for a given portfolio leads to higher prices for that portfolio. Rather, it is the marketwide order imbalance that is closely associated with the price adjustment for disaggregated portfolios.

3.6. Betting on Beta and Cross-pumping

The near-linearity between order imbalance and beta, and the large buying pressure observed for high beta stocks, in the second to last column of Table 1 suggests that the explanatory power of *ASTOV* comes mainly from high beta stocks. To examine this point, we divide the universe of stocks into beta terciles. Specifically, at the end of the month immediately preceding an announcement, stocks are sorted into three groups (top 30%, middle 40% and bottom 30%) based on betas calculated from the previous six months of daily returns. We label the value-weighted average of five-minute order imbalances for the stocks in the high, middle, and low beta terciles

[11] Specifically, there are 163 announcement days in our sample period, and hence 163 observations with $INI \times PRE = 1$ in Panel B. In contrast, since there are 54 five-minute periods between the 9:30am open and the conservative announcement cutoff at 2:00pm, there are 8,802 (= 163×54) observations with $PRE = 1$ in Panel A.

[12] A negative coefficient implies that the drift should have been even larger given the buying pressure.

HSTOV, *MSTOV*, and *LSTOV*, respectively. The last three columns of the two panels in Table 3 present the result using each of these variables as X_t in Equation (16).

Columns 3 and 4 show that *HSTOV* and *MSTOV* make both the *PRE* and *INI*×*PRE* coefficients insignificant or negative, while *LSTOV* in Column 5 cannot. In particular, the positive and significant coefficients on *PRE* in Column 5 of Panel A, for essentially all but the low beta portfolios, are striking. The strong explanatory power of *HSTOV* for all the assets considered is consistent with high beta stocks held prior to announcement days (Proposition 2) being pumped (Proposition 1) in correlated pre-announcement markets. The fact that this is also true for *MSTOV* suggests the feasibility of cross-pumping (Proposition 3): If high beta stocks are hard to trade during the quiet pre-announcement period, traders can buy mid beta stocks to positively affect the value of their existing holdings of high-beta stocks through correlated price adjustments. This is a safer option than directly pumping their holdings if they are worried about detection and prosecution. In particular, note that the drift for beta deciles 9 and 10 as well as the size 1-beta 3 portfolio is not explained by their own order flows (as seen in the significant coefficients on *PRE* in Column 1 of Panel A), but the drift becomes insignificant with the incorporation of *MSTOV* (Column 4). Thus, *MSTOV* is able to explain the significant drift for the highest beta-tercile stocks whose order flows it does not include. The availability of several trading vehicles in the mid to high beta range makes the betting-on-beta strategy easier to implement.

4. Robustness and Additional Evidence

The previous section reveals that order imbalances for high (and mid) beta stocks explain the drifts on all the assets we examine. This section provides further evidence that betting on beta and cross-pumping drive this result. In particular, mid-sized trades play a key role, beta is critical in explaining stock-level drift, and the spread in beta is substantial.

4.1. What Sized-Trades Explain the Drift?

In this section, we look for evidence that the investors driving the price-moves in the pre-FOMC period are traders who can strategically exert positive price pressure, as embedded in Proposition 3. We proceed by examining the informativeness of order imbalances stratified by trade size.

This builds on prior research (e.g. Barber et al., 2009) suggesting that trade size can separate sophisticated (institutional) investors and more naïve or noise (and presumably retail) traders. Small trades are likely to come from retail investors. While it may be presumed that institutional trades will be large, at least two factors suggest that institutions will place only medium trades. The first factor is the dramatic reduction in trade sizes due to order fragmentation by algorithmic traders, starting in the early 2000s. The second is the illiquid market in the pre-announcement period. Betting-on-beta institutions placing large trades run the risk that their pumping motive will be detected by market makers and regulators; in a quiet market, large orders are likely to draw attention. The trader would need to somehow convince the market maker that his order is not strategic, but for example, driven by liquidity reasons.

Based on Barber et al.'s five trade-size bins as well as Lee and Radhakrishna's (2000, p.103) ultimate recommendation for a three-bin approach, we define three trade-size bins: small, medium, and large trades are trades below \$10,000, between \$10,000 and \$20,000, and above \$20,000, respectively. The bin cutoffs are defined in 1991 dollars, and adjusted for inflation using the Consumer Price Index. After compiling the five-minute trade imbalance in each trade size bin by stock, we value-weight the imbalances across all high beta stocks, as defined in the previous section. This gives a decomposition of *HSTOV* by trade-size bin.

Table 4 provides the results using each of the small-, medium-, and large-trade *HSTOV* as X_t in Equation (16). We see that the medium-trade *HSTOV* makes both the *PRE* and *INI×PRE* coefficients insignificant or negative, while the small- or large-trade HSTOV does not. Interestingly, the large-trade *HSTOV* has trouble in killing the *PRE* coefficient, while the small-trade *HSTOV* does so in nullifying the *INI×PRE* coefficient. This suggests that the prevalent drift on high beta stocks is due to medium and large trades at the open on FOMC announcement days, but to small and medium trades in subsequent trading. Medium trades work throughout, allowing betting-on-beta investors to pool with liquidity traders at the open and retail traders subsequently.

4.2. Beta is the only characteristic that explains the cross section of drift

By design, the portfolio approach in the previous sections can control only for the few characteristics we sort on. To rule out the possibility that some characteristics correlated with beta are driving the drift, we regress individual stock returns on multiple characteristics. In addition to the characteristics already introduced, we construct the following attributes known to spread returns in the cross section (our variable names are parenthesized in uppercase): profitability (the earnings-to-price ratio, *EPR*), momentum (the lagged 12-month return skipping a month, *MOM*), illiquidity (Roll's effective spread measure estimated over the previous 12 months, *ROLL*), equity issuance (over the [-19, -7] month window, *ISSUE*; Pontiff and Woodgate, 2008; McLean, Pontiff and Watanabe, 2013), idiosyncratic volatility (computed monthly from the daily three-factor model, *IVOL*; Ang et al., 2006), and a lottery characteristic (a dummy variable corresponding to the intersection of low price, high idiosyncratic volatility, and high idiosyncratic skewness, *LOTT*; Kumar, 2009). To make the estimation feasible, we reduce the time-series dimension by averaging a stock's *QRET* after the initial period on each non-announcement day, with the announcement day averages computed separately for the pre- and post-announcement periods. Thus, a stock has two return observations on each non-announcement day (corresponding to the initial period and the rest-of-day average), and likewise three periods on each announcement day.

Panel A of Table 5 provides the coefficient estimates from simple panel regressions of the return on the intercept and a characteristic (denoted by *Z*) interacted with the pre-announcement dummy (*PRE*) and the initial-period dummy (*INI*), with t-statistics based on standard errors clustered by stock and period.[13] The first column with no characteristic (shown with "---" for *Z*) confirms that the strong pre-FOMC announcement drift seen in portfolio returns also exists at the stock level. Ignoring the negligible intercept estimate (-0.01 bps), a typical stock gains 7.59 bps (*PRE×INI*, t = 2.12) in the opening five minutes on an announcement day and subsequently a further 0.162 bps (*PRE*, t = 2.08) per five minutes leading up to the announcement. Both values are roughly comparable to those for the median beta decile portfolio in Panel A of Table 1.

The second column titled "*BETA*" shows that market beta completely eliminates the strong pre-FOMC announcement drift of individual stocks, as both the *PRE* and *PRE×INI* coefficients are insignificant. While the base coefficient on *BETA* is -0.078 (t = -1.79), the coefficients on its interaction terms with *PRE* and *PRE×INI* are positive and significant at 0.291 (t = 3.89) and 8.20 (t = 2.77), respectively. Since the two interaction coefficients outweigh the base coefficient, stocks with higher betas tend to see larger gains prior to FOMC announcements.[14]

The coefficients on several other characteristics are significant in the five-day announcement window. Notably, announcement days see gains for large, liquid and non-lottery

[13] We thank Mitchell Petersen for making available his Stata code for panel regressions with two-way clustering.

[14] The negative base BETA estimate implies that high beta stocks tend to earn lower returns outside the pre-announcement window. This, along with the significantly positive intercept, challenges the CAPM.

stocks. However, none of these characteristics can make both the *PRE* and *PRE*×*INI* coefficients insignificant. Both remain significantly above zero, similar to the dummy-only model in the first column, except for the case in which *IVOL* makes *PRE*×*INI* insignificant. This underscores the importance of beta in explaining the cross-sectional variation in the drift on individual stocks.

Panel B of Table 5 reports the result of a panel regression with all the characteristics and their dummy interaction terms as independent variables. The *PRE* and *PRE*×*INI* coefficients in the first row (corresponding to the constant) are insignificant, which is to be expected for a specification that includes beta. This specification demonstrates the robustness of beta as the magnitude and significance of the coefficient on beta barely budge relative to the univariate specification in Panel A. Besides beta, the size and lottery interaction coefficients retain their significance, and their signs imply that large, high beta, and non-lottery stocks gain during the pre-FOMC period.

4.3. Wide Dispersion in Beta

Table 6 shows summary statistics for the market, characteristic portfolios, and ETFs in the pre-announcement window. The statistics are computed over the number of five-minute intervals shown in the #Int column. Beta changes monthly and size and BM annually, in June. The column titled "N" shows that, on average, 5,100 NYSE, AMEX, and NASDAQ stocks are in our sample. These are allocated to the beta decile portfolios, the six size-beta portfolios, and the six size-BM portfolios. The disproportionately large number of stocks in small size portfolios follows from the fact that most NASDAQ stocks have size below the NYSE median.

There is large variation in average beta, which ranges from -0.16 to 2.05 across the beta decile portfolios. The large spread in beta points to sizeable potential gains to betting on beta if pre-announcement returns are directly related to historical beta. This is possible if market makers follow similar inference processes over time, which results in persistent betas. However, as the "Size" column shows, high beta stocks typically are smaller than mid beta stocks: the average market value in beta deciles 8 to 10 lies between 2.4 and 2.9 billion dollars compared with a range of 3.2 to 3.9 billion dollars in beta deciles 4 to 7. This makes cross-pumping potentially attractive, because buying larger and thus more liquid mid-beta stocks is easier and the resulting market move will pull up the value of high-beta holdings indirectly and thus stealthily. This also is consistent with our evidence on the explanatory power of *MSTOV*, discussed in Table 3.

The rows corresponding to the six size-beta portfolios show that size varies widely for a given level of beta. For example, the big high-beta portfolio (Size 2, Beta 3) has an average size of 10.3 billion dollars, compared to a mere 0.4 billion dollars for the small high-beta portfolio (Size 1, Beta 3). According to the *STOV* column of Table 1, these two groups of stocks have average order imbalances of 4.23 and 1.89, respectively, so big stocks are more heavily bought. In fact, within a given beta tercile, or within a given BM tercile of the six size-BM portfolios, the big stock portfolio always has more than twice the order imbalance of its small stock counterpart. Therefore, in addition to beta, the size-related patterns in imbalances likely reflect the feasibility of the betting-on-beta strategy.

5. Conclusion

FOMC rate decision announcements convey systematic news with potential implications for the broad stock market. In a quiet market that typically precedes these announcements, there will be stronger comovement in stock prices. This factor structure gives rise to the potential profitability of betting on beta and cross-pumping strategies, where investors buy high beta stocks first and other stocks subsequently with a view to driving up the market and the value of their high beta holdings even further. We provide a model that formalizes this intuition. We propose this mechanism as a potential explanation for the upward drift in stock prices before FOMC announcements.

To evaluate this explanation, we compile returns and order imbalances at the five-minute frequency for NYSE, AMEX and NASDAQ stocks over the period September 1994 to December 2014. We confirm the existence of the pre-FOMC announcement drift across a variety of assets: individual stocks, the aggregate market, characteristic portfolios based on beta, size, and BM, as well as two popular ETFs. Portfolio sorts and panel regressions for individual stock returns show that, as predicted by the betting-on-beta hypothesis, assets with higher betas gain more strongly in the pre-FOMC announcement period.

Consistent with the cross-pumping hypothesis, the order imbalance for the market and for mid- to high-beta portfolios eliminates the drift for all the assets examined. Moreover, the order imbalance in the high-beta portfolio continues to explain the drift on all assets when we only consider mid-sized trades. Therefore, the trades that explain the drift appear to come from institutional traders, also consistent with the betting-on-beta hypothesis. Collectively, our analysis suggests that institutional investors' bets on high beta stocks and subsequent cross-pumping is a partial explanation for the strong drift seen before FOMC announcements.

A. Appendix

A.1. Proofs

A.1.1. Proof of Lemma 1

Substituting (5) for P_1 in (12) and omitting the constant $\bar{y}$, we get

$$\beta = \frac{Cov(\Lambda y, y'\Lambda\delta)}{Var(y'\Lambda\delta)} = \frac{\Lambda Var(y)\Lambda\delta}{\delta'\Lambda Var(y)\Lambda\delta}. \tag{17}$$

Here, by the definition of Λ in (34),

$$\Lambda Var(y)\Lambda = Cov(v, y')\Lambda = \frac{1}{2}\Sigma_v \Lambda^{-1}\Lambda = \frac{1}{2}\Sigma_v. \tag{18}$$

Substituting into (17) and omitting the constant, 1/2, gives

$$\beta = \frac{\Sigma_v \delta}{\delta'\Sigma_v\delta} = \frac{\delta}{\delta'\delta}, \tag{19}$$

where the last equality follows because δ is an eigenvector of Σ_v and we have canceled its eigenvalue in the numerator and denominator. Since $\delta'\delta$ in the denominator is a scalar, this is proportional to δ. ∎

A.1.2. Proof of Theorem 1

The informed trader's problem is standard. Denote his terminal wealth by

$$W_i = \xi'(v - P_1). \tag{20}$$

With the price conjecture in (5), his expected wealth is

$$\max_{\xi} E_i[W_i] = \xi'(v - E_i[P_1]) = \xi'[v - P_0 - \Lambda(\bar{x} + \xi - \bar{y})], \tag{21}$$

$$\bar{x} \equiv E_i[x] = E[x], \tag{22}$$

where $E_i[]$ denotes the informed trader's expectation and $E[]$ the unconditional expectation. That is, $\bar{x}$ is the common prior about the fund manager's trade available to all participants. Assuming the symmetry of Λ, the first order condition with respect to ξ is

$$v - P_0 - \Lambda(\bar{x} - \bar{y}) - 2\Lambda\xi = 0. \tag{23}$$

The solution is

$$\xi = \frac{1}{2}\left[\Lambda^{-1}(v - P_0) + \bar{y} - \bar{x}\right]. \tag{24}$$

Substituting this into the definition of the expected order flow gives

$$\bar{y} = E[x + \xi + u] = \bar{x} + \frac{1}{2}(\bar{y} - \bar{x}), \tag{25}$$

or

$$\bar{y} = \bar{x}. \tag{26}$$

Substituting this back to (24) fixes

$$\xi = \frac{1}{2}\Lambda^{-1}\left(v - P_0\right). \tag{27}$$

We next solve the fund manager's problem. Let $E_1[]$ denote her expectation at time 1. Without knowledge about v, she holds that $E_1[v] = P_0$, $E_1[\xi] = 0$ due to (27), and hence $E_1[y] = x + E_1[\xi] = x$. Thus, her expected return given the price conjecture in (5) is

$$E_1[P_1 - P_0] = \Lambda(E_1[y] - \bar{y}) = \Lambda(x - \bar{y}). \tag{28}$$

Using this, she maximizes her expected terminal wealth in (2):

$$\begin{aligned}\max_x E_1[W] &= I_0 + [\gamma z - (1-\gamma)x]' E_1[P_1 - P_0] \\ &= I_0 + [\gamma z - (1-\gamma)x]' \Lambda(x - \bar{y}).\end{aligned} \tag{29}$$

Again assuming the symmetry of Λ, the first order condition with respect to x is

$$0 = -(1-\gamma)\Lambda(x-\overline{y}) + \Lambda[\gamma z - (1-\gamma)x]. \tag{30}$$

Canceling Λ and solving for x, we get

$$x = \frac{1}{2}\left(\overline{y} + \frac{\gamma}{1-\gamma} z\right). \tag{31}$$

Taking the unconditional expectation and using (26) gives

$$\overline{y} = \overline{x} = \frac{\gamma}{1-\gamma}\overline{z}. \tag{32}$$

Substituting this into (31) fixes

$$x = \frac{1}{2}\frac{\gamma}{1-\gamma}(z+\overline{z}). \tag{33}$$

Effectively, ξ in (27) and x in (33) decompose a multivariate version of Equation (3) in Bhattacharyya and Nanda (2013) into informational and pumping demands, respectively.

Finally, the projection theorem fixes Λ. Dropping constant x and again assuming the symmetry of Λ,

$$\begin{aligned} \Lambda &= Cov(v, y')Var^{-1}(y) = Cov(v, \xi')Var^{-1}(\xi + u) \\ &= \frac{1}{2}\Sigma_v \Lambda^{-1}\left[\frac{1}{4}\Lambda^{-1}\Sigma_v\Lambda^{-1} + \Sigma_u\right]^{-1}. \end{aligned} \tag{34}$$

Post-multiply the square bracket to both sides and rearrange to write

$$4\Lambda\Sigma_u\Lambda = \Sigma_v. \tag{35}$$

Pre- and post-multiply $\Sigma_u^{1/2}$ to both sides, complete the square on the left hand side, take the matrix square root, and solve for Λ to get the solution,

$$\Lambda = \frac{1}{2}\Sigma_u^{-1/2}(\Sigma_u^{1/2}\Sigma_v\Sigma_u^{1/2})^{1/2}\Sigma_u^{-1/2}, \tag{36}$$

which is indeed symmetric as assumed. Plugging $\Sigma_u = \sigma_u^2 I$ under Assumption 2 immediately gives Equation (10) in the theorem. Under Assumption 1, it can be further rewritten as (37) in the proof of Proposition 1, which shows that all elements of Λ are positive. ∎

A.1.3. Proof of Proposition 1

Define the normalized factor loading, $q = \delta / \sqrt{\delta'\delta}$. By Lemma 1, the vector of betas is proportional to δ and hence q. Under the factor structure, Σ_v has the spectral decomposition, $\Sigma_v = d_{vq}qq' + \sigma_\varepsilon^2(I - qq')$, where $d_{vq} = \sigma_{vM}^2\delta'\delta + \sigma_\varepsilon^2$ is the eigenvalue for eigenvector q, $I - qq'$ is the sum of outer products of all the other eigenvectors orthogonal to q, and σ_ε^2 is their common eigenvalue. The analytical solution of the price-impact coefficient matrix reduces to

$$\Lambda = \frac{1}{2\sigma_u}\Sigma_v^{1/2} = \frac{1}{2\sigma_u}[\sqrt{d_{vq}}qq' + \sigma_\varepsilon(I - qq')], \tag{37}$$

whose elements all are positive because δ and hence q are a positive vectors and $\sqrt{d_{vq}} > \sigma_\varepsilon$ (factor the above expression by qq' and evaluate the sign). Then, the k'th row of $P_1 - P_0 = \Lambda(y - \bar{y})$ is a linear function of only $q'y$, which is proportional to the aggregate order flow $\delta'y$, and the asset's own order flow y_k for any k, where subscript k generally denotes the k'th element of a vector. It follows that a multiple regression of asset k's drift on $q'y$ and y_k with an intercept gives slope coefficients $(\sqrt{d_{vq}} - \sigma_\varepsilon)q_k / 2\sigma_u > 0$ on $q'y$ and $\sigma_\varepsilon/2\sigma_u > 0$ on y_k with a perfect R-squared of 1. Here, the slope coefficient on $q'y$ is positive and proportional to q_k, which in turn is proportional to the factor loading, δ_k, and hence beta. Moreover, the slope coefficient on y_k is identical across assets.

To analyze a simple regression of asset k's drift on $q'y$ with an intercept, rewrite

$$P_1 - P_0 = a + b \cdot q'y + e, \tag{38}$$

where $a=-\sqrt{d_{vq}}qq'\bar{y}/2\sigma_u$, $b=\sqrt{d_{vq}}q/2\sigma_u$, and $e=\sigma_\varepsilon(I-qq')(y-\bar{y})/2\sigma_u$. Thus, regressing P_1-P_0 on $q'y$ gives the above intercept a, slope coefficient b, and residual e, which has mean $E[e]=0$ and satisfies the orthogonality condition, $Cov(e, q'y)=0$, because (rows of) $I-qq'$ and q are orthogonal to each other. Again, the regression slope b is proportional to q, and hence δ as well as the beta. By (34) and (35), $Var(y)=\Lambda^{-1}\Sigma_v\Lambda^{-1}/2=2\sigma_u^2I$. So, the explained sum of squares of this multivariate regression is given by $ESS=diag(Var(b\cdot q'y))=(d_{vq}/2)diag(qq')$, where $diag()$ gives a vector of diagonal elements of the argument matrix. The total sum of squares of the regression is $TSS=diag(Var(\Lambda(y-\bar{y})))=diag(\Sigma_v)/2$. Denoting the k'th element of vectors by subscript k, the regression R-squared for the k'th asset is

$$R_k^2=\frac{ESS_k}{TSS_k}=\frac{d_{vq}q_k^2/2}{\sigma_{vk}^2/2}=\frac{\sigma_{vM}^2+\sigma_\varepsilon^2/\delta'\delta}{\sigma_{vM}^2+\sigma_\varepsilon^2/\delta_k^2}. \tag{39}$$

which is always between 0 and 1 because $\delta'\delta>\delta_k^2>0$. So, the higher the loading δ_k and hence the asset's beta, the higher the R-squared. ■

A.1.4. Proof of Proposition 2

Substituting the manager's optimal trade (33) into the manager's expected wealth in (29) using the expected order flow in (32) gives

$$E_1[W]=I_0+\frac{1}{4}\frac{\gamma^2}{1-\gamma}(z-\bar{z})'\Lambda(z-\bar{z}). \tag{40}$$

It suffices to show the claim in the limit as $\bar{z}\to 0$. So, set $\bar{z}=0$. Since the capital constraint and short-selling restrictions in (6) are linear in z, they form a feasible set, Φ that is enclosed by $K+1$ hyperplanes, each being $K-1$ dimensional (If $K=2$, the set is a triangle enclosed by three straight lines). The corner on the k'th axis of this feasible set is $(hI_0/P_{0k})\iota_k$, $1 \leq k \leq K$, where ι_k is a vector with one as the k'th element and zero otherwise. Maximizing (41**Error! Reference source not found.**) is equivalent to maximizing

$$z'\Lambda z = z'QDQ'z = \left\|D^{1/2}Q'z\right\|^2 \tag{42}$$

in the feasible set, where $\| \|$ represents the Euclidian norm. Since $D^{1/2}Q'z$ is a linear transformation of z, it is also a set enclosed by K + 1 hyperplanes. (42) measures the squared distance between a point in this transformed feasible set and the origin, and is maximized at the corner that is farthest away from the origin.[15] Thus, it suffices to take the maximum of the quadratic form over the K corners of the original feasible set excluding the origin,

$$\max_{z\in\Phi} z'\Lambda z = \max_{1\leq k\leq K}\left(\frac{hI_0}{P_{0k}}\iota_k\right)'\Lambda\left(\frac{hI_0}{P_{0k}}\iota_k\right) = (hI_0)^2\frac{\Lambda_{kk}}{P_{0k}^2}, \tag{43}$$

where Λ_{kk} is the k'th diagonal element of Λ. Since hI_0 is common across the stocks, the maximum obtains at the k'th corner of the transformed feasible set, i.e., by investing all new capital in the stock with the largest Λ_{kk}/P_{0k}^2. Since $P_{0k} = v_0$ is common across the stocks under Assumption 1, this ends up being the stock with the largest factor loading (see the expression for Λ in (37) and note that the coefficient on qq', $\sqrt{d_{vq}} - \sigma_\varepsilon$, is positive) and hence beta by Lemma 1. █

A.1.5. Proof of Proposition 3

It suffices to show the claim in the limit as $\bar{z} \to 0$. With $\bar{z} = 0$, setting the first line of (13) greater than the initial capital requires that

[15] Specifically, first note that Q' represents a "rotation" in the K-dimensional space because it does not change the length of a vector ($|Q'z|^2 = z'QQ'z = z'z = |z|^2$). Thus, (42) rotates the feasible set by some angle, multiply $\sqrt{d_k}$ to the coordinates of each corner, and measure its squared distance from the origin. This is maximized at the corner that is farthest away from the origin.

$$E_1[W] = I_0 - (1-\gamma)\left(x - \frac{\gamma}{1-\gamma}z\right)'\Lambda x > I_0, \tag{44}$$

or

$$x'\Lambda x < \frac{\gamma}{1-\gamma}z'\Lambda x. \tag{45}$$

Suppose z does not hold at least the k'th asset. Let ι_k be a column vector containing 1 in the kth position and 0 elsewhere. Set $x = c\iota_k$, where c is some positive constant. Substituting into (45) and solving for c, we see that the inequality is satisfied by taking

$$c < \frac{\gamma}{1-\gamma}\frac{z'\Lambda\iota_k}{\lambda_{kk}}, \tag{46}$$

where $z'\Lambda\iota_k > 0$ (because $z \geq 0$ by assumption and all elements of Λ in (37) are positive) is the inner product of z and the kth column of Λ, and $\lambda_{kk} > 0$ is the kth diagonal element of Λ. Moreover, since the right hand side of (46) is strictly positive for any $0 < \gamma < 1$, there is a continuum of such c, i.e., there exist infinitely many profitable cross-pumping strategies. This proves the first half of the proposition.

To show the second half, denote the wealth of strategy x by $W(x)$. Then, calculating the difference in the expected wealth between two strategies x_a and x_b by (44) gives

$$\begin{aligned}
&E_1[W(x_a)] - E_1[W(x_b)] \\
&= (1-\gamma)\left[x_b'\Lambda x_b - x_a'\Lambda x_a + \frac{\gamma}{1-\gamma}z'\Lambda(x_a - x_b)\right] \\
&= \frac{1-\gamma}{2\sigma_u}\left[\begin{array}{l}\sigma_\varepsilon(x_b'x_b - x_a'x_a) + (\sqrt{d_{vq}} - \sigma_\varepsilon)(x_b'qq'x_b - x_a'qq'x_a) \\ + \frac{\gamma}{1-\gamma}\left\{\sigma_\varepsilon z'(x_a - x_b) + (\sqrt{d_{vq}} - \sigma_\varepsilon)z'qq'(x_a - x_b)\right\}\end{array}\right],
\end{aligned} \tag{47}$$

where the last equality follows from the expression for Λ in (37). Here, since x_a and x_b have an equal sum of squared shares traded, we have $x_b'x_b - x_a'x_a = 0$. Moreover, it follows from the orthogonality of both x_a and x_b to z that $z'(x_a - x_b) = 0$. Therefore, the above expression simplifies to

$$
\begin{aligned}
&E_1[W(x_a)] - E_1[W(x_b)] \\
&= (1-\gamma)\frac{\sqrt{d_{vq}} - \sigma_\varepsilon}{2\sigma_u}\left[(q'x_b)^2 - (q'x_a)^2 + \frac{\gamma}{1-\gamma}z'qq'(x_b - x_b)\right] \\
&= (1-\gamma)\frac{\sqrt{d_{vq}} - \sigma_\varepsilon}{2\sigma_u}(q'x_a - q'x_b)\left[\frac{\gamma}{1-\gamma}q'z - q'(x_a + x_b)\right].
\end{aligned}
\tag{48}
$$

Since $q'z > 0$ and $q'(x_a + x_b) > 0$, the square bracket is positive for γ close enough to 1. For such γ, $E_1[W(x_a)] > E_1[W(x_b)]$ if $q'x_a - q'x_b > 0$, i.e., if strategy x_a has a higher beta than strategy x_b by Lemma 1. In words, under strong enough short termism, cross-pumping high beta stocks earns a larger expected profit than cross-pumping low beta stocks. ■

A.2. Data Construction

From the TAQ database, we use only quotes and trades that meet no-arbitrage and eligibility conditions. Specifically, a quote must have an offer price greater than the bid price, which must be positive, and a mode flag 1, 2, 6, 10, 12, or 23. A trade must have a correction indicator of 0 (no correction) with a condition flag other than O, Z, B, T, L, G, W, J, or K.

For each domestic ordinary common stock on the NYSE, AMEX and NASDAQ (CRSP Exchange Code 1, 2, or 3 and Share Code 10 or 11) and the SPY and QQQ ETFs, we calculate the five-minute mid-quote return, volume and order imbalance. TAQ and CRSP are matched by the ticker symbol if it is unique on a given day or the first 8 characters of CUSIP, whichever matches. CUSIP matching is necessary because CRSP can have multiple share classes of a single stock with the same ticker symbol. QQQ temporarily changes its ticker symbol to QQQQ (and also CRSP PERMNO) during our sample period. We examined the price, volume, and number of shares outstanding and determined that they are identical securities for investment purposes. Our analysis adds in the period in which QQQ is traded as QQQQ.

The excess return is given by the difference between the raw return and the risk-free rate from the daily Fama-French factor file, prorated over five minutes. It is calculated as the five-minute raw return less the daily risk-free rate divided by 78, the number of five-minute intervals in the 6½ hour trading day. Using a divisor of 288, which is the number of five-minute intervals in a 24-hour day, does not change our conclusions. Using raw returns instead of excess returns increases the magnitude of the drift slightly but has no material effect on our conclusions.

Trades are signed using the Lee-Ready (1991) algorithm, as a buy if the transaction price is closer to the ask than to the bid and a sell if it is closer to the bid than the ask. Midquote trades are classified by the tick test, i.e., as a buy (sell) if the transaction-price change is positive (negative). We note the sign of each trade and also assign the trade to one of five size bins based on the dollar volume of the trade. For this, we follow Barber et al. (2009), who define inflation-adjusted cutoffs for the dollar value of each trade (DVOL) of: (1) DVOL ≤ \$5000; (2) \$5000 < DVOL ≤ \$10000; (3) \$10000 < DVOL ≤ \$20000; (4) \$20000 < DVOL ≤ \$50000; (5) \$50000 < DVOL. DVOL is defined in 1991 dollars, and we adjust the cutoffs over time using the inflation rate to keep the economic size of the bins comparable.[16] The volume and order imbalance data (total and in the trade size bins) are aggregated for five-minute windows and then within portfolios of interest.

[16] Specifically, using the monthly series CPIAUCNS from St. Louis FED's FRED database, we compute the cutoffs for any month by multiplying the raw cutoffs by the ratio of CPIAUCNS for that month to its average over the three-month period, November 1990 through January 1991. The three-month period is used by Lee and Radhakrishna (2000), whose trade size definition is adapted by Barber, Odean and Zhu (2009).

References

Ai, Hengjie, and Ravi Bansal, 2017, "Risk Preferences and The Macro Announcement Premium," *Working paper, Minnesota and Duke*.

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, "The Cross-Section of Volatility and Expected Returns," *Journal of Finance* 61, 259-299.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, "Do Retail Trades Move Markets?," *Review of Financial Studies* 22, 151-186.

Bernile, Gennaro, Jianfeng Hu and Yuehua Tang, 2016, "Can Information be Locked Up? Informed Trading Ahead of Macro-News Announcements," *Journal of Financial Economics* 121, 496-520.

Bhattacharyya, Sugato and Vikram Nanda, 2013, "Portfolio Pumping, Trading Activity and Fund Performance," *Review of Finance* 17, 885–919.

Christoffersen, Susan and Mikhail Simutin, 2015, "On the Demand for High-Beta Stocks: Evidence from Mutual Funds," *Working paper, University of Toronto*.

Cieslak, Anna, Adair Morse and Annette Vissing-Jorgenson, 2016, "Stock Returns Over the FOMC Cycle," *Working paper, Duke and Berkeley*.

Fama, Eugene F., and Kenneth R. French, 1993, "Common Risk Factors in The Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3-56.

Frazzini, Andrea and Lasse Pedersen, 2014, "Betting Against Beta," *Journal of Financial Economics* 111, 1–25.

Hu, Gang, David McLean, Jeffrey Pontiff and Qinghai Wang, 2014, "The Year-End Trading Activities of Institutional Investors: Evidence from Daily Trades," *Review of Financial Studies* 27, 1593-1614.

Kumar, Alok, 2009, "Who Gambles in the Stock Market?" *Journal of Finance* 64 (4), 1889-1933.

Kyle, Albert S., 1985, "Continuous Auctions and Insider Trading," *Econometrica* 53, 1315-1335.

Lee, Charles and Balkrishna Radhakrishna, 2000, "Inferring Investor Behavior: Evidence from TORQ Data," *Journal of Financial Markets* 3, 83-111.

Lee, Charles and Mark Ready, 1991, "Inferring Trade Direction from Intraday Data," *Journal of Finance* 46, 733-746.

Lucca, David and Emanuel Moench, 2015, "The pre-FOMC Announcement Drift," *Journal of Finance* 70 (1), 329-371.

McLean, David, Jeffrey Pontiff, and Akiko Watanabe, 2009, “Share Issuance and Cross-sectional Returns: International Evidence,” *Journal of Financial Economics* 94, 1-17.

Pasquariello, Paolo, and Yifei Wang, 2017, “Speculation with Information Disclosure,” *Working paper, Michigan*.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, “Share Issuance and Cross-sectional Returns,” *Journal of Finance* 63 (2), 921-945.

Savor, Pavel and Mungo Wilson, 2013, “How Much Do Investors Care About Macroeconomic Risk? Evidence From Scheduled Economic Announcements”, *Journal of Financial and Quantitative Analysis* 48, 343-375.

Table 1: Pre-FOMC Announcement Drift for Characteristic Portfolios and ETFs. This table shows the coefficient estimates from a regression of the excess intraday quote-midpoint portfolio return (*QRET*) on a pre-FOMC dummy (*PRE*) and an initial period dummy (*INI*) with an intercept. *QRET* is based on the national best bid-and-offer quote midpoints at five-minute intervals from the TAQ dataset. The results are presented for beta decile portfolios, six size-beta portfolios, six size-book-to-market (BM) portfolios, and two exchange-traded funds (ETFs), the S&P 500 (SPY) and the NASDAQ 100 (QQQ). The beta decile portfolios are formed at each month end using market betas estimated from the previous six months of daily returns. The six size-BM portfolios are formed by sorting stocks annually at the end of June by market capitalization (size) and the book-to-market ratio (BM) using the median size and tercile BM breakpoints for NYSE stocks, as defined in Fama and French (1993). The six size-beta portfolios are formed at each month end using beta and size. *PRE* is 1 if the five-minute period is before 2:00pm on an FOMC announcement day, and 0 otherwise. *INI* is 1 for the initial five-minute period on each day, and 0 otherwise. *STOV* is the value-weighted average, over the portfolio's member stocks, of five-minute signed volume normalized by the number of shares outstanding (in units of thousands) from the CRSP dataset, where each trade is signed using the Lee-Ready algorithm. *TOV* is its unsigned version. "Adj R^2" is the adjusted R-squared. Unless otherwise noted, the sample period is 9:30am-4:00pm during five-day windows centered on FOMC announcement days between September 27, 1994 and December 19, 2014 (shown as "full" in the Period column). t-statistics are shown in parentheses and are based on standard errors using the Newey-West correction with 16 lags. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. "#obs" is the number of observations. "Close-2pm drift" is the cumulative drift from the market close on the previous day of announcement to 2pm on the announcement day.

Asset	*PRE* (bp)		*INI* (bp)		*INI*×*PRE* (bp)		Const (bp)		Adj R^2	Period	#obs	Close-2pm drift (%)	*STOV*	*TOV*
Market, LM	0.477 ***	(5.16)	3.87	(1.40)	3.43	(0.58)	0.020	(0.41)	0.003	-3/17/11	51737	0.342	3.49	76.4
Market	0.391 ***	(4.69)	2.87	(1.05)	7.31	(1.38)	0.021	(0.48)	0.003	full	63407	0.325	2.86	79.0
Beta 1	-0.064	(-0.90)	4.41 **	(2.04)	-0.93	(-0.19)	0.025	(0.84)	0.003	full	63407	0.014	1.67	75.0
Beta 2	0.052	(0.78)	0.95	(0.57)	-0.33	(-0.11)	0.015	(0.55)	0.000	full	63407	0.042	0.56	55.5
Beta 3	0.136 *	(1.95)	1.73	(1.00)	1.04	(0.23)	-0.007	(-0.19)	0.001	full	63407	0.097	1.15	56.1
Beta 4	0.190 ***	(2.76)	-0.06	(-0.03)	3.75	(0.88)	0.053	(1.63)	0.001	full	63407	0.168	1.69	56.4
Beta 5	0.179 **	(2.35)	0.79	(0.33)	4.08	(0.85)	0.042	(1.18)	0.001	full	63407	0.168	2.00	63.7
Beta 6	0.215 **	(2.50)	-0.78	(-0.29)	11.54 **	(2.17)	0.038	(0.92)	0.003	full	63407	0.244	2.54	68.4
Beta 7	0.333 ***	(3.59)	1.28	(0.43)	10.07 *	(1.82)	0.037	(0.81)	0.003	full	63407	0.314	2.69	76.9
Beta 8	0.383 ***	(3.56)	1.23	(0.35)	11.59 *	(1.75)	0.028	(0.54)	0.003	full	63407	0.351	3.17	88.2
Beta 9	0.581 ***	(4.32)	4.14	(1.00)	14.98 *	(1.82)	-0.030	(-0.46)	0.004	full	63407	0.490	3.16	108.3
Beta 10	0.911 ***	(4.91)	6.36	(1.05)	21.10 *	(1.95)	-0.106	(-1.26)	0.006	full	63407	0.711	5.96	172.9
Size 1, Beta 1	0.023	(0.48)	3.44 **	(2.53)	2.72	(1.00)	0.041 *	(1.93)	0.008	full	63407	0.096	-1.13	57.8
Size 1, Beta 2	0.227 ***	(2.80)	0.77	(0.33)	6.95	(1.54)	0.080 **	(2.09)	0.002	full	63407	0.244	0.67	79.9
Size 1, Beta 3	0.494 ***	(3.64)	5.42	(1.49)	13.38 *	(1.94)	-0.019	(-0.30)	0.007	full	63407	0.445	1.89	137.7
Size 2, Beta 1	0.136 *	(1.86)	1.04	(0.62)	0.04	(0.01)	-0.015	(-0.39)	0.000	full	63407	0.076	1.63	56.4
Size 2, Beta 2	0.254 ***	(3.41)	0.12	(0.05)	7.09	(1.48)	0.038	(1.01)	0.002	full	63407	0.230	2.46	63.5
Size 2, Beta 3	0.631 ***	(4.71)	4.04	(0.89)	14.40 *	(1.72)	-0.032	(-0.49)	0.004	full	63407	0.509	4.23	116.3
Size 1, BM 1	0.328 ***	(3.01)	5.18 *	(1.73)	9.04	(1.61)	0.008	(0.16)	0.006	full	63407	0.324	1.34	125.0
Size 1, BM 2	0.293 ***	(3.15)	1.09	(0.41)	9.54 *	(1.87)	0.066	(1.51)	0.003	full	63407	0.300	0.59	86.1
Size 1, BM 3	0.283 ***	(3.17)	0.82	(0.33)	9.20 *	(1.82)	0.061	(1.44)	0.003	full	63407	0.286	1.03	81.2
Size 2, BM 1	0.389 ***	(4.53)	3.90	(1.47)	5.61	(1.11)	0.016	(0.36)	0.003	full	63407	0.314	2.75	77.4
Size 2, BM 2	0.398 ***	(4.58)	0.32	(0.12)	8.26	(1.48)	0.029	(0.67)	0.002	full	63407	0.317	3.27	71.5
Size 2, BM 3	0.295 ***	(3.00)	0.43	(0.13)	12.24 *	(1.87)	0.016	(0.33)	0.003	full	63407	0.295	3.77	80.7
SPY	0.462 ***	(4.92)	3.35	(1.09)	2.93	(0.51)	0.010	(0.20)	0.001	full	63407	0.318	106.70	1707.5
QQQ	0.608 ***	(3.53)	6.11	(1.23)	12.60	(1.49)	0.020	(0.23)	0.003	3/26/99-	49403	0.528	17.12	1793.4

Table 2: Multiple regression of return on aggregate and the asset's own order flows. This table shows selected coefficient estimates from the multiple regression of an asset's five-minute return on the aggregate order flow (*ASTOV*) and the asset's own order flow (*STOV*) with an intercept interacted with the pre-FOMC dummy (*PRE*) and the initial period dummy (*INI*) in Equation (15). "Adj R^2" is the adjusted R-squared. t-statistics are shown in parentheses and are based on standard errors using the Newey-West correction with 16 lags. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. "Close-2pm drift" is the cumulative drift from the market close on the previous day of announcement to 2pm on the announcement day using relevant coefficient estimates.

Asset	*PRE*×*ASTOV* (×1000)			*PRE*×*STOV* (×1000)			*PRE* (bp)			*INI*×*PRE* (bp)		Adj R^2	Close-2pm drift (%)
Beta 1	3.87	**	(2.51)	-0.69	***	(-2.86)	-0.235	***	(-3.21)	-5.40	(-0.98)	0.040	-0.179
Beta 2	1.70		(1.02)	0.44		(0.69)	-0.064		(-0.82)	-2.48	(-0.56)	0.038	-0.124
Beta 3	4.08	*	(1.88)	0.66		(0.45)	-0.065		(-0.71)	-7.22	(-0.99)	0.062	-0.218
Beta 4	5.65	***	(2.75)	2.47	*	(1.68)	-0.125		(-1.47)	-1.65	(-0.30)	0.096	-0.207
Beta 5	8.25	***	(2.89)	0.72		(0.48)	-0.213	**	(-2.08)	-1.51	(-0.24)	0.101	-0.274
Beta 6	8.13	***	(2.60)	2.65	*	(1.78)	-0.258	**	(-2.25)	6.51	(0.96)	0.102	-0.263
Beta 7	12.71	***	(3.86)	3.14	**	(2.19)	-0.305	**	(-2.40)	5.70	(0.82)	0.105	-0.300
Beta 8	15.82	***	(4.30)	1.99		(1.49)	-0.345	**	(-2.38)	5.21	(0.62)	0.105	-0.359
Beta 9	18.70	***	(3.88)	3.36	**	(2.42)	-0.320	*	(-1.83)	8.09	(0.74)	0.100	-0.371
Beta 10	32.76	***	(5.18)	-0.63		(-0.40)	-0.351		(-1.52)	9.76	(0.69)	0.104	-0.454
Size 1, Beta 1	5.21	***	(3.62)	-1.13	**	(-2.14)	-0.181	***	(-3.37)	2.10	(0.67)	0.112	-0.082
Size 1, Beta 2	12.87	***	(5.07)	-1.91	*	(-1.65)	-0.253	**	(-2.57)	4.70	(0.96)	0.130	-0.141
Size 1, Beta 3	20.25	***	(5.43)	-0.49		(-0.33)	-0.345	**	(-2.29)	6.69	(0.88)	0.145	-0.217
Size 2, Beta 1	2.86		(1.10)	0.41		(0.28)	-0.029		(-0.28)	-7.19	(-0.93)	0.056	-0.213
Size 2, Beta 2	8.79	***	(2.66)	2.74		(1.00)	-0.228	**	(-2.15)	1.94	(0.30)	0.114	-0.279
Size 2, Beta 3	21.28	***	(3.78)	1.68		(0.80)	-0.310	*	(-1.75)	5.19	(0.42)	0.102	-0.408
Size 1, BM 1	17.60	***	(5.80)	-1.76	*	(-1.76)	-0.368	***	(-2.98)	5.81	(0.96)	0.143	-0.193
Size 1, BM 2	13.74	***	(5.24)	-0.99		(-0.74)	-0.218	**	(-2.04)	7.50	(1.34)	0.127	-0.110
Size 1, BM 3	12.85	***	(4.66)	-0.10		(-0.07)	-0.219	**	(-2.08)	1.80	(0.31)	0.130	-0.200
Size 2, BM 1	18.45	***	(3.49)	-2.36		(-0.61)	-0.251	**	(-1.96)	-1.73	(-0.24)	0.129	-0.342
Size 2, BM 2	12.02	***	(3.20)	2.03		(0.68)	-0.201		(-1.63)	3.43	(0.44)	0.119	-0.275
Size 2, BM 3	10.01	***	(3.30)	2.02		(1.62)	-0.265	**	(-2.06)	6.68	(0.67)	0.098	-0.302
SPY	15.46	***	(4.49)	0.01		(0.54)	-0.224	*	(-1.66)	-1.79	(-0.23)	0.094	-0.358
QQQ	28.09	***	(5.34)	0.09	*	(1.90)	-0.488	**	(-2.19)	6.16	(0.65)	0.116	-0.405

Table 3: Simple regression of return on order flow. This table shows selected coefficient estimates from the simple regression of an asset's five-minute return on an order flow measure with an intercept interacted with the pre-FOMC dummy (*PRE*) and the initial period dummy (*INI*) in Equation (16). The order flow measure is either an asset's own order flow (*STOV*), the aggregate order flow (*ASTOV*), high- (*HSTOV*), mid- (*MSTOV*), or low-beta (*LSTOV*) stock order flow. Panels A shows the coefficient on the *PRE* dummy and Panel B the coefficient on the interaction term of the *INI* and *PRE* dummies. t-statistics are shown in parentheses and are based on standard errors using the Newey-West correction with 16 lags. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *PRE* coefficient

Asset	(1) *STOV*			(2) *ASTOV*			(3) *HSTOV*			(4) *MSTOV*			(5) *LSTOV*		
Market	-0.251	**	(-2.05)	-0.251	**	(-2.05)	0.021		(0.21)	0.061		(0.60)	0.473	***	(5.61)
Beta 1	-0.079		(-1.11)	-0.222	***	(-3.02)	-0.162	**	(-2.25)	-0.161	**	(-2.19)	-0.036		(-0.51)
Beta 2	0.059		(0.90)	-0.077		(-0.97)	0.000		(0.00)	-0.024		(-0.32)	0.080		(1.18)
Beta 3	0.190	***	(2.68)	-0.085		(-0.92)	0.029		(0.37)	0.023		(0.28)	0.170	**	(2.45)
Beta 4	0.139	**	(1.97)	-0.129		(-1.50)	0.029		(0.39)	-0.012		(-0.16)	0.255	***	(3.73)
Beta 5	0.152	*	(1.91)	-0.222	**	(-2.16)	-0.043		(-0.50)	-0.050		(-0.54)	0.243	***	(3.17)
Beta 6	0.113		(1.19)	-0.260	**	(-2.26)	-0.038		(-0.40)	-0.078		(-0.74)	0.299	***	(3.46)
Beta 7	0.080		(0.86)	-0.303	**	(-2.38)	-0.023		(-0.22)	-0.044		(-0.40)	0.418	***	(4.43)
Beta 8	0.163		(1.40)	-0.350	**	(-2.41)	-0.076		(-0.61)	-0.004		(-0.03)	0.472	***	(4.33)
Beta 9	0.325	**	(2.38)	-0.341	*	(-1.95)	-0.014		(-0.09)	0.122		(0.82)	0.681	***	(5.07)
Beta 10	0.374	*	(1.92)	-0.312		(-1.35)	0.109		(0.53)	0.323		(1.62)	1.031	***	(5.53)
Size 1, Beta 1	0.022		(0.48)	-0.177	***	(-3.09)	-0.095	*	(-1.94)	-0.104	*	(-1.95)	0.050		(1.05)
Size 1, Beta 2	0.151	**	(2.15)	-0.197	*	(-1.94)	-0.037		(-0.43)	-0.022		(-0.24)	0.287	***	(3.59)
Size 1, Beta 3	0.203	*	(1.67)	-0.247		(-1.56)	0.005		(0.04)	0.071		(0.48)	0.576	***	(4.22)
Size 2, Beta 1	0.179	**	(2.36)	-0.051		(-0.49)	0.050		(0.60)	0.047		(0.51)	0.164	**	(2.22)
Size 2, Beta 2	-0.018		(-0.19)	-0.231	**	(-2.18)	-0.005		(-0.06)	-0.035		(-0.38)	0.331	***	(4.38)
Size 2, Beta 3	0.114		(0.75)	-0.317	*	(-1.78)	0.023		(0.15)	0.173		(1.15)	0.736	***	(5.47)
Size 1, BM 1	0.139		(1.47)	-0.262	**	(-2.02)	-0.045		(-0.40)	-0.012		(-0.10)	0.391	***	(3.58)
Size 1, BM 2	0.221	***	(2.67)	-0.183		(-1.63)	-0.013		(-0.14)	0.016		(0.15)	0.361	***	(3.88)
Size 1, BM 3	0.223	***	(2.82)	-0.207	*	(-1.90)	-0.042		(-0.45)	-0.009		(-0.09)	0.347	***	(3.93)
Size 2, BM 1	-0.061		(-0.53)	-0.292	**	(-2.25)	0.003		(0.03)	0.045		(0.43)	0.472	***	(5.43)
Size 2, BM 2	0.068		(0.60)	-0.191		(-1.58)	0.063		(0.62)	0.094		(0.91)	0.475	***	(5.43)
Size 2, BM 3	0.111		(1.09)	-0.242	*	(-1.90)	-0.018		(-0.16)	-0.009		(-0.08)	0.383	***	(3.85)
SPY	0.427	***	(4.54)	-0.212		(-1.57)	0.065		(0.58)	0.132		(1.17)	0.573	***	(5.98)
QQQ	0.570	***	(3.36)	-0.459	**	(-1.99)	-0.019		(-0.10)	0.074		(0.39)	0.778	***	(4.40)

Panel B: *INI×PRE* coefficient

Asset	(1) *STOV*		(2) *ASTOV*		(3) *HSTOV*		(4) *MSTOV*		(5) *LSTOV*	
Market	1.083	(0.16)	1.083	(0.16)	0.787	(0.10)	3.578	(0.60)	6.953	(1.30)
Beta 1	0.867	(0.20)	-6.979	(-1.11)	-7.654	(-1.11)	-5.468	(-1.01)	-0.827	(-0.17)
Beta 2	-0.426	(-0.14)	-2.503	(-0.58)	-3.111	(-0.63)	-2.095	(-0.58)	-0.334	(-0.10)
Beta 3	1.422	(0.32)	-5.368	(-0.87)	-4.587	(-0.73)	-2.511	(-0.49)	0.998	(0.22)
Beta 4	1.766	(0.41)	-1.459	(-0.26)	-1.805	(-0.29)	0.398	(0.09)	3.936	(0.91)
Beta 5	4.587	(1.02)	-1.522	(-0.23)	-2.418	(-0.34)	0.723	(0.13)	4.066	(0.84)
Beta 6	10.347 *	(1.81)	6.194	(0.89)	6.400	(0.80)	8.230	(1.39)	11.331 **	(2.11)
Beta 7	8.502	(1.42)	5.337	(0.76)	4.738	(0.60)	7.219	(1.17)	9.898 *	(1.77)
Beta 8	7.906	(1.02)	5.111	(0.57)	4.525	(0.45)	7.759	(1.03)	11.298 *	(1.69)
Beta 9	12.742	(1.21)	8.017	(0.78)	7.835	(0.70)	10.721	(1.20)	14.001 *	(1.69)
Beta 10	13.832	(1.04)	10.877	(0.80)	10.685	(0.73)	15.275	(1.29)	19.715 *	(1.80)
Size 1, Beta 1	3.752	(1.59)	-0.671	(-0.18)	-0.665	(-0.16)	0.608	(0.20)	2.592	(0.95)
Size 1, Beta 2	7.050 *	(1.72)	1.181	(0.21)	1.200	(0.19)	3.553	(0.74)	6.659	(1.47)
Size 1, Beta 3	8.057	(1.22)	5.320	(0.63)	5.152	(0.56)	8.529	(1.16)	12.805 *	(1.85)
Size 2, Beta 1	-0.157	(-0.03)	-6.261	(-0.87)	-5.618	(-0.77)	-3.572	(-0.58)	0.018	(0.00)
Size 2, Beta 2	4.192	(0.79)	1.823	(0.29)	1.359	(0.19)	3.789	(0.71)	7.042	(1.46)
Size 2, Beta 3	7.588	(0.60)	6.507	(0.60)	6.025	(0.50)	9.760	(1.04)	13.531	(1.60)
Size 1, BM 1	7.600	(1.46)	2.028	(0.29)	1.787	(0.23)	4.931	(0.82)	8.709	(1.54)
Size 1, BM 2	10.134 **	(2.20)	3.251	(0.52)	3.635	(0.52)	5.678	(1.05)	9.121 *	(1.80)
Size 1, BM 3	3.991	(0.81)	2.963	(0.47)	2.595	(0.37)	5.494	(0.99)	8.768 *	(1.73)
Size 2, BM 1	2.639	(0.46)	-0.337	(-0.05)	-0.747	(-0.11)	2.147	(0.38)	5.206	(1.02)
Size 2, BM 2	6.811	(0.90)	1.761	(0.23)	1.704	(0.20)	4.182	(0.66)	7.979	(1.42)
Size 2, BM 3	10.191	(1.09)	5.979	(0.66)	5.374	(0.54)	8.908	(1.16)	11.643 *	(1.77)
SPY	3.923	(0.66)	-2.798	(-0.37)	-3.311	(-0.40)	-0.237	(-0.04)	1.930	(0.33)
QQQ	12.368	(1.51)	6.594	(0.66)	5.333	(0.54)	9.588	(1.06)	11.830	(1.39)

Table 4: Simple regression of return on high-beta stock order flow by trade size. This table shows selected coefficient estimates from the simple regression of an asset's five-minute return on the small-, mid-, or large-size order flow of high beta stocks with an intercept interacted with the pre-FOMC dummy (*PRE*) and the initial period dummy (*INI*) in Equation (16). Panels A shows the coefficient on the *PRE* dummy and Panel B the coefficient on the interaction term of the *INI* and *PRE* dummies. t-statistics are shown in parentheses and are based on standard errors using the Newey-West correction with 16 lags. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *PRE* coefficient (bp)

Asset	Small			Mid			Large		
Market	0.147	*	(1.75)	0.094		(0.91)	0.298	***	(2.88)
Beta 1	-0.155	**	(-2.19)	-0.147	**	(-2.09)	-0.046		(-0.67)
Beta 2	-0.006		(-0.09)	-0.003		(-0.05)	0.075		(1.10)
Beta 3	0.033		(0.47)	0.057		(0.74)	0.147	*	(1.90)
Beta 4	0.047		(0.69)	0.058		(0.77)	0.192	***	(2.64)
Beta 5	-0.006		(-0.07)	0.003		(0.04)	0.156	*	(1.84)
Beta 6	-0.001		(-0.01)	0.027		(0.29)	0.200	**	(2.09)
Beta 7	0.064		(0.69)	0.054		(0.50)	0.260	**	(2.45)
Beta 8	0.064		(0.61)	0.023		(0.18)	0.263	**	(2.06)
Beta 9	0.179		(1.35)	0.081		(0.51)	0.419	***	(2.68)
Beta 10	0.380	**	(2.13)	0.199		(0.92)	0.712	***	(3.24)
Size 1, Beta 1	-0.091	*	(-1.91)	-0.068		(-1.42)	0.026		(0.55)
Size 1, Beta 2	-0.025		(-0.31)	0.023		(0.27)	0.221	***	(2.68)
Size 1, Beta 3	0.078		(0.59)	0.085		(0.59)	0.454	***	(3.31)
Size 2, Beta 1	0.049		(0.65)	0.072		(0.88)	0.160	*	(1.94)
Size 2, Beta 2	0.057		(0.75)	0.057		(0.65)	0.213	**	(2.44)
Size 2, Beta 3	0.233	*	(1.79)	0.116		(0.72)	0.466	***	(2.85)
Size 1, BM 1	0.013		(0.12)	0.013		(0.12)	0.299	***	(2.73)
Size 1, BM 2	0.006		(0.06)	0.046		(0.48)	0.285	***	(3.05)
Size 1, BM 3	-0.027		(-0.30)	0.029		(0.31)	0.267	***	(2.92)
Size 2, BM 1	0.163	*	(1.86)	0.081		(0.75)	0.269	**	(2.42)
Size 2, BM 2	0.160	*	(1.82)	0.145		(1.45)	0.317	***	(3.04)
Size 2, BM 3	0.021		(0.22)	0.056		(0.51)	0.273	**	(2.46)
SPY	0.199	**	(2.09)	0.152		(1.33)	0.361	***	(3.14)
QQQ	0.162		(0.93)	0.012		(0.05)	0.461	**	(2.25)

Panel B: *INI×PRE* coefficient (bp)

Asset	Small		Mid		Large	
Market	7.342	(1.32)	5.958	(0.84)	2.173	(0.30)
Beta 1	-0.052	(-0.01)	-2.676	(-0.39)	-7.251	(-1.14)
Beta 2	0.482	(0.15)	0.763	(0.18)	-3.013	(-0.64)
Beta 3	0.350	(0.07)	-1.799	(-0.28)	-3.270	(-0.56)
Beta 4	4.040	(0.85)	2.583	(0.42)	-0.948	(-0.17)
Beta 5	4.284	(0.81)	2.316	(0.33)	-1.267	(-0.19)
Beta 6	11.564 **	(2.00)	10.425	(1.47)	7.682	(1.03)
Beta 7	10.009 *	(1.67)	10.422	(1.38)	6.096	(0.82)
Beta 8	12.139 *	(1.76)	11.330	(1.29)	5.936	(0.62)
Beta 9	14.744 *	(1.66)	13.462	(1.25)	9.944	(0.94)
Beta 10	21.046 *	(1.88)	20.167	(1.46)	13.450	(0.96)
Size 1, Beta 1	2.832	(0.95)	2.466	(0.62)	-0.097	(-0.02)
Size 1, Beta 2	6.593	(1.35)	6.247	(1.01)	2.512	(0.43)
Size 1, Beta 3	12.424 *	(1.75)	12.227	(1.41)	7.430	(0.85)
Size 2, Beta 1	-0.589	(-0.10)	-2.617	(-0.37)	-4.396	(-0.65)
Size 2, Beta 2	7.219	(1.38)	6.007	(0.89)	2.517	(0.38)
Size 2, Beta 3	14.884 *	(1.71)	13.619	(1.26)	7.948	(0.70)
Size 1, BM 1	7.970	(1.36)	7.387	(1.01)	3.815	(0.53)
Size 1, BM 2	9.117 *	(1.69)	9.008	(1.33)	5.098	(0.76)
Size 1, BM 3	8.821 *	(1.67)	8.154	(1.22)	4.068	(0.61)
Size 2, BM 1	5.349	(1.02)	3.768	(0.57)	0.747	(0.11)
Size 2, BM 2	8.807	(1.50)	7.569	(1.00)	2.788	(0.35)
Size 2, BM 3	13.467 *	(1.90)	12.063	(1.35)	6.302	(0.68)
SPY	2.521	(0.42)	0.697	(0.09)	-1.749	(-0.22)
QQQ	9.569	(1.12)	7.524	(0.73)	7.964	(0.83)

Table 5: Determinants of Individual Stock Returns. This table reports coefficient estimates from panel regressions of the quote midpoint return (*QRET*). Panel A shows the result of simple regressions, in each of which the independent variables include a constant and a stock characteristic shown as *Z* in the first row as well as their interaction terms with the pre-FOMC dummy (*PRE*) and the initial period dummy (*INI*). Panel B shows a multiple regression including all the characteristics comprising a total of 40 independent variables. The characteristics are market beta (*BETA*), market capitalization (*SIZE*), the book-to-market ratio (*BM*), the earnings-to-price ratio (*EPR*), prior 12-month return (*MOM*), Roll's effective spread measure (*ROLL*), equity issuance (*ISSUE*), idiosyncratic volatility from the Fama-French 3-factor model (*IVOL*) and a lottery dummy (*LOTT*). The sample consists of NYSE, AMEX, and NASDAQ common stocks. The sample period before averaging is 9:30am-4:00pm during five-day windows centered on FOMC announcement days between September 27, 1994 and December 19, 2014. t-statistics are shown in parentheses and are based on standard errors clustered by stock and period. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Simple regressions

Variable (Z)	---			BETA (×10^4)			SIZE (×10^9)			BM (×10^6)			EPR (×10^4)		
Const (bp)	-0.01		(-0.17)	0.05	**	(2.09)	-0.01		(-0.20)	-0.01		(-0.18)	-0.01		(-0.26)
INI (bp)	5.24	***	(3.68)	5.22	***	(7.88)	5.36	***	(3.83)	5.27	***	(3.68)	5.41	***	(3.77)
PRE (bp)	0.162	**	(2.08)	-0.073		(-1.60)	0.155	**	(1.99)	0.162	**	(2.08)	0.160	**	(2.04)
PRE×INI (bp)	7.59	**	(2.12)	0.96		(0.55)	7.55	**	(2.14)	7.57	**	(2.11)	7.67	**	(2.12)
Z				-0.078	*	(-1.79)	0.040		(0.85)	0.038		(0.29)	0.039	***	(4.97)
Z×INI				0.02		(0.02)	-4.31	***	(-2.86)	-3.63		(-0.89)	-1.66	***	(-6.48)
Z×PRE				0.291	***	(3.89)	0.277	***	(3.25)	-0.032		(-0.10)	0.023		(1.40)
Z×PRE×INI				8.20	***	(2.77)	1.34		(0.41)	2.32		(0.18)	-0.57		(-0.74)
#Obs	8402817			8402586			8402602			8402602			8375807		
Adj. R^2	0.0013			0.0016			0.0013			0.0013			0.0014		

Panel A: Continued

Variable (Z)	MOM (×10^4)			ISSUE (×10^3)			ROLL (×10^5)			IVOL (×10^2)			LOTT (×10^4)		
Const (bp)	-0.01		(-0.10)	0.02		(0.51)	-0.01		(-0.25)	0.11	**	(2.11)	0.03		(0.56)
INI (bp)	5.42	***	(3.84)	4.27	***	(3.04)	5.50	***	(3.68)	-0.83		(-0.53)	3.12	**	(2.14)
PRE (bp)	0.157	**	(1.99)	0.167	**	(2.15)	0.170	**	(2.09)	0.209	***	(2.61)	0.224	***	(2.87)
PRE×INI (bp)	7.65	**	(2.11)	7.66	**	(2.13)	7.95	**	(2.12)	5.11		(1.38)	7.10	**	(2.00)
Z	-0.023		(-0.72)	-0.040	***	(-8.02)	0.028	*	(1.81)	-0.037	***	(-4.91)	-0.134	***	(-6.28)
Z×INI	-1.21		(-1.33)	1.37	***	(9.63)	-1.74	***	(-3.70)	1.96	***	(8.94)	7.76	***	(12.67)
Z×PRE	0.038		(0.62)	-0.007		(-0.72)	-0.053	**	(-1.97)	-0.015		(-0.92)	-0.227	***	(-4.10)
Z×PRE×INI	-0.43		(-0.15)	0.06		(0.20)	-2.44	**	(-2.07)	0.80		(1.54)	1.79		(1.31)
#Obs	8402473			8025805			8402515			8402133			8402602		
Adj. R^2	0.0014			0.0015			0.0014			0.0028			0.0018		

Panel B: Multiple regression

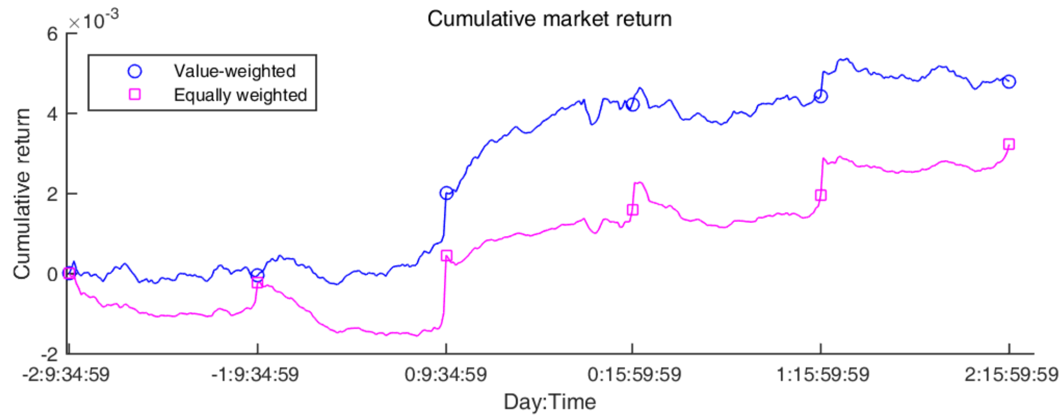
Variable (Z)	Z			Z×INI			Z×PRE			Z×PRE×INI		
Const (×10^4)	0.183	***	(5.55)	-1.18		(-1.29)	-0.018		(-0.35)	-2.08		(-1.00)
BETA (×10^4)	-0.066		(-1.59)	0.05		(0.04)	0.283	***	(3.72)	8.85	***	(2.93)
SIZE (×10^9)	-0.048		(-1.22)	0.98		(0.87)	0.124	*	(1.95)	0.96		(0.38)
BM (×10^6)	-0.091		(-0.74)	-0.42		(-0.11)	0.002		(0.01)	5.24		(0.40)
EPR (×10^4)	0.020	***	(2.71)	-0.74	***	(-3.20)	0.016		(1.04)	-0.18		(-0.26)
MOM (×10^4)	-0.034		(-1.06)	-0.39		(-0.42)	-0.005		(-0.08)	-0.94		(-0.35)
ISSUE (×10^3)	-0.032	***	(-6.82)	0.91	***	(7.06)	-0.005		(-0.51)	-0.34		(-1.17)
ROLL (×10^5)	-0.007		(-0.88)	-0.77	***	(-3.22)	-0.001		(-0.05)	-0.24		(-0.41)
IVOL (×10^2)	-0.030	***	(-3.54)	1.69	***	(7.05)	0.003		(0.19)	0.98		(1.61)
LOTT (×10^4)	-0.045		(-1.54)	2.72	***	(3.69)	-0.212	***	(-4.11)	-0.16		(-0.09)
#Obs						8,003,694						
Adj. R^2						0.0033						

Table 6: Summary statistics. This table shows summary statistics of the market portfolio, characteristic portfolios, and the ETFs. #Int is the number of five-minute intervals in the sample period. *N* is the average number of stocks. Beta is the average value-weighted beta with respect to the CRSP value-weighted market return. Size is the average equally weighted market capitalization. BM is the average equally weighted book-to-market ratio. *QRET* is the average value-weighted five-minute quote midpoint return. t-statistics are shown in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Asset	#Int	N	Beta	Size	BM	QRET (bp)		
Market	8,802	5,100				0.600	***	(5.38)
Beta 1	8,802	479	-0.16	0.3	0.93	0.026		(0.26)
Beta 2	8,802	483	0.19	1.5	0.92	0.078		(0.98)
Beta 3	8,802	490	0.39	2.9	0.79	0.180	*	(1.83)
Beta 4	8,802	497	0.56	3.9	0.71	0.311	***	(3.32)
Beta 5	8,802	502	0.71	3.9	0.70	0.311	***	(3.05)
Beta 6	8,802	505	0.87	3.5	0.65	0.452	***	(3.90)
Beta 7	8,802	508	1.03	3.2	0.63	0.581	***	(4.79)
Beta 8	8,802	509	1.22	2.9	0.62	0.648	***	(4.69)
Beta 9	8,802	510	1.50	2.9	0.58	0.905	***	(5.21)
Beta 10	8,802	509	2.05	2.4	0.59	1.313	***	(5.85)
Size 1, Beta 1	8,802	1,240	0.21	0.1	0.93	0.178	***	(3.10)
Size 1, Beta 2	8,802	1,399	0.81	0.4	0.73	0.450	***	(4.69)
Size 1, Beta 3	8,802	1,080	1.62	0.4	0.64	0.823	***	(5.57)
Size 2, Beta 1	8,802	109	0.32	12.8	0.56	0.141		(1.24)
Size 2, Beta 2	8,802	512	0.80	11.6	0.51	0.425	***	(4.18)
Size 2, Beta 3	8,802	363	1.53	10.3	0.47	0.940	***	(5.44)
Size 1, BM 1	8,802	1,054	1.13	0.4	0.23	0.599	***	(5.00)
Size 1, BM 2	8,802	1,277	0.95	0.3	0.60	0.555	***	(5.11)
Size 1, BM 3	8,802	1,246	0.90	0.2	1.60	0.529	***	(4.90)
Size 2, BM 1	8,802	466	1.02	14.3	0.24	0.581	***	(5.25)
Size 2, BM 2	8,802	344	0.96	9.8	0.57	0.586	***	(4.98)
Size 2, BM 3	8,802	153	0.97	7.8	1.21	0.545	***	(4.00)
SPY	8,802	1				0.588	***	(4.51)
QQQ	6,858	1				0.975	***	(4.68)

Figure 1: Cumulative Market Return and Signed Share Turnover.

The figure shows the cumulative return (top panel) and cumulative signed share turnover (lower panel) for the five days centered on each FOMC announcement day. Days are labeled -2 through +2 (the announcement day is day 0), and appear first on the time axis, followed by the time of the day. The return and signed turnover are value and equally weighted averages computed across all NYSE, AMEX and NASDAQ stocks with valid quotes and trades. Cumulation starts at the open on day -2. In the turnover panel, the left (right) vertical axis refers to value- (equally-) weighted turnover.



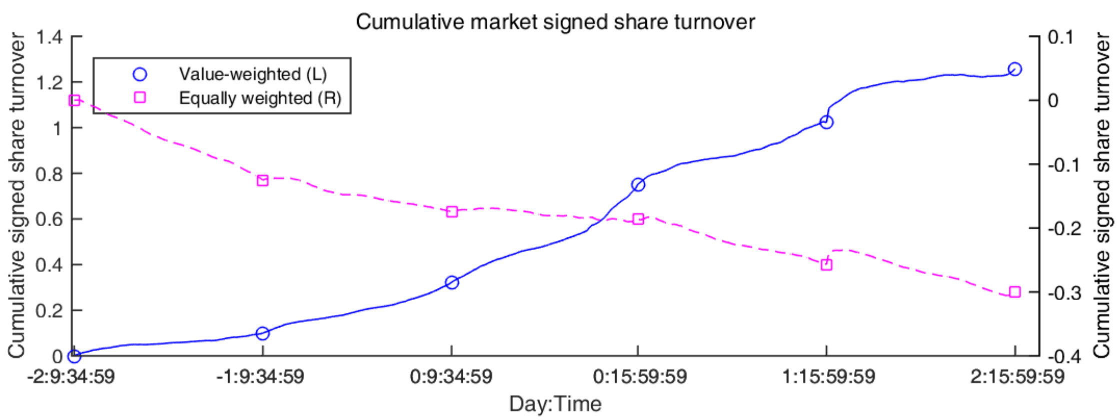


Figure 2: Cumulative Returns of Beta-sorted Portfolios around FOMC Announcements.
The figure shows the cumulative intraday return for selected portfolios formed on beta in the three days centered on FOMC announcement. Days are labeled -1 through +1 (the announcement day is day 0), and appear first on the time axis, followed by the time of the day. The return is the value-weighted average in each portfolio, and computed across all NYSE, AMEX and NASDAQ stocks with valid quotes and trades. Cumulation starts at the open on day -1.

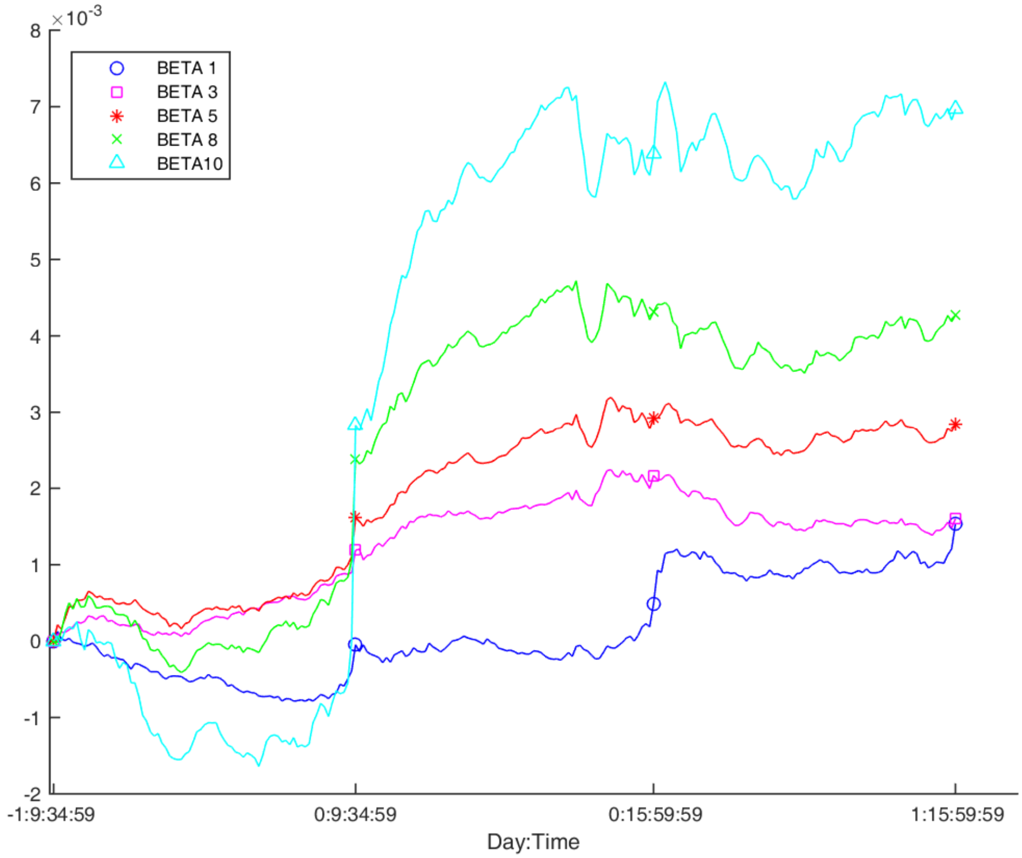


Figure 3: Returns and Trades of Beta-sorted Portfolios.
The figure shows the average quote midpoint returns (*QRET*, left axis) and signed share turnover (*STOV*, right axis) of beta-sorted decile portfolios during the pre- and post-FOMC announcement periods on announcement days (panels A and B, respectively) as well as the day before (Day -1, panel C) and the day following (Day 1, panel D) FOMC announcements.