The Quote Not Taken: The Effect of Market Structure on Liquidity Provision in Equity Markets

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Abstract

Global equity markets have become increasingly fragmented, with off-exchange trading now accounting for the majority of volume in the U.S. This paper presents new evidence that off-exchange order flow predicts next-day on-exchange prices, creating an unusual return reversal that benefits off-exchange market makers. A long-short trading strategy based on publicly available flow data generates sizable abnormal returns. From 2014 to 2022, this short-term reversal cost off-exchange investors an estimated $193 million, nearly half of which materialized within the first five minutes of market open. While the presence of informed auctioneers mitigates the sensitivity of flow reversal returns to observable risk factors, it does not reduce the overall magnitude of these reversals. Unlike previously studied liquidity provision strategies, this reversal occurs intraday rather than overnight and remains robust to value-weighting.

1. Introduction

A historic shift occurred in U.S. equity markets in November 2024: for the first time ever, more trading volume was executed off-exchange than on-exchange. This trend has persisted into 2025.[1] The European Union is experiencing a similar shift, where approximately 40% of the trading volume takes place off-exchange.[2] Even as the volume off-exchange increases, new exchanges continue to emerge. The Texas Stock Exchange, for example, recently raised $161 million and plans to begin trading in 2025.[3] The rise of electronic trading has dramatically transformed the market structure; only 40 years ago the vast majority of equity trading took place at a few centralized physical exchanges. A natural question arises: Does the growing fragmentation of the world's largest and most liquid equity markets materially affect asset prices? This paper provides evidence that off-exchange flows predict next-day on-exchange prices, benefiting market makers with access to both venues and to the detriment of those who submit inelastic trade orders off-exchange.

Off-exchange flows exhibit day-to-day autocorrelation. Using a signal derived from publicly available trade data, one can roughly predict next-day (and overnight) off-exchange flows. Stocks with abnormally large predicted next-day trade imbalances experience next-day return reversals. Large positive imbalances lead to positive overnight returns but negative intraday returns, while large negative imbalances precede low overnight returns and high intraday returns. A trading strategy which forms a long-short portfolio of large imbalance stocks earns an overnight alpha of 15 basis points (approximately 3% monthly, t-stat = 9.50)

[1]See Off-Exchange Trading Increases Across All Types of Stocks (NASDAQ)
[2]See Equity Primary Markets and Trading Report (AFME)
[3]See TXSE— Homepage

and a next-day intraday alpha of 22 basis points (approximately 5% monthly, t-stat = 12.67). Although this return is sizable, it is within the range of other liquidity provision strategies. However, this return pattern deviates from the existing literature on liquidity provision in several key ways: unlike other return reversal strategies, which generate monotonic returns from close to close, this strategy's returns revert after the opening auction. Additionally, it remains robust to value weighting and is not fully explained by common market-wide indicators such as implied volatility (Nagel (2012)) or limits to arbitrage capital (Hu, Pan, and Wang (2013)). This paper provides a novel measure of adverse selection risk derived from order flow data which is effective at predicting returns to both flow reversal and return reversal strategies.

Further analysis reveals that the magnitude of this return reversal is greater on the NASDAQ than on the NYSE. However, after controlling for stock level observable characteristics, the difference unwinds. Designated auctioneers on the NYSE are offered greater access to order flow information and are incentivized to provide liquidity. Consistent with the incentive structure, the return reversal for NYSE stocks is less sensitive to stock-level risks and flows. However, it is still as large, if not larger, on average, than on the NASDAQ This may be due to a lack of competition or a conflict of interest as many designated auctioneers operate in off-exchange venues. As new exchanges emerge and current exchanges are evaluated, an alternative market structure creating a different equity pricing behavior has meaningful implications for investors, listed firms, and regulatory agencies.

These findings are important for both policy making and academic purposes. While a market structured to separate retail and liquidity traders from informed competitive traders can be helpful for reducing noise and trading costs (see, for example, Baldauf, Mollner, and

Yueshen (2024)), the correlation between off-exchange flows and short-term price movement implies that the "uninformed" traders are buying (selling) when prices are temporarily high (low). This effectively acts as a cash transfer from off-exchange traders to cross-market makers, beyond any other trading costs they incur. While this may be viewed as a cost of trading with cross-market makers off-exchange, investors and regulators should be aware of this yet to be documented cost.

A rough approximation of losses for these investors can be made using imbalance estimates and off-exchange execution data. Investors whose off-exchange trades are executed at the opening auction have lost an aggregated $193 million over the course of that same day, $88 million of which occurred within the first 5 minutes of market open.

From an academic perspective, researchers often use opening auction prices as an important benchmark to understand overnight vs. intraday risk premia (Hendershott, Livdan, and Rösch (2020)), as well as to measure reactions to news such as earnings announcements or to estimate the drift of earnings announcements. The evidence of predictable price deviations uncorrelated with fundamental risks suggests that these opening prices may be biased. I propose using '5-minute post-auction prices' instead of opening auction clearing prices, as these better reflect underlying values after initial off-exchange trading pressure resolves.

This paper contributes to the existing literature on market structure, liquidity provision, and intraday asset pricing. Although numerous papers have been written about the effect of market structure and fragmentation on outcomes such as liquidity provision and market quality (see, for example, Buti, Rindi, and Werner (2017), Ozik, Sadka, and Shen (2021), and Bessembinder, Hao, and Zheng (2020)), few papers provide conclusive evidence that off-exchange flows directly and significantly affect exchange prices. In addition to predictable price impact, this analysis contributes by identifying a pricing behavior whose sensitivity to observable risk changes based on the security's auction structure.

There has been a growing interest in risk premia at different times of the day. Lou, Polk, and Skouras (2019) argue that different investor types may trade at different times of the day, and find that profits to well known trading strategies occur either entirely overnight or during the day. They document that reversal strategies tend to earn their returns overnight. While consistent with previous literature surrounding liquidity provision strategies, this is inconsistent with the reversal strategy provided by this paper.

The remainder of this paper is organized as follows: Section 2 explains the market structure and theoretical framework. Section 3 explains the data and descriptive statistics. Section 4 presents methodology and results, and Section 5 provides a conclusion.

2. Market Structure and Theoretical Framework

2.1. On and Off-Exchange

Equity markets are currently separated into on-exchange and off-exchange platforms. The primary exchanges in the United States are the NYSE and the NASDAQ, the former has a physical location in New York while the latter is purely online. Off-exchange platforms usually do not have a physical location, instead operating virtually. Off-exchange activity can be further categorized into two groups: Alternative Trading Systems (ATS) and non-ATS segments. ATS function by connecting traders without the owner of the ATS under any obligation to ensure transaction closure. These systems do not publicly display their limit order book, earning them the moniker 'dark pools.'

Non-ATS platforms usually operate as single-dealer platforms or wholesalers, where a trader can go directly to a market maker and trade. While some market makers operate primarily on exchange, those who operate a single dealer platform all are very active across segments. I refer to these players as "cross-market makers," (CMMs) as they are active across market segments. As of December 2025, the majority of dollar volume in US equity markets is executed off-exchange, and the majority of off-exchange trading is executed by non-ATS platforms, rather than through dark pools. For the remainder of this section, I will consider off-exchange traders to be generally credibly less informed, while on-exchange traders are more informed or at least unable to signal their lack of information.

A separating equilibrium is sustainable when off-exchange traders can credibly signal their status as liquidity or noise traders. Consider two examples:

1. A **mutual fund** that seeks to match a specific index and trades with a market maker using a publicly verifiable signal, such as past price movement.

2. **Retail traders**, who, on average, tend to be less informed than professional investors. In exchange for a small fee, brokerages route retail order flow to wholesalers, who take the other side of these less-informed trades in a process known as Payment for Order Flow (PFOF).

Uninformed investors opt to trade off-exchange because they receive slightly better prices than they would on-exchange, a benefit commonly referred to as price improvement. The tendency of off-exchange traders to be less informed and to trade at lower spreads is well documented in the market microstructure literature (see, for example, Battalio and Jennings (2023), Brown et al. (2024), Elsas, Johanning, and Theissen (2022)), although the degree of competition in this market is a matter of some debate.

2.2. Theoretical Framework Setup

To formalize the setup, consider a market structure with two venues for trading where the same risky asste is traded. I will refer to these as the "on-exchange" and the "off-exchange" markets. The on-exchange market is a Kyle (1985) market in the style of Nagel (2012), with uninformed liquidity traders and competitive risk-averse market makers and informed traders. In the off-exchange market, a profit maximizing cross-market maker receives separate uninformed trade orders which they must either match or send to the competitive on-exchange market. I assume a single risky asset in 0 net supply, and a riskless asset in perfect elastic supply with an interest rate of 0. There is a single period of trading, with a pre-period where signals are observed and a post period where values are realized and assets are liquidated. Let the final value of the risky asset be given by

$$V^* = V_0 + \delta$$

Where V_0 is the initial value of the risky asset observed in the pre-period, and $\delta \sim N(0, \sigma_\delta^2)$. There are 5 participants in this market:

- **Off-Exchange Liquidity Traders**: These investors trade off-exchange and submit demand K_T for the risky asset during the trading period, where $K_T \sim N(\mu_K, \sigma_K^2)$. These traders are able to credibly signal their type as liquidity traders, and thus able to access the off-exchange market. I will examine 2 cases, one where μ_K is publicly observed and one where it is not.

- **Cross-Market Maker**: The CMM is a risk-neutral, profit maximizing participant. They receive order flow K_T from off-exchange liquidity traders decide how much to fill, ψ and how much to send to the on-exchange market, $1-\psi$. Their optimization problem can be represented as

$$\max_{\psi} \mathbb{E}\left[(P_T(\psi K_T) - V^*)(1-\psi)K_T \mid K_T, V_0\right]$$

where P_T is the price of the asset set by the on-exchange market maker during the trading period, and which will be a function of the amount of order flow sent on on-exchange, ψK_T.

- **On-Exchange Liquidity Traders**: These investors trade on-exchange and submit demand Z_T for the risky asset during the trading period, where $Z_T \sim N(0, \sigma_Z^2)$. These traders are *unable* to credibly signal themselves as liquidity traders, and thus unable to access the off-exchange market.

- **Informed Investors**: Informed investors are also unable to signal an uninformed type and consequently they solely participate in the on-exchange market. They submit order flow Y_T to maximize their CARA utility after having observed δ. Thus their demand function can be written:

$$Y_T = \frac{1}{\theta}\mathbb{E}\left[V^* - P_T(Y_T) \mid \delta, Y_T, V_0, \mu_K\right]$$

where θ is the inverse slope of demand, capturing the level risk-aversion of the informed investor as well as the riskiness of final payoff.

- **On-Exchange Market Makers**: These market makers have CARA utility functions and set prices based on net outstanding orders they observe on-exchange. Similar to Nagel (2012), I write their demand function as

$$M_T = \frac{1}{\gamma}\mathbb{E}\left[V^* - P_T \mid P_T, X_T, \mu_K\right]$$

where X_T is the net-imbalance of order flow on-exchange.

To sustain a separating equilibrium, I assume that the CMM gives some ϵ discount to the uninformed demand they receive. I further assume Z_T, K_T, δ_t are all i.i.d.

2.3. Theoretical Framework Results

I explore 2 cases, one where μ_K is know by all participants prior to trading, and one where it is not. In both cases the the equilibrium is linear and as such, $\psi = 1/2$. See Appendix B for proofs for this and the following results.

Case 1: Let μ_K be publicly observable and market makers and informed investors have rational expectations about the distribution of uninformed demand. The expectation of price movement, conditional on public information prior to trading, can then be given as:

$$\mathbb{E}\left[P_T - V_0 | \, V_0, \mu_K\right] = \gamma(1-\alpha)\frac{\mu_k}{2} \tag{1}$$

$$\mathbb{E}\left[V_T - P_T | \, V_0, \mu_K\right] = -\gamma(1-\alpha)\frac{\mu_k}{2} \tag{2}$$

Where α is the fraction of μ_K which informed trader choose to fill, solved for as $\alpha = \frac{\gamma}{2\theta+\gamma}$. As (1) is strictly positive and (2) is symmetrically negative, we observe a clear reversal pattern even when off-exchange uninformed demand is non-zero and anticipated through the risk-baring channel.

Case 2: Let μ_K be unknown to market participants except for the CMM. The expectation of price movement from the CMM's information set is then given by:

$$\mathbb{E}\left[P_T - V_0 | V_0, \mu_K\right] = (\gamma + \lambda)\frac{\mu_k}{2} \tag{3}$$

$$\mathbb{E}\left[V_T - P_T | V_0, \mu_K\right] = -(\gamma + \lambda)\frac{\mu_k}{2} \tag{4}$$

Where λ is given by $\frac{\beta^2\sigma_\delta^2}{\beta^2\sigma_\delta^2+\sigma_Z^2+\sigma_K^2}$, similar to the usual price impact function provided by Kyle models. Again, (1) is strictly positive and (2) is symmetrically negative, so we observe a clear reversal pattern.

The difference between the reversal in Case 1 and Case 2 to can be simplified to the difference between $1 - \alpha$ and λ. This generates a useful and intuitive prediction for the empirical section. If uninformed demand originating from off-exchange markets has the same price impact as on-exchange flows, then the reversal is at least partially due to mispricing. Otherwise, if the price impact is a function only of relative risk aversions and

Applying this finding to the US stock market structure, cross-market makers would send half of their received order flow to the exchange. However, note that this is conditional on the transferred order flow having the same price impact λ as on exchange demand. Two frictions may prevent this in actual markets, the first is the size of order flow. If the order is sufficiently small, on-exchange prices will be unaffected and the cross-market maker will have lost out on potential revenue by transferring demand to on-exchange. The second is related, the timing of execution is expected to be very rapid. During market hours, trading is fairly continuous and CMMs are expected to compete on the speed of execution as well as the execution price. This discourages the build up of small trades to become a large enough order as to have a meaningful effect on on exchange prices. It may also discourage the segmentation of order flow as the CMM must wait for the on-exchange price to change before benefiting.

2.4. Opening Auctions

An exception to these frictions can be found in the opening auctions, and for that reason the execution prices in opening auctions are a key focus of this paper. Liquidity demanding orders may build up overnight, allowing for the bunching and segmentation of order flow. Equity market auctions are similar to Kyle models, in that they clear at a single price and quantity and a rough signal for the imbalance in demand can be observed. The source of the orders are anonymous to market participants except for the auctioneers. If there is a build of off-exchange order flow overnight and CMM's are sending some fractions of this demand to opening auctions, we should expect for there to be a meaningful amount of off-exchange orders executed at the close of the opening auction and for these orders to have a measurable effect on prices.

Once trades occur, execution data is recorded in the publicly available real-time stream of price and volume information for registered securities, often displayed on a ticker or electronic display. Competitive market participants would react to the availability of order-flow information and push prices to reflect fundamental values and risk exposure. This leads to another prediction: prices will reverse quickly after the close of the opening auction, as noisy signals about past order flow origination are revealed.

Auction set-up is unique to the exchange on which the security is traded. The NYSE appoints Designated Market Makers (DMMs) for each ticker. Roughly 1/3 of NYSE stocks are managed by Citadel, 1/3 are managed by Global Trading Services, and the rest by de minimis market makers. DMMs are appointed de facto auctioneers for their securities, and are instructed to minimize after auction variance while maintaining reasonable opening and closing times. The DMM has the power to delay an auction, and is incentivized to provide liquidity for through a small fee paid by the exchange to the DMM. As the auctioneer, DMMs have additional access to flow data that other market participants lack. The NASDAQ, on the other hand, automates all their auctions. The majority of auction volume for each stock occurs on that stock's primary exchange, allowing for a comparison of auction mechanisms on price movement. If DMM auctioneers receive additional information about order flows and are incentivized to provide liquidity, we would expect to see lower return reversal for stocks on the NYSE than for those on the NASDAQ.

2.5. Risk and Returns

Up to this point, flow effects on prices and return reversals should be observable ex-post, but not necessarily ex-ante. This paper provides evidence that an ex-ante measure of off-exchange flow trade imbalances forecast return reversals consistent with the previously stated predictions. To determine whether this is consistent with a model of a concentrated market of CMM's earning economic profits or a competitive market rewarding risk exposure, regress returns to a strategy which profits from the expected return reversal on previous day measures of risk.

We can use these measures of risk to evaluate the competition of on-exchange market making. We would expect predictable return magnitudes to be smaller and primarily correlated with risk factors in a competitive exchange of informed participants.

3. Data

3.1. Sources

Intraday statistics, including order flow imbalances and 5-minute prices, are calculated from TAQ (Ticker and Quote) data. Included in this data source are on which exchange trades took place, including if they occured off-exchange. Other stock level data is taken from CRSP and COMPUSTAT. I limit my sample from 2013-2022, using stocks with share code 10 or 11 and share class listed as A or missing. Additionally, I drop which have median closing price lower than \$1.00. To keep my findings as general as possible, I also drop so-called "meme stocks" from the entirety of my analysis (see A.1 for the list of stocks excluded). To get intraday returns for factor portfolios, I identify stocks in the CRSP/COMPUSTAT universe, assign them to their respective portfolios, and then recreate the daily portfolios from stocks included in my sample. I follow the documentation on Ken French's website to recreate HML, SMB, and Momentum portfolios. I create a daily re-balancing portfolio which shorts the top decile of previous day returns and buys the lowest decile of previous day returns as a representative short-term reversal portfolio.

3.2. Variable Definitions

1. **Order Flow Imbalances:** Using the Lee and Ready (1991) algorithm, I sign each trade and calculate the dollar weighted imbalance for each stock each day as

$$\frac{\sum_i (p_i s_i|\text{Buy})_i - \sum_i (p_i s_i|\text{Sell})_i}{\sum_i (p_i s_i|\text{Buy})_i + \sum_i (p_i s_i|\text{Sell})_i}$$

   Where p_i is the execution price and s_i is the number of shares for each trade i. For most of the analysis, I use the previous day's off-exchange order flow imbalance. Stock-days with missing values are treated as 0's, no imbalance.

2. **Composition Risk:** To create a measure of off-exchange composition risk, I divide the total off-exchange round-lot (trades with orders of at least 100 shares) dollar volume by the total off-exchange volume for each stock each day as

$$\frac{\sum_i (p_i s_i | s_i \geq 100)}{\sum_i p_i s_i}$$

   As odd lot trades are usually not considered be made by informed traders, this acts as a potential measure of adverse selection risk. Stock-days with missing values are treated as 1's.

Fama-Macbeth Covariates

All variables in Fama-Macbeth regressions are demeaned and standardized using full-sample standard deviations except for returns and constants.

3. **Spread:** The previous day's dollar weighted average effective spread

$$\frac{\sum_i |p_i - m_i| \times s_i}{\sum_i s_i}$$

where m_i is the quoted midpoint at the time of execution.

4. **Volatility:** The previous day's standard deviation of execution prices

$$\sigma_p = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (p_i - \overline{p})^2},$$

3.3. Portfolio Construction

To create a Flow Reversal Portfolio, I flag stocks whose previous day off-exchange order flow imbalance is greater (less) than the 20 day rolling mean + 2 times the rolling standard deviation off-exchange order flow imbalance:

$$\mathbb{1}\left(OFI^{\text{off}}_{t-1} > \mu^{\text{off}}_{t-1,t-20} + 2\sigma^{\text{off}}_{t-1,t-20}\right) \text{ or } \mathbb{1}\left(OFI^{\text{off}}_{t-1} < \mu^{\text{off}}_{t-1,t-20} + 2\sigma^{\text{off}}_{t-1,t-20}\right)$$

Additionally, stock must have at least \$10,000 worth of off-exchange trades on date $t-1$. The Flow Reversal Strategy then short-sells stocks with an abnormal buy imbalance from the close of date $t-1$ to the close of date t, while buying stocks with an abnormal sell imbalance and holding for the same period of time.

This portfolio is short an average of 131 stocks and long an average of 112 stocks every day. Holding just overnight produces an annualized sharpe ratio of 4.27, while holding just the next day produces an annualized sharpe ratio of 5.54.

4. Methodology and Results

4.1. Flow Reversal as a Trading Strategy

I begin by plotting the cumulative returns to a flow reversal strategy in Figure 1, starting from the close of $t-1$ when the flows of $t-1$ have been fully observed but the closing auction can still be participated in. An equally weighted flow reversal portfolio drops 15 basis points overnight, but regains 6 basis points a mere 5 minutes after market open. The portfolio continues to gain throughout the day and somewhat over the next couple of trading days. A value weighted portfolio trends in the same direction, although with smaller magnitudes. This portfolio drops 6 basis points overnight, but regains 2.5 basis points within the first 5 minutes of market open.

I compare these cumulative returns to a standard return reversal strategy in Figure 2. As the name implies, return reversals are most often associated with liquidity provision and return reversal like strategies. However, it is rare to find a return reversal strategy which, after identification, continues it's previously observed trajectory before reversing. Usually, the reversal begins to occur if not mostly occurs overnight. We see the difference in behavior in the Equally Weighted figure; the portfolios move in opposite directions from

$t-1$ close to t open. The return reversal portfolio is monotonically increasing throughout the observed window, while the flow reversal portfolio bottoms out at the t opening auction before increasing.

The Value Weighted plot in Figure 2 further emphasizes the distinction between this and standard return reversal strategies. The return reversal portfolio no longer produces significant close to close returns, while the flow reversal strategy is able to.

To check if these returns are correlated with usual market factors, I regress the daily returns of the flow reversal portfolios on Fama French 3 factor portfolios with additional factor portfolios for momentum and short-term reversal. Table 1 presents the results. The flow reversal portfolios produce significant alphas during overnight and intraday periods, as well as during the 5 minutes after market open. This is consistent with the prediction that after an auction, when trade data is made available, competitive agents will act quickly to move prices back towards their fundamental value.

4.2. Reversal Returns and Time-Series Risk

Nagel (2012) shows that during his sample period the returns to liquidity provision are correlated with and can be predicted by market level implied volatility. I test a similar hypothesis. In addition to the VIX, I introduce a novel measure of adverse selection risk which I refer to as composition risk. Table 2 gives the results to a set of regressions predicting next-day returns to reversal strategies using previous day risk measures. I find that both the VIX and Composition Risk are helpful in predicting next-day returns, not only for a flow reversal portfolio but also for return reversal portfolios.

4.3. Reversal Returns in the Cross-Section

To further understand what is driving these abnormal returns, I next plot flow reversal returns by exchange and subsequently run Fama-Macbeth style regressions. Given that the exchanges have different methods of operating their opening auctions, it is reasonable to expect a difference in return behavior from flow reversal portfolios. I plot the cumulative returns in Figure 5. The magnitude of reversal is much larger for a portfolio consisting of only stocks primarily traded on the NASDAQ than the NYSE. However, there are many fundamental differences between stocks listed on either exchange. The decision of where to list themselves is an endogenous outcome of firm behavior, so these stocks are not directly comparable. Controlling for observable differences is a necessary first step for any further inference.

Table 3 presents the results to running a Fama-Macbeth regression on stock level characteristics. For simplicity, this table only uses stocks which were flagged to have abnormally large off-exchange buy imbalances the previous day, allowing us to isolate what may be driving returns for this subsample. Each day, flagged stock returns are regressed on previous day observable characteristics, including intraday volatility, size, traded volume, effective spread, and previous day return. Additionally, I add an exchange dummy variable to observe whether return magnitudes still differ after controlling for the listed covariates.

Factors associated with implied risk and previous day order imbalance seem to drive the majority of next-day reversal. Stocks with higher effective spreads, higher order imbalances, and smaller market caps are associated with larger next-day reversals. Interestingly, the Composition risk factor is predictive in the equally weighted regression, but is insignificant in the value weighted regression. The NYSE dummy is not significant in any of the regressions.

Table 4 gives the results to a similar set of regressions, but now with additional interaction terms for the exchange and stock level risk factors. The estimated coefficients imply that reversals for stocks on the NYSE are less sensitive to composition risk and off-exchange order flow imbalances. However, the dummy variable by itself is still insignificant. As the covariates are demeaned, this implies that on average, the reversals are not smaller when a Designated Market Maker runs the auction. In fact, although insignificant, an positive coefficient for overnight returns and negative coefficient for intraday returns suggests that reversals have larger magnitudes on the NYSE, despite not being as sensitive to stock level risks.

4.4. Calculating Losses

What is the cost to off-exchange investors of trading at the opening auction? I calculate a simple metric to arrive at a conservative estimate. I estimate opening auction buy-sell imbalances using the previous day's off-exchange imbalance. I calculate:

$$\sum_{i,t} OFI^{\text{off}}_{i,t-1} * r_{i,t} * OFV_{i,t}$$

where $OFI^{\text{off}}_{i,t-1}$ is the previous day's off-exchange imbalance, $r_{i,t}$ is the intraday return, and $OFV_{i,t}$ is the off-exchange dollar volume at the opening auction, for all dates i and tickers t. This calculation estimates a total loss of $193,761,052.37. Performing the same calculation but only using the five minute return estimates a total loss of $87,744,069.27.

5. Conclusion

The inherent opacity of investment funds makes it challenging to assess how market structure shapes participant decisions. This paper contributes to a better understanding of equity market dynamics by identifying a new pricing pattern driven by profit-maximizing cross-market makers. While resembling other liquidity provision strategies, this pattern is distinct in its timing and robustness. The result is that off-exchange liquidity demanders experience worse returns on average. Having informed auctioneers doesn't seem to decrease the magnitude of these reversals, and further research is needed to explore the conflicts of interest currently materializing in equity markets.

Figure 1: Correlation in Off-Exchange Order Flow Imbalances

This figure presents a histogram of ticker-level coefficients estimated from a regression of off-exchange order flow imbalance on its one-day lag. Only stocks with at least one year of data are included in the sample.

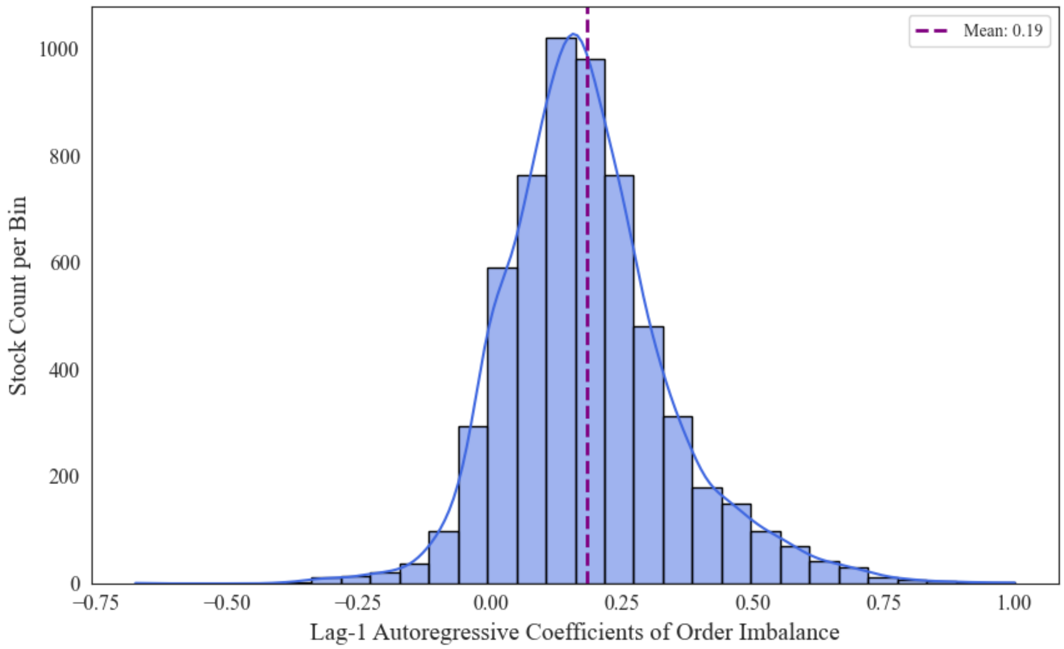
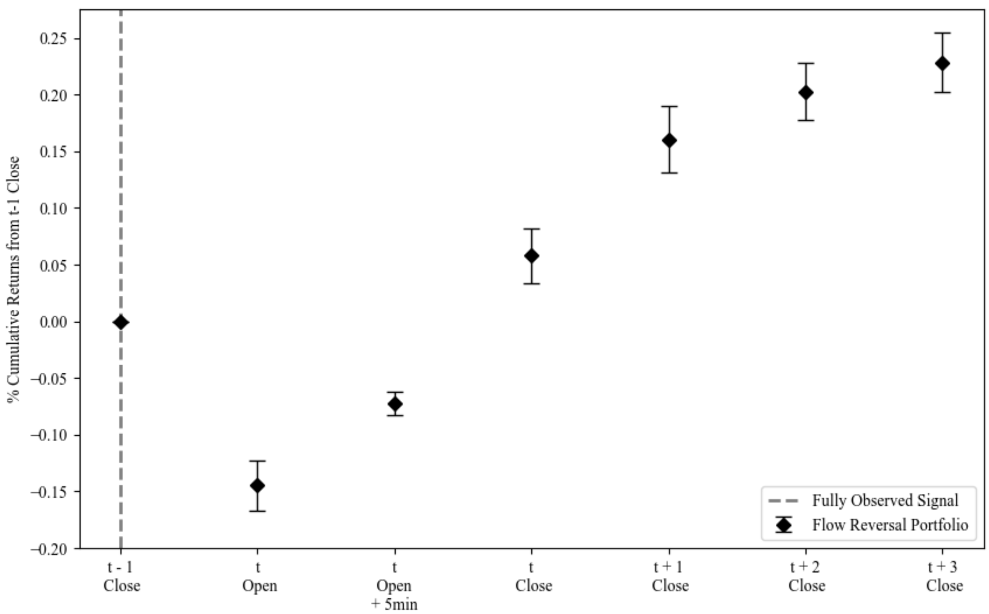


Figure 2: Flow Reversal Portfolio Returns

This figure shows returns to a flow reversal strategy: short-selling stocks with abnormally large positive imbalances while simultaneously buying stocks with large negative imbalances in off-exchange flows at date t-1. Panel A presents the results for a portfolio which equally weights the stocks, while Panel B presents the results for a portfolio which weights the stocks by by their respective market capitalization. Newey-West HAC standard errors with 20 lags are used to provide 95% confidence intervals.

A. Equally Weighted



B. Value Weighted

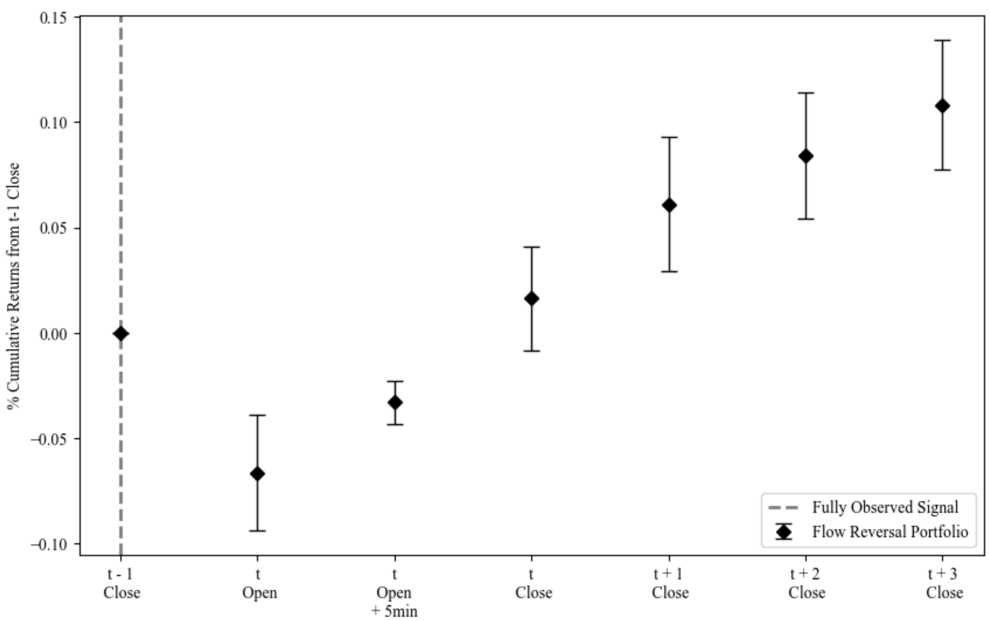
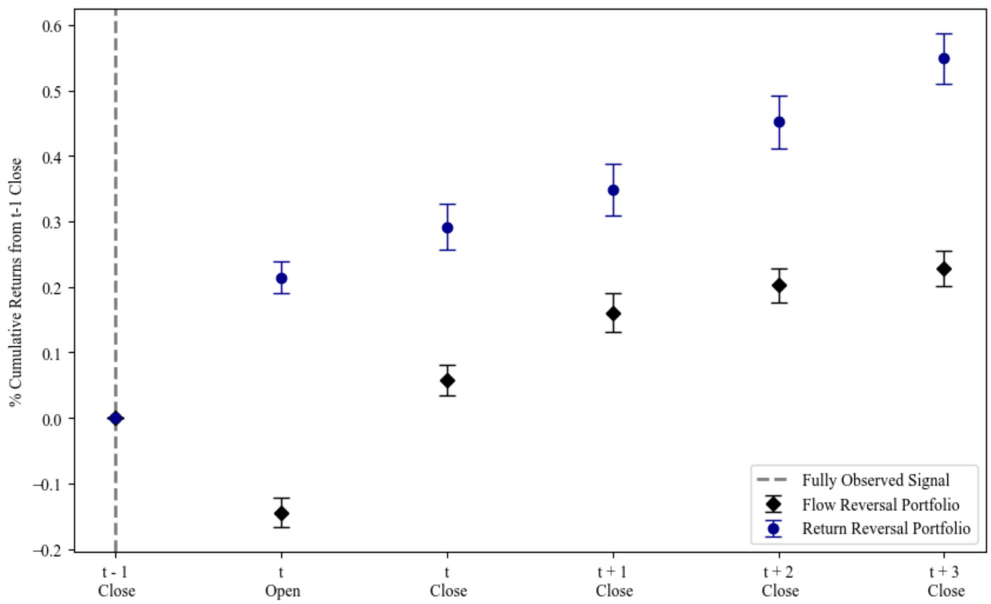


Figure 3: Flow Reversal and Return Reversal Comparison

This figure shows returns to a flow reversal strategy: short-selling stocks with abnormally large positive imbalances while simultaneously buying stocks with large negative imbalances in off-exchange flows at date t-1, and compares these returns to the returns to a portfolio which engages in a simple return reversal strategy: buying the stocks in the lowest decile of returns and shorting-selling the stocks in the highest decile of returns at date t-1. Panel A presents the results for a portfolio which equally weights the stocks, while panel B presents the results for a portfolio which weights the stocks by by their respect market capitalization. Newey-West HAC standard errors with 20 lags are used to provide 95% confidence intervals.

Equally Weighted



Value Weighted

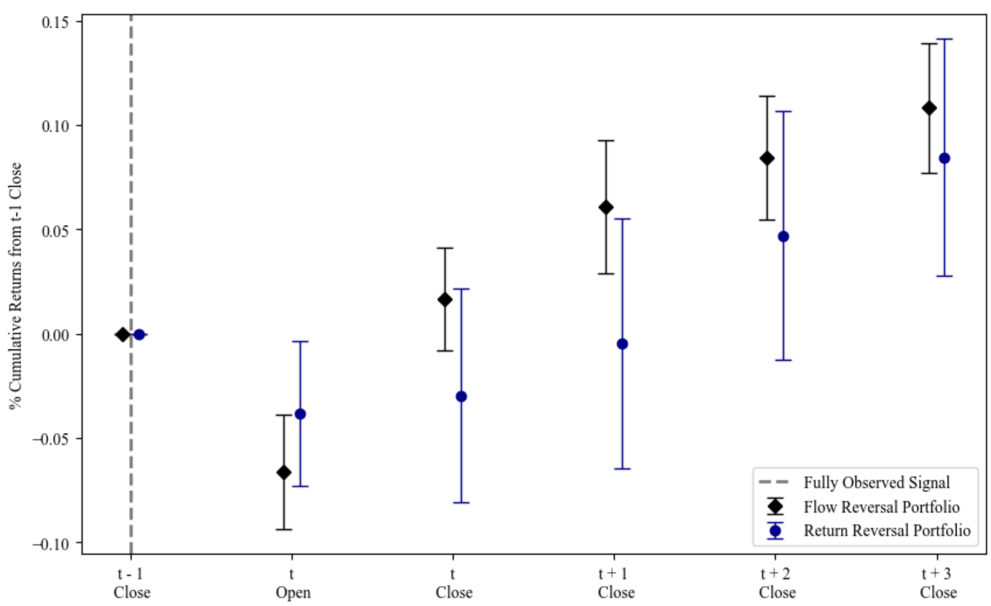


Figure 4: Flow Reversal Returns and the VIX

This figure plots the 60-trade day rolling average returns of an equally weighted flow reversal strategy and compares this to the 60-trade day rolling average of the VIX.

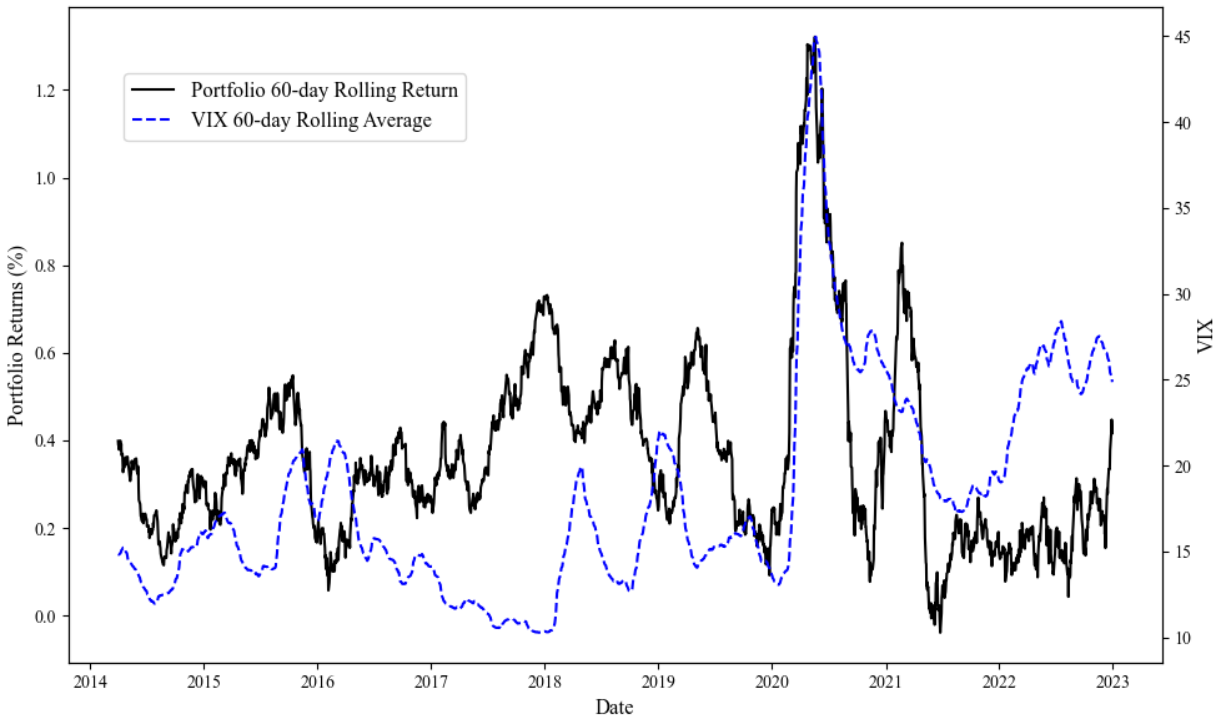


Figure 5: Flow Reversal Returns: NYSE vs. NASDAQ

This figure shows average returns to a daily flow reversal strategy for equities listed only on the NYSE and separately for equities listed only on the NASDAQ. Newey-West HAC standard errors with 20 lags are used to provide 95% confidence intervals.

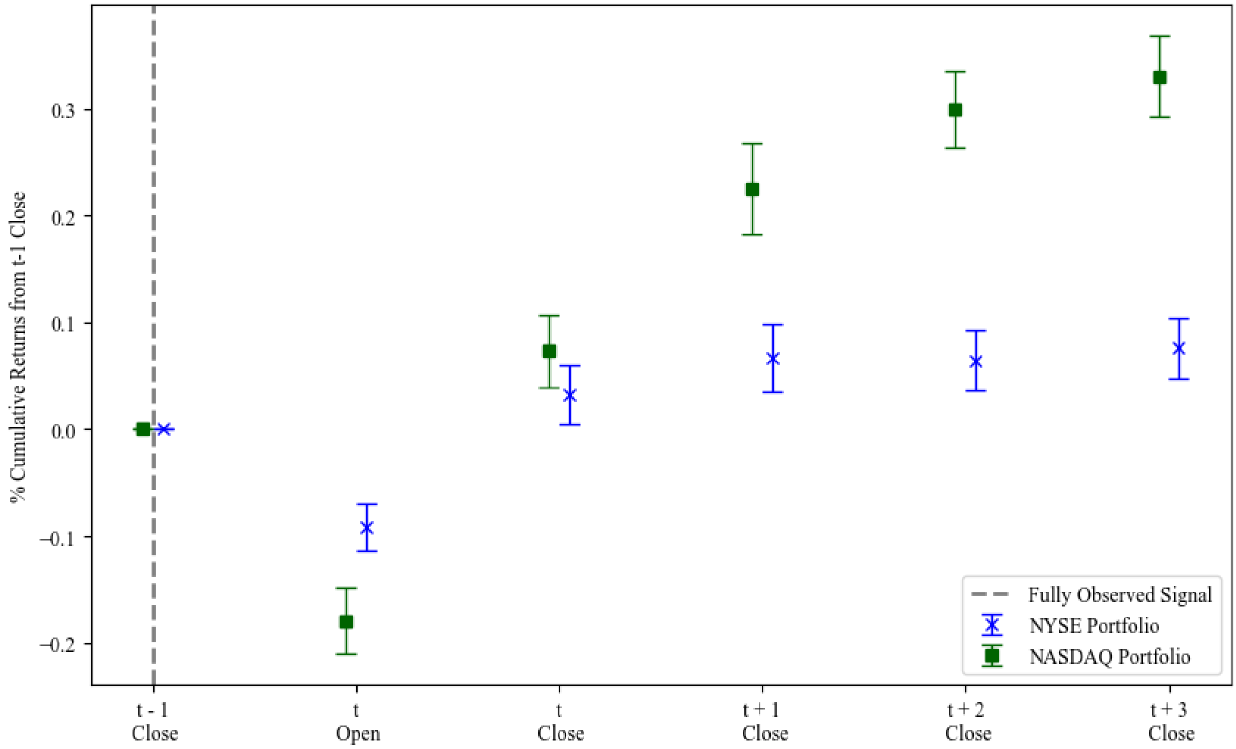


Table 1: Factor Regressions

This table presents coefficients for a long-short flow reversal strategy regressed on market, small-minus-big, high-minus-low, momentum, and short-term reversal portfolios. The flow reversal portfolio is constructed by short-selling stocks with abnormally large positive imbalances while simultaneously buying stocks with large negative imbalances in off-exchange flows the previous day (date t-1). Returns are split into 3 time periods: Overnight Returns (t-1 close to t open), 5-Minute Returns (t open to 5-minutes after that stock's opening auction), and Intraday Returns (t open to t close). Equally weighted flow reversal returns and value weighted flow reversal returns are presented separately for each time period. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns		5 Minute Returns		Intraday Returns	
	EW	VW	EW	VW	EW	VW
Alpha (%)	-0.15***	-0.05***	0.08***	0.04***	0.22***	0.10***
	(-9.50)	(-2.78)	(10.86)	(4.97)	(14.81)	(7.16)
Mkt	-0.07	-0.13**	0.02***	-0.01	-0.02	-0.09
	(-2.08)	(-3.93)	(0.38)	(-0.17)	(-1.29)	(-3.31)
Smb	-0.41***	0.03	-0.04	-0.06	-0.02***	-0.01
	(-2.92)	(0.27)	(-1.69)	(-1.69)	(-2.79)	(-1.70)
Hml	-0.01	0.32***	0.04	0.05	0.06	0.12***
	(-0.12)	(3.92)	(1.18)	(1.31)	(1.78)	(3.54)
Mom	0.00	0.05	-0.06	-0.01	0.01	0.02
	(0.08)	(0.56)	(-1.32)	(-0.22)	(0.30)	(0.53)
Rev	0.12**	0.06	0.03	-0.01	0.07	-0.02
	(2.52)	(0.84)	(1.47)	(-0.34)	(3.35)	(-1.13)
Obs.	2265	2265	2265	2265	2265	2265

Table 2: Predicting Reversal Returns with Risk

This table presents coefficients estimated by regressing returns to reversal strategies on measures of risk taken from the previous day. VIX is taken from the CBOE implied volatility index, divided by $\sqrt{250}$. Composition Risk a daily measure calculated as the dollar weighted fraction of off-exchange odd lot trades divided by total off-exchange trade volume across the the entire sample of equities. The flow reversal portfolio is constructed by short-selling stocks with abnormally large positive imbalances while simultaneously buying stocks with large negative imbalances in off-exchange flows the previous day (date t-1). Flow reversal returns are split into 2 time periods: Overnight Returns (t-1 close to t open), and Intraday Returns (t open to t close). The return reversal strategy is constructed by purchasing stocks in the decile with the lowest returns from the previous day while short-selling stocks in the highest decile of previous day returns. Both portfolios are equally weighted. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns		Intraday Returns		Close to Close Returns	
	Flow Reversal	Flow Reversal	Flow Reversal	Flow Reversal	Return Reversal	Return Reversal
Constant	-0.07**	0.10	0.18***	0.02	0.22***	-0.01
	(-1.96)	(0.97)	(5.21)	(0.28)	(6.10)	(-0.06)
VIX	-0.06*	-0.08**	0.04	0.06**	0.06**	0.09***
	(-1.66)	(-2.21)	(1.32)	(2.04)	(2.14)	(3.22)
Composition Risk		-0.05**		0.05**		0.07**
		(-2.22)		(2.29)		(2.12)
Obs.	2265	2265	2265	2265	2265	2265

Table 3: Buy-side Imbalance Fama-Macbeth Regressions

This table presents coefficients from Fama-MacBeth style regressions. Overnight and intraday returns of stocks with large positive off-exchange imbalances from the previous day are regressed on lagged covariates. Equally weighted results use OLS, while value-weighted results use WLS with market capitalization as weights. Covariates are demeaned and standardized using the full-sample standard deviation. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns		Intraday Returns	
	VW	EW	VW	EW
Off-Ex Imbalance	0.02***	0.05***	-0.02**	-0.05***
	(2.85)	(5.64)	(-2.21)	(-5.92)
On-Ex Imbalance	0.00	-0.00	-0.00	0.01
	(0.20)	(-0.39)	(-0.61)	(1.08)
Return	0.53*	-0.14	-0.92***	0.02
	(1.72)	(-0.51)	(-2.80)	(0.06)
Spread	0.16**	0.23***	-0.37***	-0.37***
	(2.08)	(4.70)	(-4.41)	(-5.75)
Dollar Volume	0.07*	-0.02	-0.14***	-0.56***
	(1.69)	(-0.45)	(-3.20)	(-10.36)
Composition Risk	0.02	0.12***	-0.01	0.03
	(0.86)	(7.35)	(-0.29)	(1.68)
Size	-0.11***	-0.10**	0.09***	0.58***
	(-3.67)	(-2.09)	(2.93)	(11.91)
Volatility	0.01	0.01	0.01	0.03*
	(0.38)	(0.61)	(0.70)	(1.82)
NYSE	-0.03	-0.01	0.00	-0.04
	(-1.64)	(-0.45)	(0.01)	(-1.64)
Constant	0.19***	0.25***	-0.11**	-0.05***
	(5.66)	(6.44)	(2.67)	(-1.45)

Table 4: Buy-side Imbalance Fama-Macbeth Regressions with Interactions

This table presents coefficients from Fama-MacBeth style regressions. Overnight and intraday returns of stocks with large positive off-exchange imbalances from the previous day are regressed on lagged covariates. Both columns are equally weighted. Covariates are demeaned and standardized using the full-sample standard deviation. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns	Intraday Returns
Off-Ex Imbalance	0.07***	-0.06***
	(6.03)	(-3.89)
On-Ex Imbalance	-0.00	0.00
	(-0.44)	(-0.26)
Return	-0.19	-0.24
	(-0.69)	(-0.71)
Spread	0.31***	-0.42***
	(4.72)	(-5.95)
Dollar Volume	-0.04	-0.55***
	(-0.70)	(-9.42)
Composition Risk	0.15***	0.02
	(8.44)	(0.76)
Size	-0.08*	0.53***
	(-1.73)	(9.44)
Volatility	-0.00	0.02
	(-0.02)	(1.55)
NYSE	0.04	-0.01
	(0.96)	(-0.13)
NYSE * (Composition Risk)	**-0.05****	**0.09****
	(-2.69)	**(2.05)**
NYSE * (Spread)	0.00	0.00
	(0.04)	(0.07)
NYSE * (Off-Ex Imbalance)	**-0.03*****	0.05
	(-2.79)	(1.52)
Constant	0.23***	-0.08**
	(6.22)	(-2.31)

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Appendix

I exclude the following stocks from my sample:
GME, BBBY, BB, AMC, CLOV, TSLA, KOSS, NOK, ZOM, SNDL, WISH, XSPA, PLTR, SPCE.

Appendix A: Tables

Table A.1: Continuous Imbalance Measure Fama-Macbeth Regressions

This table presents coefficients from Fama-MacBeth style regressions. The setup is similar to that of Table 3, but the entire sample is included instead to only those which were identified as having had large positive imbalances. Equally weighted results use OLS, while value-weighted results use WLS with market capitalization as weights. Covariates are demeaned and standardized using the full-sample standard deviation. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns		Intraday Returns	
	VW	EW	VW	EW
Off-Ex Imbalance	0.01***	0.02***	-0.01***	-0.02***
	(8.46)	(10.28)	(-5.56)	(-9.60)
On-Ex Imbalance	0.004***	0.002**	-0.003***	0.00
	(4.23)	(2.67)	(-3.27)	(1.43)
Return	0.43**	-1.65***	-0.63*	-0.87***
	(2.13)	(-9.41)	(-1.94)	(-4.20)
Spread	0.08***	0.06***	-0.17***	-0.04***
	(4.27)	(12.94)	(-4.82)	(-6.41)
Dollar Volume	0.06***	0.18***	-0.04*	-0.16***
	(3.92)	(10.44)	(-1.92)	(-9.04)
Composition Risk	-0.01*	0.02***	0.01	0.00
	(-1.90)	(6.45)	(1.27)	(0.63)
Size	-0.04***	-0.21***	0.04*	0.18***
	(-3.78)	(-11.46)	(1.93)	(9.26)
Volatility	0.00	-0.00**	0.01*	0.002***
	(0.78)	(-2.14)	(1.77)	(4.43)
NYSE	-0.01	0.01**	-0.02	-0.00
	(-1.29)	(2.16)	(-1.53)	(-0.08)
Constant	0.08***	0.09***	-0.05*	-0.05**
	(3.77)	(4.86)	(-1.98)	(-2.32)

Table A.2: Fama-Macbeth Regressions with Auction Volume

This table presents coefficients from Fama-MacBeth style regressions. The setup is similar to that of Table 3, but the entire sample is included instead to only those which were identified as having had large positive imbalances. Additionally, I include a variable for the pre-auction imbalance, the log dollar volume off-exchange during the opening auction, and that volume interacted with the previous day's off-exchange order imbalance. Equally weighted results use OLS, while value-weighted results use WLS with market capitalization as weights. Covariates are demeaned and standardized using the full-sample standard deviation. Newey-West HAC standard errors (20 lags) are used, with t-statistics in parentheses.

	Overnight Returns		Intraday Returns	
	VW	EW	VW	EW
Off-Ex Imbalance	0.01***	0.02***	0.00	-0.01***
	(2.71)	(7.89)	(0.15)	(-4.54)
Pre-Imbalance	0.05***	0.12***	0.01***	0.02***
	(15.03)	(26.43)	(3.96)	(4.55)
Off-Ex Auction Volume	0.07***	0.39***	0.03***	0.01
	(4.40)	(8.52)	(2.96)	(1.27)
Off-Ex Auction Volume * Imbalance	0.00	-0.003**	-0.00**	-0.00
	(0.88)	(-2.33)	(-2.48)	(-1.91)
On-Ex Imbalance	0.003***	0.003***	-0.003***	0.003
	(3.89)	(3.37)	(-2.74)	(1.51)
Return	0.26	-1.76***	-0.62*	-0.88***
	(1.35)	(-10.23)	(-1.93)	(-4.25)
Spread	0.10***	0.08***	-0.17***	-0.04***
	(4.98)	(14.00)	(-4.94)	(-6.23)
Dollar Volume	-0.00	-0.11***	-0.07***	-0.16***
	(-0.33)	(-3.02)	(-3.39)	(-10.48)
Composition Risk	-0.00	0.03***	0.01*	0.00
	(-0.53)	(8.34)	(1.90)	(0.76)
Size	-0.07***	-0.27***	0.03	0.18***
	(-4.24)	(-13.07)	(1.64)	(8.93)
Volatility	-0.00	-0.00***	0.01*	0.00***
	(-0.98)	(-3.50)	(1.83)	(4.53)
NYSE	0.03***	0.09***	0.01	0.01
	(2.90)	(8.21)	(0.86)	(1.13)
Constant	0.06***	-0.03	-0.06**	-0.06**
	(2.65)	(-1.46)	(-2.42)	(-2.63)

Appendix B: Proofs

In case 1, I assume that μ_K and V_o are publicly observed by all participants. To begin, I posit and later verify the following:

$$P_t = V_0 + (X_T - (1-\alpha)\mu_K\psi)(\gamma+\lambda) + \gamma(1-\alpha)\mu_K\psi \tag{A1}$$

$$Y_t = \beta\delta - \alpha\psi\mu_K \tag{A2}$$

where $X_T = Y_T + Z_T + \psi K_T$, and the informed investor's demand is a function of their observed signal and the uninformed expected demand. α represents the amount of uniformed demand the informed investors are willing to fill.

As stated earlier, the CMM solves

$$\max_{\psi} \mathbb{E}\left[(P_T(\psi K_T) - V^*)(1-\psi)K_T \mid K_T, V_0\right]$$

Substituting in the pricing function and taking the CMM's expectation, we get

$$\max_{\psi}\{[(\psi K_T)(\gamma+\lambda) + \gamma(1-\alpha)\mu_K\psi](1-\psi)K_T\}$$

Solving the maximization problem results in

$$2(K_T-\mu_K)(\gamma+\lambda)\psi + 2\gamma(1-\alpha)\mu_K\psi = (K_T-\mu_K)(\gamma+\lambda) + \gamma(1-\alpha)\mu_K$$

which permits at least one real solution:

$$\psi = \frac{1}{2} \tag{A3}$$

So we can fix the amount ψ sent by the CMM to the exchange at $1/2$. With this it is easier to solve for an equilibrium. I first verify the consistency of $Y_t = \beta\delta - \alpha\psi\mu_K$. Substituting in the pricing function into the demand function of the informed investors, we get that:

$$Y_T = \frac{1}{\theta}\mathbb{E}\left[V^* - V_0 + (X_T - (1-\alpha)\frac{\mu_K}{2})(\gamma+\lambda) + \gamma(1-\alpha)\frac{\mu_K}{2} \mid \delta, Y_T, V_0, \mu_K\right]$$

$$\implies Y_T = \frac{1}{\theta}\left[\delta - (\beta\delta)(\gamma+\lambda) + \gamma(1-\alpha)\frac{\mu_K}{2}\right]$$
$$\implies Y_T = \frac{(1-\beta(\gamma+\lambda))}{\theta}\delta + \frac{\gamma\mu_K}{2\theta}(1-\alpha)$$

This is consistent with (A2). Solving for β and α:

$$\beta = \frac{\delta}{\theta} + \gamma + \lambda \tag{A4}$$

$$\alpha = \frac{\gamma}{2\theta+\gamma} \tag{A5}$$

The joint normality of the asset and uninformed demand from both groups implies that

$$\mathbb{E}\left[V^* \mid X_T, V_0, \mu_K\right] = V_0 + \frac{\beta^2\sigma_\delta^2}{\beta^2\sigma_\delta^2 + \sigma_Z^2 + \sigma_K^2}(X_T - (1-\alpha)\frac{\mu_K}{2}) \tag{A6}$$

Imposing market clearing, such that $M_T + Y_T + Z_T + \frac{K_T}{2} = 0$, gives us our equilibrium pricing function:

$$\mathbb{E}\left[\frac{1}{\gamma}(V^* - P_T) + Y_T + Z_T + \frac{K_T}{2} \mid X_T, V_0, \mu_K\right] = 0$$

$$\implies P_t = V_0 + (X_T - (1-\alpha)\frac{\mu_K}{2})(\gamma + \lambda) + \gamma(1-\alpha)\frac{\mu_K}{2}$$

which is consistent with the posited pricing function (A1).

□

Case 2 is solved for in a similar fashion to Case 1, but market participants (except for the CMM) mistakenly believe that $\mu_K = 0$. The pricing function and informed demand functions are essentially the same as Nagel (2012):

$$P_t = V_0 + (X_T)(\gamma + \lambda) \tag{A7}$$

$$Y_t = \beta\delta \tag{A8}$$

In this case, the transferred flows ψK_T will have a linear price impact. The CMM's maximization problem is quite straight forward, and is again resolved with $\psi = 1/2$.

The equilibrium result follows directly from Nagel (2012). The affect on the trading period price will then be the equilibrium price impact $(\gamma + \lambda)$ multiplied by the transferred flow $K_T/2$.

□