

Retail Order Flow Imbalances: Informed Trading or Liquidity Provision?*

Yashar H. Barardehi Dan Bernhardt
Zhi Da Mitch Warachka

February 21, 2022

Abstract

We show that to provide liquidity to institutional investors wholesalers internalize unbalanced levels of retail order flow. The Tick Size Pilot highlights how wholesaler incentives affect the magnitude and composition of internalized retail trade imbalances (*Mroib*, Boehmer et al. 2021). Large imbalances signify high institutional liquidity demand and coincide with high institutional trading costs. Consistent with retail order flow providing liquidity rather than being informed, intraday returns move in the same direction as institutional trading, in the opposite direction of internalized retail trading, as retail trade imbalances are inversely related to institutional trade imbalances. The subsequent unwinding of institutional price pressure explains the association between internalized retail imbalances and future short-term returns. Long-term return reversals conditional on these imbalances are also inconsistent with informed retail trading.

Keywords: Retail Trade, Institutional Trade, Payment for Order Flow, Liquidity, Microstructure

*We thank Yakov Amihud, Terry Hendershott, Charles Jones, Mete Kilic (discussants), Dermot Murphy, Thomas Ruchti, Andriy Shkilko, Chester Spatt, as well as the seminar and conference participants at Cal Poly - SLO and the 15th California Corporate Finance Conference for helpful comments. Barardehi (barardehi@chapman.edu) is at the Argyros School of Business & Economics, Chapman University and the U.S. Securities and Exchange Commission. Bernhardt (danber@illinois.edu) is at Department of Economics at the University of Illinois and the University of Warwick. Da (zda@nd.edu) is at the Mendoza College of Business, University of Notre Dame. Warachka (warachka@chapman.edu) is at the Argyros School of Business & Economics, Chapman University. The Securities and Exchange Commission disclaims responsibility for any private publication or statement of any SEC employee or Commissioner. This article expresses the authors' views and does not necessarily reflect those of the Commission, the Commissioners, or other members of the staff. Any errors are our own.

1 Introduction

The question of whether retail investors primarily trade on private information or provide liquidity to other market participants has motivated competing strands of the asset pricing literature.¹ This question has proved challenging to answer due to the difficulty in observing retail trading activity.² Boehmer, Jones, Zhang, and Zhang (2021, henceforth BJZZ) address this unobservability issue. They recognize that off-exchange U.S. equity transactions featuring sub-penny prices other than the quote mid-point *necessarily* reflect retail orders internalized (executed) by wholesalers. The authors use this insight to develop a normalized “marketable retail order flow imbalance” measure denoted *Mroib* from publicly-available data sources. BJZZ show that this imbalance predicts stock returns for several weeks, and interpret nearly half of this return predictability as suggestive evidence of informed trading by retail investors.

Our paper is the first to establish how wholesalers internalize retail order flow to provide liquidity to institutional investors. We show that the unwinding of institutional price pressure, rather than retail informed retail trading, explains the return predictability of imbalances in internalized retail order flow.³ We motivate our analysis by observing that wholesalers exercise tremendous discretion over internalization by deciding which retail orders to internalize and offer price improvement. For instance, wholesalers choose to internalize 70% of marketable retail orders routed to them by retail brokers,⁴ while non-marketable limit orders account for 20% of internalized retail order flow even though they comprise over 30% of the retail order flow handled by wholesalers. Furthermore, while the vast bulk of internalized marketable orders receive sub-penny price improvements, a still substantial 60% of internalized non-marketable limit order flow also receive sub-penny price improvements and hence

¹See Barber and Odean (2000, 2008), Kumar and Lee (2006), Kaniel et al. (2008), Barber et al. (2008), Foucault et al. (2011), Kaniel et al. (2012), Kelley and Tetlock (2013), and Barrot et al. (2016), among others.

²This has led some researchers to use proprietary, non-representative data sets (see Boehmer et al. 2021).

³Throughout the paper, “retail imbalance” refers to the subset of retail order flow that receives price improvement as a result of wholesaler internalization.

⁴See the Committee on Capital Markets Regulation’s [2021 report](#).

influence *Mroib*. Moreover, sub-penny price improvements for non-marketable orders tend to exceed those for marketable orders, suggesting contractually-driven outcomes. Our empirical evidence, in conjunction with institutional details, indicates that wholesaler discretion regarding which orders to internalize reflects responses to institutional liquidity demand.

We link wholesaler internalization decisions to both off-exchange market-making opportunities and inventory control considerations. We establish that the imbalances captured by *Mroib* reflect the incentives of wholesalers to internalize unequal amounts of retail buy and sell orders in response to institutional traders demanding to sell and buy, respectively, when the institutions face high trading costs elsewhere. Our findings highlight a mechanism, undetected in prior empirical studies, in which Payment for Order Flow (PFOF) by wholesalers can harm displayed liquidity (Parlour and Seppi 2003). Finally, we document how institutional price pressure provides an explanation for the distinct dynamics of intraday and overnight returns (Lou et al. 2019).

Figure 1: Retail Imbalances versus Institutional Imbalances and Implementation Shortfalls. This figure plots institutional trade imbalances constructed from ANcerno data and institutional-trade implementation shortfalls against imbalances in internalized retail order flow (*Mroibvol*). Each week, stocks are sorted in deciles according to their respective retail order flow imbalance. The average institutional trade imbalance and average implementation shortfall are then calculated within each decile each week. Time-series averages of these weekly averages for each decile are plotted from 2010–2014.

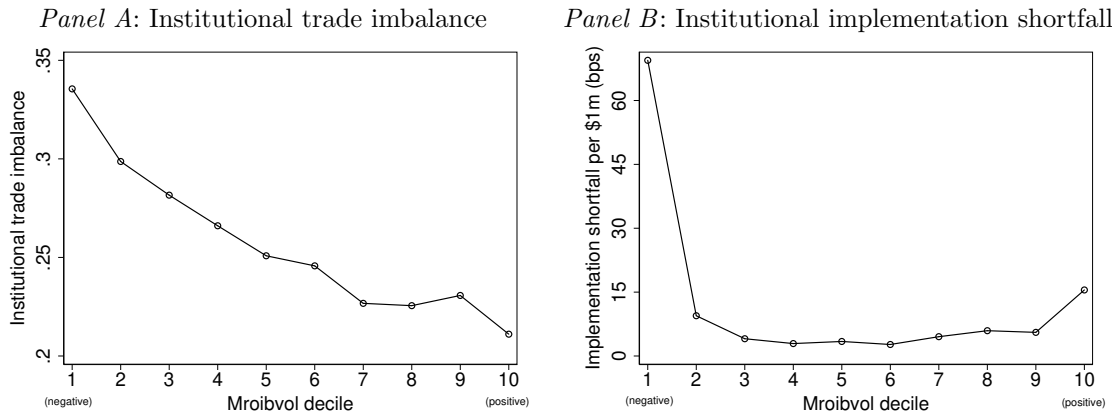


Figure 1 suggests that large internalized retail order flow imbalances reflect the internalization decisions of wholesalers in response to the liquidity demands of institutions facing

high trading costs.⁵ Panel A shows that institutional trade imbalances are inversely related to retail imbalances; while Panel B documents that institutional trading costs are highest when retail imbalances are largest in absolute value (most unbalanced).

To understand the economics of retail order flow internalization, one first needs to understand the retail order execution process in U.S. equity markets. This process begins with a retail investor choosing an order type (market, marketable limit, non-marketable limit), as Figure 1 illustrates, and placing their order with a broker.⁶ A retail broker receiving an order usually outsources its handling to one of the multiple wholesalers who provide trade execution services in return for the option to fill orders before other market participants have an opportunity. Broker-wholesaler interactions are governed by negotiated terms that reflect the competition among wholesalers and trading venues for order flow. A wholesaler decides whether to internalize a retail order and make the requisite payment for order flow (PFOF) to the retail broker or to reroute the order to a market center as illustrated in Figure 2. The “best execution” duty of brokers requires the execution of internalized orders at prices no worse than the National Best Bid and Offer prices (NBBO).⁷ This often leads internalized retail trades to feature execution prices with sub-penny increments, reflecting marginal price improvements relative the quoted prices. We find that these sub-penny price improvements tend to be notably *larger* for orders executed inside the NBBO.

A wholesaler’s motive to internalize retail orders and pay PFOF reflects off-exchange market-making opportunities, where a wholesaler trades as a principal against order flow

⁵Hu (2009) reports that execution costs measured using ANcerno data are larger for buy trades than sell trades in down markets. That execution costs are higher when *Mroib* is extremely negative than when it is extremely positive is consistent with liquidity being lower in down markets (Chordia et al. 2002).

⁶Market and marketable limit orders seek immediate execution, while non-marketable limit orders require execution at prices that are better than prevailing best-quoted prices.

⁷For example, [FINRA Regulatory Notice 21-23](#) reminds member entities that “...firms that provide payment for order flow for the opportunity to internalize customer orders cannot allow such payments to interfere with their best execution obligations ...” U.S. Securities & Exchange Commission (2021) describes “best execution” as that “at the most favorable terms reasonably available under the circumstances, generally, the best reasonably available price.” Retail brokers justify receiving PFOF on internalized retail order flow by offering retail investors price improvements relative to the best prevailing quotes.

from opposing sides, buying low and selling high. When retail order flow is unbalanced, internalizing all the order flow exposes the wholesaler to inventory risk, which can be managed in several ways. One option is to trade on a riskless basis at a market center, executing the retail flow without accumulating inventory but incurring the cost of liquidity-take or access fees. A second option is for the wholesaler to re-route the orders to other market centers, in which case some orders may not fill but no cost is incurred. As a third option, a wholesaler may match the imbalance in retail order flow with an opposing imbalance in institutional order flow on its affiliated Single Dealer Platform (SDP). The distinguishing feature of an SDP is that a wholesaler acts as a principal against a select set of institutional investors who access the SDP for a fee, allowing the wholesaler to learn their identities and willingness to pay for liquidity. Most important for our paper, in circumstances where internalized retail order flow may otherwise be balanced, the demand for liquidity by institutions can induce imbalances in internalized retail order flow as a wholesaler matches retail and opposing institutional order flow on its SDP or other trading venues.⁸ Put differently, a wholesaler internalizes unbalanced retail order flow when providing liquidity to institutions is their best option.

We provide a simple framework that describes the profit-maximizing internalization choices of a wholesaler who interacts with retail investors via internalization and with institutional investors via its SDP. The wholesaler incurs inventory costs from holding positions that deviate from its preferred holdings. We show that in the absence of institutional liquidity demand, a wholesaler internalizes roughly equal amounts of retail buy and sell orders, resulting in near-zero $Mroib$. In contrast, high institutional demand leads a wholesaler to internalize retail order flow (observable in TAQ data) to offset institutional order flow (unobservable in TAQ data), resulting in extreme positive or negative $Mroib$.

⁸While economic incentives suggest that wholesalers can likely extract the highest rents from liquidity provision on their SDPs, they still may provide liquidity to institutional investors on other venues. For example, as high-frequency liquidity providers, wholesalers possess the sophistication that allows them to compete with other liquidity providers on both exchanges and ATSs. As such, unbalanced internalized retail order flow may also be triggered by institutional liquidity demand that wholesalers face outside SDPs.

Crucially for *Mroib*, in addition to marketable orders, wholesalers internalize a *non-trivial* share of non-marketable limit orders. SEC Rule 606 filing disclosures reveal that non-marketable limit order volume comprises about 20% of internalized order flow, with most of the remaining 80% comprised of marketable orders.⁹ Importantly, over 12% of all off-exchange trading volume associated with sub-penny price improvements are executed inside the NBBO, suggesting that they originate from non-marketable retail orders. By implication, roughly 60% (12% divided by 20%) of internalized non-marketable limit order flow also receive price improvement and hence influence *Mroib*. Moreover, even though non-marketable limit orders are less profitable to internalize (due to being priced closer to the NBBO midpoint), wholesalers pay PFOF for them that is, on average, over double what they pay to internalize marketable orders. This higher PFOF reflects competition from other wholesalers as well as exchanges that provide higher liquidity rebates to non-marketable (liquidity-providing) orders than marketable (liquidity-consuming) orders. The choice of wholesalers to internalize non-marketable limit orders and offer high PFOF signifies high institutional liquidity demand.

We use the Tick Size Pilot to demonstrate formally how wholesaler decisions to internalize limit orders influence *Mroib*. An exogenous increase in the minimum quoted spread that preserves the minimum penny tick size increases the off-exchange liquidity provision profits of wholesalers. We show that this wider quoted spread increases internalization. Conversely, a joint increase in the minimum quoted spread *and* the tick size (a) sharply reduces internalization and (b) greatly increases $|Mroib|$. By raising the risk of execution at far less favorable prices, the larger tick size discourages the submission of market orders by retail investors. This reduction in retail market orders reduces internalization and results in non-marketable limit orders comprising a larger share of internalized order flow. The accompanying increase in $|Mroib|$ reflects the greater influence of non-marketable limit orders, whose costly

⁹From [FINRA Regulatory Notice 01-30](#), broker/dealers must “make publicly available quarterly reports about the routing of customer orders.” This requirement is known as Rule 606 of Regulation NMS.

internalization may be justified when institutional liquidity demand is unusually high.

We then extend the analysis in BJZZ along several important dimensions. First, using ANcerno and FINRA data, we document that the internalization of more retail sell orders than buy orders is associated with (i) more institutional buy volume than sell volume, and (ii) more covering of short interest by short sellers. Second, we show that institutional order flow imbalances and $Mroib$ are both more extreme when institutional trading costs are higher. For example, higher $|Mroib|$ is associated with higher implementation shortfalls, wider quoted spreads, and lower depth. The association between more extreme $Mroib$ and high institutional trading costs is consistent with internalization by wholesalers being an expensive source of liquidity that is largely accessed when institutional liquidity demand is high. Third, more extreme $Mroib$ is associated with greater price improvement as the increased internalization of non-marketable retail limit orders occurs when institutional liquidity demand and trading costs are high. Fourth, consistent with retail liquidity provision to institutions, but not informed retail trading, contemporaneous *intraday* prices move in the same direction as institutional trade imbalances and hence in the *opposite* direction of $Mroib$.¹⁰

Cross-sectional regressions of stock returns on $Mroib$ reveal that higher $Mroib$ is associated with higher near-term future weekly returns (e.g., subsequent 12 weeks) but *lower* distant future weekly returns (e.g., weeks 39 through 60), which is inconsistent with informed retail trading. The near-term return predictability of $Mroib$ is reconciled by price reversals following price pressure from persistent institutional trading, especially institutional buying (Hendershott and Seasholes 2007, Akepanidtaworn et al. 2021). Thus, negative current $Mroib$ (retail selling, institutional buying) tends to be associated with lower future returns for several weeks due to the unwinding of institutional price pressure. Decomposing daily returns into intraday and overnight returns sheds light on the liquidity-driven nature of these dynamics—we document intraday institutional price pressure, especially from institutional

¹⁰To clarify, BJZZ’s algorithm constructs $Mroib$ exclusively from transactions executed during regular trading hours. Thus, intraday returns are the relevant metric for examining $Mroib$ ’s price impact.

buying, is followed by overnight reversals.

2 Literature Review

Our paper contributes to the literature on the information content of internalized retail order flow by highlighting how the economic incentives of wholesalers influence internalization. Consistent with retail liquidity provision, Easley et al. (1996) and Bessembinder and Kaufman (1997) report that internalized orders are less informed. Ernst et al. (2021) find evidence of delayed release of information regarding internalized order flow to the market, providing incentives for institutions to pursue such order flow to conceal intended position sizes.

We are the first to identify wholesaler internalization choices that serve as a vehicle for retail investors to provide liquidity to institutional investors. As such, we extend the literature on liquidity provision by retail investors (e.g., Kaniel et al. 2008; Kaniel et al. 2012). Consistent with Kelley and Tetlock (2013), we find that the use of retail non-marketable orders to meet institutional liquidity demand underlies return predictability of retail order flow. Barrot et al. (2016) uses proprietary data to identify liquidity provided by retail investors that does not receive compensation because retail investors (i) trade before price pressure from institutional trading is fully realized, and (ii) do not unwind positions before price pressure reverts. We extend these insights using comprehensive data that covers all NMS common shares.

Theoretical models have identified conditions under which order flow internalization harms market quality, liquidity, or welfare (e.g., Battalio and Holden 1995; Bernhardt et al. 2001; Parlour and Rajan 2003; Parlour and Seppi 2003). However, empirical studies motivated by these predictions find modest support (e.g., Battalio et al. 1997; Battalio et al. 2003; Peterson and Sirri 2003; Battalio 2012). We contribute to this debate by showing that non-marketable limit orders are the marginal order type in the internalization process. Were these non-marketable orders to reach the limit order book, they would improve liquidity and (if round lot orders) tighten bid-ask spreads on exchanges. However, PFOF arrangements fa-

cilitate the execution of non-marketable limit orders by wholesalers, preventing these orders from reaching exchanges when the demand for liquidity is high.

While a simple interpretation of $Mroib$'s return predictability might suggest that retail investors are informed, such an interpretation is at odds with institutional details and our many empirical findings.¹¹ Importantly, all of our findings are reconciled by properties of institutional liquidity demand. For example, large negative and large positive internalized retail order flow imbalances *both* predict higher distant future weekly returns than intermediate values of $Mroib$, strongly suggesting that the cross-sectional variation in distant future returns is influenced by a liquidity premium captured by the absolute value of $Mroib$. Our companion paper Barardehi et al. (2022) formally establishes this. They use average $|Mroib|$ as a stock-specific measure of *institutional* liquidity costs. They establish the relevance of these liquidity measures for institutional investors by highlighting how these measures vary with measures of institutional trading costs and institutional holding horizons. While traditional liquidity measures are no longer priced in recent years, this institutional liquidity measure yields economically large liquidity premia even after implementing the most conservative filters and estimation methods commonly used in empirical asset pricing literature to offset the impacts of penny stocks, microstructure noise, tail observations, etc.

Finally, we contribute to research identifying and understanding differences between intraday and overnight returns. Cliff et al. (2008) and Berkman et al. (2012) document that overnight returns are positive and intraday returns are negative, on average. Hendershott et al. (2020) show that CAPM holds overnight but not intraday, and attribute intraday deviations from CAPM to noise trading. Bogousslavsky (2021) finds that arbitragers tend to close positions near the end of a trading day. Intraday return variation induced by closing arbitrage positions allows a mispricing factor to explain intraday returns but not overnight

¹¹See also Barber et al. (2021), who show that when internalized trade volume is abnormally high (top decile), extremely positive $Mroib$ (top quintile) is followed by negative abnormal returns, suggesting that informed retail trade does not underlie this outcome.

returns. Lou et al. (2019) find that intraday and overnight returns exhibit strong persistence vis à vis past intraday and overnight returns, respectively, but strong reversals relative to overnight and intraday returns. They posit that clientele effects underlie these patterns. However, we establish that persistence in institutional order flow leads to the accumulation of price pressure during consecutive trading days that is partially reversed each night. This partial overnight reversal in conjunction with daytime persistence explains the distinct autocorrelations of daytime versus overnight returns. This reflects that liquidity premia are primarily embedded into intraday returns, driving deviations of intraday returns from CAPM.

3 Institutional Details and Hypothesis Development

The execution of a retail order in U.S. equity markets follows one of several paths depending on the decisions of three entities: a retail investor, a retail broker (broker-dealer), and an off-exchange market maker (wholesaler).¹² The retail investor chooses an order type and may, but rarely does, indicate a preferred trading venue. Instead, the retail broker determines whether to handle the retail order by routing to a trading venue or to outsource its handling to a wholesaler. In practice, wholesalers handle nearly all retail orders, making wholesaler decisions to internalize retail order flow crucial.

Order type choice: A retail order is “directed” if a retail investor specifies a particular trading venue(s). Directed orders comprise a tiny fraction of the orders received by brokers. For example, about 0.01% of the orders received by TD Ameritrade in the first quarter of 2020 were directed. By default, the retail broker determines where to route “non-directed” orders.

Retail investors choose an order type from alternatives that include market, marketable limit, and non-marketable limit order types.¹³ Figure 1 illustrates the relevant order types in our analysis. As the average (equally-weighted) quoted spread in our sample is 6¢, suppose

¹²A wholesaler is an example of an over-the-counter (OTC) market maker.

¹³Our categorization of order types is consistent with Rule 606 filings. The “other” order type category includes orders that are similar to non-marketable limit orders such as stop or stop-loss orders.

the current best bid and ask prices are \$9.97 and \$10.03, respectively, when a retail trader submits an order. A market order demands immediate execution at the best available price. Ignoring price improvement, a market buy order would be executed at the best possible ask price at the time of execution, which is \$10.03 if the best ask price does not change in the interim. A marketable limit order also seeks immediate execution at the best price, but specifies a price equal to the current best quote. Thus, should the best price move against the investor, the limit order may not be executed. A marketable buy limit order at \$10.03 will either be executed at the best price (\$10.03 or lower) or enter the limit order book at \$10.03 if the best ask price increased above \$10.03 in the interim. A non-marketable buy limit order specifies a price below \$10.03, while an *attractive* non-marketable buy limit order specifies a price below \$10.03 but above the quote mid-point of \$10.00.¹⁴

Order routing by a broker-dealer: In practice, retail brokers commonly route *all* of their order flow to wholesalers according to common negotiated terms. A wholesaler makes payment for order flow and provides execution services to brokers in exchange for access to retail order flow before other market participants. The levels of PFOF largely reflect competition against rival wholesalers and exchanges that offer liquidity rebates. Consistent with the “best execution” duties of brokers and wholesalers, in addition to PFOF, the wholesaler offers sub-penny price improvement (PI) that is passed on by the broker to the retail investor submitting the order to ensure its execution price is never worse than the best quoted price displayed on exchanges at the time of the transaction.¹⁵

The above details highlight the need to distinguish *quoted prices* from *execution prices*. For limit orders, a retail investor *quotes* a price for the order, while market orders seek execution at best available prices. Rule 612 of RegNMS generally requires all orders to be quoted

¹⁴Rapid updates in the order book preclude permanent distinctions between marketable and non-marketable limit orders. A change in the best quoted price can cause a non-marketable order to become marketable or vice versa. We refer to order types based on their status at the time a wholesaler receives them.

¹⁵See FINRA [Regulatory Notice 21-23](#) for details on best execution. On exchanges, the SEC’s Order Protection Rule guarantees execution at the national best quoted price.

at penny increments. However, retail trade execution is governed by the “best execution” duties of retail brokers. In particular, the execution of any retail market order *or* retail limit order may involve sub-penny price improvements, and hence sub-penny execution prices.¹⁶ Figure 5 shows that the most common sub-penny price improvement is 0.01¢ and that over 70% of orders receiving this tiny amount are priced at the NBBO when executed, indicating that they are marketable orders. However, larger price improvements of 0.1¢, 0.2¢, 0.25¢, 0.3¢, and 0.4¢ also occur and these larger amounts are *several* times more likely to be given to orders inside the NBBO. This latter result indicates that orders receiving more PFOF also tend to have more PI.

Internalization by a wholesaler: The process by which wholesalers trade against retail order flow is referred to as internalization. In May 2012, internalized retail order flow comprised roughly 8% of all trading volume on NMS stocks (Tuttle 2014). Wholesalers are usually registered brokers, but they are not subject to the rules of registered exchanges. Most notably, wholesalers can execute trades at sub-penny prices despite the 1¢ minimum tick size. This flexibility allows wholesalers to coordinate with retail brokers and execute retail orders at sub-penny prices after offering price improvements that fulfill their “best execution” duties.

Wholesalers do not internalize all retail order flow routed to them via retail brokers. Panel A in Table 1 reports the distribution of order types across all non-directed and all internalized orders, along with average PFOF for each order type. Market orders and marketable limit orders account for a disproportionately large share of orders receiving PFOF, indicating that wholesalers prefer to internalize marketable orders relative to non-marketable orders. Simple calculations reveal that the share of non-marketable limit orders receiving PFOF is only one fourth that of marketable orders. In addition, non-marketable limit orders that are internalized receive over double the PFOF per share as market and marketable limit orders. Further

¹⁶See the response to question 13 in [Rule 612 FAQs](#). Some exchanges also offer Retail Liquidity Programs that allow for sub-penny execution prices when retail orders can be matched inside the bid-ask spread, but such transactions are rare (see NYSE Retail Liquidity Program’s [Fact Sheet](#)).

calculations suggest that about 70% of marketable orders receiving price improvement get PI of no more than 0.1¢ while 70% of non-marketable orders receiving PI get strictly more than 0.1¢. Thus, non-marketable limit orders are both more costly to internalize and less profitable to fill due to their inside-quote pricing. This suggests that they should primarily be internalized only when high institutional liquidity demand offers compensating profits.¹⁷

Most wholesalers own Single Dealer Platforms (SDPs), also known as ping pools, where a select set of institutions and institutional brokers trade against the wholesaler.¹⁸ By 2017, over 2.5% of all trading in NMS stocks occurred in ping pools,¹⁹ or roughly 30% of all internalized order retail flow. An institution may “ping” a wholesaler, which signals an unusually high demand for liquidity, encouraging the wholesaler to intermediate between retail and institutional order flow, rather than between retail order flow on each side of the market. This outcome highlights how retail investors provide liquidity to institutions when liquidity is scarce, and why, when they do, internalized retail order flow receiving sub-penny price improvements is unbalanced in the opposite direction of institutional liquidity demand. Institutions with high liquidity demand are prepared to pay more to wholesalers, allowing wholesalers to pay sufficient PFOF to compete with exchange rebates.²⁰ Figure 2 illustrates the market-structure aspects relevant for retail order flow internalization/execution and PFOF.

Market and marketable limit orders are less expensive for a wholesaler to internalize than

¹⁷That the average PFOF for non-marketable limit orders slightly exceeds 0.3¢ is consistent with competition from exchanges offering such liquidity-making rebates. Spatt (2020) highlights how liquidity fee/rebate tiers incentivizes brokers to allow wholesalers to handle their non-marketable orders because wholesalers receive higher rebates. Upon receipt of a non-marketable order, a wholesaler may submit an identically-priced order to an exchange, and then, if executed, internalize the standing retail limit order against their own inventory and pay PFOF to the broker.

¹⁸Trading that does not occur on exchanges or ATSs has attracted the attention of regulators. For example, FINRA [Regulatory Notice 18-28](#) describes the nature of SDP trading, a major component of non-ATS trading, and highlights the agency’s transparency concerns that led to [Regulatory Notice 19-29](#), which expanded the transparency of OTC trading volume in December 2019.

¹⁹[Trader VIP Clubs, ‘Ping Pools’ Take Dark Trades To New Level](#), *Bloomberg*, Jan 16, 2018.

²⁰Non-marketable orders executed on exchanges receive rebates of up to 0.3¢ per share. That the average PFOF for these orders slightly exceeds 0.3¢ is consistent with competition from liquidity-making rebates offered by exchanges.

non-marketable limit orders. Referring to the example, a market buy at \$10.03 is more profitable to fill than an attractive non-marketable buy limit order at \$10.01 or \$10.02. Even so, a wholesaler may profit from executing an internalized marketable limit buy order or an attractive non-marketable limit buy order at a price at or below the \$10.00 midpoint against a counter-party who is a retail investor submitting sell orders or an institutional investor pinging the wholesaler to indicate a strong selling interest on its SDP.

The above institutional details suggest the following hypotheses:

Hypothesis 1: *Informed trading is not the primary determinant of imbalances in the number or volume of retail orders receiving price improvement. Instead, off-exchange sub-penny trade executions reflect the economic incentives of wholesalers to internalize retail order flow.*

Hypothesis 2: *The internalization of non-marketable limit orders and the corresponding price improvements for these orders are determined by institutional liquidity demand. This demand reflects institutional trading costs, which determine the economic incentives of wholesalers to internalize retail order flow.*

Hypothesis 3: *Liquidity provision underlies the ability of retail imbalances to predict future returns. In the near-term, return predictability reflects the reversal of short-term price pressure associated with institutional liquidity consumption.*

4 Data

We follow BJZZ in constructing our main sample. Our sample spans January, 2010 through December, 2014, covering common shares listed on the NYSE, AMEX, and NASDAQ.²¹ We use daily open and close price information from CRSP's Daily Stock File to calculate three measures of daily returns: the standard close-to-close (CC) return, the open-to-close intra-day (ID) return, and the close-to-open overnight (ON) return. Our construction accounts

²¹We do not include 2015, which is in BJZZ's sample because our ANcerno institutional trade data ends in 2014. Unreported results verify that all findings that do not require ANcerno data are robust to adding 2015.

for overnight adjustments and, to minimize variations due to bid-ask bounce, is based on the quote midpoints at close. We then aggregate daily log-return observations into overlapping 5-day rolling windows to construct daily cross-sections of 5-day (weekly) returns, as in BJZZ. We include a stock-day observation in our sample if it had a closing price of at least \$1 at the end of the previous calendar month.

We use BJZZ’s algorithm to construct measures of internalized retail order flow. Using TAQ data, we focus on round-lot orders executed off-exchange (transactions with exchange flag “D”) that feature sub-penny execution prices.²² A transaction is classified as a retail buy order if the sub-penny (sub-tick) increment exceeds 0.6¢ and is classified as a retail sell order if the sub-penny increment is less than 0.4¢.²³ We construct daily, normalized measures of imbalance in internalized retail order flow trade frequency and trade volume. $Mroibtrd = (Mrbtrd - Mrstrd)/(Mrbtrd + Mrstrd)$ divides the difference between the number of internalized retail buy and internalized retail sell orders by their sum, while $Mroibvol = (Mrbvol - Mrsval)/(Mrbvol + Mrsval)$ is the normalized difference in internalized trade volume. Panel B in Table 1 reports the summary statistics for these measures, which closely match the BJZZ summary statistics. We then aggregate these daily observations of normalized internalized retail order flow imbalances into overlapping 5-day rolling windows to construct daily cross-sections of 5-day (weekly) internalized retail order flow imbalances.

Using Quote and NBBO files in Daily TAQ database, we match each identified internalized retail transaction with the National Best Bid and Offer prices at the same millisecond. We calculate the daily fractions of internalized retail volume executed at prices that are at least 1¢ better than the NBBO at the time of transaction. We then match 5-day rolling

²²As in BJZZ, our findings are robust to including odd-lots.

²³This algorithm has minimal, if any, mis-classifications for transactions that correspond to non-binding penny quoted spreads. For example, sample 606 filings from the fourth quarter of 2020 for E*TRADE, TD Ameritrade and Charles Schwab reveal that PFOF for market and marketable limit orders ranged between 0.09 to 0.19 cents per share, while the average PFOF for non-marketable limit orders did not exceed 0.34 cents per share.

average of these factions with the 5-day (weekly) internalized retail order flow imbalances.

ANcerno data provides institutional trade sizes, buy versus sell indicators, execution prices, and stock identifiers for the 2010–2014 period. We aggregate institutional buy and sell trade separately at the stock-day level to construct institutional buy and sell volumes. Using these volumes, we construct the institutional analogue of $Mroibvol$ denoted $Inroibvol$. We also construct implementation shortfall measures. For each institutional buy trade, the implementation shortfall equals the execution price minus that day’s open price divided by the open price and scaled by the trade’s dollar value in millions. Similarly, for each institutional sell trade, the implementation shortfall equals that day’s open price minus the execution price divided by the open price and scaled by the trade’s dollar value in millions. The mean implementation shortfall at the stock-day level is given by the value-weighted average across buy and sell implementation shortfalls. To maintain consistency with our other analysis, we aggregate institutional trading outcomes over 5-day rolling windows to construct daily cross-sections of 5-day (weekly) institutional trading outcomes.

We construct stock characteristics using information from CRSP’s Daily and Monthly Stock Files and Compustat. Using CRSP data, we construct each stock’s return volatility using daily observations from the preceding month (VOLAT). A stock’s book-to-market (BM) ratio equals its most recent book value of equity divided by its market capitalization from the previous month.²⁴ Past return measures include the previous month’s return (RET_{-1}) and the compound return over the preceding 5 months ($RET_{(-6,-2)}$). The previous month’s turnover (TO) equals the ratio of the previous month’s share volume to shares outstanding, and Size equals the firm’s market capitalization at the end of the previous month.

We obtain the identifying information for control and treatment stocks in the U.S. Tick Size Pilot program (TSP) from FINRA’s website, focusing on Test Groups 1 and 2 of the program. For each stock, we construct daily observations over the 10 trading days prior to im-

²⁴Book value is defined as Compustat’s shareholder equity value (`seq`) plus deferred taxes (`txdb`).

plementation of TSP on 10/03/2016 as well as the 10 trading days after full implementation on 10/17/2016.²⁵ From Daily TAQ’s Trades, Quotes, and NBBO files, we obtain trade and quote information to match off-exchange transactions executed at sub-penny prices with the national best bid and ask prices at the time of transaction based on millisecond timestamps. Then, for each stock-day, we construct the following outcome variables: (1) the absolute value of *Mroibtrd*; (2) the absolute value of *Mroibvol*; (3) size-weighted average relative percentage price improvement, which divides the relative price improvement for a sub-penny-executed transaction (i.e., the difference between the best quoted price and the transaction price) by the mid-point of best bid and ask; (4) total dollar-denominated price improvement, which is the sum of dollar relative price improvements across all sub-penny-executed transactions; (5) the total share volume of trades receiving price improvement; and (6) the size-weighted average sub-tick (sub-penny) fraction of trades receiving price improvement.

5 Initial Analysis

We first replicate the findings of BJZZ. We then extend their analysis to provide evidence that liquidity provision by retail investors to institutional investors underlies both near-term and distant future weekly returns conditional on *Mroib*.²⁶ Panel B in Table 1 provides summary statistics that closely match those reported in Table I of BJZZ, confirming that our construction of *Mtoibtrd* and *Mroibvol* parallels their methodology. We estimate the predictability of weekly returns conditional on *Mroibvol* by estimating:

$$R_{j,w+i} = c_w^0 + c_w^1 Mroibvol_{j,w-1} + c_w^{2\top} \text{controls}_{j,w-1} + u_{j,w+i}, \quad (1)$$

where $R_{j,w+i} \in \{CCR_{j,w+i}, IDR_{j,w+i}, ONR_{j,w+i}\}$ denotes weekly (rolling 5-day) close-to-close, intraday, and overnight returns, respectively, of stock j in week $w+i$. $Mroibvol_{j,w-1}$

²⁵Implementation consists of three phase-ins with different subsets of control stocks experiencing tick size changes on 10/03/2016, 10/10/2016, and 10/17/2016. For more details about the Tick Size Pilot program see <https://www.sec.gov/rules/sro/nms/2015/34-74892.pdf>.

²⁶Our sample period spans 2010–2014, while BJZZ’s spans 2010–2015.

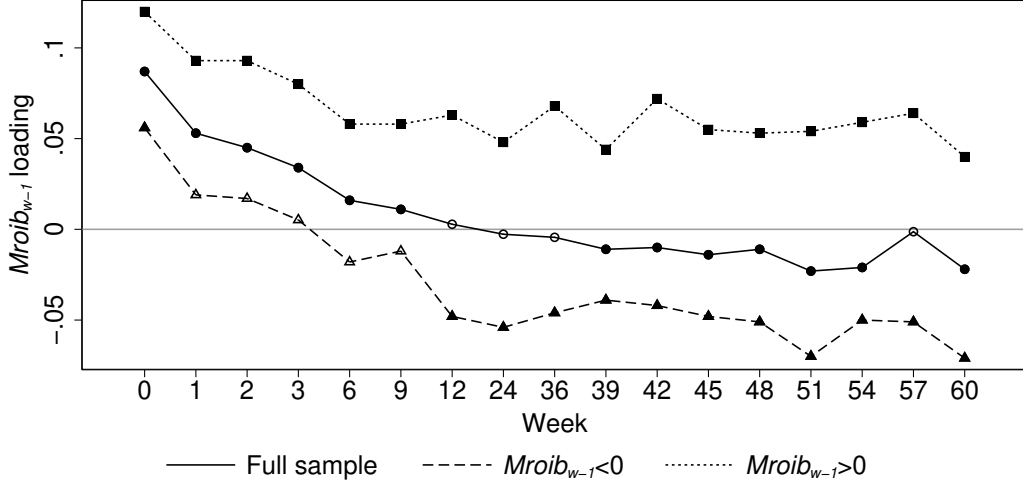
denotes the imbalance in the trading volume of internalized retail order flow receiving price improvement in the previous week. We estimate equation (1) both unconditionally and conditional on the *sign* of $Mroibvol_{j,w-1}$ to examine its return predictability separately when this order flow imbalance is negative and positive. Control variables include the previous week’s return (R_{w-1}) in percentage points, the previous month’s return (RET_{-1}), the return over the five months prior to the last month ($RET_{(-7,-2)}$), return volatility (VOLAT), as well as the natural logs of turnover ($\ln(TO)$), market capitalization ($\ln(Size)$), and book-to-market ratio ($\ln(BM)$). As in BJZZ, we estimate equation (1) using Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags.

Table 2 presents the estimation results for $i = 0$. The second column of this table corresponds to the second column of Table III in BJZZ. Our point estimate (\hat{c}_w^1) of 0.087% is nearly identical to BJZZ’s estimate of 0.09%. The coefficients for the control variables are also similar to those reported by BJZZ. We next extend BJZZ along three dimensions. First, we estimate the weekly return predictability of $Mroibvol_{j,w-1}$ for up to 60 weeks ahead (beyond the 12 weeks estimated in BJZZ). Second, we characterize this return predictability conditional on the sign of $Mroibvol_{j,w-1}$. Third, we decompose returns into intraday and overnight components.

Striking evidence obtains. As Figure 2 illustrates, the coefficients on $Mroibvol_{j,w-1}$ become *uniformly negative* after 39 weeks, which is difficult to reconcile with informed retail trading.²⁷ Moreover, although a negative $Mroibvol_{j,w-1}$ yields a positive coefficient for the current week’s close-to-close return ($i = 0$), this coefficient declines and becomes *negative* by week $w + 6$, again inconsistent with retail sell orders being informed, since “retail sell order flow” realizes weekly losses due to persistent price appreciation after 6 weeks. In contrast, a positive $Mroibvol_{j,w-1}$ always yields a positive coefficient for weekly returns across all horizons (see Table 3 for tabulated results).

²⁷Our index starts at $i = 0$, while BJZZ’s index starts at $k = 1$.

Figure 2: **Internalized Order Flow and the Cross-sections of Future Weekly Returns.** This figure shows the associations between internalized retail order flow and future week $w+i$ returns (in %), with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 42, 45, 48, 51, 54, 57, 60\}$. Returns reflect the quoted mid-points at the close. According to equation (1), week $w+i$ returns in each sample are regressed on $Mroibvol_{w-1}$, whose loadings are plotted in future weeks for both the unconditional analysis and the analysis conditional on the sign of $Mroibvol_{w-1}$. The estimated loadings are from Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2014, excluding observations when the previous month-end's closing price is below \$1. Statistically significant and insignificant loadings at the 10% type one error are identified by filled and hollow symbols, respectively.



Decomposing returns into intraday and overnight returns uncovers further asymmetries in the loadings conditional on the sign of $Mroibvol_{j,w-1}$. For overnight returns, \hat{c}_w^1 is positive following negative $Mroibvol_{j,w-1}$ (retail selling, institutional buying), but negative and insignificant following positive $Mroibvol_{j,w-1}$ (retail buying, institutional selling). Barclay and Hendershott (2003) and Jiang et al. (2012), among others, show that overnight price movements are information-driven. However, the insignificant negative relation between net retail buying imbalances and next week's overnight returns indicates that retail buys are not informed.²⁸ Moreover, informed retail trading cannot explain why \hat{c}_w^1 switches sign for intraday returns when $Mroibvol_{j,w-1}$ switches sign.²⁹

²⁸Furthermore, retail short selling is limited, suggesting that informed trading does not underlie the association between net retail selling imbalances and next week's overnight returns.

²⁹Table 3 shows that the asymmetry in the predictability of close-to-close returns also holds for intraday and overnight returns, which is further at odds with retail investors being informed.

6 The Economics of Internalization

This section highlights the key economic features underlying our results. We first provide a framework that shows how the economic choices of wholesalers drive the association between institutional liquidity demand and *Mroib*. We show that in the absence of institutional liquidity demand, the internalization incentives of wholesalers result in minimal *Mroib* imbalances, whereas high institutional liquidity demand leads to highly imbalanced *Mroib*. We then exploit exogenous shocks driven by the U.S. Tick Size Pilot to make inferences about the economic choices of wholesalers as predicted by our simple framework. Finally, we establish that (1) *Mroib* is negatively related to institutional order flow from both long-only investors and short sellers; (2) more imbalanced *Mroib* is associated with higher institutional trading costs and abnormally low stock liquidity; and (3) intraday prices move in the opposite direction of *Mroib*, consistent with the direction of institutional price pressure.

6.1 Wholesaler Incentives, *Mroib*, and Institutional Liquidity

We now provide a setting that illustrates the economic incentives underlying a wholesaler’s decisions about which retail orders to internalize, and the consequences for the level of *Mroib*.

Broker-dealers route nearly all order flow to wholesalers. In return, the wholesaler provides execution for a subset of these orders and PFOF. To give perspective, in 2020, TDAmeritrade received PFOF of \$0.0012 for each liquidity-taking marketable order, and an average of about \$0.0034 for liquidity-making limit orders, which exceeds the maximum liquidity rebate of \$0.003 that an exchange can offer (an inverted exchange pays far less for liquidity-taking orders—see Battalio, Corwin and Jennings (2016) for details on make/take rebate/fee schedules). The small premia above what an exchange would offer reflects the bargaining position of the broker-dealer who understands the value to a wholesaler of that order flow to risklessly intermediate between two parties, earning the difference in the prices paid by the two sides.

Suppose that the public information value of a share is V , and there is a four tick spread. Thus, the bid is $\$(V - 2t)$ and the ask is $\$(V + 2t)$. The distribution of retail orders routed by the broker-dealer to a wholesaler is given by

- n_{-2}^s marketable sell orders at $\$(V - 2t)$
- n_{-1}^s limit sell orders at $\$(V - t)$
- n_0^s limit sell orders and n_0^b limit buy orders at $\$V$
- n_1^b limit buy orders at $\$(V + t)$
- n_2^b marketable buy orders at $\$(V + 2t)$

To illustrate the economics, we assume that there is more retail sell interest than retail buy interest so that $n_{-j}^s \geq n_j^b$, for $j = 0, 1, 2$, and we define $\Delta_j = n_{-j}^s - n_j^b \geq 0$. To reduce the number of cases that we need to enumerate, we assume that (a) $n_{-2}^s \leq n_2^b + n_1^b$, and (b) $n_{-2}^s + n_{-1}^s \leq n_2^b + n_1^b + n_0^b$. Qualitatively similar implications obtain when these assumptions do not hold.

The wholesaler chooses whether to internalize a retail order in return for giving the broker-dealer PFOF, or to reroute it directly to an exchange, in which case all rebates (or fees) go to the retail broker, where the rebate for liquidity-making limit orders exceeds that for liquidity-taking market orders.³⁰ The broker-dealer obtains $PFOF_j$ in return for outsourcing the execution of a type j order to the wholesaler.

Price improvement of $PI_M > 0$ must be offered to marketable orders in order to satisfy best execution duties. We allow for the possibility that only some internalized non-marketable orders receive price improvement. For simplicity, we assume that the fraction $\alpha_{NM} \geq 0$ of non-marketable orders that receive price improvement of $PI_{NM} > 0$ does not depend on their location in the book. As we later show, a large share of trade executions

³⁰A third possibility in practice is that the wholesaler can post similarly-priced orders out of its own inventory on an exchange, and fill the order received if its proprietary order is executed on an exchange, where upon execution, the wholesaler internalizes the retail order and pays PFOF.

with sub-penny price improvements are inside the NBBO, indicating that α_{NM} is non-trivial. To ease presentation, we assume that the total PFOF plus PI offered is less than half a tick, so that it is profitable to intermediate buy and sell orders than are one tick apart.

It is costly for the wholesaler to hold inventory that deviates by q from its preferred inventory level of 0. We assume that these costs rise convexly in q , i.e., $c(q) - c(q - 1)$ is strictly increasing in q , where $c(1) - c(0)$ is assumed to be less than the expected liquidity rebate, consistent with tiny deviations from optimal inventory levels not being that costly.

We first highlight the economic forces for balanced levels of M_{roib} in the absence of institutional liquidity demand. When a wholesaler is not “pinged” by an institution, it is strictly profitable for the wholesaler to internalize marketable sell orders and limit sell orders at $\$(V - t)$ simultaneously with marketable buy orders and limit buy orders at $\$(V + t)$, as the PFOF plus PI paid is less than the profit obtained by intermediating these orders. Thus, at least $\min\{n_{-2}^s + n_{-1}^s, n_2^b + n_1^b\} = n_2^b + n_1^b$ is filled on each side by the wholesaler’s internalization. The BJZZ algorithm identifies the subset of those internalized orders that receives price improvement, which comprise a total of $2(n_2^b + \alpha_{NM}n_1^b)$.

After filling these orders, the distribution of the remaining retail orders is given by

- 0 marketable sell orders at $\$(V - 2t)$
- $n_{-2}^s + n_{-1}^s - (n_2^b + n_1^b)$ limit sell orders at $\$(V - t)$
- n_0^s limit sell orders and n_0^b limit buy orders at $\$V$
- 0 limit buy orders at $\$(V + t)$
- 0 marketable buy orders at $\$(V + 2t)$

Next observe that it is optimal for the wholesaler to internalize some of the remaining limit

sell orders at $\$(V - t)$ by holding inventory, stopping at the inventory imbalance of q^* where

$$\begin{aligned} t - (c(q^*) - c(q^* - 1)) &\geq t - PFOF_1 - PFOF_0 - 2\alpha_{NM}PI_1 \\ &> t - (c(q^* + 1) - c(q^*)). \end{aligned}$$

That is, the wholesaler stops internalizing orders when the marginal profit from internalizing by holding more unbalanced inventory would be less than that from simultaneously filling a non-marketable limit sell order at $\$(V - t)$ and a non-marketable limit buy order at $\$V$. Again, BJZZ's algorithm identifies fraction α_{NM} of these orders.

When $n_{-2}^s + n_{-1}^s - (n_2^b + n_1^b) > q^*$, the wholesaler fills the remaining limit sell orders at $\$(V - t)$ with limit buy orders at $\$V$. The dealer then submits all remaining limit orders³¹ at $\$V$ to exchanges. Thus, absent institutional liquidity demand, for $n_{-2}^s + n_{-1}^s \leq n_2^b + n_1^b + q^*$, internalization order imbalances identified by the BJZZ algorithm equal

$$|Mroibvol| = \frac{(n_2^s + \alpha_{NM}n_1^s) - (n_{-2}^b + \alpha_{NM}n_{-1}^b)}{n_2^b + \alpha_{NM}n_1^b + n_{-2}^s + \alpha_{NM}n_{-1}^s} = \frac{\Delta_2 + \alpha_{NM}\Delta_1}{n_2^b + n_{-2}^s + \alpha_{NM}(n_1^b + n_{-1}^s)}.$$

$|Mroibvol|$ reaches a maximum at $n_{-2}^s + n_{-1}^s = n_2^b + n_1^b + q^*$, where substituting for $\Delta_1 = q^* - \Delta_2$ yields

$$|Mroibvol| = \frac{\alpha_{NM}q^* + (1 - \alpha_{NM})\Delta_2}{2(n_2^b + \alpha_{NM}n_1^b) + \alpha_{NM}q^* + (1 - \alpha_{NM})\Delta_2}.$$

For $n_{-2}^s + n_{-1}^s > n_2^b + n_1^b + q^*$, $|Mroibvol|$ falls with further increases in n_{-1}^s , as sell orders at $\$V - t$ are crossed with buy orders at $\$V$, while the denominator rises due to the “crossing” of the fraction α_{NM} receiving price improvement. Thus, if $\alpha_{NM} = 1$, then a peak of

$$|Mroibvol| = \frac{q^*}{2(n_2^b + n_1^b) + q^*}$$

is reached, and if $\alpha_{NM} = 0$, then the peak is

$$|Mroibvol| = \frac{q^* - \Delta_1}{2n_2^b + q^* - \Delta_1}$$

³¹That is, the n_0^s limit sell orders, and the $n_0^b - q^* - (n_{-2}^s + n_{-1}^s - (n_2^b + n_1^b))$ remaining limit buy orders.

Thus, with no institutional liquidity demand, we predict that internalization of retail orders should be roughly balanced.

Now suppose there is significant institutional liquidity demand. Such demand, when non-zero, is likely large relative to retail order flow, reflecting the much larger positions that institutions take, and the fact that there is little point for an institution to ping a wholesaler for a small position. To highlight how institutional demand changes *Mroib* measures, suppose now that there is extensive institutional sell demand in the setting above, where previously there were relatively small negative (sell) retail trade imbalances.

Internalized order flow is an expensive source of liquidity for institutions. To see why, first note the straightforward direct effect—an institution seeking to sell shares must compensate a wholesaler for the profits that the wholesaler would otherwise obtain by internalizing retail sell orders. More subtly, an institution must also compensate a wholesaler for the foregone possibility of using the internalized retail buy orders to profitably fill retail sell orders without distorting the wholesaler’s inventory—retail buy orders that are used to fill institutional sell orders cannot be used to fill retail sell orders. Finally, a wholesaler may have some bargaining power in negotiations with institutions. This logic implies that an institution interested in selling shares on an SDP must compensate the wholesaler via a combination of a low purchase price p_s and SDP access fees.

To begin suppose that the institution seeks to sell more than $n_2^b + n_1^b + n_0^b + q_s^*$ where

$$\begin{aligned} V - p_s - (c(q_s^*) - c(q_s^* - 1)) &\geq 0 \\ &> V - p_s - (c(q_s^* + 1) - c(q_s^*)). \end{aligned}$$

Then a wholesaler will internalize the retail buy orders received ($n_2^b + n_1^b + n_0^b$) to fill the institution’s sell orders, and continue to fill them via increasing its inventory only up to the point ($n_2^b + n_1^b + n_0^b + q_s^*$) where the marginal profit from internalization exceeds the marginal increase in inventory costs. Now, all retail sell orders are rerouted to other trading venues

so that, rather than being negative, $Mroibvol$ takes on its maximum value of one.

From this point, as one reduces institutional sell demand, one eventually reaches the level $(n_2^b + n_1^b + n_0^b + q_s^*)$ below which a wholesaler now fills all of the institution's orders. To do this, a wholesaler uses all retail buy orders while distorting its inventory to the minimum extent needed, and still reroutes all retail sell orders to trading venues. Thus, on this range, the marginal order is accommodated out of inventory, so $Mroibvol = 1$, remaining maximally tilted in the opposite direction of true retail order flow imbalance, $\frac{\sum_j \Delta_j}{\sum_j (n_j^b + n_{-j}^s)} < 0$.

With further reductions, one reaches a level of institutional sell demand at which the marginal inventory cost just falls below the profit from filling a marketable retail sell order. At this point, a wholesaler starts to internalize marketable retail sell orders, causing $|Mroibvol|$ to begin to fall, as first more attractive retail sell limit orders are internalized, and then limit buy orders at $\$V$ are rerouted to other trading venues instead of being internalized.

Taken together the observations with and without institutional liquidity demand reveal that (i) small $Mroib$ imbalances are an indication of the absence or near absence of net institutional demand, while (ii) very large $Mroib$ imbalances indicate unbalanced net institutional liquidity demand with the opposite sign of $Mroib$.

6.2 Minimum Tick Sizes and Internalization

In this section, we exploit the design of the U.S. Tick Size Pilot to establish that variation in $Mroibtrd$ and $Mroibvol$ reflects the internalization decisions of wholesalers. We first establish that the profitability of off-exchange liquidity provision drives wholesalers to internalize retail orders. We then show that non-marketable orders are the marginal order type considered for internalization.

The SEC implemented the U.S. [Tick Size Pilot](#) program (TSP) On October 3, 2016. This program offered an experimental design for studying the causal impact of the minimum tick size on trading outcomes. The program included 2,400 securities. To ensure that stocks were

randomly assigned to control and treatment groups, stocks were sorted into 27 categories based on share price, market-capitalization, and trading volume terciles. Across these categories, stocks were randomly assigned to three treatment groups that each contained 400 stocks. Treatment stocks in Test Group 1 were subject to a minimum quoted spread of 5¢ but could trade at price increments of 1¢—the *quote rule* (Rindi and Werner 2018). Treatment stocks in Test Groups 2 and 3 were subject to a minimum quoted spread of 5¢ and had to trade at price increments of 5¢—the *trade rule* (Rindi and Werner 2018). Test Group 3 stocks were also subject to a Trade-At Prohibition provision that is less relevant for our study.³²

A key exception to the minimum tick size applied to retail trades. Although retail trades had to be quoted using the minimum tick size, they could be executed at sub-penny prices off-exchange. However, for Test Groups 2 and 3, the program required a minimum price improvement of \$0.005 should the broker-dealer/wholesaler decide to offer price improvement. BJZZ’s algorithm is designed to detect sub-penny execution prices in a 1¢ tick size regime, but it can be scaled to detect sub-tick execution prices in any tick size regime. To accomplish this, for Test Groups 2 and 3, after the activation of the Trade Rule, we re-scale the command in BJZZ’s algorithm that classifies trades according to small versus large sub-penny increments by a factor of 5. Thus, borrowing BJZZ’s notation, we replace “ $Z_{jt} = 100 * \text{mod}(P_{jt}, 0.01)$ ” by “ $Z_{jt}^5 = 20 * \text{mod}(P_{jt}, 0.05)$ ”, where Z_{jt}^5 reflects the *sub-tick* execution price (P_{jt}) increment when the tick size is \$0.05. With this scaling, $Z_{it}^5 \in [0, 1]$ and transactions can be again classified into retail buy and retail sell trades as in Section 4.

The TPS provides an ideal setting to study the economics of retail order flow internalization by wholesalers since the experiment impacts (i) the order type choices of investors and (ii) the profitability of off-exchange liquidity provision (Rindi and Werner 2018). These impacts let us conclude that variation in $Mroibtrd$ and $Mroibvol$ is determined by wholesaler decisions to internalize specific retail orders. We use the following Difference-in-Difference

³²Unreported results reveal qualitatively similar findings for groups 2 and 3.

(DiD) methodology to examine the causal impact of a tick size change:

$$X_{j,d} = b_0^g + b_1^g(\text{Post}_d) + b_2^g(\text{Treat}_j^g) + b_3^g(\text{Post}_j) \times (\text{Treat}_d^g) + u_{j,d}. \quad (2)$$

Here $d \in [-11, -1]$ indexes the 11 trading days ending on 10/02/2016, and $d \in [0, 10]$ indexes the 11 trading days beginning on 10/17/2016.³³ $X_{j,d}$ is stock j 's outcome variable on trading day d ; Post_d is an indicator variable that equals 0 if $d < 0$ and 1 if $d \geq 0$. Treatment_j^g is an indicator variable that equals 0 if stock j is in the control group and 1 if stock j is in the treatment group for Test Group $g \in \{1, 2\}$. The coefficient b_3^g captures the treatment effects associated with Test Group g . To ensure that estimated treatment effects are unaffected by outliers, we use both OLS and quantile (median) regressions to estimate equation (6.2). Following the standard practice in the literature (e.g., Rindi and Werner 2019, Griffith and Roseman 2019, and Albuquerque et al. 2020), we condition estimates on quoted spread levels prior to the introduction of TSP.

Table 4 presents estimation results for Test Group 1, and Figure 3 provides complementary visual evidence. The quote test tends to marginally increase relative price improvement (as a percentage), especially for treatment stocks with tighter pre-TSP spreads.³⁴ More substantively, the quote rule raises the average and median volume of sub-penny-executed trades by 9% and 63% relative to the corresponding intercept, respectively, with similar increases discernible in the total dollar-amount of daily price improvement.³⁵ This suggests that wholesalers internalize retail orders more aggressively in response to the quote rule. The

³³Our event window excludes the 10 trading days spanning 10/03/2016 through 10/16/2016 to account for the staggered phase-in of tick size changes for treated stocks. There were three phase-ins of treated stocks in Test Groups 1 and 2 stocks: 5 stocks from each group on 10/03/2016, 92 stocks from each group on 10/10/2016, and the remaining 303 stocks on 10/17/2016.

³⁴Note that the effects on “Relative %-PI” for stocks with non-binding pre-TSP spreads are negative. This likely reflects the fact that quoting within bid-ask spreads that exceed 5¢ is now restricted by the minimum 5¢ spread. As a result, some non-marketable limit orders must be quoted at prices closer to the best quoted price, mechanically reducing the distance between their execution price and the best quoted price on the same side of the quotes midpoint.

³⁵Rindi and Werner (2018) find no discernible effect on consolidated volumes of treated stocks in TSP, indicating that our findings are likely orthogonal to any stock-level volume effect.

effects are stronger for stocks with tighter pre-TSP quoted spreads—stocks that are more likely to have binding quote test restrictions.

Consider a low spread stock for which the 5¢ minimum spread reflects an exogenously-widened quoted spread. For example, suppose marketable limit buy and sell orders were quoted at best prices of \$10.02 and \$9.99, respectively, before the spread was widened to \$10.03 and \$9.98. This widening of the spread increases depth at the best price, facilitating larger transactions (Rindi and Werner 2019). However, the aggregate amount of order flow that a wholesaler would otherwise have internalized is unaffected,³⁶ replacing the set of attractive non-marketable limit orders with marketable limit orders.³⁷ More importantly, widening the quoted spread increased the profitability of off-exchange liquidity provision at the midpoint, increasing the willingness of wholesalers to internalize order flow.

Table 4 reports that the intensity of sub-penny-executed retail trades, as measured by the total volume of price-improved trades, the total dollar price improvement, or size-weighted relative price improvement, all increase due to the minimum 5¢-spread. In contrast, the absolute values of *Mroibvol* and *Mroibtrd* decrease, moving in the *opposite* direction of retail order flow internalization intensity. That is, *Mroibvol* and *Mroibtrd* respond to the economic incentives of wholesalers regarding retail order flow internalization rather than retail trading per se.

Table 5 presents estimation results for Test Group 2 that introduced a 5¢ tick. Figure 4 provides complementary visual evidence. In contrast to the quote-rule treatment, this trade-rule treatment caused the absolute values of *Mroibtrd* and *Mroibvol* to increase dramatically, even though the treatment *sharply reduced* the volume of sub-penny-executed (internalized) trades. For stocks with tight spreads, median internalized trade volume fell by 47% relative

³⁶Werner et al. (2019) find that the wider spread incentivized the submission of limit orders, resulting in a longer queue at the bid and ask, while volume was unchanged.

³⁷For example, consider two stocks, one with a mandated 5¢ spread and the other with a 5¢ spread that was non-mandated (pre-existing). There can be attractive non-marketable limit orders with the latter but not the former.

to the corresponding intercept, while trade volume is unchanged for stocks with wide spreads.

The key feature of the trade rule is that it quintupled the trading increment. This impacted the composition of retail orders as market orders risked execution at prices 5¢ further from current best prices (i.e., by further than 1¢). This led retail traders to rely more on marketable limit orders in lieu of market orders. By the time a wholesaler begins handling orders flagged as marketable limit, some have become non-marketable due to changes in the order book in the interim. The overall effect is to increase the share of non-marketable limit orders, which reduces internalization.³⁸ Importantly, the increases we find in the absolute values of *Mroibtrd* and *Mroibvol* allow us to attribute the increased variation in *Mroib* to the increased internalization of non-marketable limit orders. We posit that these effects manifest themselves in the increased sensitivity of *Mroib* to institutional liquidity demand, as non-marketable limit orders are the marginal retail orders used to provide liquidity to institutions through internalization. Section 7.4 provides support for this prediction when *Mroib* is constructed from retail orders with price improvement levels that are relatively more likely to be given to non-marketable orders.

These findings based on the TSP reinforce the conclusion that variations in *Mroibtrd* and *Mroibvol* reflect wholesaler incentives to internalize retail order flow, rather than informed trading. Indeed, in light of our previous findings, an informed retail trading interpretation would imply that wholesalers would not be profit maximizing—internalizing more toxic (informed retail) orders while also paying more PFOF + PI is at odds with notions of profit-maximization. In contrast, the willingness to pay more for internalizing these marginal orders is consistent with them being needed to provide liquidity when institutional demand is high.

³⁸Our estimates likely understate the actual effect because wholesaler incentives to internalize order flow increase with a wider 5¢ spread.

6.3 Interaction Between Institutional and Retail Order Flow

Our next analysis links *Mroibvol* imbalances with the demand for liquidity by institutions on the opposite side.³⁹ We first examine the variation in *Mroibvol* against contemporaneous intraday and overnight returns. We find intraday prices move in the opposite direction of retail imbalances—contrary to premises of being driven by aggressive informed retail trade. Instead, intraday prices move in the same direction as institutional order flow imbalances. We then link *Mroibvol* imbalances to institutional order flow, institutional trading costs, and stock liquidity, showing that the most extreme retail and institutional order flow imbalances are associated with the highest institutional trading costs, the highest spreads, and the least depth. We also find that institutional order flow from mutual fund or short seller trades is negatively correlated with retail order flow. These findings reinforce how large *Mroibvol* imbalances are a symptom of wholesalers using retail order flow to provide liquidity to institutions.

Table 6 summarizes the relationships between *Mroibvol* and various contemporaneous outcomes across 10 *Mroibvol* portfolios. While close-to-close returns monotonically increase from -2bps in the bottom *Mroibvol* portfolio to 30bps in the top *Mroibvol* portfolio, this pattern is not due to price pressure from retail order flow. Decomposing daily returns into their intraday and overnight components reveals that intraday returns decrease monotonically from 10bps in the bottom *Mroibvol* portfolio to -14bps in the top *Mroibvol* portfolio.⁴⁰ As most internalized (price-improved) trades are market and marketable-limit orders, the *negative* association between *Mroibvol* and intraday returns is inconsistent with retail price pressure. This negative association is at odds with notions of informed retail trading as they would require a negative price impact from “informed” orders submitted by retail investors.

In sharp contrast to intraday returns, overnight returns are positively related to *Mroibvol*.

³⁹Our analysis focuses on *Mroibvol* but, as in BJZZ, similar empirical results obtain for *Mroibtrd*.

⁴⁰Recall that BJZZ’s algorithm constructs retail order flow imbalances using off-exchange transactions executed during regular trading hours.

Indeed, the signs of intraday and overnight returns differ for eight of the ten *Mroibvol* deciles.⁴¹ This opposing return pattern can be understood by examining institutional trading. Recall that institutional and retail imbalances are negatively correlated, as wholesalers internalize this portion of retail order flow to meet institutional demand. Average institutional order flow falls from 33.6% in the bottom *Mroibvol* decile to 21.1% in the top *Mroibvol* decile. Thus, when institutional order flow imbalances skew toward more buying, internalized retail order flow imbalances skew toward more selling. Moreover, short selling activity also occurs on the opposite side of internalized retail order flow as increased short interest (increased short selling) is associated with a larger positive internalized retail order flow imbalance. Importantly, directional (as opposed to liquidity provider) short sellers, whose aggregate positions are reflected in short interest data, are known to be informed (Desai et al. 2002; Engelberg et al. 2013; Boehmer and Wu 2013). Thus, the negative association between such short selling activity and *Mroibvol* represents further evidence against the informativeness of retail orders priced at sub-pennies. Instead, these findings suggest that the intraday price movements reflect institutional price pressure that is followed by overnight reversals.

Our next analysis identifies the economic roots of internalized trade imbalances, showing that they reflect variation in the extent of institutional liquidity demand relative to extant liquidity on other venues. Such uninformed institutional liquidity demand provides wholesalers with profitable intermediation opportunities. Such opportunities are more lucrative when institutional trading costs are higher (spreads are wide, depth near best prices is low). Wholesalers can detect these institutional liquidity demand shocks indirectly by observing unfilled block orders on their affiliated ATSs (dark pools), or directly through heightened participation in their SDPs (ping pools). To meet this institutional demand, the endogenous response of wholesalers is to gear their internalization toward retail orders from the opposite side, including non-marketable orders (see Section 6.2). This imbalanced internalization lets

⁴¹We also find that intraday returns are generally negative while overnight returns are generally positive, consistent with the asset pricing literature (Cliff et al. (2008), Berkman et al. (2012), and Lou et al. (2019)).

wholesalers fill these profitable institutional orders off-exchange. This economic logic finds strong support in the data.

Table 6 documents that institutional implementation shortfalls are highest, spreads are widest, and depth is lowest when *Mroibvol* is highest in absolute value, i.e., at the extreme deciles of *Mroibvol*. Concretely, implementation shortfall per \$1m worth of institutional order size is 69bps and 15bps when *Mroibvol* is at its lowest and highest deciles, respectively, while balanced *Mroibvol* is associated with roughly 3bps of such costs. Similarly, average dollar and relative quoted spreads in the lowest and highest *Mroibvol* deciles are essentially double those when *Mroibvol* is relatively balanced. Lastly, the ratio of internalized retail trades executed at prices that are superior to the NBBO by 1¢ or more rises by 33% as *Mroibvol* goes from its intermediate levels to the two extremes. This is an indication of more aggressive internalization of retail non-marketable limit orders when institutional liquidity demand on the opposite side is higher.

To hammer this U-shaped relationship home, we construct a stock-specific measure of abnormal realized off-exchange institutional liquidity. For each stock-day, we divide the number of large off-exchange mid-point executions⁴² by the same stock’s average of this quantity over the sample period. Higher values of this measure indicate greater liquidity. We find that extreme *Mroibvol* is associated with the least abnormal off-exchange midpoint execution, indicating that internalization of retail order flow is more prevalent when off-exchange liquidity is abnormally scarce.

Table 6 also reveals that intraday and overnight returns in the extreme *Mroibvol* deciles reflect more than the unwinding of price pressure. This observation is clearest in *Mroibvol*’s bottom decile where price pressure from institutional buying is 0.098%, but the contemporaneous overnight reversal of -0.116% exceeds this price pressure. To study this phenomena more accurately, a 5-day overnight return is constructed that omits the first close-to-open

⁴²TAQ data transactions with trade venue flag ‘D’ that are at least 1,000 shares and worth at least \$50k.

return and adds the overnight return on the sixth day. This adjustment properly aligns the timing of intraday price pressure and overnight reversals”. We see that this adjustment *exacerbates* the disconnect between the intraday “price pressure” and the subsequent (next-day) overnight “reversals” that average -0.134% when *Mroibvol* is in decile 1. In fact, comparing intraday and “next-day” overnight returns when *Mroibvol* is in decile 1 versus decile 5 reveals differences of $0.098 - (-0.063) = 0.161\%$ and $-0.0138 - 0.257 = -0.379\%$, respectively. The analogous differences when *Mroibvol* is in decile 10 versus decile 5 are $-0.138 - (-0.063) = -0.075\%$ and $0.456 - 0.257 = 0.199\%$, respectively. Thus, weekly overnight returns revert by far more than is needed to offset intraday returns, especially when *Mroibvol* is extremely negative. We next reconcile this pattern by establishing that institutional buy order flow is more persistent than institutional sell order flow. As a result, institutional buy order flow predicts returns and, in turn, is predicted by internalized retail order flow (with an inverse relation) over longer horizons.

7 Why Does *Mroib* Predict Returns?

7.1 Dynamics of Institutional and Retail Order Flows

This section shows that overnight reversals exceed intraday price pressure (during the same week) because overnight reversals also reflect the unwinding of institutional price pressure accumulated in prior weeks. This effect is more salient when more retail sell orders have been internalized, presumably to provide liquidity for institutional buy orders. A recent literature finds that long-only fund managers accumulate long positions slowly, but sell quickly, largely to fund purchases. This asymmetry is consistent with institutional buying, but not selling, being motivated by a fund manager’s best ideas (Akepanidaworn et al. 2021). This would lead long positions to be accumulated more gradually to conceal their presence, prolonging the unwinding of price pressure. Hendershott and Seasholes (1994) also document that the short positions of market makers, which reflect institutional buying, are associated

with subsequent price reversals that last up to 11 trading days. In contrast, price reversals that follow the accumulation of long positions by market makers, which reflect institutional selling, only last for 7 trading days.

We estimate

$$\begin{aligned} X_{j,w} = & a^0 + \sum_{i=1}^6 a_i^1 Inoibvol_{j,w-i} + \sum_{i=1}^6 a_i^2 [I(Inoibvol_{j,w-i} < 0)] \\ & + \sum_{i=1}^6 a_i^3 [I(Inoibvol_{j,w-i} < 0) \times Inoibvol_{j,w-i}] + \epsilon_{j,w}, \end{aligned} \quad (3)$$

where $X \in \{Inoibvol, Mroibvol\}$; and $I(\cdot)$ is an indicator function that equals 1 if $Inoibvol < 0$ and equals 0 otherwise. The models are estimated using Fama-MacBeth regressions, with standard errors corrected using the Newey-West methodology with 6 lags. On average across stocks, ANcerno covers less than 7% of the total daily trading volume reported by CRSP.⁴³ To reduce the noise attributable to a lack of coverage we use the subset of stocks for which the share of ANcerno-reported volume relative to CRSP is above-average.

Columns (1)–(4) in Table 7 present the $AR(k)$ estimates for $Inoibvol$, showing that past positive and negative institutional order flows, especially those with longer lags, predict current institutional order flows differently. The most recent week’s positive and negative $Inoibvol$ predict current week’s $Inoib$ similarly, with point estimates of 0.33 and 0.35 for positive and negative $Inoibvol_{w-1}$, respectively. However, these coefficients sharply diverge for $k > 1$, where the loadings of negative $Inoibvol_{w-i}$ become 30-70% smaller than those on their positive $Inoibvol_{w-i}$ counterparts. This finding is consistent with the more gradual accumulation of institutional buy positions found in the literature. This persistent institutional buying drives the accumulation of positive price pressure whose unwinding extends beyond the subsequent close-to-open to subsequent days, while institutional selling is less persistent.

Columns (5)–(8) in Table 7 highlight how past institutional order flow predicts future

⁴³Hu et al. (2018) report similar coverage over a longer sample period. Nevertheless, modest coverage does not invalidate the representativeness of ANcerno data (Puckett and Yan 2011, Anand et al. 2012, and Jame 2018).

internalized retail order flow, reinforcing our earlier conclusion that wholesalers intermediate trades between institutional and retail investors. Consistent with the stronger auto-correlation for institutional buying, and retail sell orders being internalized to provide liquidity for institutional buy orders, $Inoibvol_{w-i}$ loads with negative and significant coefficients.⁴⁴ Mirroring the weaker auto-correlation in institutional order flow when $Inoibvol_{w-i} < 0$, the loadings for $Inoibvol_{w-i}$ become positive for $k > 2$. These dynamics indicate that the most negative $Mroibvol_w$ observations, i.e., those in decile 1 of Table 6, are disproportionately more likely to arise following persistent institutional buying pressure whose unwinding makes the current week’s overnight returns more negative.

These statistical findings contain insights about the pecking order that institutions consider in the pursuit of liquidity. The negative correlation between past positive institutional order flow and current internalized retail order flow is consistent with institutions resorting to SDPs, and hence wholesaler PFOF, only after exhausting less expensive sources of liquidity.

7.2 Institutional Trading and Short-Term Return Predictability

We next establish that $Mroib$ ’s short-term return predictability is a liquidity-driven phenomenon. Due to the persistence of institutional order flow, especially institutional buying, overnight price reversals associated with extreme $Mroibvol$ magnitudes extend into future week(s). To the extent that institutional order flow is persistent, subsequent abnormal overnight price reversals remain nontrivial, creating distinguishable differences between close-to-close returns that follow extremely negative and extremely positive internalized retail order flow imbalances.

⁴⁴The only exception to statistical significance appears in column (8) for $Inoibvol_{w-5}$.

To highlight the persistence of institutional order flow, we estimate

$$\begin{aligned} Inoibvol_{j,w} = & c^0 + \sum_{i=1}^6 c_i^1 Mroibvol_{j,w-i} + \sum_{i=1}^6 c_i^2 [I(Inoibvol_{j,w-i} < 0)] \\ & + \sum_{i=1}^6 c_i^3 [I(Inoibvol_{j,w-i} < 0) \times Mroibvol_{j,w-i}] + \epsilon_{j,w}, \end{aligned} \quad (4)$$

with variable definitions and estimation approaches identical to those in equation (3). As Table 8 demonstrates, the first and second lags of internalized retail order flow load with significantly negative coefficients when these lagged internalized order flows correspond to positive institutional flow. That is, when institutional order flow is positive, greater internalization of retail sell orders relative to buy orders is associated with abnormally high institutional buy pressure up to two weeks forward. This effect, as discussed above, drives subsequent abnormally negative overnight returns that skews subsequent weeks' close-to-close returns downward. As such, *Mroibvol* appears to predict future close-to-close returns, even though it merely captures price reversals following institutional buy pressure.⁴⁵

7.3 Long-Term Return Predictability and Liquidity Premia

This section revisits the return predictability of *Mroibvol* to offer a unifying explanation for the patterns documented in Section 5. We analyze *Mroibvol*'s long-term return predictability, especially cross-sectional return differences after conditioning on the sign of *Mroibvol*_{*w*-1}. We show that long-term return predictability reflects liquidity premia required by institutional investors to hold less liquid assets (Amihud and Mendelson 1986).

Table 9 documents the relationships between close-to-close, intraday, and overnight weekly returns conditional on *Mroibvol*_{*w*-1}. Consistent with *Mroibvol*_{*w*-1}'s short-term return predictability, close-to-close returns for week *w* monotonically increase from the bottom decile of *Mroibvol*_{*w*-1} to the highest decile. Most of the return variation is concentrated in the

⁴⁵Lou et al. (2019) document that overnight and intraday returns display persistence relative to overnight and intraday returns, respectively, but reversals relative to intraday and overnight returns.

extreme deciles (deciles 1, 9, and 10). Furthermore, consistent with $Mroibvol_{w-1}$'s declining impact on close-to-close returns in Table 3, the return difference between the bottom and top deciles of $Mroibvol_{w-1}$ rapidly decline in subsequent weeks, nearly disappearing by week $w+12$. Instead, a striking U-shaped pattern in close-to-close returns across the $Mroibvol_{w-1}$ portfolios begins to emerge by week $w+3$, strengthening sharply in subsequent weeks. For example, average week $w+12$'s close-to-close returns in deciles 1 and 10 of $Mroibvol_{w-1}$ (0.15% and 0.18%, respectively) are more than double that in decile 6 (0.07%). Similar patterns extend to all future weeks. This U-shaped pattern implies that future returns are inversely related to negative $Mroibvol_{w-1}$ and positively related to positive $Mroibvol_{w-1}$. These distinct relationships reinforce the earlier negative and positive coefficients from regressing weekly returns on negative and positive $Mroibvol_{w-1}$, respectively (see Table 3).

To relate the U-shaped pattern to liquidity premia, focus on lower $Mroibvol_{w-1}$ deciles. In Section 7.2, we found evidence that the short-term negative overnight returns associated with extremely negative $Mroibvol_{w-1}$ likely reflect extended price reversals of previously-accumulated long institutional positions. These price reversals are temporary and reflect preceding price pressure from institutional trading. In contrast, a liquidity premium implies *long-term* return differences according to the level of liquidity. The strong association between liquidity measures, institutional trading costs, and retail order flow internalization indicates that stocks with more extreme $Mroibvol_{w-1}$ are less liquid. Hence, these stocks command higher *permanent* expected return premia (higher cross-sectional returns) as compensation for illiquidity. Week $w+i$ returns for the bottom decile of $Mroibvol_{w-1}$ demonstrate the net effect of temporary price reversals and characteristic liquidity premia. Initially, price pressure dominates but a liquidity premium eventually dominates cross-sectional returns, which become negatively correlated with negative $Mroibvol_{w-1}$. Conversely, when $Mroibvol_{w-1}$ is positive, disentangling short-term and long-term effects in close-to-close returns is more difficult since their impacts on returns have the same sign.

Decomposing close-to-close returns into intraday and overnight components enables us to identify when liquidity premia are realized during the day and contribute to the recent asset pricing literature that documents important time-of-day return disparities that are important to asset pricing anomalies. For example, Hendershott et al. (2020) report that CAPM predictions hold overnight but not during the day; and Lou et al. (2019) and Bogouslavsky (2021) find that most return anomalies accrue during the trading day rather than overnight. Consistent with these findings, our decomposition of close-to-close returns reveals that the U-shaped pattern in future close-to-close returns across $Mroibvol_{w-1}$ portfolios are largely attributable to intraday returns. In fact, overnight returns follow a \cap -shaped pattern across the 10 $Mroibvol_{w-1}$ portfolios. Attributing the U-shaped pattern in intraday returns to liquidity premia allows us to identify an economic mechanism that explains why return anomalies differ between intraday and overnight returns. In particular, liquidity premia are realized during the trading day, but not overnight.

In Appendix A, we decompose $Mroib$ into persistence, contrarian trading and residual components as in BJZZ to see which components underlie the predictability of future returns. We attribute $Mroib$'s long-term predictive power solely to the residual component, finding that *both* extreme negative and extreme positive residuals are associated with higher future returns. These findings further confirm liquidity-driven explanations of return predictability.

7.4 Implications of Sub-penny Price Improvement Size

We conclude our analysis by delving deeper into the link between institutional liquidity demand and the magnitudes of sub-penny price improvements that wholesalers offer when internalizing retail orders. We show that in equilibrium, stronger institutional demand for liquidity as manifested by more extreme institutional order flow and price pressure, is associated not only with larger sub-penny price improvements but also a higher probability that wholesalers internalize retail non-marketable limit orders.

Figure 5 plots the histogram of sub-penny price improvements associated with internalized retail trades of 100 randomly selected stocks. Over 80% of offered levels of price improvement are at 0.01¢, 0.1¢, 0.2¢, 0.25¢, 0.3¢, or 0.4¢, suggesting the contractually-driven price improvement schedule underlying these magnitudes. Importantly, we find a strong relationship between the size of sub-penny price improvements and the likelihood with which they are offered to non-marketable limit orders. In fact, the fraction of internalized retail orders whose execution price is at least 1¢ better than the NBBO at the time of transaction goes from 2.3% to 30.8% as the size of sub-penny price improvement rises from 0.01¢ to 0.4¢. To give a different perspective, orders at the NBBO receive price improvement of at least 0.1¢ only 47% of the time, while orders inside the NBBO receive price improvement of at least 0.1¢ over 70% of the time. Recognizing that non-marketable orders are more likely to be used by sophisticated retail investors, this evidence is inconsistent with wholesalers “price discriminating” against informed limit orders as suggested by BJZZ. Our next analysis reinforces this interpretation.

Figure 5 shows that the median level of sub-penny price improvement is 0.1¢. This leads us to construct two versions of *Mroibvol*, one based on internalized retail orders with “small” sub-penny price improvements of less than 0.1¢ and one based on “large” price improvements of at least 0.1¢.⁴⁶ We then compare the relationships between key institutional trading outcomes—implementation shortfalls, institutional order flow, intraday returns (proxy of institutional price pressure), and overnight return (proxy of unwinding of institutional price pressure)—and each of the two versions of *Mroibvol*.

Panel A in Figure 6 shows that implementation shortfalls display far stronger U-shaped patterns in high-sub-penny than in low-sub-penny *Mroibvol*. That is, the most extreme high-sub-penny *Mroibvol* observations realize when institutional trading costs are highest,

⁴⁶In unreported results, we find that the predictive power of *Mroib* for short-term future returns is not affected by the size of sub-penny price improvements used to construct the *Mroib* measures with a 0.1¢ cutoff. BJZZ classify transactions into those with small versus large price improvement using a 0.2¢ cutoff. The 0.2¢ cutoff leads to assignment of over 75% of internalized retail trades to the “small” sub-penny group, introducing noise to *Mroib* measures constructed using trades with “large” price improvements.

suggesting that unbalanced internalization of non-marketable limit orders while offering large price improvements tend to realize when institutional liquidity is scarce. Panel B shows a sharp inverse relationship between institutional order flow and high-sub-penny $Mroibvol$, highlighting the role of institutional liquidity demand in driving unbalanced and expensive internalization of retail orders on the opposite side. In contrast, institutional order flow is weakly U-shaped in low-sub-penny $Mroibvol$, indicating limited net institutional buying when retail buy interest is high. Consistent with these insights, Panels C and D show that intraday returns reflect institutional price pressure followed by overnight reversals. In particular, as high-sub-penny $Mroibvol$ rises, intraday returns, reflecting institutional price pressure, monotonically fall, while overnight returns reverse, moving in the opposite direction. In contrast, with small-sub-penny $Mroibvol$, intraday returns mirror the weak U-shaped pattern in institutional trade imbalances, followed by analogous reversals in overnight returns.

8 Conclusion

Wholesalers acting as off-exchange market makers in U.S. equity markets internalize retail order flow and provide payment for order flow to execute retail orders routed to them by retail brokers. Rule 606 disclosures indicate that while wholesalers prefer to internalize marketable orders, which are both less costly and more profitable to internalize than non-marketable orders, they also internalize a large fraction of non-marketable orders.

Our paper is the first to identify a mechanism by which wholesaler internalization serves as a vehicle for retail orders to provide liquidity to institutions when liquidity is scarce. In turn, we shed light on the economic mechanisms underlying the return predictability of imbalances in internalized retail order flow denoted $Mroib$ by Boehmer, Jones, Zhang, and Zhang (2021). In a nutshell, we find that variation in $Mroib$ and its return predictability reflect institutional liquidity demand, rather than informed retail trade. To fill institutional liquidity demand, wholesalers internalize unequal amounts of buy and sell retail order flow,

as manifested by large *Mroib* magnitudes, causing *Mroib* to be inversely related to institutional order flow. We show that the absolute value of *Mroib* is largest when institutional liquidity is most costly—when implementation shortfalls are highest, spreads are widest, depth is lowest, and mid-point off-exchange liquidity is scarce. Institutional price pressure drives intraday returns, causing them to be inversely related to *Mroib*. In turn, the predictive power of *Mroib* for subsequent week returns is attributable to price reversals that follow this institutional price pressure.

Our analysis informs policymakers about how existing retail order internalization practices may impact market quality for different market participants. Institutional investors may seek liquidity on Single Dealer Platforms affiliated with wholesalers, keeping their orders from being exposed to potentially toxic order flow on exchanges and other trading venues. However, even when sub-penny execution prices realized in this process reflect best execution quality for retail orders, they have a cost. Non-marketable limit orders are the marginal order types in the internalization process. If routed to exchanges, such orders could tighten bid-ask spreads. However, in less liquid markets where institutional trading costs are high, internalizing these orders, rather than adding them to the limit order book, is in the best interests of retail brokers, wholesalers, and institutional investors. As a result, these non-marketable retail limit orders fail to reach exchanges and hence fail to tighten spreads when liquidity is scarce. Even though internalization facilitates liquidity provision by retail investors to institutional investors, retail investors are typically minimally compensated via price improvements and, recently, zero-commission trade execution (Jain et al. 2020). Instead, most compensation for the provision of liquidity by retail traders to institutions accrues to wholesalers via the profits from near-riskless principal trading and to broker-dealers via PFOF.

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Tables and Figures

Table 1: **Summary Statistics.** Panel A reports (1) distributions of retail order types among all non-directed orders received by retail brokers; (2) distributions of retail order types among non-directed orders that are internalized and receive PFOF; and (3) PFOF amount per 100 shares for different retail order types. All quantities are extracted from Charles Schwab, TD Ameritrade, and E*TRADE's 606 filing disclosures for the final quarter of 2020. When applicable, quantities reflect dollar-weighted averages across the top-5 wholesalers handling retail orders for the respective broker. Panel B reports summary statistics for daily measures of internalized order flows for our sample of NYSE-, AMEX-, and NASDAQ-listed common shares during the 2010–2014 period. *Mrbvol* and *Mrsvol* denote trading volumes for internalized trades classified as retail buy and retail sell, respectively. *Mrbtrd* and *Mrstrd* denote the number of internalized trades classified as retail buy and retail sell, respectively. *Mroibvol* and *Mroibtrd* then denote normalized imbalances in internalized retail order flow based on trading volume and trade frequency, respectively.

Panel A: Retail Orders Receiving Payment for Order Flow									
	Charles Schwab			TD Ameritrade			E*TRADE		
	Non-directed orders (%)	Orders receiving PFOF (%)	PFOF (cents per 100 shares)	Non-directed orders (%)	Orders receiving PFOF (%)	PFOF (cents per 100 shares)	Non-directed orders (%)	Orders receiving PFOF (%)	PFOF (cents per 100 shares)
Market	52.9	57.2	9.0	18.8	44.7	12.0	49.3	53.7	19.9
Marketable limit	4.8	14.1	9.0	9.2	24.2	12.0	5.8	12.9	18.8
Non-marketable limit	33.8	21.1	29.6	31.9	21.2	33.5	35.0	18.0	29.3
Other order types	8.5	7.6	10.0	40.2	9.9	9.4	9.9	15.5	15.8
Total	100	100	—	100	100	—	100	100	—

Panel B: Internalized Retail Order Flow						
	N	Mean	St. dev.	Median	Q1	Q3
<i>Mrbvol</i>	4,627,339	46,345	288,628	5,850	1,395	23,157
<i>Mrsvol</i>	4,627,339	46,249	270,718	6,333	1,559	24,346
<i>Mrbtrd</i>	4,627,339	108	389	23	6	79
<i>Mrstrd</i>	4,627,339	106	349	24	6	81
<i>Mroibvol</i>	4,627,339	−0.035	0.453	−0.025	−0.286	0.209
<i>Mroibtrd</i>	4,627,339	−0.030	0.430	−0.008	−0.263	0.200
<i>Mroibvol</i> > 0	2,154,810	0.330	0.295	0.233	0.101	0.471
<i>Mroibvol</i> < 0	2,448,368	−0.357	0.301	−0.265	−0.522	−0.115
<i>Mroibtrd</i> > 0	2,088,865	0.321	0.282	0.232	0.111	0.435
<i>Mroibtrd</i> < 0	2,329,910	−0.347	0.290	−0.261	−0.500	−0.123

Table 2: Internalized Retail Order Flow and the Cross-section of Next Week's Returns. This table presents estimates of the association between internalized retail order flow and the cross-section of the next week's returns (in percentage points). Daily returns are calculated based on the mid-points of best bid and ask prices at close as well as open prices, decomposing each day's close-to-close returns into intraday (open-to-close) and overnight (close-to-open) before aggregating each return type into weekly observations. Each of the three return cross-sections is decomposed based on the sign of previous week's internalized order flow to form a total of nine samples. According to equation (1), week w returns in each sample are regressed on week $w - 1$'s internalized order flows ($Mroibvol_{w-1}$) and control variables including last week's return (R_{w-1}), last month's return (RET_{-1}), the return over the preceding five months ($RET_{(-7,-2)}$), volatility (VOLAT), and natural logs of turnover ($\ln(TO)$), market capitalization ($\ln(Size)$), and book-to-market ratio ($\ln(BM)$). Estimates are based Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags. Sample includes NMS common shares from Jan 2010 – Dec 2014, excluding observations with previous month-end's closing price below \$1. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

Dependent Variable	Close-to-close return			Overnight return			Intraday return		
	All	$Mroibvol_{w-1}$ Negative	Positive	All	$Mroibvol_{w-1}$ Negative	Positive	All	$Mroibvol_{w-1}$ Negative	Positive
Constant	0.0063 [0.02]	-0.37 [-1.08]	0.28 [0.83]	0.58*** [4.58]	0.59*** [4.48]	1.05*** [6.88]	-0.57** [-2.10]	-0.96*** [-3.33]	-0.77*** [-2.66]
$Mroibvol_{w-1}$	0.087*** [13.73]	0.056*** [3.75]	0.12*** [7.37]	0.12*** [25.53]	0.16*** [20.54]	-0.0050 [-0.55]	-0.029*** [-4.41]	-0.10*** [-6.90]	0.13*** [8.49]
R_{w-1}	-0.021*** [-5.86]	-0.018*** [-4.93]	-0.022*** [-5.78]	0.00090 [0.50]	-0.0031 [-1.61]	0.0038* [1.89]	-0.022*** [-7.07]	-0.015*** [-4.59]	-0.026*** [-7.64]
$RET_{(-1)}$	0.21 [1.14]	0.39** [2.12]	0.014 [0.07]	-0.19** [-2.30]	-0.15* [-1.84]	-0.18* [-1.84]	0.40** [2.47]	0.54*** [3.43]	0.20 [1.07]
$RET_{(-7,-2)}$	0.063 [0.84]	0.091 [1.18]	0.044 [0.53]	0.061** [2.45]	0.047* [1.83]	0.058* [1.83]	0.0024 [0.03]	0.044 [0.63]	-0.014 [-0.18]
$\ln(TO)$	-0.037*** [-3.60]	-0.032*** [-3.08]	-0.047*** [-3.95]	0.036*** [8.89]	0.030*** [7.43]	0.036*** [6.79]	-0.073*** [-8.16]	-0.063*** [-6.64]	-0.083*** [-8.05]
VOLAT	-6.44*** [-3.55]	-6.55*** [-3.73]	-6.17*** [-2.89]	9.68*** [11.02]	8.20*** [10.05]	11.5*** [9.39]	-16.1*** [-10.03]	-14.7*** [-9.21]	-17.7*** [-9.33]
$\ln(Size)$	0.020 [1.47]	0.036** [2.49]	0.0065 [0.45]	-0.033*** [-5.31]	-0.030*** [-4.65]	-0.054*** [-7.57]	0.053*** [4.39]	0.065*** [5.22]	0.061*** [4.75]
$\ln(BM)$	0.058*** [2.73]	0.045** [2.12]	0.064*** [2.66]	-0.038*** [-6.10]	-0.025*** [-3.88]	-0.046*** [-5.26]	0.096*** [4.75]	0.070*** [3.43]	0.11*** [5.06]
Observations	3,330,408	1,875,061	1,448,395	3,330,408	1,875,061	1,448,395	3,330,408	1,875,061	1,448,395

Table 3: **Internalized Order Flow and the Cross-sections of Future Weeks' Returns.** This table presents estimates of the associations between internalized retail order flow and the cross-sections of future week $w + i$ returns (in percentage points), with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 42, 45, 48, 51, 54, 57, 60\}$. Daily returns are calculated based on the mid-points of best bid and ask prices at close as well as open prices, decomposing each day's close-to-close returns into intraday (open-to-close) and overnight (close-to-open) before aggregating each return type into weekly observations. Each of the three return cross-sections for a given week $w + i$ is decomposed based on the sign of week $w - 1$'s internalized order flow to form a total of nine samples. According to equation (1), week $w + i$ returns in each sample are regressed on week $w - 1$'s internalized order flows ($Mroibvol_{w-1}$), whose loadings are reported in the table, and control variables including last week's return (R_{w-1}), last month's return (RET_{-1}), the return over the preceding five months ($RET_{(-7,-2)}$), volatility (VOLAT), and natural logs of turnover ($\ln(TO)$), market capitalization ($\ln(Size)$), and book-to-market ratio ($\ln(BM)$). Estimates are based Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags. Sample includes NMS common shares from Jan 2010 – Dec 2014, excluding observations with previous month-end's closing price below \$1. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

Dep. Var. =	Close-to-close return			Overnight return			Intraday return		
	$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
Week	All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
w	0.087*** [13.73]	0.056*** [3.75]	0.12*** [7.37]	0.12*** [25.53]	0.16*** [20.54]	-0.0050 [-0.55]	-0.029*** [-4.41]	-0.10*** [-6.90]	0.13*** [8.49]
$w + 1$	0.053*** [8.54]	0.019 [1.26]	0.093*** [5.32]	0.090*** [25.16]	0.14*** [20.52]	-0.015 [-1.56]	-0.037*** [-6.16]	-0.12*** [8.86]	0.11*** [6.55]
$w + 2$	0.045*** [7.31]	0.017 [1.21]	0.093*** [4.95]	0.077*** [21.24]	0.12*** [17.30]	-0.025*** [-2.81]	-0.032*** [-5.07]	-0.11*** [7.55]	0.12*** [6.76]
$w + 3$	0.034*** [6.04]	0.0052 [0.38]	0.080*** [4.71]	0.067*** [20.56]	0.12*** [16.00]	-0.031*** [-3.56]	-0.033*** [-5.76]	-0.11*** [8.05]	0.11*** [6.87]
$w + 6$	0.016*** [2.62]	-0.018 [-1.28]	0.058*** [3.32]	0.050*** [14.56]	0.11*** [15.25]	-0.033*** [-3.77]	-0.034*** [-6.05]	-0.13*** [9.49]	0.091*** [5.83]
$w + 9$	0.011** [1.98]	-0.012 [-0.89]	0.058*** [3.23]	0.038*** [10.15]	0.087*** [12.64]	-0.052*** [-6.18]	-0.026*** [-4.82]	-0.099*** [-7.67]	0.11*** [6.76]
$w + 12$	0.0028 [0.53]	-0.048*** [-3.54]	0.063*** [3.53]	0.042*** [12.54]	0.077*** [12.06]	-0.016* [-1.86]	-0.039*** [-7.06]	-0.12*** [9.93]	0.079*** [4.96]
$w + 24$	-0.0027	-0.054***	0.048***	0.025***	0.067***	-0.037***	-0.028***	-0.12***	0.085***

Continued on next page

Table 3 – *continued from previous page*

Dep. Var. =	Close-to-close return			Overnight return			Intraday return		
Week	$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
	All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
	[−0.45]	[−3.69]	[2.76]	[7.83]	[10.76]	[−4.19]	[−4.43]	[8.66]	[4.99]
$w + 36$	−0.0044 [−0.68]	−0.046*** [−2.86]	0.068*** [4.18]	0.030*** [7.57]	0.065*** [8.88]	−0.019** [−2.40]	−0.034*** [−5.51]	−0.11*** [7.82]	0.087*** [5.69]
$w + 39$	−0.011* [−1.78]	−0.039*** [−2.60]	0.044*** [2.76]	0.016*** [4.41]	0.043*** [6.42]	−0.043*** [−5.13]	−0.027*** [−4.79]	−0.082*** [−5.97]	0.087*** [5.43]
$w + 42$	−0.010* [−1.85]	−0.042*** [−3.09]	0.072*** [3.99]	0.019*** [4.96]	0.058*** [8.01]	−0.042*** [−4.70]	−0.029*** [−5.29]	−0.10*** [7.75]	0.11*** [6.97]
$w + 45$	−0.014** [−2.37]	−0.048*** [−3.21]	0.055*** [3.04]	0.015*** [3.65]	0.053*** [6.79]	−0.045*** [−4.82]	−0.029*** [−5.14]	−0.10*** [7.62]	0.100*** [6.12]
$w + 48$	−0.011* [−1.82]	−0.051*** [−3.17]	0.053*** [3.04]	0.023*** [6.48]	0.056*** [8.33]	−0.036*** [−4.21]	−0.033*** [−5.64]	−0.11*** [7.46]	0.088*** [5.78]
$w + 51$	−0.023*** [−3.61]	−0.070*** [−4.95]	0.054*** [3.18]	0.015*** [3.81]	0.047*** [5.77]	−0.036*** [−3.90]	−0.038*** [−6.00]	−0.12*** [8.32]	0.091*** [5.60]
$w + 54$	−0.021*** [−3.43]	−0.050*** [−3.31]	0.059*** [3.59]	0.011*** [2.97]	0.043*** [5.90]	−0.037*** [−3.69]	−0.032*** [−5.40]	−0.093*** [−6.74]	0.096*** [6.19]
$w + 57$	−0.0013 [−0.21]	−0.051*** [−3.30]	0.064*** [3.38]	0.011*** [2.76]	0.036*** [5.11]	−0.037*** [−4.16]	−0.012** [−1.98]	−0.087*** [−6.17]	0.10*** [5.35]
$w + 60$	−0.022*** [−3.54]	−0.071*** [−4.67]	0.040** [2.27]	0.014*** [3.53]	0.040*** [5.03]	−0.038*** [−4.08]	−0.036*** [−6.16]	−0.11*** [8.11]	0.078*** [4.60]

Table 4: **Retail Order Internalization and Tick Size Pilot *Quote Rule***. This table reports OLS and quantile (median) regression estimates of equation (6.2), comparing stocks in Test Group 1 to control stocks. Panels A and C report results for stocks whose average quoted spread in during August, 2016 was below sample median; and Panels B and D report results for stocks with above-median spreads. Sample periods spans the 10 trading day prior to implementation of TSP on 10/03/2016 as well as the 10 trading days following the full implementation of TSP on 10/17/2016 for Test Group 1 stocks. Outcome variables are constructed using trade and quote information of sub-penny-executed off-exchange transactions, and they include (1) the absolute value of *Mroibtrd*; (2) the absolute value of *Mroibvol*; (3) size-weighted average relative % price improvement, defined as the difference between the closer best quoted price and the transaction price, divided by the mid-point of best bid and ask; (4) total price improvement, defined as the sum, in dollars of, dollar price improvements, with respect to the closer best quoted price, across all sub-penny-executed transactions; and (5) the total share volume, in round lots, of trades receiving price improvement. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

	Panel A: Low-spread stocks, OLS					Panel B: High-spread stocks, OLS				
	Outcome variable					Outcome variable				
	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol
Intercept	0.31*** [198.21]	0.39*** [225.90]	0.19*** [40.11]	367.2*** [34.55]	14517.1*** [74.77]	0.31*** [173.36]	0.39*** [208.29]	0.19*** [45.46]	367.2*** [34.87]	14517.1*** [89.14]
PrePost	-0.047*** [-17.74]	-0.047*** [-16.08]	0.015* [1.92]	31.3* [1.76]	6277.4*** [18.90]	0.10*** [32.11]	0.12*** [34.77]	0.19*** [24.48]	153.5*** [7.83]	-8964.6*** [-32.32]
Treat	-0.012*** [-3.15]	-0.0099** [-2.33]	-0.0010 [-0.09]	7.60 [0.29]	462.3 [0.97]	-0.012*** [-2.76]	-0.0099** [-2.15]	-0.0010 [-0.10]	7.60 [0.30]	462.3 [1.16]
PrePost*Treat	0.0034 [0.54]	0.0015 [0.21]	0.0045 [0.24]	86.9** [2.05]	1360.3* [1.70]	-0.019** [-2.46]	-0.010 [-1.25]	-0.047** [-2.51]	-24.9 [-0.53]	-334.1 [-0.49]

	Panel C: Low-spread stocks, Quantile regression					Panel D: High-spread stocks, Quantile regression				
	Outcome variable					Outcome variable				
	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol
Intercept	0.23*** [132.83]	0.32*** [136.29]	0.068*** [99.87]	84.8*** [73.16]	4893*** [71.81]	0.23*** [102.92]	0.32*** [112.02]	0.068*** [79.44]	84.8*** [72.70]	4893*** [107.96]
PrePost	-0.029*** [-9.81]	-0.040*** [-10.07]	0.019*** [16.64]	39.9*** [20.60]	4389*** [37.65]	0.097*** [24.58]	0.14*** [27.06]	0.090*** [56.62]	47.5*** [21.89]	-3506*** [-45.42]
Treat	-0.014*** [-3.40]	-0.015*** [-2.62]	-0.00099 [-0.60]	4.16 [1.47]	-86 [-0.52]	-0.014*** [-2.63]	-0.015** [-2.15]	-0.00099 [-0.48]	4.16 [1.46]	-86 [-0.78]
PrePost*Treat	0.014** [2.04]	0.011 [1.18]	0.040*** [14.56]	141.7*** [30.63]	3057*** [10.87]	-0.023** [-2.44]	-0.0075 [-0.61]	-0.025*** [-6.46]	19.8*** [3.82]	927*** [4.85]

Table 5: **Retail Order Internalization and Tick Size Pilot *Trade Rule***. This table reports OLS and quantile (median) regression estimates of equation (6.2), comparing stocks in Test Group 2 to control stocks. Panels A and C report results for stocks whose average quoted spread in during August, 2016 was below sample median; and Panels B and D report results for stocks with above-median spreads. Sample periods spans the 10 trading day prior to implementation of TSP on 10/03/2016 as well as the 10 trading days following the full implementation of TSP on 10/17/2016 for Test Group 1 stocks. Outcome variables are constructed using trade and quote information of sub-penny-executed off-exchange transactions, and they include (1) the absolute value of *Mroibtrd*; (2) the absolute value of *Mroibvol*; (3) size-weighted average relative % price improvement, defined as the difference between the closer best quoted price and the transaction price, divided by the mid-point of best bid and ask; (4) total price improvement, defined as the sum, in dollars of, dollar price improvements, with respect to the closer best quoted price, across all sub-penny-executed transactions; and (5) the total share volume, in round lots, of trades receiving price improvement. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

Panel A: Low-spread stocks, OLS						Panel B: High-spread stocks, OLS					
	Outcome variable					Outcome variable					
	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	
Intercept	0.31*** [198.89]	0.39*** [225.93]	0.19*** [40.04]	369.0*** [34.91]	14695.6*** [75.76]	0.31*** [172.60]	0.39*** [207.06]	0.19*** [44.89]	369.0*** [35.58]	14695.6*** [90.92]	
PrePost	-0.056*** [-21.80]	-0.065*** [-22.28]	0.0089 [1.15]	62.1*** [3.54]	7917.6*** [23.91]	0.087*** [27.91]	0.10*** [31.63]	0.18*** [23.53]	147.3*** [7.76]	-8872.9*** [-32.19]	
Treat	0.0043 [1.13]	0.011** [2.53]	0.015 [1.33]	-36.0 [-1.38]	-1382.4*** [-2.92]	0.0043 [0.98]	0.011** [2.32]	0.015 [1.49]	-36.0 [-1.41]	-1382.4*** [-3.51]	
PrePost*Treat	0.032*** [5.13]	0.076*** [10.79]	0.0063 [0.33]	-11.7 [-0.27]	-3277.9*** [-4.07]	0.042*** [5.44]	0.052*** [6.27]	-0.0059 [-0.30]	17.7 [0.37]	591.6 [0.88]	

Panel C: Low-spread stocks, Quantile regression						Panel D: High-spread stocks, Quantile regression					
	Outcome variable					Outcome variable					
	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	Mroibtrd	Mroibvol	Relative %-PI	Relative \$-PI	PI shr vol	
Intercept	0.22*** [125.61]	0.31*** [131.66]	0.068*** [102.76]	85.3*** [70.72]	4948*** [71.84]	0.22*** [97.95]	0.31*** [111.11]	0.068*** [79.70]	85.3*** [72.43]	4948*** [109.61]	
PrePost	-0.036*** [-11.86]	-0.052*** [-13.06]	0.015*** [13.95]	58.5*** [29.23]	5796*** [49.29]	0.075*** [18.57]	0.12*** [23.75]	0.082*** [52.31]	46.8*** [21.69]	-3296*** [-42.81]	
Treat	0.0058 [1.31]	0.0065 [1.12]	0.00064 [0.39]	-4.75 [-1.60]	-546*** [-3.25]	0.0058 [1.03]	0.0065 [0.94]	0.00064 [0.31]	-4.75 [-1.64]	-546*** [-4.96]	
PrePost*Treat	0.027*** [3.71]	0.091*** [9.32]	0.047*** [17.48]	26.1*** [5.32]	-2326*** [-8.13]	0.028*** [2.75]	0.092*** [7.45]	0.018*** [4.50]	15.9*** [2.90]	120 [0.64]	

Table 6: **Portfolios of *Mroibvol*: Contemporaneous Return, Liquidity, Institutional Trading, and Short Interest.** The table presents the cross-sectional relationship between weekly *Mroibvol* and the contemporaneous return, institutional trade, and liquidity outcomes. Outcome variables include (1) returns (close-to-close, intraday, and overnight returns, with a version of overnight returns shifted by one day); (2) liquidity (dollar and relative quoted spreads, depth, in shares, and abnormal off-exchange midpoint executions of larger trades); (3) institutional trading (order flow and implementation shortfall, in bps/\$1m); and (4) short interest (% change in bi-weekly short interest). Each weekly cross-section is sorted into deciles of *Mroibvol*. The the average of an outcome variable Y is calculated by *Mroibvol* decile in each cross-section before the averages of mean- Y time-series are calculated. For short interest, bi-weekly relative % changes in short interest are constructed and *Mroibvol* is aggregated over two-week periods, before forming *Mroibvol* portfolios. Median short interest changes by *Mroibvol* and stock size tercile, before averaging the time-series of medians.

	Deciles of internalized retail order flow imbalance (<i>Mroibvol</i>)									
	1	2	3	4	5	6	7	8	9	10
<i>Mroibvol</i>	−2.043	−1.132	−0.745	−0.467	−0.238	−0.033	0.173	0.417	0.763	1.607
Ratio of inside quote executions	0.158	0.135	0.126	0.123	0.121	0.122	0.120	0.122	0.132	0.162
Returns (%)										
Close-to-close return	−0.019	0.091	0.135	0.179	0.219	0.249	0.269	0.290	0.267	0.321
Intraday return	0.098	0.053	0.019	−0.005	−0.063	−0.118	−0.176	−0.210	−0.237	−0.138
Overnight return	−0.116	0.038	0.117	0.184	0.283	0.367	0.445	0.500	0.505	0.459
Next-day overnight return	−0.134	0.019	0.100	0.166	0.257	0.340	0.423	0.490	0.488	0.456
Institutional Trading										
Order flow imbalance	0.336	0.299	0.282	0.266	0.251	0.246	0.227	0.226	0.231	0.211
Implementation shortfall	69.44	9.45	4.05	2.92	3.41	2.70	4.54	5.94	5.55	15.51
Change in Short Interest (%)										
Small stocks	−2.58	−1.90	−1.38	−0.87	−0.61	0.22	0.16	0.70	1.21	2.25
Mid-sized stocks	−0.70	−0.54	−0.39	−0.10	−0.01	0.29	0.26	0.37	0.63	0.41
Large stocks	−1.16	−0.58	−0.72	−0.33	−0.25	−0.27	0.06	0.04	0.20	0.80
Liquidity										
Dollar quoted spread (¢)	8.9	6.8	5.8	5.4	5.3	5.7	5.4	5.5	6.4	9.3
Relative quoted spread (bps)	69	46	38	33	31	32	31	34	43	70
Ask-side depth	972	1,288	1,409	1,557	1,738	1,857	1,893	1,751	1,500	905
Bid-side depth	972	1,306	1,449	1,602	1,790	1,935	2,000	1,864	1,618	960
Large midpoint executions	0.78	0.87	0.92	0.97	0.99	1.02	1.05	1.03	1.04	0.95

Table 7: **Asymmetric Persistence in Institutional Order Flow: Implications for Retail Flow Internalization.** This table presents estimates of the predictive power of past institutional order flow, conditional on it sign, for both current institutional order flow and current internalized retail order flow. Columns (1)–(4) report estimation results of equation (3) for $i \in \{3, 4, 5, 6\}$ and $X = Inoibvol_w$. Columns (5)–(8) report estimation results of equation (3) for $i \in \{3, 4, 5, 6\}$ and $X = Mroibvol_w$. Fama-MacBeth regressions are used with Newey-West-corrected standard errors using 6 lags. The sample contains stocks with average ANcerno-to-CRSP daily volume of 6.8% or higher. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

	Dependent variable: $Inoibvol_w$				Dependent variable: $Mroibvol_w$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.065** [2.46]	0.038 [1.42]	0.023 [0.86]	0.0088 [0.32]	-0.16*** [-14.54]	-0.15*** [-13.32]	-0.15*** [-12.50]	-0.14*** [-11.77]
$Inoibvol_{w-1}$	0.33*** [58.36]	0.33*** [59.42]	0.33*** [58.50]	0.33*** [58.00]	-0.016*** [-7.43]	-0.016*** [-7.86]	-0.016*** [-7.66]	-0.016*** [-7.58]
$I(Inoibvol_{w-1} < 0) \times Inoibvol_{w-1}$	0.020*** [2.71]	0.022*** [2.98]	0.022*** [3.03]	0.023*** [3.24]	0.0083*** [2.63]	0.0085*** [2.69]	0.0081** [2.56]	0.0085*** [2.65]
$Inoibvol_{w-2}$	0.075*** [17.07]	0.072*** [16.60]	0.071*** [16.60]	0.069*** [15.35]	-0.0067*** [-3.41]	-0.0062*** [-3.06]	-0.0060*** [-2.94]	-0.0059*** [-2.90]
$I(Inoibvol_{w-2} < 0) \times Inoibvol_{w-2}$	-0.023*** [-3.06]	-0.020*** [-2.70]	-0.020*** [-2.68]	-0.018** [-2.46]	0.0059* [1.85]	0.0051 [1.57]	0.0046 [1.38]	0.0044 [1.31]
$Inoibvol_{w-3}$	0.062*** [13.26]	0.048*** [10.52]	0.045*** [9.90]	0.043*** [9.65]	-0.0069*** [-3.40]	-0.0054*** [-2.64]	-0.0052** [-2.53]	-0.0050** [-2.41]
$I(Inoibvol_{w-3} < 0) \times Inoibvol_{w-3}$	-0.017*** [-2.63]	-0.014** [-2.14]	-0.012* [-1.86]	-0.011* [-1.79]	0.0091*** [3.09]	0.0079*** [2.66]	0.0078*** [2.63]	0.0077** [2.54]
$Inoibvol_{w-4}$		0.052*** [12.29]	0.040*** [9.65]	0.037*** [8.77]		-0.0055*** [-2.64]	-0.0048** [-2.30]	-0.0050** [-2.40]
$I(Inoibvol_{w-4} < 0) \times Inoibvol_{w-4}$		-0.023*** [-3.51]	-0.021*** [-3.20]	-0.019*** [-2.90]		0.0078** [2.58]	0.0080*** [2.69]	0.0078*** [2.60]
$Inoibvol_{w-5}$			0.041*** [10.22]	0.031*** [7.73]			-0.0041** [-2.11]	-0.0028 [-1.38]
$I(Inoibvol_{w-5} < 0) \times Inoibvol_{w-5}$			-0.029*** [-4.14]	-0.025*** [-3.78]			0.00047 [0.16]	0.000084 [0.03]
$Inoibvol_{w-6}$				0.037*** [9.35]				-0.0044** [-2.15]
$I(Inoibvol_{w-6} < 0) \times Inoibvol_{w-6}$				-0.026*** [-3.79]				0.0019 [0.63]
Observations	976,110	976,110	976,110	976,110	976,110	976,110	976,110	976,110

Table 8: **Predictability of Institutional Order Flow Using Internalized Retail Trading Imbalance.** This table presents estimates of the predictive power of past internalized order flow, conditional the sign the corresponding institutional order flow, for current institutional order flow. Equation (4) for $i \in \{3, 4, 5, 6\}$ and $X = Inoibvol_w$ is estimated using Fama-MacBeth regressions with Newey-West-corrected standard errors using 6 lags. The sample contains stocks with average ANcerno-to-CRSP daily volume of 6.8% or higher. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

	(1)	(2)	(3)	(4)
Constant	1.04*** [39.71]	1.09*** [40.99]	1.14*** [41.98]	1.17*** [43.14]
$Mroibvol_{w-1}$	-0.020*** [-3.69]	-0.021*** [-3.74]	-0.021*** [-3.74]	-0.020*** [-3.57]
$I(Inoibvol_{w-1} < 0) \times Mroibvol_{w-1}$	0.021*** [2.85]	0.020*** [2.78]	0.020*** [2.81]	0.021*** [2.79]
$Mroibvol_{w-2}$	-0.013** [-2.43]	-0.014** [-2.56]	-0.013** [-2.43]	-0.013** [-2.38]
$I(Inoibvol_{w-2} < 0) \times Mroibvol_{w-2}$	0.025*** [3.41]	0.025*** [3.39]	0.025*** [3.42]	0.024*** [3.30]
$Mroibvol_{w-3}$	-0.0043 [-0.72]	-0.0063 [-1.13]	-0.0054 [-0.93]	-0.0067 [-1.14]
$I(Inoibvol_{w-3} < 0) \times Mroibvol_{w-3}$	0.017** [2.38]	0.018*** [2.59]	0.019*** [2.59]	0.020*** [2.72]
$Mroibvol_{w-4}$		0.0047 [0.70]	0.0054 [0.87]	0.0035 [0.57]
$I(Inoibvol_{w-4} < 0) \times Mroibvol_{w-4}$		0.0017 [0.23]	0.0038 [0.51]	0.0038 [0.52]
$Mroibvol_{w-5}$			-0.0058 [-1.08]	-0.0065 [-1.20]
$I(Inoibvol_{w-5} < 0) \times Mroibvol_{w-5}$			-0.0036 [-0.45]	-0.0018 [-0.22]
$Mroibvol_{w-6}$				0.0025 [0.42]
$I(Inoibvol_{w-6} < 0) \times Mroibvol_{w-6}$				0.0056 [0.63]
Observations	976,110	976,110	976,110	976,110

Table 9: **Portfolios of *Mroibvol* and Future Weekly Returns.** The table presents the cross-sectional relationships between *Mroibvol* and future weekly (%) returns. Each cross-section is sorted into portfolios (deciles) of $Mroibvol_{w-1}$ to calculate portfolio-specific averages of future close-to-close (*CCR*), intraday (*IDR*), and overnight (*ONR*) returns in week $w + i$, with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 42, 45, 48, 51, 54, 57, 60\}$. The means of the time-series of portfolio future returns are presented by *Mroibvol* decile.

Week	Variable	Deciles of $Mroibvol_{w-1}$									
		1	2	3	4	5	6	7	8	9	10
w	<i>CCR</i>	0.07	0.14	0.14	0.16	0.17	0.15	0.16	0.18	0.28	0.42
	<i>IDR</i>	0.08	0.05	-0.03	-0.06	-0.12	-0.19	-0.22	-0.23	-0.14	0.03
	<i>ONR</i>	-0.01	0.09	0.17	0.22	0.29	0.34	0.38	0.41	0.42	0.40
$w + 1$	<i>CCR</i>	0.13	0.15	0.14	0.15	0.15	0.14	0.17	0.16	0.21	0.34
	<i>IDR</i>	0.10	0.01	-0.06	-0.09	-0.14	-0.19	-0.21	-0.20	-0.16	-0.01
	<i>ONR</i>	0.03	0.14	0.21	0.24	0.29	0.33	0.38	0.36	0.37	0.35
$w + 2$	<i>CCR</i>	0.14	0.16	0.17	0.16	0.16	0.15	0.16	0.17	0.21	0.31
	<i>IDR</i>	0.10	0.02	-0.03	-0.08	-0.13	-0.18	-0.20	-0.20	-0.15	-0.02
	<i>ONR</i>	0.04	0.14	0.20	0.24	0.29	0.34	0.36	0.37	0.35	0.33
$w + 3$	<i>CCR</i>	0.17	0.20	0.18	0.18	0.17	0.17	0.17	0.18	0.23	0.29
	<i>IDR</i>	0.10	0.04	-0.03	-0.07	-0.12	-0.17	-0.18	-0.18	-0.13	-0.01
	<i>ONR</i>	0.07	0.16	0.22	0.25	0.29	0.33	0.35	0.36	0.35	0.30
$w + 6$	<i>CCR</i>	0.19	0.17	0.19	0.18	0.16	0.16	0.18	0.18	0.21	0.26
	<i>IDR</i>	0.09	-0.01	-0.04	-0.08	-0.14	-0.17	-0.16	-0.16	-0.11	-0.03
	<i>ONR</i>	0.10	0.18	0.23	0.26	0.29	0.33	0.34	0.34	0.33	0.29

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Table 9 – *continued from previous page*

Week	Variable	Deciles of $Mroibvol_{w-1}$									
		1	2	3	4	5	6	7	8	9	10
$w + 9$	<i>CCR</i>	0.14	0.16	0.16	0.13	0.13	0.12	0.10	0.11	0.15	0.19
	<i>IDR</i>	0.02	−0.02	−0.06	−0.12	−0.16	−0.19	−0.22	−0.22	−0.16	−0.07
	<i>ONR</i>	0.12	0.18	0.22	0.24	0.29	0.31	0.32	0.32	0.31	0.26
$w + 12$	<i>CCR</i>	0.15	0.12	0.11	0.10	0.08	0.07	0.07	0.09	0.12	0.18
	<i>IDR</i>	0.04	−0.04	−0.09	−0.14	−0.18	−0.22	−0.23	−0.19	−0.17	−0.09
	<i>ONR</i>	0.11	0.16	0.19	0.24	0.25	0.29	0.30	0.28	0.29	0.27
$w + 24$	<i>CCR</i>	0.21	0.18	0.19	0.15	0.14	0.13	0.13	0.15	0.16	0.22
	<i>IDR</i>	0.06	−0.02	−0.04	−0.10	−0.13	−0.16	−0.18	−0.15	−0.12	−0.02
	<i>ONR</i>	0.15	0.20	0.23	0.25	0.27	0.30	0.31	0.30	0.28	0.24
$w + 36$	<i>CCR</i>	0.22	0.21	0.20	0.17	0.15	0.13	0.14	0.15	0.17	0.20
	<i>IDR</i>	0.09	0.03	−0.01	−0.06	−0.10	−0.13	−0.15	−0.13	−0.10	−0.04
	<i>ONR</i>	0.13	0.19	0.21	0.22	0.25	0.27	0.29	0.27	0.27	0.24
$w + 39$	<i>CCR</i>	0.16	0.17	0.16	0.14	0.13	0.11	0.10	0.10	0.13	0.14
	<i>IDR</i>	0.03	−0.01	−0.04	−0.06	−0.10	−0.14	−0.16	−0.15	−0.11	−0.07
	<i>ONR</i>	0.13	0.18	0.20	0.20	0.23	0.26	0.26	0.25	0.24	0.21
$w + 42$	<i>CCR</i>	0.18	0.15	0.13	0.13	0.12	0.11	0.09	0.08	0.12	0.15
	<i>IDR</i>	0.05	−0.01	−0.05	−0.07	−0.11	−0.15	−0.17	−0.16	−0.12	−0.05
	<i>ONR</i>	0.12	0.16	0.18	0.20	0.23	0.25	0.26	0.25	0.23	0.20

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Table 9 – *continued from previous page*

Week	Variable	Deciles of $Mroibvol_{w-1}$									
		1	2	3	4	5	6	7	8	9	10
$w + 45$	<i>CCR</i>	0.19	0.17	0.15	0.14	0.12	0.10	0.09	0.10	0.12	0.14
	<i>IDR</i>	0.06	0.00	−0.05	−0.07	−0.12	−0.16	−0.17	−0.15	−0.11	−0.06
	<i>ONR</i>	0.13	0.18	0.20	0.21	0.24	0.26	0.26	0.25	0.23	0.20
$w + 48$	<i>CCR</i>	0.14	0.13	0.11	0.09	0.07	0.05	0.06	0.04	0.06	0.10
	<i>IDR</i>	0.02	−0.02	−0.08	−0.11	−0.17	−0.19	−0.19	−0.20	−0.17	−0.10
	<i>ONR</i>	0.12	0.16	0.18	0.21	0.23	0.25	0.25	0.24	0.23	0.20
$w + 51$	<i>CCR</i>	0.13	0.10	0.12	0.07	0.02	0.02	0.01	0.03	0.04	0.07
	<i>IDR</i>	0.01	−0.07	−0.08	−0.13	−0.19	−0.21	−0.23	−0.22	−0.18	−0.11
	<i>ONR</i>	0.11	0.17	0.20	0.21	0.22	0.23	0.24	0.24	0.22	0.18
$w + 54$	<i>CCR</i>	0.08	0.10	0.08	0.08	0.04	0.01	0.00	−0.01	0.03	0.06
	<i>IDR</i>	−0.04	−0.05	−0.09	−0.12	−0.16	−0.21	−0.22	−0.23	−0.18	−0.11
	<i>ONR</i>	0.12	0.15	0.17	0.20	0.20	0.22	0.22	0.22	0.21	0.16
$w + 57$	<i>CCR</i>	0.07	0.03	0.04	0.01	−0.01	−0.01	−0.01	0.02	0.03	0.05
	<i>IDR</i>	−0.07	−0.11	−0.13	−0.17	−0.20	−0.22	−0.23	−0.20	−0.18	−0.11
	<i>ONR</i>	0.13	0.14	0.18	0.19	0.20	0.21	0.22	0.21	0.21	0.15
$W + 60$	<i>CCR</i>	0.08	0.07	0.04	0.01	0.00	0.00	−0.01	−0.02	0.00	0.00
	<i>IDR</i>	−0.04	−0.08	−0.13	−0.18	−0.21	−0.22	−0.24	−0.23	−0.21	−0.17
	<i>ONR</i>	0.12	0.15	0.17	0.19	0.21	0.22	0.23	0.22	0.21	0.17

Figure 1: **Retail Order Types:** This figure uses buy orders to illustrate different retail order types from a wholesaler's perspective. When best bid and ask prices are \$9.97 and \$10.03 respectively, market and marketable limit buy orders seek execution at prices at or below the best ask of \$10.03. Non-marketable retail buy orders quoted above the midpoint, \$10.00, but below \$10.03 may be profitable to execute if internalized. Non-marketable retail buy orders quoted above the best bid, \$9.97, but below the midpoint, \$10.00, are unlikely to be profitable to execute if internalized and hence are likely routed to an exchange and added the order book. Non-marketable retail buy orders quoted at or below the best bid price of \$9.97 are most likely to be routed to an exchange and added to the order book.

58

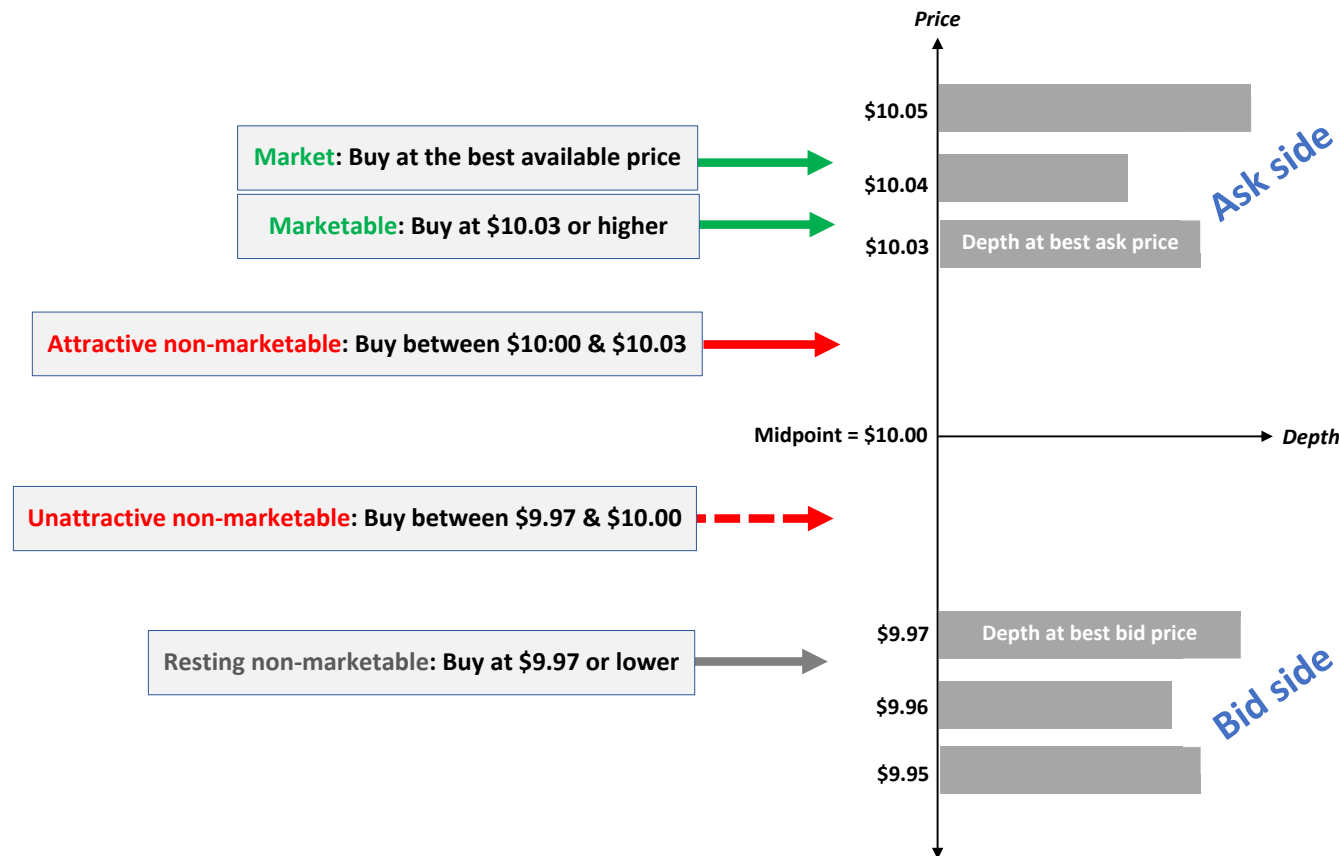


Figure 2: Retail Order Flow Internalization and PFOF.

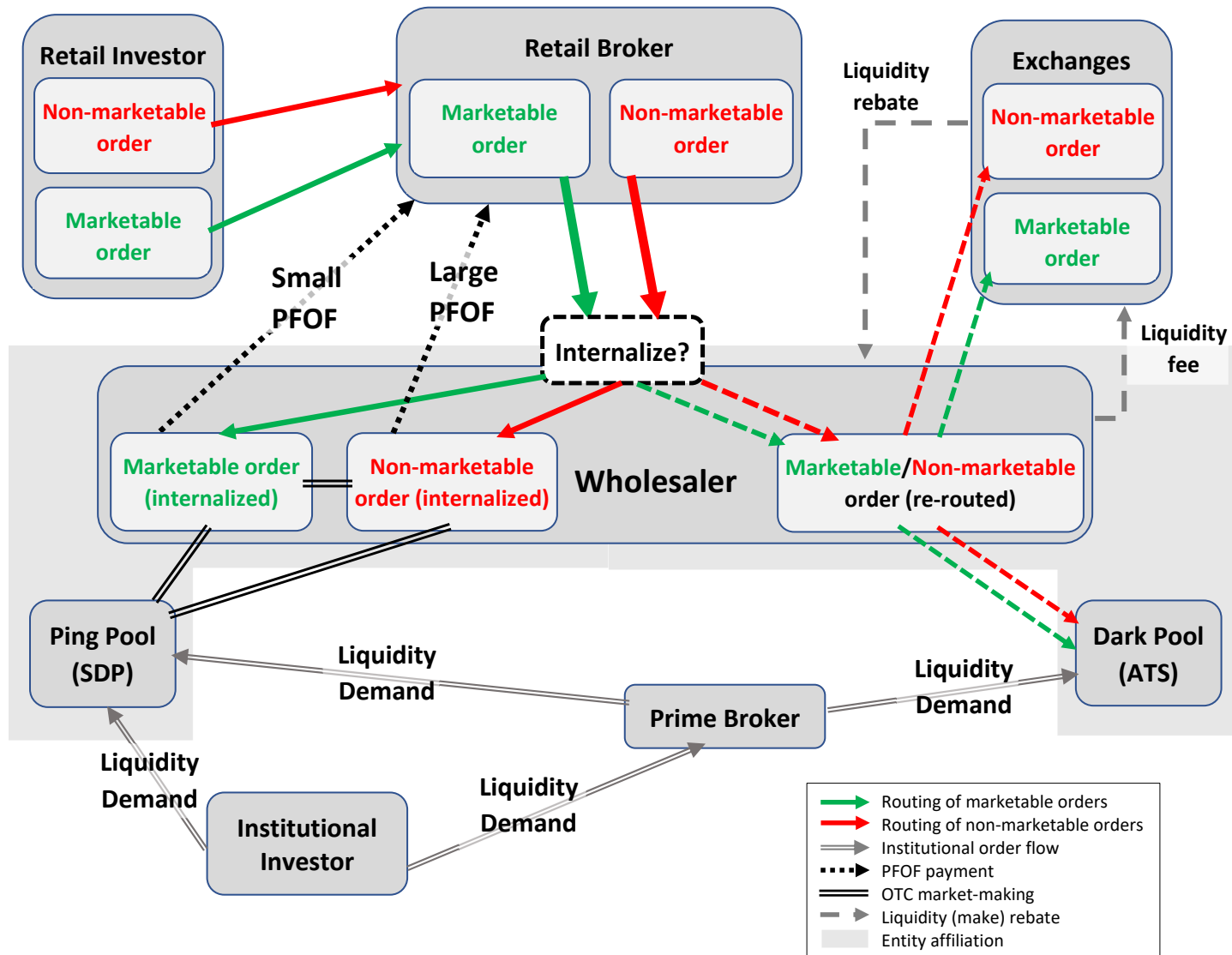


Figure 3: **Tick Size Pilot: Quote Rule.** This figure provides visual evidence associated with the results of the Difference-in-Difference specification in equation (6.2) for Test Group 1. The sample period spans the 10 trading days prior to the TSP's implementation on 10/03/2016 as well as the 10 trading days following its full implementation on 10/17/2016. The figure plots the daily medians for six outcome variables across the control and treatment groups. The outcome variables are constructed using trade and quote information for sub-penny-executed off-exchange transactions and include: (A) the absolute value of $Mroibtrd$; (B) the absolute value of $Mroibvol$; (C) size-weighted average relative % price improvement (difference between the relevant best quoted price and the transaction price, divided by the mid-point of the best bid and ask); (D) total price improvement (sum of dollar-denominated price improvements with respect to the relevant best quoted price across all sub-penny-executed transactions); and (E) the total share volume of trades receiving price improvement.

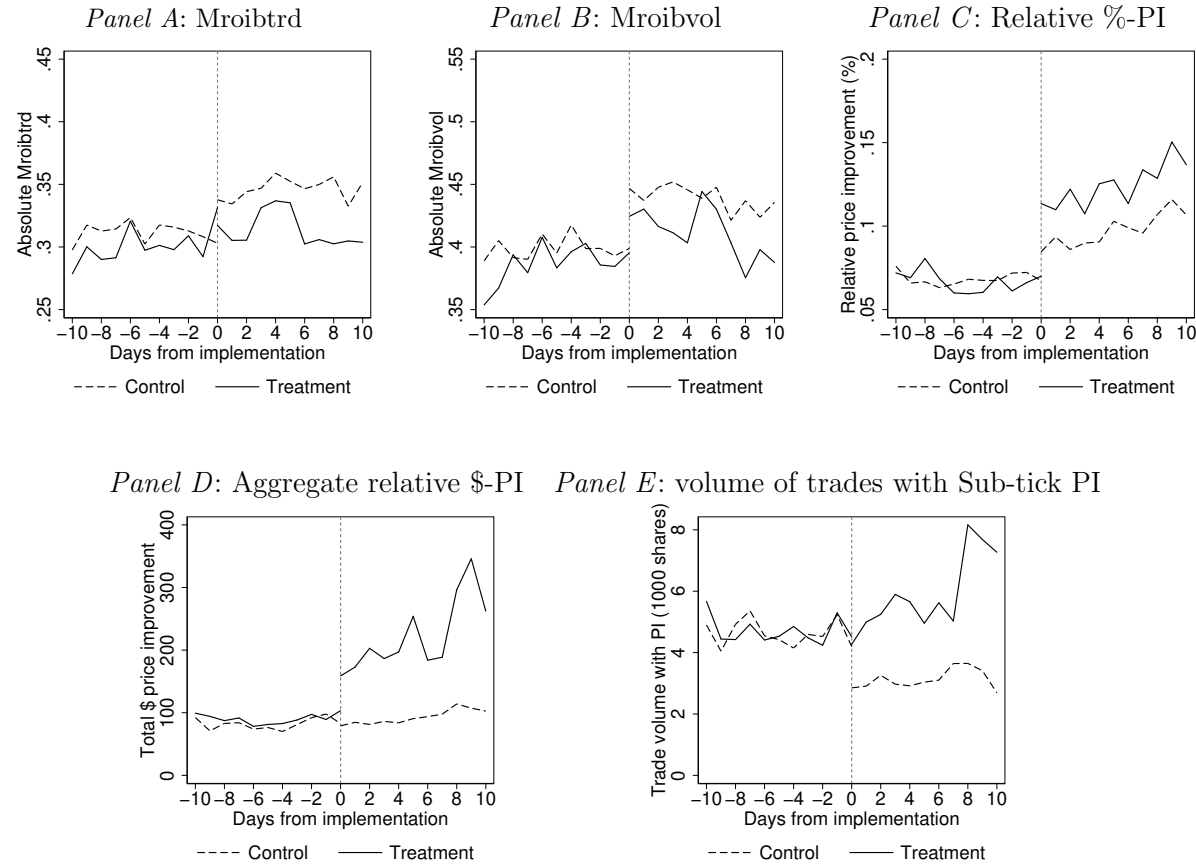


Figure 4: **Tick Size Pilot: Trade Rule.** This figure provides visual evidence associated with the results of the Difference-in-Difference specification in equation (6.2) for Test Group 2. The sample period spans the 10 trading days prior to the TSP's implementation on 10/03/2016 as well as the 10 trading days following its full implementation on 10/17/2016. The figure plots the daily medians for six outcome variables across the control and treatment groups. The outcome variables are constructed using trade and quote information for sub-penny-executed off-exchange transactions and include: (A) the absolute value of $Mroibtrd$; (B) the absolute value of $Mroibvol$; (C) size-weighted average relative % price improvement (difference between the relevant best quoted price and the transaction price, divided by the mid-point of the best bid and ask); (D) total price improvement (sum of dollar-denominated price improvements with respect to the relevant best quoted price across all sub-penny-executed transactions); and (E) the total share volume of trades receiving price improvement.

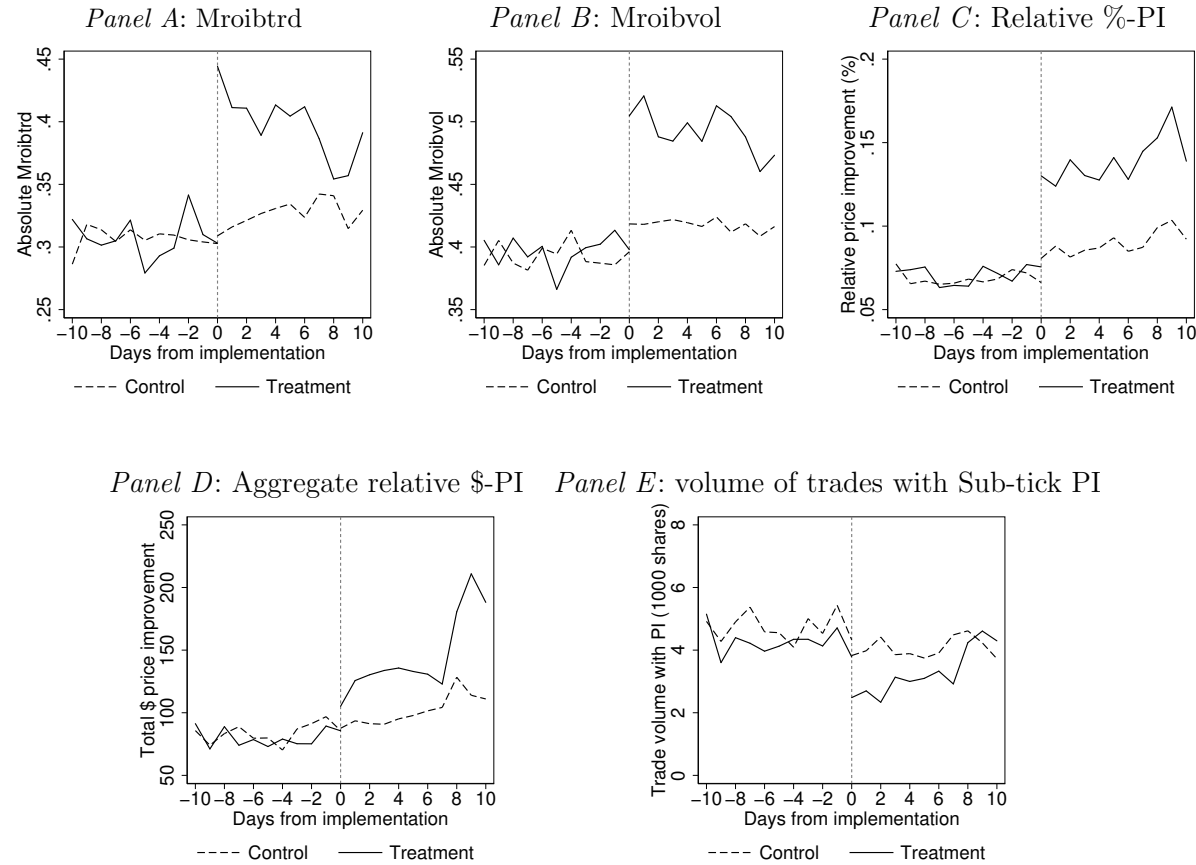


Figure 5: **Distributions of Sub-penny and the Probability of Inside-Quotes Execution.**

This figure plots a histogram of sub-penny price improvements (in cents) associated with transactions of 50 NYSE- and 50 NASDAQ-listed randomly selected stocks. Sub-penny price improvements are defined as the sub-penny transaction price increments $Z\text{¢}$ when $Z \in (0, 0.4]$ and as $1 - Z$ when $Z \in [0.6, 1)$. The figure also reports, for the 6 most frequent sub-penny price improvement outcomes, the percentage of corresponding transactions whose prices are by at least 1¢ better than the NBBO at the time of transaction. These ratios (in %) appear at the top of the bar representing the respective level of sub-penny transaction price increment

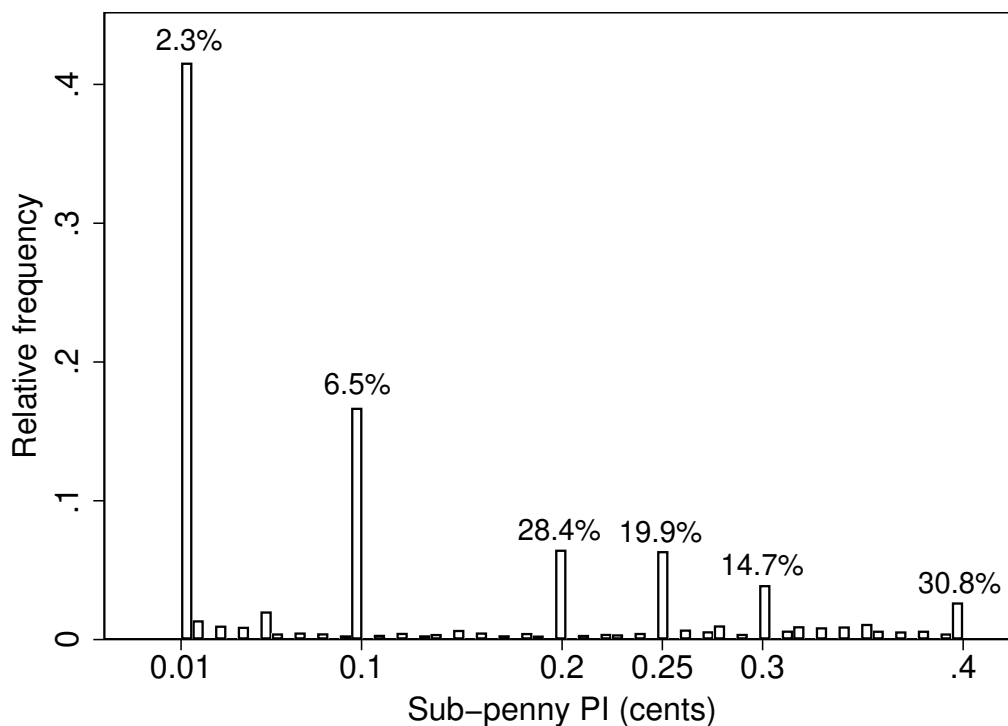
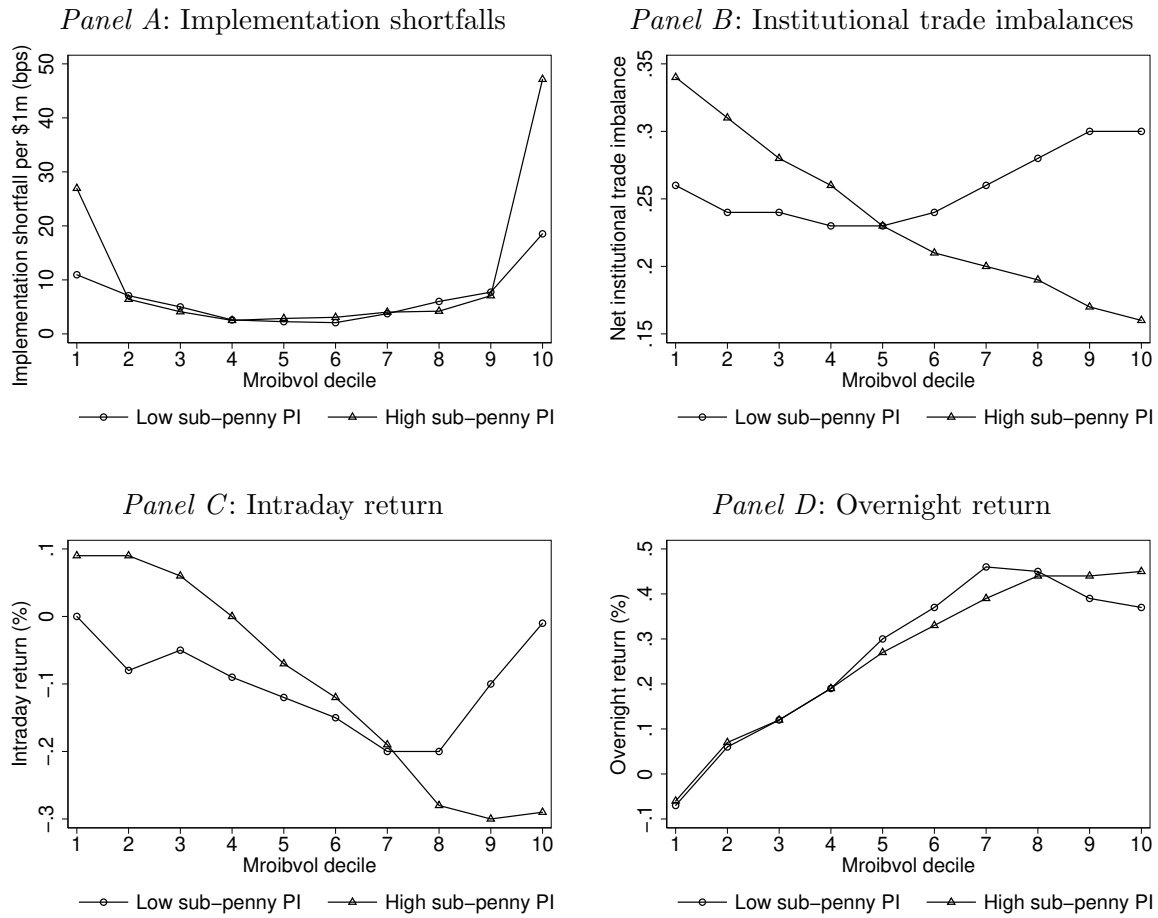


Figure 6: **Implementation Shortfalls, Institutional Order Flow, Intraday Returns, and Overnight Returns Conditional on the Magnitude of Price Improvement.** This figure compares contemporaneous implementation shortfalls, institutional net trade imbalance, intraday returns, and overnight returns when *Mroibvol* is constructed using retail trades with sub-penny price improvements that are low ($< .01\text{¢}$) versus high ($\geq .01\text{¢}$). Stocks are first sorted each day into deciles of low-sub-penny *Mroibvol* and high-sub-penny *Mroibvol*. Then, each outcome variable is plotted across the deciles of both *Mroibvol* measures. Panel A plots median implementation shortfalls (in basis points per million dollars), Panel B plots average net institutional trade imbalance, Panel C plots average intraday returns, and Panel D plots average overnight returns.



Appendix

A Decomposition of *Mroib*'s Predictive Power

We verify that the long-term return predictability associated with negative and positive internalized retail order flow imbalances is not attributable to persistence in such internalization or contrarian trading. Following BJZZ, we decompose weekly internalized retail order flow imbalances and estimate the cross-sectional specification

$$Mroibvol_{j,w-1} = \lambda_w^0 + \lambda_w^1 Mroibvol_{j,w-2} + \lambda_w^2 R_{w-2} + \eta_{j,w-1} \quad (5)$$

to construct

$$\text{Persistence}_{j,w-1} = \hat{\lambda}_w^1 Mroibvol_{j,w-2}, \quad (6)$$

$$\text{Contrarian}_{j,w-1} = \hat{\lambda}_w^1 R_{j,w-2}, \quad (7)$$

$$\text{Other}_{j,w-1} = \lambda_w^0 + \hat{\eta}_{j,w-1}. \quad (8)$$

By construction, $Mroibvol_{j,w-1} = \text{Persistence}_{j,w-1} + \text{Contrarian}_{j,w-1} + \text{Other}_{j,w-1}$. Substituting these components for $Mroibvol_{j,w-1}$ in equation 1, we estimate

$$\begin{aligned} R_{j,w+i} &= d_w^0 + d_w^{1p} (\text{Persistence}_{j,w-1}) + d_w^{1c} (\text{Contrarian}_{j,w-1}) + d_w^{1o} (\text{Other}_{j,w-1}) \\ &+ d_w^{2\top} \text{controls}_{j,w-1} + u_{j,w+i}, \end{aligned} \quad (9)$$

with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 42, 45, 48, 51, 54, 57, 60\}$. We fit Fama-MacBeth regressions with Newey-West-corrected standard errors using 6 lags.

Table A.1 reports estimated predictive powers of these three components of internalized retail order flow for future weekly returns. First note that our “Persistence” and “Other” coefficients for week w 's close-to-close returns of 0.32% and 0.08%, respectively, are quite close to their counterparts of 0.27% and 0.08% in BJZZ. Comparing the coefficients for the residual term, Other_{w-1} , in Table A.1 to those of $Mroibvol_{w-1}$ in Table 3 reveals that the significance of an $Mroibvol_{w-1}$ coefficient almost always corresponds to the significance of Other_{w-1} 's counterpart coefficient. For example, with week $w+i$'s close-to-close return as the dependent variable, when $Mroibvol_{w-1}$ has a negative coefficient for $k > 39$, $Mroibvol_{w-1} < 0$ also has a negative coefficient. A similar finding applies when $Mroibvol_{w-1} > 0$ has a positive coefficient. Contrary to BJZZ's interpretation that significant Other_{w-1} coefficients indicate informed trading, the results conditioning on the sign of $Mroibvol_{w-1}$ indicate that the predictive power associated with this residual component reflects liquidity-driven price dynamics.

Table A.1: **Decomposition of $Mroibvol$'s Predictive Power for Future Weekly Returns (%)**. This table presents a decomposition to the overall predictive power of $Mroibvol_{w-1}$ for future returns into those of persistence, contrarian trading, and residual components. Daily returns are calculated based on the mid-points of best bid and ask prices at close as well as open prices, decomposing each day's close-to-close returns into intraday (open-to-close) and overnight (close-to-open) before aggregating each return type into weekly observations. $Mroibvol_{w-1}$ is decomposed into Persistence, Contrarian, and Other components according to equation (5). Each of the three return cross-sections for a given week $w + i$, with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 41, 45, 58, 51, 54, 57, 60\}$, is decomposed based on the sign of week $w - 1$'s internalized order flow to form a total of nine samples. According to equation (9), week $w + i$ returns in each sample are regressed on week $w - 1$'s Persistence, Contrarian, and Other components of the internalized order flow ($Mroibvol_{w-1}$), whose loadings are reported in the table, and control variables including last week's return (R_{w-1}), last month's return (RET_{-1}), the return over the preceding five months ($RET_{(-7,-2)}$), volatility (VOLAT), and natural logs of turnover ($\ln(TO)$), market capitalization ($\ln(Size)$), and book-to-market ratio ($\ln(BM)$). Estimates are based Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags. Sample includes NMS common shares from Jan 2010 – Dec 2014, excluding observations with previous month-end's closing price below \$1. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

Dependent Variable =		Close-to-close return			Overnight return			Intraday return		
		$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
Week	Component	All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
w	Persistence	0.32***	0.27***	0.43***	0.51***	0.47***	0.48***	-0.19***	-0.20***	-0.058
		[8.76]	[6.60]	[8.20]	[23.73]	[19.69]	[15.02]	[-5.53]	[-4.85]	[-1.21]
	Contrarian	1.22	0.86	1.56*	-0.74**	-0.78*	-0.42	1.97**	1.64	1.98**
		[1.48]	[0.88]	[1.79]	[-2.21]	[-1.80]	[-1.12]	[2.18]	[1.52]	[2.07]
	Other	0.079***	0.045***	0.12***	0.10***	0.15***	-0.013	-0.025***	-0.10***	0.13***
		[13.39]	[3.17]	[7.26]	[23.43]	[19.30]	[-1.46]	[-3.96]	[-6.97]	[8.71]
$w + 1$	Persistence	0.27***	0.27***	0.31***	0.43***	0.43***	0.40***	-0.16***	-0.16***	-0.092*
		[7.43]	[5.99]	[6.21]	[20.64]	[17.88]	[14.18]	[-4.45]	[3.75]	[-1.77]
	Contrarian	-0.80	-1.40	-0.22	-0.39	-0.34	-0.31	-0.42	-1.06	0.094
		[-0.85]	[-1.34]	[-0.20]	[-1.02]	[-0.81]	[-0.57]	[-0.48]	[1.11]	[0.10]
	Other	0.046***	0.011	0.085***	0.078***	0.13***	-0.023**	-0.032***	-0.12***	0.11***
		[7.74]	[0.76]	[4.94]	[22.98]	[18.46]	[-2.48]	[-5.72]	[8.61]	[6.70]
$w + 2$	Persistence	0.20***	0.19***	0.24***	0.39***	0.39***	0.34***	-0.19***	-0.20***	-0.098**
		[5.84]	[4.32]	[5.06]	[19.06]	[15.03]	[11.30]	[-5.46]	[-4.62]	[-1.98]
	Contrarian	-0.80	-0.80	-1.05	-0.78*	-0.41	-1.25	-0.027	-0.38	0.20
		[-1.04]	[-0.96]	[-0.88]	[-1.71]	[-0.93]	[-1.60]	[-0.04]	[-0.58]	[0.23]
	Other	0.042***	0.015	0.083***	0.067***	0.11***	-0.033***	-0.025***	-0.097***	0.12***
		[7.10]	[1.07]	[4.53]	[19.39]	[16.11]	[-3.67]	[-4.21]	[-7.18]	[6.87]

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Table A.1 – *continued from previous page*

Dependent Variable =		Close-to-close return			Overnight return			Intraday return		
Week	Component	$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
		All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
$w + 3$	Persistence	0.11*** [3.41]	0.076* [1.93]	0.18*** [3.95]	0.33*** [18.06]	0.30*** [12.67]	0.32*** [10.96]	−0.22*** [−6.96]	−0.22*** [5.74]	−0.14*** [−3.18]
	Contrarian	−2.06 [−1.60]	−2.24* [−1.72]	−2.10 [−1.46]	0.16 [0.41]	0.49 [1.04]	−0.29 [−0.59]	−2.23* [−1.68]	−2.74* [1.88]	−1.81 [−1.34]
	Other	0.031*** [5.97]	0.0033 [0.24]	0.075*** [4.43]	0.059*** [18.98]	0.11*** [15.66]	−0.039*** [−4.45]	−0.027*** [−5.01]	−0.11*** [7.82]	0.11*** [7.06]
$w + 6$	Persistence	0.12*** [3.48]	0.13*** [3.09]	0.13*** [2.64]	0.29*** [14.27]	0.29*** [12.46]	0.27*** [8.25]	−0.17*** [−4.94]	−0.16*** [−4.03]	−0.14*** [−2.87]
	Contrarian	0.091 [0.09]	0.43 [0.37]	−0.067 [−0.06]	−0.71 [−1.33]	−0.083 [−0.16]	−1.20* [−1.78]	0.80 [0.95]	0.51 [0.54]	1.13 [1.03]
	Other	0.015*** [2.63]	−0.020 [−1.56]	0.057*** [3.28]	0.043*** [13.28]	0.099*** [14.39]	−0.037*** [−4.33]	−0.028*** [−5.24]	−0.12*** [−9.55]	0.093*** [6.08]
$w + 9$	Persistence	0.016 [0.48]	0.031 [0.76]	0.025 [0.57]	0.20*** [9.45]	0.24*** [9.64]	0.13*** [3.60]	−0.19*** [−5.95]	−0.20*** [−5.19]	−0.10** [−2.42]
	Contrarian	−1.23* [−1.68]	−1.09 [−1.08]	−1.22* [−1.73]	−0.54 [−1.06]	−0.45 [−0.75]	−0.79 [−1.40]	−0.69 [−1.20]	−0.64 [−0.90]	−0.43 [−0.60]
	Other	0.011* [1.94]	−0.012 [−0.95]	0.055*** [3.06]	0.031*** [9.13]	0.079*** [12.01]	−0.056*** [−6.85]	−0.020*** [−3.85]	−0.092*** [−7.40]	0.11*** [6.90]
$w + 12$	Persistence	0.018 [0.45]	0.0063 [0.13]	0.042 [0.83]	0.21*** [9.67]	0.19*** [7.59]	0.21*** [6.36]	−0.19*** [−5.08]	−0.18*** [−4.03]	−0.17*** [−3.62]
	Contrarian	0.11 [0.19]	0.47 [0.67]	−0.72 [−0.85]	−0.029 [−0.06]	−0.032 [−0.06]	−0.17 [−0.28]	0.14 [0.19]	0.50 [0.66]	−0.56 [−0.70]
	Other	0.0037 [0.73]	−0.050*** [−3.82]	0.069*** [3.88]	0.035*** [10.78]	0.070*** [11.36]	−0.021** [−2.39]	−0.031*** [−5.96]	−0.12*** [−9.82]	0.090*** [5.65]
$w + 24$	Persistence	−0.028 [−0.84]	−0.13*** [−2.94]	0.11** [2.30]	0.14*** [6.78]	0.13*** [5.04]	0.14*** [4.45]	−0.17*** [−5.14]	−0.26*** [−6.34]	−0.032 [−0.68]
	Contrarian	−0.36 [−0.46]	−1.11 [−1.08]	0.20 [0.29]	−0.46 [−1.12]	−0.59 [−1.29]	−0.25 [−0.42]	0.096 [0.11]	−0.52 [−0.47]	0.45 [0.53]
	Other	−0.0021 [−0.37]	−0.049*** [−3.44]	0.045*** [2.60]	0.022*** [6.75]	0.064*** [10.28]	−0.042*** [−4.71]	−0.024*** [−3.94]	−0.11*** [−8.39]	0.087*** [5.04]

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Table A.1 – *continued from previous page*

Dependent Variable =		Close-to-close return			Overnight return			Intraday return		
Week	Component	$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
		All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
$w + 36$	Persistence	−0.00053 [−0.01]	−0.019 [−0.40]	0.052 [1.12]	0.12*** [5.92]	0.14*** [5.06]	0.094*** [2.99]	−0.12*** [−3.62]	−0.16*** [−3.47]	−0.042 [−0.97]
	Contrarian	0.44 [0.36]	−0.40 [−0.35]	1.56 [1.00]	0.42 [0.81]	0.30 [0.41]	0.69 [1.28]	0.018 [0.02]	−0.70 [−0.87]	0.87 [0.65]
	Other	−0.0027 [−0.43]	−0.045*** [−2.84]	0.069*** [4.21]	0.027*** [7.16]	0.061*** [8.52]	−0.020*** [−2.63]	−0.029*** [−4.94]	−0.11*** [−7.68]	0.089*** [5.80]
$w + 39$	Persistence	−0.052 [−1.40]	−0.065 [−1.38]	−0.019 [−0.40]	0.075*** [3.45]	0.054** [2.03]	0.057* [1.85]	−0.13*** [−3.53]	−0.12*** [−2.69]	−0.077 [−1.54]
	Contrarian	0.41 [0.47]	0.60 [0.74]	−0.13 [−0.11]	0.015 [0.04]	0.31 [0.67]	−0.18 [−0.39]	0.39 [0.44]	0.29 [0.35]	0.049 [0.04]
	Other	−0.0090 [−1.55]	−0.037*** [−2.58]	0.045*** [2.80]	0.014*** [4.09]	0.042*** [6.46]	−0.045*** [−5.41]	−0.023*** [−4.33]	−0.079*** [−5.94]	0.090*** [5.65]
$w + 42$	Persistence	−0.031 [−0.80]	−0.094** [−2.12]	0.098* [1.85]	0.073*** [3.34]	0.050* [1.84]	0.085*** [2.60]	−0.10*** [−2.95]	−0.14*** [−3.42]	0.013 [0.25]
	Contrarian	−0.72 [−0.93]	−1.08 [−1.24]	−0.20 [−0.21]	−0.13 [−0.41]	0.025 [0.07]	−0.15 [−0.19]	−0.58 [−0.74]	−1.10 [−1.38]	−0.042 [−0.04]
	Other	−0.010* [−1.93]	−0.041*** [−3.07]	0.069*** [3.78]	0.016*** [4.36]	0.056*** [7.92]	−0.045*** [−5.04]	−0.026*** [−5.03]	−0.097*** [−7.63]	0.11*** [6.87]
$w + 45$	Persistence	0.0032 [0.09]	0.015 [0.34]	0.016 [0.33]	0.12*** [5.62]	0.12*** [4.68]	0.096*** [3.28]	−0.11*** [−3.37]	−0.10** [−2.50]	−0.080* [−1.81]
	Contrarian	−0.63 [−0.49]	−0.59 [−0.52]	−0.80 [−0.51]	0.10 [0.23]	0.64 [1.15]	−0.61 [−1.15]	−0.73 [−0.57]	−1.23 [−0.98]	−0.19 [−0.14]
	Other	−0.014** [−2.30]	−0.049*** [−3.30]	0.054*** [3.01]	0.011*** [2.83]	0.051*** [6.51]	−0.048*** [−5.17]	−0.025*** [−4.49]	−0.100*** [−7.59]	0.10*** [6.32]
$w + 48$	Persistence	−0.083** [−2.20]	−0.11** [−2.43]	−0.022 [−0.42]	0.12*** [4.95]	0.12*** [4.04]	0.093*** [2.96]	−0.20*** [−5.77]	−0.22*** [−5.61]	−0.12** [−2.35]
	Contrarian	−2.48*** [−3.07]	−2.14** [−2.16]	−3.00*** [−3.76]	−1.11** [−2.40]	−1.11 [−1.43]	−1.03*** [−2.92]	−1.37** [−2.00]	−1.03 [−1.30]	−1.97*** [−2.61]
	Other	−0.0049 [−0.87]	−0.050*** [−3.15]	0.061*** [3.48]	0.021*** [6.12]	0.054*** [8.13]	−0.037*** [−4.48]	−0.025*** [−4.52]	−0.10*** [−7.39]	0.098*** [6.39]

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Table A.1 – *continued from previous page*

Dependent Variable =		Close-to-close return			Overnight return			Intraday return		
Week	Component	$Mroibvol_{w-1}$			$Mroibvol_{w-1}$			$Mroibvol_{w-1}$		
		All	Negative	Positive	All	Negative	Positive	All	Negative	Positive
$w + 51$	Persistence	−0.035	−0.074	0.052	0.10***	0.097***	0.096***	−0.14***	−0.17***	−0.044
		[−0.93]	[−1.56]	[1.19]	[4.60]	[3.12]	[2.97]	[−3.65]	[−3.54]	[−0.97]
	Contrarian	−1.86**	−1.79**	−2.21**	−0.63	−0.72	−0.55	−1.23**	−1.06	−1.66**
		[−2.42]	[−2.13]	[−2.40]	[−1.34]	[−1.13]	[−1.26]	[−2.13]	[−1.45]	[−2.26]
	Other	−0.022***	−0.069***	0.055***	0.011***	0.044***	−0.039***	−0.034***	−0.11***	0.094***
$w + 54$	Persistence	−0.013	−0.0068	0.020	0.11***	0.10***	0.094***	−0.12***	−0.11**	−0.074
		[−0.35]	[−0.15]	[0.38]	[4.84]	[3.90]	[2.90]	[−3.29]	[−2.55]	[−1.56]
	Contrarian	−1.16*	−1.14	−1.32*	0.28	0.47	−0.013	−1.45**	−1.61**	−1.31*
		[−1.79]	[−1.36]	[−1.68]	[0.85]	[1.02]	[−0.03]	[−2.45]	[−2.28]	[−1.80]
	Other	−0.019***	−0.048***	0.060***	0.0077**	0.041***	−0.042***	−0.027***	−0.089***	0.10***
		[−3.24]	[−3.24]	[3.66]	[2.11]	[5.67]	[−4.13]	[−4.77]	[−6.61]	[6.56]
$w + 57$	Persistence	−0.053	−0.094**	0.030	0.081***	0.082***	0.061*	−0.13***	−0.18***	−0.031
		[−1.35]	[−2.04]	[0.57]	[3.43]	[2.85]	[1.72]	[−3.80]	[−4.09]	[−0.67]
	Contrarian	0.67	0.41	0.99	1.02***	1.03**	1.00**	−0.35	−0.62	−0.017
		[0.79]	[0.48]	[1.01]	[2.82]	[2.46]	[2.26]	[−0.39]	[−0.62]	[−0.02]
	Other	−0.0015	−0.051***	0.065***	0.0071*	0.033***	−0.040***	−0.0086	−0.084***	0.10***
		[−0.25]	[−3.41]	[3.42]	[1.93]	[4.76]	[−4.58]	[−1.47]	[−6.10]	[5.56]
$w + 60$	Persistence	−0.058	−0.046	−0.045	0.13***	0.14***	0.090***	−0.19***	−0.18***	−0.13**
		[−1.34]	[−0.90]	[−0.80]	[5.36]	[4.35]	[2.69]	[−4.64]	[−3.74]	[−2.47]
	Contrarian	−0.87	−0.82	−1.12	0.41	0.41	0.47	−1.28	−1.22	−1.59
		[−1.04]	[−0.72]	[−1.03]	[0.73]	[0.56]	[0.68]	[−1.23]	[−0.96]	[−1.39]
	Other	−0.020***	−0.071***	0.045**	0.012***	0.036***	−0.038***	−0.032***	−0.11***	0.083***
		[−3.34]	[−4.78]	[2.57]	[3.06]	[4.75]	[−4.17]	[−5.59]	[−8.11]	[4.90]