Uncovering the Liquidity Premium in Stock Returns Using Retail Liquidity Provision*

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Abstract

In response to institutional liquidity demand, wholesalers internalize retail trades. The resulting imbalances in internalized retail order flow coincide with institutional price pressures whose reversals yield a positive relation between these imbalances and future returns. We measure stock-level illiquidity using the likelihood/intensity with which wholesalers facilitate such retail liquidity provision to institutions. Unlike existing illiquidity measures, these easy-to-construct new measures have economically-meaningful relations with institutional holding horizons at stock and investor levels, and yield annualized liquidity premia of 2.7–3.2% post-2010. Thus, we uncover a channel through which a subset of internalized retail order flow predicts the cross-section of returns.

Keywords: Cross-section of Stock Returns, Microstructure, Institutional Trading Costs, Internalized Retail Trade, Liquidity Premium

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 Institutional liquidity measures developed by this paper are available at Yashar Barardehi's website. Any errors are our own.

1 Introduction

Various studies have documented that retail order flow predicts the cross-section of stock returns. However, the source of this predictive power is less clear. Some studies simply attribute this return predictability to a subset of retail investors possessing stock-specific information (e.g., Kelley and Tetlock (2013), Fong, Gallagher, and Lee (2014), and Boehmer, Jones, Zhang, and Zhang (2021)). Conversely, Kaniel, Saar, and Titman (2008) argue that retail investors may effectively trade against institutional investors whose trades exert price pressures that eventually reverse, leading to a positive association between retail order flow and future returns.[1] The challenge for testing this mechanism is that order flow segmentation prevents institutional investors from directly interacting with marketable retail order flow. We address this challenge by using microstructure features of modern U.S. equity markets that allow publicly available data to uncover an economic mechanism underlying *indirect* retail-institutional order flow interactions. We establish that absolute imbalances in an easily-observable subset of retail trades provide novel measures of stock liquidity that also capture implicit institutional trading costs. We then document the strong explanatory power of these liquidity measures for expected returns, uncovering a new channel through which retail order flow predicts stock returns.

We provide the first evidence of wholesalers intermediating between retail and institutional investors in modern equity markets, wherein a wholesaler chooses to "internalize" unequal amounts of retail buy vs. sell orders to offset inventory accumulated from providing liquidity to institutional investors on the opposite side of the market. We obtain imbalances in long-only institutional and short-seller trading interests from ANcerno and FINRA data that we link to imbalances in a select subset of internalized marketable retail orders identified using the algorithm proposed by Boehmer et al. (2021), henceforth BJZZ.[2] Crucially, the BJZZ algorithm differentially identifies a subset of retail orders that wholesalers internalize to provide liquidity to institutions.[3]

[1]To clarify, we are interested in *unconditional* return predictability of retail order flow. Some studies examined this return predictability conditional on imminent earnings announcement (e.g., Kaniel, Liu, Saar, and Titman (2012); Boehmer et al. (2021)).

[2]Importantly, using data from 58 brokers and 6 wholesalers, SEC (2022) implies BJZZ's algorithm identifies less than 40% of all marketable retail orders. Barber, Huang, Jorion, Odean, and Schwarz (2022), using self-generated trades, and Battalio, Jennings, Salgam, and Wu (2022), using proprietary wholesaler data, obtain similar conclusions.

[3]Battalio et al. (2022) also find BJZZ's algorithm might mis-classify institutional trades as retail trades. Robustness analyses, reported in Section 5.2 and Internet Appendix C.3, indicate that this does not impact the algorithm's ability to identify retail trades internalized by wholesalers to provide liquidity to institutional clients.

Like BJZZ, we find imbalances in internalized marketable retail flow, denoted $Mroib$, vary across stocks and robustly predict future stock returns for several weeks. However, rather than informed retail trading, we attribute this return predictability to the subsequent unwinding of institutional price pressure, consistent with Kaniel et al. (2008).[4] We provide evidence that large imbalances in these observable internalized retail trades—large $|Mroib|$—reflect the internalized retail orders used by wholesalers to balance their inventories when providing liquidity to institutional investors, especially when liquidity is scarce. This leads us to propose stock-level averages of $|Mroib|$ as liquidity measures. These easy-to-construct liquidity measures proxy for cross-sectional variation in institutional trading costs and, unlike existing liquidity measures, are related to investor holding horizons as predicted by theory. In further contrast, our liquidity measures identify annualized liquidity premia of 2.74–3.20%, associated with one standard deviation reduction in liquidity, post 2010 when existing liquidity measures fail to explain the cross-section of expected stock returns.

Figure 1. Retail Imbalances versus Institutional Imbalances and Price Impacts. This figure plots institutional trade imbalances and institutional-trade price impacts constructed from ANcerno data against imbalances in the volumes of observable internalized retail orders ($Mroibvol$). Each week, stocks are sorted into deciles according to their respective internalized retail order flow imbalance. The averages of institutional trade imbalances and institutional price impacts are then calculated within each decile each week using ANcerno data from 2010–2014. Time-series means of these averages are plotted by $Mroibvol$ decile.

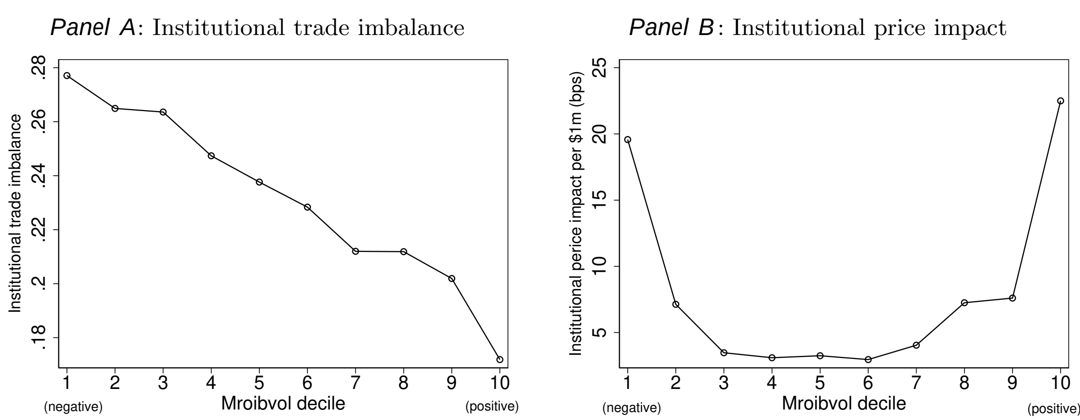


Figure 1 illustrates two properties of $Mroib$ that highlight the liquidity provision facilitated by retail order flow internalization. Panel A shows that institutional trade imbalances are inversely related to BJZZ-identified retail imbalances,[5] while Panel B shows that institutional price impacts

[4]Internet Appendix C.3 proposes improvements to BJZZ's algorithm that reinforce $Mroib$'s return predictability.

[5]Table 2 shows that short sellers are net buyers (sellers) when $Mroibvol$ is negative (positive), even though we have to aggregate observations over bi-weekly horizons rather than daily. The positive average institutional trade imbalance in Figure 1 is expected as mutual funds experienced net inflows in the 2010–2014 post-crisis period.

are highest when these retail imbalances are the most extreme. These patterns suggest that large imbalances in this internalized retail order flow reflect the internalization choices of wholesalers in response to the opposing liquidity demand imbalances of institutions facing high trading costs.

The U.S. equity market structure provides wholesalers, a group of high-frequency market makers, a competitive advantage in providing liquidity to institutions in less liquid markets. Wholesalers interact with institutional investors on exchanges, Alternative Trading Systems (ATSs), and their own Single-Dealer Platforms (SDPs). On the other side, retail brokers outsource the handling of nearly all customer orders to wholesalers in return for payment for order flow (PFOF) or sub-penny price improvements (PI) for their customers. Wholesalers can then choose to (i) internalize retail orders by executing them against their own capital and offering PI; (ii) execute retail orders on a riskless principal basis, without PI, by rerouting orders to ATSs or exchanges; or (iii) reroute retail orders to another wholesaler. Hence, wholesalers secure the option to fill retail orders before these orders are exposed to other market participants, effectively segmenting order flow.[6] Reflecting this segmentation, U.S. wholesalers do not compete with retail investors when providing liquidity to institutions.[7] Instead, wholesalers can use retail flow as an ***exclusive*** inventory management mechanism (Baldauf, Mollner, and Yueshen (2022)). Thus, wholesalers can offset inventory accumulated from filling unbalanced institutional order flow by ***choosing*** to internalize disproportionately more retail order flow from the opposing side of the market, especially when liquidity is scarce.[8]

Crucially, the internalized retail orders that facilitate this intermediation often involve sub-penny retail execution prices due to PI and are observable by BJZZ's algorithm. As detailed in Section 3.2, most retail trades not identified by this algorithm are of two types: (1) retail trades chosen by the wholesaler for riskless principal execution on an ATS or exchange; (2) retail orders internalized by the wholesaler due to regulatory requirements rather than by choice.

We document more unbalanced internalized retail flow and higher marginal costs of internalization to wholesalers in the form of greater PI or PFOF when institutional liquidity demand is more

[6]Wholesaler internalization choices determine whether other market participants may directly interact with these retail orders. Practitioners describe internalized orders as "inaccessible liquidity" (Cowen Market Structure 2021).

[7]See Korajczyk and Murphy (2019) for high-frequency market makers' interactions with institutional investors in Canada, where unlike the U.S., all retail orders are routed to public venues, e.g., exchanges.

[8]Simultaneous offsetting of institutional inventory using retail orders also mitigates wholesalers' exposure to toxic (informed) institutional orders. Section 3.2 also notes that wholesalers may use institutional-sourced liquidity to offset inventory accumulated due to retail order flow imbalance. Such executions require abundant liquidity as a wholesaler uses institutional-sourced midpoint liquidity to fill unbalanced retail order flow at the midpoint. Importantly, the BJZZ algorithm facilitates identification of ***scarce*** liquidity by excluding such mid-point-filled retail trades.

unbalanced and trading costs are higher. This evidence indicates that wholesalers respond to the increased demand for liquidity from liquidity-constrained institutional investors by internalizing costlier retail order flow. Intuitively, wholesalers are willing to exercise their ***option*** to internalize costlier retail order flow in order to facilitate inventory management when filling unusually profitable institutional orders in less liquid markets. Internet Appendix A provides a simple theoretical framework that links internalization choices to the costs of internalization. We then use exogenous variations in the profits and costs of internalization generated by the Tick Size Pilot to document causally the effect of wholesaler choices on $Mroib$.

Cross-sectional tests highlight the impact of institutional liquidity demand on $Mroib$. Internalization of more (less) retail sell orders than buy orders is associated with higher (lower) net institutional buy volume, and more covering (accumulation) of short interest. Consistent with a lack of institutional counter-parties to offset institutional imbalances on ATSs, a larger $|Mroib|$ is associated with abnormally low quote-midpoint liquidity. In addition, larger $|Mroib|$ is associated with wider quoted spreads and lower quoted depth. These revealed low levels of liquidity present wholesalers with opportunities to fill institutional orders at wide spreads while maintaining a balanced inventory by internalizing costlier retail order flow. Finally, 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 thus in the ***opposite*** direction of $Mroib$.[9]

Cross-sectional regressions of stock returns on $Mroib$ reveal that higher $Mroib$ is associated with higher near-term future weekly returns (through 12 weeks). Consistent with Kaniel et al. (2008), Internet Appendix C attributes the near-term return predictability of $Mroib$ to price reversals following price pressure induced by persistent institutional trading, especially institutional buying (Hendershott and Seasholes (2007), Akepanidtaworn, Di Mascio, Imas, and Schmidt (2020)). Specifically, negative current $Mroib$ (retail selling, institutional buying) is associated with lower future returns for several weeks due to the unwinding of institutional price pressure. Further decomposing daily returns into intraday and overnight returns sheds further light on the liquidity-driven price dynamics, with intraday institutional price pressure being followed by overnight reversals. Crucially, the relation between $Mroib$ and future returns becomes $\cup$-shaped after 6 weeks. This $\cup$-shape pattern persists for well beyond a year, and is consistent with a liquidity premia demanded

[9] $Mroib$ reflects regular-hour trades, making intraday returns the relevant metric.

by institutional investors for holding less liquid stocks, which tend to have high values of $|Mroib|$, and hence give rise to the $\cup$-shape relationship.

The economic mechanism uncovered by our analysis and the availability of data for large cross-sections of stocks motivate our use of $|Mroib|$ to proxy illiquidity and institutional trading costs. We construct stock-level liquidity measures $ILMT$ and $ILMV$ by averaging daily absolute imbalances in, respectively, the number of trades and trading volumes involving BJZZ-identified internalized retail order flow. Comparing these ILMs to existing liquidity measures reveals that they are among the few that are positively related to institutional price impacts in the cross-section.

We then provide direct evidence that ILMs capture the liquidity concerns of institutional investors better than existing measures by linking the liquidity of fund manager holdings based on different liquidity measures to their holding horizon. As Amihud and Mendelson (1986) observe, managers with longer holding horizons should be more willing to invest in illiquid stocks, implying a positive relation between a manager's holding horizon and the measured illiquidity of their equity under management (EUM). We calculate the illiquidity of EUMs using 15 different liquidity measures. For each measure, we examine the relation between the illiquidity of a fund manager's EUM and their holding horizon. Existing liquidity measures all deliver a non-monotone relation between measured EUM illiquidity and holding horizon. In contrast, ILMs induce a more monotone positive relation, consistent with Amihud and Mendelson's prediction.

We then investigate the relation between illiquidity and holding horizon at the stock level. To do this, we calculate the average holding horizon of fund managers in individual stocks (Gaspar, Massa, and Matos (2005); Cella, Ellul, and Giannetti (2013)) and then regress different stock-level liquidity measures in quarter q on the stock's average institutional holding horizon as well as its volatility, market capitalization, and institutional ownership in quarter $q-1$. The R^2s obtained in regressions using ILMs are 3.5-24.2 times larger than those using existing liquidity measures. Moreover, after orthogonalizing ILMs with respect to existing liquidity measures, the residual ILMs continue to exhibit the predicted positive relation with holding horizon. Conversely, the reverse orthogonalizations only deliver the expected relation with holding horizon for quoted spread and quoted depth. In sum, ILMs are the only liquidity measures that have economically meaningful relations with holding horizon at *both* the investor and stock levels.

Next, we establish that ILMs explain expected stock returns. Fama-MacBeth (1973) specifications regress stock returns in month m on ILMs in month $m-2$ as well as an array of stock characteristic controls.[10] Skipping month $m-1$ ensures that returns in month m are not confounded by short-term reversals following large retail order flow imbalances.[11] As in the prior literature, we find existing high- and low-frequency liquidity measures are not priced (or have negative liquidity "premia") in the 2010–2019 period. In contrast, ILMs are priced with economically significant liquidity premia: a one standard deviation increase in $ILMT$ ($ILMV$) is associated with an annualized liquidity premium of 2.74% (3.20%), comparable to the institutional price impacts computed from ANcerno data that are priced with an annualized premium of 3.8% over 2010-2014.[12]

Portfolio sorts confirm the economic magnitude of the liquidity premia associated with ILMs. Each month, we sort stocks into deciles based on their $ILMT$s or $ILMV$s in month $m-2$, skip month $m-1$, and examine portfolio returns in month m. The high-minus-low return spreads involving deciles 1 and 10, after a Fama-French three-factor adjustment, are 0.86% and 1.06% per ***month*** for $ILMT$ and $ILMV$, respectively. Value-weighting returns after removing stocks with smallest 20% market-capitalizations, reduces these risk-adjusted returns to 0.58% and 0.46%, respectively. Robustness tests confirm that risk-adjusted return spreads associated with ILMs exceed those based on existing liquidity measures. Moreover, unlike with existing liquidity measures, significant risk-adjusted return spreads are associated with ILMs between intermediate deciles, such as spreads between decile 2 vs. 9, decile 3 vs. 8, and decile 4 vs. 6.

The regression and portfolio results are confirmed by a battery of robustness tests that use alternative estimation approaches, employ specifications that weight observations unequally, and apply various filters that remove small and/or low-priced stocks from the sample. Our highly robust results enable us to conclude that liquidity premia conditional on ILMs hold among stocks that are the most likely to be held by institutional investors. In terms of economic magnitude, a one standard deviation increase in ILMs is associated with annualized liquidity premia between 2.74–3.74%. Similarly, depending on whether "penny stocks" are included in the sample, annualized risk-adjusted return spreads associated with portfolios based on ILMs range between 4.08–15.24%.

Our liquidity measures reveal that stock returns still reflect economically meaningful trading

[10] Internet Appendix H demonstrates robustness to constructing ILMs over three months, m 4 to m 2.

[11] Consistent with the stock-specific temporal persistence in ILMs, the use of ILMs from month m 1 or skipping more than one month leaves our qualitative findings unaffected.

[12] ANcerno data became unavailable in 2015, preventing liquidity premia estimates using institutional price impacts.

costs incurred by institutional investors when entering and exiting stock positions. As reported by Di Maggio, Egan, and Franzoni (2022), institutional price impacts exhibit a standard deviation of 64bps in recent years. This heterogeneity implies investors should demand a liquidity premium that accounts for stock-level institutional price impacts.[13] Our liquidity premia findings are consistent with these trading costs of institutional investors who collectively hold about 70% of publicly-traded equity in the U.S. (Blume and Keim (2012)) in recent years.[14] According to Amihud (2019), "illiquidity has a number of dimensions that are hard to capture in a single measure, including fixed costs, variable costs—price impact costs that increase in the traded quantity—and opportunity costs." The multifaceted nature of liquidity became even more complicated in the post-RegNMS era where spreads are often a few pennies and depth is negligible in fragmented markets. Indeed, a recent literature cautions against using existing liquidity measures to proxy for institutional trading costs post-RegNMS.[15] We overcome the empirical challenges of measuring liquidity in the modern era by developing liquidity measures based on identifiable intermediation by wholesalers between retail and institutional investors when liquidity is scarce. The likelihood and intensity with which wholesalers engage in such intermediation comprise a persistent stock "characteristic" that explains the cross-sectional variation in expected stock returns.

2 Contributions to the Literature

Our paper extends the literature on the relationship between retail order flow and future returns, some of which documents the return predictability of retail order flow.[16] While studies such as Kelley and Tetlock (2013), Fong et al. (2014), and Boehmer et al. (2021) attribute this return predictability to informed retail trades, Kaniel et al. (2008) posit that unbalanced retail order flow

[13] With quarterly re-balancing and a 50% turnover ratio, annualized round-trip execution costs rise by 4 2 0.5 64bps = 2.56% per year in response a one standard deviation increase in price impacts. This estimate is close to the liquidity premium estimates inferred from our regression analysis, where one standard deviation increase in ILM is associated with 2.47–3.20% increased expected returns.

[14] In contrast, Asparouhova, Bessembinder, and Kalcheva (2010), Ben-Rephael, Kadan, and Wohl (2015), Drienko, Smith, and von Reibnitz (2019), Harris and Amato (2019), and Amihud (2019), among others find vanishing liquidity premia in recent decades using traditional liquidity measures.

[15] Goyenko, Holden, and C. A. Trzcinka (2009), Chordia, R. Roll, and Subrahmanyan (2011), Kim and Murphy (2013), Holden and Jacobsen (2014), Angel, Harris, and Spatt (2011), O'Hara (2015), Eaton, Irvine, and Liu (2021). Barardehi, Bernhardt, and Davies (2019) propose alternative measures.

[16] E.g., Barber and Odean (2000), Barber and Odean (2008), Kumar and Lee (2006), Foucault, Sraer, and Thesmar (2011), Kaniel et al. (2008), Barrot, Kaniel, and Sraer (2016), Kaniel et al. (2012), Kelley and Tetlock (2013), Fong et al. (2014).

reflects strong institutional liquidity demand on the opposite side of the market, which exerts price pressure that subsequently reverses. They suggest institutional investors offer "price concessions" to "entice" retail investors' liquidity provision, a mechanism hard to reconcile with segmented retail and institutional order flows in today's U.S. equity markets. We provide evidence that wholesalers' exclusive access to retail flow allows them to intermediate between retail and institutional investors. These intermediation choices are reflected by the opposite imbalances in internalized marketable retail orders identified using the algorithm proposed by Boehmer et al. (2021), i.e., $Mroib$, especially when liquidity is scarce. Our findings reinforce Barrot et al. (2016)'s notion of unintentional liquidity provision by retail investors; and are consistent Kaniel et al. (2008)'s conclusions in that we find $Mroib$'s return predictability reflects return reversals following institutional investors' consumption of retail-sourced liquidity.[17] Most importantly, we uncover a new channel for return predictability of retail order flow by showing that institutional trading costs and illiquidity can be proxied by $|Mroib|$, which robustly explains the cross-section of expected returns.

We also contribute to a vast literature that designs stock liquidity measures or examines their implications for asset pricing.[18] Our paper develops a proxy of illiquidity using an easily-observable subset of retail trades, distinguishing our liquidity measures from those in the literature. For example, observing the endogenous responses of sophisticated investors to time-varying liquidity, Barardehi et al. (2019) develop trade-time liquidity measures that reflect per-dollar price impacts measured over successive time intervals required for execution of stock-specific fixed dollar values. Bogousslavsky and Collin-Dufresne (2022) use the volatility in total order flow in a given week as a metric of liquidity *risk*, and document its ability to predict next week's return.[19] Finally, we establish the superior performance of our liquidity measures vis à vis sixteen existing liquidity measures along three dimensions: (1) correlation with institutional price impacts; (2) correlation with institutional holding horizons; and (3) robust ability to explain the cross-section of expected returns. Our findings indicate that even though the BJZZ algorithm measures overall retail trading

[17]Theoretical and empirical studies on the link between internalization and market quality includes Battalio and Holden (1995), Battalio, Greene, and Jennings (1997), Battalio, Greene, Hatch, and Jennings (2002), Peterson and Sirri (2003), Parlour and Rajan (2003), Parlour and Rajan (2003), Battalio (2012), and Amirian and Norden (2021).

[18]E.g., Roll (1984), Glosten and Harris (1998), Brennan and Subrahmanyan (1996), Pástor and Stambaugh (2003), Hasbrouck (2009), Goyenko et al. (2009), Chordia et al. (2011), Kim and Murphy (2013), Barardehi et al. (2019), Bogousslavsky and Collin-Dufresne (2022), among many others.

[19]Bogousslavsky and Collin-Dufresne (2022)'s measure is based on second moments, in contrast to most liquidity measures that employ first moments. These authors are interested in identifying *high-frequency* liquidity risk, rather than a persistent stock characteristic that captures the average costs of entering and exiting stock positions.

and order imbalance with large errors, it can be used to construct effective liquidity measures in modern U.S. equity markets.

3 Institutional Details

3.1 Retail Trade Execution

Executions of retail orders in U.S. equity markets are subject to "best execution" principles.[20] Wholesalers, e.g., Virtu and Citadel, handle the vast majority retail orders on behalf of retail brokers, e.g., Charles Schwab and E*Trade. These high-frequency market makers compete over providing execution quality to retail trades (Battalio and Jennings (2022)), ensuring best execution principles are met in addition to providing payment for order flow (PFOF) to certain brokers.[21]

Retail orders handled by wholesalers are executed in two ways. According to SEC (2022) nearly 20% of marketable retail orders are rerouted for riskless principal execution, where a wholesaler quotes an identical order on exchanges/ATSs and fills the retail order once that proprietary order is executed.[22] The remaining 80% of marketable retail order executions are internalized, a process by which wholesalers execute retail order flow against their own inventory.[23] Wholesalers are usually registered brokers, but are not subject to the rules of registered exchanges or ATSs. 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 reflecting price improvements that fulfill "best execution" duties and improve execution quality.

Panel A in Table 1 reports the distribution of order types across all non-directed orders[24] and all retail volume executed by wholesalers, along with the average PFOF for each order type. Market orders and marketable limit orders account for a disproportionately large share of executed volume receiving PFOF, indicating that wholesalers prefer internalizing marketable orders over

[20] SEC (2021) describes "best execution" as being "at the most favorable terms reasonably available under the circumstances, generally, the best reasonably available price." See FINRA Regulatory Notice 21-23 for more details.

[21] In addition to receiving order flow from brokers, a wholesaler may also receive retail orders from other wholesalers.

[22] Most retail orders originally placed as non-marketable limit orders are routed to exchange limit order books for riskless principal execution. However, a subset of orders organically placed as marketable limit orders become non-marketable when received by the wholesaler due to rapid quote updates.

[23] In May 2012, internalized orders comprised roughly 8% of consolidated volume in NMS stocks (Tuttle (2022)). Reflecting increased retail investor participation, this fraction was 20% in September 2021 (Rosenblatt (2021)).

[24] Retail investors may use a "directed order" to specifying a particular trading venue. However, 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.

non-marketable orders. Calculations suggest the share of executed volume of non-marketable limit orders receiving PFOF is only one fourth that of marketable orders. Of note, non-marketable limit orders executed by wholesalers receive over twice as much PFOF per share as marketable orders.

PFOF and PI combine to determine the direct internalization costs to a wholesaler. PFOF and average PI often reflect pre-negotiated terms between brokers and wholesalers, with brokers often trying to obtain the most favorable average PI for their retail customers. However, there is significant variation in PI across individual transactions. Calculations in Section C.3 that compare each execution price with the corresponding NBBO suggest that over 50% of observable internalized marketable orders receive sub-penny PI of no more than 0.1¢. In contrast, underscoring the significant variation in wholesaler internalization costs, over 35% of internalized orders are executed at prices that are inside the NBBO by over 1¢.

Institutional details suggest two channels underlie these large PIs. Most importantly, the Manning rule requires wholesalers with access to proprietary data feeds on odd-lot liquidity to use any inside-quote liquidity to determine best execution terms. Due to the 1¢ tick size, inside-quote odd-lot liquidity is quoted at 1¢ price increments. Thus, when such liquidity exists, to price improve over the "best available price" some internalized marketable retail orders must receive greater-than-1¢ PI. Second, internalized orders executed at prices over 1¢ inside the NBBO may be inside-NBBO non-marketable limit orders, originally placed as marketable orders.[25] Internalizing such non-marketable limit orders is very costly, even when executed at minimal PI because non-marketable orders receive much higher PFOF.

3.2 Implications for BJZZ's Algorithm

Wholesalers internalize about 80% of the marketable retail orders received (SEC (2022)),[26] and BJZZ's algorithm identifies only a select subset of these trades. The algorithm's systematic selection

[25] Consistent with internalization of some non-marketable limit orders, Virtu Financial reports that Virtu "reflects a substantial percentage", but not *all*, of non-marketable orders handled by them on exchanges. That 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 incentivize brokers to let wholesalers handle their non-marketable orders because wholesalers receive higher rebates. Upon receipt of a non-marketable order, the wholesaler may execute it on a riskless principal basis by submitting an identically-priced order to an exchange/ATS. If it is executed, the wholesaler fills the standing retail limit order and pays PFOF to the broker.

[26] Wholesalers typically receive four times as much marketable as non-marketable retail order volume, and they internalize a much smaller percentage of those non-marketable orders according to Rule 606 filings, industry reports (Measuring Retail Execution Quality by Virtu Financial), and our analysis of TAQ data.

of a subset of retail trades is ***key*** to our analysis for at least three reasons.

First, the BJZZ algorithm excludes retail trades filled at the NBBO. Wholesalers have three main options when handling retail orders: (1) internalize them; (2) execute them on a riskless principal basis by rerouting orders to exchanges/ATSs, where non-midpoint sub-penny execution prices are prohibited; and (3) reroute them to another wholesaler. Over 42% (8%) of rerouted (all) retail orders fill at the NBBO (SEC (2022)), implying that the algorithm excludes retail trades that wholesalers ***choose*** not to internalize.

Second, the algorithm excludes midpoint-filled retail trades that account for a large share of omitted trades and reflect the best execution requirements of brokers. These requirements ***force*** wholesalers to internalize orders at the midpoint when they detect undisplayed midpoint liquidity, e.g., due to pinging some exchange/ATS for midpoint liquidity. SEC (2022) reports that over 31% of all retail orders are filled at the quote midpoint (also see Battalio et al. (2022)). Importantly, such trades reflect regulatory requirements and not the endogenous internalization choices of wholesalers to source liquidity for their institutional clients. Hence, excluding these trades, which tend to occur when institutional midpoint liquidity is abundant, improves our identification of retail trades internalized by wholesalers to provide liquidity to institutional investors when liquidity is scarce.[27]

Finally, reflecting wholesaler internalization choices, 55% of retail trades reflect non-midpoint internalized orders that receive PI (SEC (2022)), and BJZZ's algorithm picks up such trades with sub-penny PI.[28] Collectively, the BJZZ algorithm, by focusing on a selected subset of retail trades, makes observable those retail trades that wholesalers ***choose*** to internalize; and this selection underlies the strength of our liquidity measures.

3.3 Wholesalers and Institutional Liquidity Demand

Most wholesalers, including Citadel Securities and Virtu Americas LLC, own Single Dealer Platforms (SDPs). On SDPs, also known as ping pools, a select set of institutions and institutional

[27] Alternatively, midpoint trades may reflect wholesaler competition to provide execution quality (Battalio and Jennings (2022)). Importantly, such executions require abundant liquidity to facilitate wholesaler inventory management, as a wholesaler uses institutional-sourced midpoint liquidity to fill unbalanced retail order flow at the midpoint. Hence, such intermediation should be excluded from an analysis of scarce liquidity, and BJZZ algorithm excludes it.

[28] Less than 1/3 of PI are in round-pennies (SEC (2022)) and not picked up by the algorithm, but such internalized trades likely reflect wholesaler responses to regulatory requirements like the Manning rule when inside quote liquidity exists, indicative of abundant liquidity. SEC (2022) reports that broker-dealers commonly use proprietary order-book data feeds that are more comprehensive than the SIP. Like retail trades filled at the midpoint, the algorithm's exclusion of these trades helps our analysis of wholesaler choices when liquidity is scarce.

brokers trade against the wholesaler.[29] SDPs date back to 2005, and were originally referred to as Electronic Liquidity Providers (BestEx Research (2022)). By 2017, over 2.5% of all trading in NMS stocks occurred on SDPs, comprising roughly 30% of all internalized retail order flow.[30] An institution may "ping" a wholesaler on its affiliated SDP, often using Indication of Interest or Immediate or Cancel orders to signal an unusually high demand for liquidity. This signal encourages the wholesaler to intermediate between retail and institutional investors by providing the institution with liquidity sourced from retail order flow.[31] In 2021, Citadel and Virtu combined to execute almost 17% of consolidated U.S. trading volume by internalizing retail orders, and their affiliated SDPs accounted for over 4% of this volume (Rosenblatt (2021)). Put differently, they internalized about 425 shares of retail orders per 100 shares of institutional orders filled on their SDPs.

When wholesalers use internalized retail buy (sell) order flow to fill unbalanced institutional sell (buy) liquidity demand, the internalized retail orders often receive sub-penny price improvements. Consequently, the corresponding $Mroib$ will be unbalanced and inversely related to institutional liquidity demand. As institutions with high liquidity demand are prepared to pay more to wholesalers, wholesalers can pay higher internalization costs in the form of high PI or high PFOF, internalizing orders that are executed by more that 1¢ inside the NBBO. This leads to a positive relation between $|Mroib|$ and the intensity with which these high-cost retail orders are internalized.

4 Data

To analyze wholesaler intermediation between retail and institutional investors, we construct our sample following BJZZ for the period January, 2010 to December, 2014, covering common shares listed on the NYSE, AMEX, and NASDAQ.[32] We use daily open and close prices from CRSP to calculate daily close-to-close (CC), intraday open-to-close (ID), and overnight, close-to-open (ON) returns. We account for overnight adjustments and, to minimize the impact of bid-ask bounce,

[29]Trading 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.

[30]See Tuttle (2022) and Trader VIP Clubs, 'Ping Pools' Take Dark Trades to New Level, *Bloomberg*, Jan 16, 2018.

[31]For example, VEQ Link, Virtu's SDP, explicitly advertises Virtu's Client Market Making service as the link between its SDP and their retail-broker clients. We emphasize that retail orders are not "redirected" to SDPs. To profit from its intermediation, the wholesaler uses its own capital to fill both institutional orders and retail orders.

[32]We exclude 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.

returns are on based quote midpoints at close. We 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 observations with a previous-month-end's closing price of at least $1.

We follow BJZZ to construct measures of observable internalized retail order flow based on the selected sample identified by their algorithm. Using TAQ data, we focus on round-lot off-exchange trades with sub-penny prices.[33] Transactions are classified as retail buy and sell orders if the sub-penny increments exceed 0.6¢ and are below 0.4¢, respectively.[34] We construct daily, normalized measures of imbalance in internalized retail 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 $Mroibvol = (Mrbvol - Mrsvol)/(Mrbvol + Mrsvol)$ is the normalized difference in internalized trade volume. Panel B in Table 1 reports these measures' summary statistics, which closely match those in BJZZ.[35] We then aggregate these daily observations of normalized internalized retail order flow imbalances into overlapping 5-day rolling windows, constructing daily cross-sections of 5-day (weekly) internalized retail order flow imbalances. We also follow BJZZ to construct stock characteristics, including volatility (VOLAT), book-to-market (BM),[36] previous month's return ($RET\ _{1}$), the compound return over the preceding 5 months ($RET_{(\ 6,\ 2)}$), and previous month's turnover (TO).

From TAQ data, 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 average of these fractions with 5-day (weekly) $Mroib$ measures.

ANcerno data from 2010-2014 provide institutional trade sizes, buy versus sell indicators, execution prices, and stock identifiers. We aggregate institutional buy and sell trades separately at the stock-day level to construct the institutional analogue of $Mroibvol$ denoted $Inroibvol$. To construct institutional price impact measures we calculate volume-weighted average buy and sell execution

[33] As in BJZZ, our findings are robust to including odd-lots.

[34] Internet Appendix C.3 shows that the algorithm mis-classifies subsets of buy and sell orders. Correcting for this mis-classification using quote midpoints marginally reinforces our qualitative findings.

[35] Simple calculations reveal that $Mroib$ daily imbalances are large enough to meet most institutional liquidity demands. The sum $Mrbvol + Mrsvol$ averages over 92k shares, or over $1.8 million for a $20 average share price. Hence, a one standard deviation change in $Mroibvol$ is worth over $800k, which exceeds the $500k average dollar value of daily institutional trade reported by ANcerno (Hu, Jo, Wang, and Xie (2018)).

[36] Book value is defined as Compustat's shareholder equity value (seq) plus deferred taxes (txdb).

prices across institutional investors for each stock-day. The price impact of a typical institutional buy trade equals the average execution price minus the open price divided by the open price and scaled by the trade's dollar value in millions. Similarly, the price impact of a typical institutional sell trade equals open price minus the average execution price divided by the open price and scaled by the trade's dollar value in millions. We then aggregate institutional trading outcomes over 5-day rolling windows to construct daily cross-sections of 5-day (weekly) institutional trading outcomes.

To analyze liquidity premia, we construct a sample spanning January 2010 through December 2019, of common shares listed on the NYSE, AMEX, and NASDAQ. We construct two daily institutional liquidity proxies as $|Mroibtrd|$ and $|Mroibvol|$. We use WRDS Daily Indicators, TAQ, and CRSP data to construct the following liquidity measures: (1) time-weighted dollar quoted spreads (QSP); (2) time-weighted share depth (ShrDepth); (3) size-weighted dollar effective spread (EFSP); (4) size-weighted dollar realized spread (RESP); (5) size-weighted price impacts (PIMP);[37] (6) monthly estimates of Kyle's λ, constructed by regressing 5-minute returns (calculated from quote midpoints) on the contemporaneous signed square root of net order flow (estimated using the Lee-Ready algorithm) from the respective month;[38] (7) Amvist liquidity measure, defined as the daily ratio of absolute return to turnover; (8) Roll (1984)'s measure of effective spreads; (9) Amihud (2002)'s measure (ILLIQ); (10) Barardehi, Bernhardt, Ruchti, and Weidemier (2021)'s open-to-close measure (ILLIQ_OC); (11 & 12) Barardehi et al. (2019)'s trade-time liquidity measures (BBD and WBBD);[39] (13) our trade-based institutional liquidity measure ($ILMT$), which averages $|Mroibtrd|$; (14) our volume-based institutional measure ($ILMV$), which averages $|Mroibvol|$. We also construct a stock-specific institutional price impact measure (InPrIm) using ANcerno data from 2010–2014 to directly capture post-trade institutional trading costs per $100k of trade. For each stock-month, we calculate a size-weighted average of institutional price impacts (defined above) associated with individual institutional trades reported by ANcerno.

For all liquidity measures (including $IMLT$ and $IMLV$), we construct two versions; one over a 1-month-horizon that averages daily liquidity proxies and another that averages daily liquidity proxies over rolling three-month windows with monthly updates. For each ILM measure, we also

[37]In unreported analysis, we verify our liquidity measures also outperform spread and price impact measures constructed relative to quote midpoints.

[38]We follow Holden and Jacobsen (2014) in cleaning the data, matching transactions with the corresponding NBBO with millisecond timestamps.

[39]The sample period for these measures is 2010 to 2017 rather than 2010-2019.

calculate corresponding daily averages of the share of volume occurring at sub-penny prices to total daily trading volume. These measures, denoted SPVS, help isolate extreme ILM magnitudes reflecting excessively-infrequent sub-penny trading at the stock level.

We construct a set of stock characteristics for our asset pricing analysis using data from CRSP and Compustat. For stock j in month m, $RET_{j,m\ \ 1}$ and $RET^{m\ \ 12}_{j,m\ \ 2}$, respectively, capture compound returns over the preceding month and the 11 months prior; $M_{j,m\ \ 12}$ reflects market-capitalization based on the closing price 12 months earlier; $DYD_{j,m\ \ 1}$ reflects dividend yield, i.e., the ratio of total dividend distributions over the 12 months ending in month $m-2$ divided by the closing price at the end of month $m-2$. The book-to-market ratio, $BM_{j,m\ \ 1}$, is the most recently reported book value divided by market capitalization at the end of month $m-1$.[40] We obtain three-factor Fama-French betas for each stock from Beta Suite by WRDS. Our approach employs weekly data from rolling horizons that span the preceding 104 weeks, requiring a minimum of 52 weeks. For each stock month, the set of betas represent estimates from the estimation horizon ending in the last week of that month. As in Ang, Hodrick, Zhing, and Zhang (2006), we use a CAPM regression using daily observations in each month to construct monthly idiosyncratic volatility measures.

We construct measures of holding horizon using institutional ownership (13F filings data). Following Gaspar et al. (2005) and Cella et al. (2013), for each institutional investment manager, we calculate a "churn ratio" at the stock-quarter level. For a given manager in quarter q, the churn ratio for an individual stock in her portfolio is defined as the change in the value of that stock in the manager's portfolio relative to that in quarter $q-1$ that is not attributable to variation in its price, divided by the average value of the manager's holdings of that stock in quarters q and $q-1$. We aggregate manager-quarter churn ratios across all managers holding that stock, with each manager's churn ratio weighted by the fraction of institutional ownership held by that manager in the underlying stock. For each stock-quarter, we use the moving average of these weighted mean churn ratios over the preceding four quarters to measure a manager's holding horizon. We also calculate a weighted average churn ratio at the manager-quarter level using each manager's fractional holding in a stock relative to their overall holdings as weights. We define standardized holding horizons at the manager and stock levels using rank statistics of their churn ratios. Specifically, we use 1 minus churn ratio percentile statistics in a quarter to measure institutional holding horizons.

[40] We use the "linktable" from WRDS to match stocks across CRSP and Compustat, dropping stocks without links.

5 Internalized Retail Order Flow Imbalance (*Mroib*)

This section provides cross-sectional evidence of the impact of institutional liquidity demand on $Mroib$. We show that extremely positive or extremely negative $Mroib$ both signify wholesalers intermediating between retail and institutional investors when the demand for liquidity by institutional investors is unbalanced and liquidity is scarce. We then analyze $Mroib$'s return predictability, providing extensive evidence that $Mroib$'s return predictability is not due to informed retail trading but rather the unwinding of institutional price pressure.

5.1 *Mroib* and Trading Activity

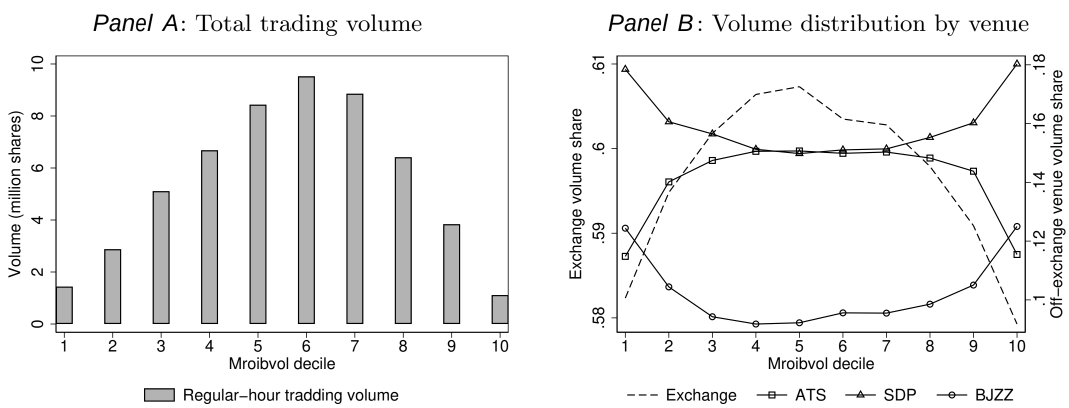
We first examine how $Mroib$ is related to overall trading volume and to the distribution of trading volume across four sources of trading activity: exchanges, ATSs, SDPs, and internalized retail order flow. This analysis provides insights into how each of these sources contributes to the overall trading activity as a function of the prevailing liquidity conditions. We obtain aggregate ATS and non-ATS off-exchange trading volumes at the stock-week level for 01/2019 through 06/2019 from FINRA.[41] Aggregate non-ATS volume is primarily comprised of internalized retail order flow and SDP trading volume (see FINRA Regulatory Notice 18-28). We decompose non-ATS weekly volume into the trading volume identified as retail by BJZZ's algorithm and a residual component. The residual volume is mostly a combination of internalized retail orders executed at (or near) the midpoint and SDP executed institutional volume. Since the midpoint internalized retail volume should be relatively higher when ATS liquidity is high, the opposite should hold for SDP volume.[42] It follows that subtracting this "BJZZ volume" from non-ATS volume yields an over-estimate of SDP volume, especially when ATS midpoint liquidity is high. We construct overall trading volume at the stock-week level from daily observations provided by WRDS Intraday Indicators.

Panel A in Figure 2 reveals that a striking ∩-shaped relationship obtains between trading volume and $Mroibvol$, indicating that a large (absolute) $Mroib$ imbalance is associated with scarce

[41] These data are available from 10/2017. To avoid the effects of the Tick Size Pilot on both ATS and non-ATS volume (Comerton-Forde, Grégoire, and Zhong (2019)), we do not use data from years 2017–2018. Our access to institutional trade data from ANcerno ends in 2014, so we cannot directly examine the relationship between $Mroib$ and institutional trading outcomes, as in Section 5.2, when ATS and non-ATS volume data are available.

[42] Most of the rest of the residual component reflects the internalized retail orders that receive either full-cent PI or zero PI. We show that wholesalers offer greater PI when $Mroib$ is more imbalanced. This suggests that when $Mroib$ is more imbalanced, full-cent PI is more likely and zero cent PI is less likely.

Figure 2. Retail Imbalances versus Trading Volume and Volume Distribution Across Venues. This figure plots total trading volume during regular hours and the cross-venue distribution of trading volume against imbalances in internalized retail order flow ($Mroibvol$). Each *calendar* week, stocks are sorted into deciles according to their respective internalized retail order flow imbalance. Average trading volume as well as average shares of the volume executed on exchanges, on ATSs, on SDPs, and via internalization calculated within each decile each week. Time-series averages of these weekly averages for each decile are plotted from 01/2019 through 06/2019. Weekly ATS and non ATS volumes are obtained from FINRA. The non-ATS volume is decomposed into BJZZ volume, calculated using TAQ data, and SDP volume which is estimated as the difference between non-ATS and BJZZ (internalized retail) volume.



liquidity. Total trading volume is over 80% lower in the extreme (unbalanced) $Mroibvol$ deciles than in the middle deciles that feature near-zero (balanced) $Mroibvol$ levels. The relative absence of trading volume when $Mroibvol$ is unbalanced signifies a decrease in overall liquidity. As a result, the probability that an institutional investor can find another institutional counterparty with whom to trade falls, leaving HFMMs as the primary source for liquidity. Consistent with this, Panel B in Figure 2 presents a break-down of trading volume according to the source of trading activity. The shares of trading volume executed on exchanges and ATS are both over 2bps lower when $Mroibvol$ is at its two most extreme (unbalanced) deciles than when it is close to balanced. The absence of trade on exchanges and ATSs when $Mroibvol$ is most unbalanced is offset by increases of over 2bps in the shares of trading volume executed via SDPs and the internalization of retail order flow. Moreover, (1) BJZZ's algorithm excludes all internalized retail trades executed at the midpoint and (2) midpoint ATS liquidity is notably more abundant when $Mroibvol$ is closer to zero, so our estimates of SDP volume are likely especially biased upwards for intermediate levels of $Mroibvol$. This suggests that the true ∪-shaped pattern of SDP volume share in $Mroibvol$ is *even stronger* than that reported in Figure 2. Importantly, both sources of non-ATS trading activity almost exclusively reflect wholesaler trades.

These findings indicate that when liquidity is scarce, institutional investors access liquidity provided by wholesalers, encouraging wholesalers to internalize more retail orders. These interactions between institutional investors and wholesalers would lead to imbalances in wholesaler inventory absent their ability to internalize retail orders. To avoid inventory imbalances, wholesalers internalize retail orders, resulting in unbalanced $Mroib$ on the opposite side of the imbalance in institutional order flow. We next provide evidence that $Mroib$ imbalances are in response to wholesalers experiencing a high demand for liquidity from institutions by relating $Mroib$ to institutional order flow imbalances, institutional trading costs and price pressure, and internalization costs.

5.2 *Mroib*, Institutional Trading, and Liquidity

Table 2 summarizes the relationships between $Mroibvol$ and various contemporaneous outcomes across deciles of $Mroibvol$. Close-to-close returns rise monotonically from −2bps in the bottom $Mroibvol$ decile to 30bps in the top decile. However, this pattern is ***not*** due to price pressure from retail order flow. To show this, we decompose daily returns into intraday and overnight components. Doing so reveals that intraday returns ***fall*** monotonically from 10bps in the bottom $Mroibvol$ decile to −14bps in the top decile.[43] 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 also at odds with informed retail trading, as it would imply a negative price impact of "informed" orders.

In sharp contrast to intraday returns, overnight returns are positively related to $Mroibvol$. The signs of intraday and overnight returns differ for eight of the ten $Mroibvol$ deciles, in particular for the more extreme, unbalanced $Mroibvol$ deciles. We next investigate different trading outcomes to understand these patterns.

Table 2 shows that, like intraday returns, trade imbalances from both long-only institutional investors and short sellers are negatively related to $Mroibvol$. Average institutional flow falls from 27.7% in the bottom decile to 17.2% in the top decile. Short selling activity also occurs on the opposite side of internalized retail order flow: increased short interest is associated with larger positive internalized retail order flow imbalances. Importantly, directional (as opposed to

[43]Recall that BJZZ's algorithm only uses ***regular-hour*** off-exchange transactions.

liquidity-providing) short sellers, whose aggregate positions are reflected in short interest data, are known to be informed (Desai, Ramesh, Thiagarajan, and Balachandran (2002); Engelberg, Reed, and Ringgenberg (2012); Boehmer and Wu (2013)). The negative association between such short selling activity and *Mroibvol* comprises further evidence against the informativeness of retail orders executed at sub-pennies, pointing instead to institutional price pressure driving intraday price movements.

We next show that the negative association between *Mroib* and institutional trade imbalance does not reflect incorrectly signed institutional trades picked up by BJZZ's algorithm (Battalio et al. (2022)). TAQ data contain ANcerno-reported institutional trades, including those with sub-penny price increments that the algorithm picks up. Battalio et al. (2022) suggest the algorithm incorrectly signs 80% of those trades. To preclude the possibility that *Mroib* imbalances simply reflect mistakenly-included institutional trade imbalances on the opposite side, we apply the algorithm to execution prices of ANcerno trades to construct BJZZ-implied institutional trade imbalances in ANcerno data. If our results reflect mis-classified institutional trades that enter *Mroib*, then BJZZ-implied institutional trade imbalances must be positively related to *Mroib*. Table 2 shows this imbalance is negative on average, while the analogue for actual institutional imbalance is positive, consistent with Battalio et al. (2022)'s finding that the algorithm signs most institutional trades incorrectly. More importantly BJZZ-implied institutional trade imbalances exhibit no discernible pattern in *Mroib*, establishing that *Mroib*'s negative correlation with ANcerno institutional trade imbalances is a robust feature. Section C.3 provides additional robustness analyses.

We next show that extreme values of *Mroibvol* are associated with less liquid markets. To do this, we construct a stock-specific measure of abnormal realized off-exchange institutional liquidity. For each stock-day, we divide the volume of large off-exchange mid-point executions[44] by the average of this quantity over the sample period for that stock. Higher values of this measure indicate greater midpoint liquidity. The bottom row in Table 2 shows abnormally low levels of block trades receive off-exchange midpoint execution when *Mroibvol* is more extreme. That is, large internalized retail order flow imbalances are more common when off-exchange liquidity is abnormally scarce. Together with imbalances in institutional liquidity demand, this finding indicates that institutional investors

[44] TAQ data transactions with trade venue flag 'D' that are at least 1,000 shares, worth at least $50k, and executed at a price within 0.1¢ of the corresponding quote midpoint.

have trouble locating counter-parties with whom to trade at the midpoint.

Liquidity is also scarce on exchanges when $Mroibvol$ is more extreme. Table 2 shows that spreads are widest and depth at the NBBO is lowest for the extreme deciles of $Mroibvol$. Specifically, median price impacts per $1m transaction for the average stock are 19bps and 22bps for the lowest and highest $Mroibvol$ deciles, respectively. In contrast, balanced $Mroibvol$ is associated with only 3bps of such costs. Moreover, strikingly, average dollar and relative quoted spreads in the lowest and highest $Mroibvol$ deciles are roughly ***double*** those when $Mroibvol$ is relatively balanced.

The lack of mid-point liquidity on ATSs means that institutional investors with pressing liquidity needs must turn to venues where they are more likely to trade with HFMMs as intermediaries. Using a wholesaler's SDP allows an institution to trade against a single HFMM—the wholesaler—to conceal its trades. Even when institutional investors opt for exchanges, the exclusive access of wholesalers to segmented retail flow provides them competitive advantages over other HFMMs, making wholesalers more willing to fill institutional orders and thereby creating imbalances in $Mroibvol$.

Importantly, most executions on SDPs and exchanges take place at or near the NBBO because liquidity on these venues is quoted at round-penny increments. In turn, since spreads are wider due to the lack of liquidity, filling institutional demands is unusually lucrative. This suggests that wholesalers may be willing to pay more than normal to internalize retail trade to fill those unusually lucrative institutional orders. Consistent with this argument, the ratio of internalized retail trades executed at prices that are superior to the NBBO by 1¢ or more rises by 33% as $Mroibvol$ diverges from intermediate levels to the two extremes (also see Section C.3). That is, wholesalers incur more costly retail internalization on one side of the market when institutional liquidity demand on the opposite side is abnormally high.

Reverse causality, i.e., wholesalers filling more institutional orders to offset imbalances in internalized retail order flow, cannot explain our findings. For this reverse explanation to hold, the liquidity available to institutions has to ***improve*** when $Mroib$ is extreme, since wholesalers would need to attract institutional flow by offering abnormally high ATS midpoint liquidity or by improving quoted prices and depth on exchanges. Therefore, under the alternative explanation, an abnormal abundance of retail trading interest on one side of the market would predict that wholesalers internalize retail orders with minimal PI. However, Table 2 reports the exact opposite pattern—high *Mroib* is associated with both higher institutional trading costs and higher internalization costs.[45]

These findings also relate our study to the literature on liquidity timing.[46] Investors with a pressing need to quickly establish or unwind a position may have limited ability to time their trades. This leads Anand, Irvine, Puckett, and Venkataraman (2013) to classify institutional investors as "liquidity demanding" and "liquidity supplying" with the former incurring higher trading costs. Institutional investors accessing liquidity via the internalization of retail order flow in our study are likely "liquidity demanding" institutions. Battalio, Hatch, and Salgam (2022) document higher execution shortfalls for institutional "parent" orders that seek liquidity on SDPs that are typically operated by wholesalers who obtain liquidity by internalizing retail order flow.[47] Our analysis extends these insights by showing that institutions differentially access the liquidity provided by internalized retail order flow when mid-point off-exchange liquidity is scarce. This indicates how wholesalers gain from their access to segmented retail order flow, which they can use for inventory management purposes to offset high institutional demand in less liquid markets.

Our collective findings allow us to attribute the negative association between intraday returns and *Mroib* to institutional price pressure that occurs in the opposite direction of *Mroib* imbalances. As such, we reconcile the opposing patterns in overnight returns as price reversals follow institutional price pressure from the preceding intraday period.

Table 2 also reveals that intraday and overnight returns in the extreme *Mroibvol* deciles reflect more than just the immediate unwinding of price pressure. Most obviously, price pressure from institutional buying is 0.098% in *Mroibvol*'s bottom decile, but the contemporaneous overnight reversal of -0.116% is even larger—a finding that deviates from the stylized fact that unconditional intraday and overnight average returns are negative and positive, respectively (Cliff, Cooper, and Gulen (2008); Berkman, Koch, Tuttle, and Zhang (2012)). To study these phenomena more precisely, we

[45]This is not to say that wholesalers do not use institutional liquidity to provide liquidity to retail investors. Section 3.2 discusses why this type of intermediation, which most likely happens when liquidity is abundant, is not picked up by the BJZZ algorithm, implying that it may not drive our findings.

[46]Research on endogenous liquidity consumption includes Campbell, Ramadorai, and Vuolteenaho (2005), O'Hara (2015), Collin-Dufresne and Fos (2015), Kacperczyk and Pagnotta (2019), and Barardehi and Bernhardt (2021).

[47]This evidence suggests that institutions resort to off-exchange liquidity on SDPs to conceal their intended position sizes by exploiting the delayed reporting of off-exchange trade executions to the Security Information Processor (Ernst, Skobin, and Spatt (2021)). While there may be limited "information leakage" associated with seeking liquidity on SDPs (see BestEx Research), institutional traders have only worse alternatives when mid-point liquidity is limited on ATSs, as trading on exchanges is far more transparent by design.

construct a 5-day overnight return that omits the first close-to-open return and adds the overnight return on the sixth day. This adjustment aligns the timing of intraday price pressure and overnight reversals. 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 vs. 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 vs. decile 5 are $-0.138 - (-0.063) = -0.075\%$ and $0.456 - 0.257 = 0.199\%$. Thus, weekly overnight returns revert by far more than is needed to offset intraday returns, especially when $Mroibvol$ is extremely negative. Internet Appendix C.1 reconciles 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 retail imbalance (with an inverse relation) over longer horizons. These findings are consistent with Campbell, Ramadorai, and Schwartz (2009).

5.3 Return Predictability of *Mroib*

We next formally examine the return predictability of $Mroib$. Our findings are inconsistent with $Mroib$ capturing informed retail order flow. In contrast, near-term future weekly returns conditional on $Mroib$ are consistent with price reversals following liquidity consumption by institutional investors. We then analyze $Mroibvol$'s long-term return predictability, providing evidence consistent with extreme $Mroibvol$ stocks being less liquid, and hence requiring greater liquidity premia.

Panel B in Table 1 provides summary statistics that closely match those in Table I of BJZZ, confirming that our construction of $Mroibtrd$ and $Mroibvol$ parallels theirs.[48] We estimate the predictability of weekly returns conditional on $Mroibvol$ by estimating:

$$R_{j,w+i} = c_w^0 + c_w^1 Mroibvol_{j,w\ \ 1} + c_w^{2\,>} \text{controls}_{j,w\ \ 1} + u_{j,w+i}, \tag{1}$$

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 $w+i$. $Mroibvol_{j,w\ \ 1}$ denotes the imbalance in the trading volume of internalized retail order flow receiving sub-penny price im-

[48] Slight differences arise since our sample period spans 2010–2014, while BJZZ's spans 2010–2015.

provement in the previous week. We estimate equation (1) to examine $Mroibvol_{j,w-1}$'s return predictability separately for future returns measured over different segments of a day. 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 3 presents estimation results for week $i = 0$. The second column corresponds to the second column of Table III in BJZZ. Our point estimate ($\hat{c}^1_w$) of 0.087% is nearly identical to their estimate of 0.09%. Coefficients on control variables are also similar to BJZZ's estimates. However, we document a striking difference between $Mroibvol_{w-1}$'s loadings when overnight and intraday returns serve as dependent variables. Specifically, $Mroibvol_{w-1}$ predicts next week's overnight return with the "correct" positive sign, whereas it predicts next week's intraday return with a ***negative*** coefficient.

These findings are consistent with temporally-persistent institutional price pressures over successive trading sessions and the partial reversals that occur overnight in between daily trading sessions, i.e., overnight. Table 2 established that $Mroibvol$ imbalances were inversely related to both contemporaneous institutional trade imbalance and price pressure, as reflected by intraday returns. Hence the negative predictive power of $Mroibvol$ for future intraday returns is consistent the persistent institutional price pressure across successive trading days. Internet Appendix C.1 provides direct evidence of this using ANcerno data, confirming existing evidence in the literature (e.g., Campbell et al. (2009) and Akepanidtaworn et al. (2020)). The positive association between current $Mroibvol$ and future overnight returns, implies a negative association between current institutional price pressure and future overnight returns. This is consistent with reversals that follow institutional price pressure (Hendershott and Seasholes (2007)). In sum, these findings allow us to attribute $Mroib$'s short-term return predictability to price dynamics driven by institutional liquidity consumption, rather that informed retail trading.

Our analysis of the the link between current $Mroib$ and longer-term future returns reinforces our interpretation that attributes $Mroib$'s short-term return predictability to institutional consumption of retail-sourced liquidity. Kaniel et al. (2008) document stronger such return predictability for less liquid stocks. Moreover, less liquid stocks are known to command liquidity premia in the form of greater expected returns. Consistent with these insights, Table 4 shows that stocks with more extreme $Mroibvol$ in week $w-1$ are associated with higher returns in the future. Even though week w returns are monotinically positively related to $Mroibvol_{w-1}$, the return difference between the bottom and top deciles of $Mroibvol_{w-1}$ falls rapidly over time, nearly disappearing by week $w+12$. Instead, a striking ∪-shaped pattern in close-to-close returns across $Mroibvol_{w-1}$ deciles emerges at 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 over double that in decile 6 (0.07%). This ∪-shaped pattern holds in all future weeks—future returns are inversely related to negative $Mroibvol_{w-1}$ and positively related to positive $Mroibvol_{w-1}$.[49]

Hence, we relate the ∪-shaped pattern in longer future returns to liquidity premia. A liquidity premium associated with expected trading costs as a stock characteristic 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 suggests that stocks with more extreme $Mroibvol_{w-1}$ are less liquid. Hence, these stocks should command higher ***permanent*** expected return (higher cross-sectional returns) as compensation that institutional investors require to hold less liquid assets (where entering and exiting positions is costlier), as Amihud and Mendelson (1986) first argued. To make clear that liquidity premia drive the long-term ∪-shaped pattern in returns, we focus on lower $Mroibvol_{w-1}$ deciles, where Internet Appendix C.2 provides evidence that the positive relationship between near-term returns and $Mroibvol_{w-1}$ in lower $Mroibvol$ deciles likely reflects extended price reversals following price pressure from previously-accumulated long institutional positions.[50] Clearly, this positive relationship is temporary and is eventually dominated by the liquidity premia that underlie the ∪-shaped pattern in longer-term future returns.[51]

[49] See Interned Appendix B for formal estimates of these distinct relationships.

[50] In high $Mroibvol_{w-1}$ deciles, disentangling short-term and long-term effects in close-to-close returns is more difficult since their impacts on returns have the same sign.

[51] Untabulated findings indicate that decomposing close-to-close returns into intraday and overnight components can identify when liquidity premia are realized during the day and contribute to the asset pricing literature documenting time-of-day return disparities that are important to asset pricing anomalies. Our decomposition of close-to-close returns reveals that the [-shaped pattern in future close-to-close returns as $Mroibvol_{w-1}$ rises from low deciles to high are due to intraday returns. In fact, overnight returns follow a \-shaped pattern in $Mroibvol_{w-1}$. Thus, we provide an economic mechanism that reconciles why intraday and overnight return anomalies differ—the [-shaped pattern in intraday returns reflect liquidity premia, and liquidity premia are realized only when there is trade. These findings are complementary to the conclusions of Bogousslavsky (2021), and, contrary to Lou, Polk, and Skouras (2019), provide a rational explanation for the negative correlation between successive intraday and overnight returns.

Investigating $Mroibvol$'s dynamics provides further evidence that $Mroib$ does not reflect informed directional retail trading. Instead, the likelihood and intensity of extreme $Mroib$ occurrences reflect a stock characteristic, indicative of the extent to which institutional investors consume retail-sourced liquidity through wholesalers when liquidity is scarce. This analysis is motivated by BJZZ's finding that $Mroib$ persists over time—their regression of weekly $Mroibvol$ on lagged $Mroibvol$ yields a coefficient of 0.22 (BJZZ, p. 2265). BJZZ use a linear model to estimate the dynamics of $Mroibvol$, but their assumed $AR(1)$ process fails to capture the heterogeneity in the dynamics of retail imbalances. To show this mis-specification we adopt a non-parametric approach to estimate the distribution of $Mroibvol$ in week $w + i$ conditional on week $w - 1$.

Panel A in Figure 3 reveals that stock-weeks with extreme negative and extreme positive $Mroibvol$ quantities in week $w - 1$ also tend to have extreme imbalances in week $w + 12$. This pattern also holds more generally for different weeks $w + i$. Crucially, stocks with extremely negative $Mroibvol$ in week $w - 1$ are likely to have extremely negative **or** positive $Mroibvol$ in week $w+12$. Put differently, extreme retail selling "pressure" predicts ***both*** extreme retail selling ***and*** extreme retail buying "pressure" 13 weeks forward. So, too, stocks with extremely positive $Mroibvol$ in week $w - 1$ are likely to have extremely positive **or** negative $Mroibvol$ in week $w + 12$.[52] To show these findings are inconsistent with a linear formulation of $Mroib$'s persistence, we use simulated data from an $AR(1)$ process as a benchmark—Panel B in Figure 3 shows that very different non-parametric estimates obtain from those in Panel A.

Motivated by these collective findings, we next show that $Mroib$ can be used to construct stock liquidity measures that better capture institutional trading costs than existing liquidity measures. Importantly, reflective of their ability to capture liquidity and institutional trading considerations, these measures are strongly priced in the cross-section of stocks, even in recent years.

6 *ILM* Characteristics

This section highlights the important characteristics of our liquidity measures and contrasts them with existing liquidity measures.

[52]Controlling for stock characteristics leaves the qualitative patterns unaffected.

6.1 ILMs, Existing Liquidity Measures, and Institutional Price Impacts

To begin, we investigate how institutional liquidity measures (ILMs) are related to key stock characteristics. We then examine how ILMs compare with existing liquidity measures in exhibiting correlations with future post-trade institutional price impacts.

We construct weekly $ILMT$ and $ILMV$ for each stock by averaging $|Mroibtrd|$ and $|Mroibvol|$, respectively, over 5-day rolling windows to obtain weekly observations. We then match these weekly observations with stock characteristics constructed at the end of the preceding calendar month (see Section 4). After excluding stocks whose previous month's closing price are below \$2 (results are robust to excluding stocks with closing prices below \$5), we sort each weekly cross-section into deciles of $ILM \in \{ILMT, ILMV\}$. We then calculate stock characteristic averages by ILM decile and date before computing the time-series averages of these averages across dates by ILM deciles. Table 5 demonstrates that high-ILM stocks, i.e., less liquid stocks according to ILMs, tend to be small growth stocks with relatively poor recent returns and low CAPM betas.

We next show that for less liquid stocks, according to various measures of liquidity, including ILMs, lower liquidity in month $m-2$ is associated with higher realized post-trade institutional price impacts in month m. However, for more liquid stocks, this monotone relationship obtains only based on a handful of liquidity measures, including ILMs. We sort each monthly cross-section in month m into deciles of a given liquidity measure, constructed in $m-2$, with decile 1 (10) containing the most (least) liquid stocks. We then calculate a time-series average of the institutional price impacts of the median stock in each liquidity decile.[53] Panel A in Figure 4 shows that for more liquid stocks (those in liquidity deciles 1–5), future institutional price impacts only rise monotonically with "improved" liquidity as measured by Kyle's lambda, Amihud measures, trade-time liquidity measures, and ILMs—institutional price impacts display no systematic patterns in other liquidity measures. Panel B in Figure 4 shows that for less liquid stocks (liquidity deciles 6–10), worsened liquidity according to most standard liquidity measures (movements from decile 6 to 10) is associated with increased future institutional price impacts. The bottom line is that

[53] Using order statistics rather than simple correlation coefficients lets us identify potential non-linearities and non-monotonicities. Order statistics ensure that the tails of the distributions do not exert undue influence on our estimates and confound interpretations. These considerations are especially relevant for institutional price impacts obtained from ANcerno data that covers less than 7% of CRSP-reported volume for the average stock (3.5% of volume for the median stock). Using stock portfolios rather than individual stocks as test assets sharply reduces measurement error (and noise) that would otherwise impact stock-level estimates.

most liquidity measures can proxy institutional trading costs for less liquid stocks, while a few, including ILMs, also do so for more liquid stocks.[54] The decline in the ability of traditional market microstructure measures to capture these trading costs in the past two decades reflects numerous significant changes to the equity trading environment.

6.2 Persistence of Institutional Liquidity Measures

We next investigate the temporal persistence in $ILMT$ and $ILMV$ at the stock level to determine whether they comprise a stock characteristic. The institutional liquidity measures $ILMT$ and $ILMV$ used in our asset pricing tests average daily $|Mroibtrd|$ and $|Mroibvol|$ observations over one month.[55] To examine the persistence in these measures, we regress $ILMT$ and $ILMV$ on their lags from the six preceding months. These Fama-MacBeth regressions correct for auto-correlated error terms using Newey-West standard errors based on 6 lags, as do the rest of our regression analyses. We exclude stocks priced below $2, before estimating equally-weighted and value-weighted regressions (with weights computed using a stock's market capitalization in the previous month).

Table 6 documents strong persistence in ILMs: past ILM levels strongly predict future levels. That is, stocks with high ILMs in one month tend to have high ILMs in future months. This holds even when we weight observations by market capitalization, indicating that persistence is not attributable to the illiquidity of small stocks. This persistence indicates that our liquidity measures represent a stock characteristic that is long-lasting enough to impact institutional investors with extended holding horizons and hence justify the existence of a liquidity premium in stock returns.

7 Liquidity and Institutional Holding Horizon

Our next analyses are motivated by the testable hypotheses in Amihud and Mendelson (1986) that (a) at the investor level, investors with longer holding horizons are predicted to hold less liquid stocks, and (b) at the stock level, less liquid stocks are predicted to be held by institutional investors with longer holding horizons.

[54] Internet Appendix D shows that excluding stocks for which sub-penny volume comprises a low share of total volume leavs our qualitative findings unaffected. As such, the prevalence of sub-penny trade execution does underlie the variation in ILM and its ability to proxy institutional trading costs.

[55] Constructions of $Mroibtrd$ and $Mroibvol$ include all transactions. However, our findings are robust to focusing only on round-lot transactions. Odd-lots are only reported by TAQ after 2013.

7.1 Investor-Level Analysis

To calculate the liquidity of an institutional investor's Equity Under Management (EUM), we first calculate the weighted average of each liquidity measure across all stocks held by individual fund managers. We weight observations by the fraction of an investor's total dollar-denominated portfolio value in a stock. Other EUM characteristics, including volatility, market capitalization, and institutional ownership, are computed using a similar methodology in the previous quarter. We follow Gaspar et al. (2005) and Cella et al. (2013) to construct investor-level churn ratios in the previous quarter. The churn ratio captures the frequency at which a fund enters and exits positions, and hence is inversely related to its holding horizon. The churn ratio is calculated at the stock-quarter level, and then weighted by holdings at the manager-quarter level (see Section 4).

We estimate semi-parametric relations at the investor level between EUM liquidity and holding horizons, defined as 1 minus churn ratio percentiles, after controlling for other EUM characteristics. Each quarter, we obtain regression residuals from fitting EUM illiquidity as a function of volatility, market capitalization, and institutional ownership. We then sort each quarterly cross-section into percentile statistics of residual EUM liquidity and holding horizon, independently. Finally, for each liquidity measure, we fit a local polynomial of the residual EUM liquidity percentiles as a function of holding horizon percentile statistics.

Figure 5 illustrates that EUM illiquidity measured by existing liquidity measures, including quoted and relative spreads, quoted depth at best prices, Kyle's lambda, Amihud measure, and trade-time measures display a strong ∩-shaped pattern with respect to holding horizon. In contrast, ILM-based EUM illiquidity displays a more monotonically increasing pattern with holding horizon despite flattening for the longest holding horizons.

7.2 Stock-Level Analysis

Institutional investors hold about 70% of U.S. equity, so the relation between holding horizon and liquidity should extend to the individual stock level. That is, less liquid stocks should be held by institutional investors with longer holding horizons after controlling for other stock characteristics.

To test whether different illiquidity measures yield estimates consistent with this prediction, we follow Vovchak (2014). For each stock in each quarter, we first calculate the weighted-average churn ratio across all investors holding the stock. The weight assigned to an investor's churn ratio is the fraction held by the investor relative to all institutional investment in the stock. We then calculate moving averages over the four preceding quarters for these churn ratios to obtain a stock-quarter measure of institutional turnover. Finally, we regress each liquidity measure at the end of a quarter on the institutional holding horizon percentile (1 minus churn ratio percentile), controlling for volatility, market capitalization, and institutional ownership from the previous quarter. We estimate Fama-MacBeth regressions with Newey-West standard errors based on 6 lags.

Panel A in Table 7 reports that for most liquidity measures, the institutional holding horizon percentile has a coefficient with the expected sign. However, differences show up in R^2 magnitudes. The R^2s associated with $ILMT$ and $ILMV$ are 0.61 and 0.63, respectively, indicating that holding horizon explains a large amount of the variation in investor-level portfolio liquidity based on ILMs. In contrast, the R^2s associated with existing liquidity measures are notably smaller—the next highest R^2 is 0.44 and most are far lower, with some only marginally different from zero.

To further highlight that ILMs better capture the concerns of institutional investors, we orthogonalize the ILM measures with respect to the other liquidity measures. To do this we use Fama-MacBeth regressions, first regressing $ILMT$ and $ILMV$ on existing liquidity measure X, denoting the respective residuals by Z_{ILMT} and Z_{ILMV}. We then examine the ability of holding horizon to explain variation in these residuals. Next, we reverse the specification and regress each existing liquidity measure, separately, on $ILMT$ and $ILMV$, denoting these respective residuals as Y_{ILMT} and Y_{ILMV}. Finally, we examine the ability of holding horizon to explain variation in these residuals.

The top four rows in Panel B of Table 7 report that, relative to every existing liquidity measure, $ILMT$ and $ILMV$ have incremental liquidity-related implications for institutional investors. In contrast, the bottom four rows in Panel B of Table 7 report that the coefficients for holding horizon have their expected sign ***only*** for dollar quoted/effective spread, relative effective spread, and quoted depth. Moreover, the R^2s in these specifications indicate that for these four liquidity measures, the variation in the Y_{ILMT} and Y_{ILMV} residuals explained by holding horizon (and stock characteristics) is less than one-twentieth of the variation in the Z_{ILMT} and Z_{ILMV} residuals explained by holding horizon (and stock characteristics). That is, institutional holding horizons better explain ILM residuals than they explain residuals of existing liquidity measures. In sum,

ILMs have incremental implications for investors relative to existing liquidity measures, but the converse is not true.

Overall, ILMs are the only liquidity measures whose relations with holding horizons at ***both*** at the investor and stock levels match the prediction of Amihud and Mendelson (1986).

8 Liquidity Premia

We next contrast the extent to which ILMs and existing liquidity measures predict the cross-section of expected stock returns over the recent 2010–2019 period. We show that, unlike existing measures, ILMs robustly predict the cross-section of stock returns, with economically-large liquidity premia. Long-short portfolios reinforce these findings.

8.1 Regression Analysis

To examine the abilities of ILMs and the other liquidity measures described in Section 4 to predict future monthly returns, we first estimate the following Fama-MacBeth regression

$$RET_{j,m} = \gamma_m^0 + \gamma_m^{LIQ}\left(LIQ_{j,m\ \ 2}\right) + \Gamma^{>}\mathrm{CONT}_{j,m\ \ 1} + u_{j,m}, \tag{2}$$

with Newey-West-corrected standard errors using 6 lags where the dependent variable $RET_{j,m}$ is stock j's return in month m. $LIQ_{j,m\ \ 2}$ denotes one of the liquidity measures obtained at the end of month $m-1$ for stock j. $\mathrm{CONT}_{j,m\ \ 1}$ denotes a vector of control variables containing betas from the three-factor Fama-French model, book-to-market ratio, market capitalization, dividend yield, idiosyncratic volatility, and the previous month's return as well as the return from the prior 11 months. Green, Hand, and Zhang (2017) examine the return predictability of a comprehensive list of 94 stock characteristics and find their predictive power to fall sharply after 2003. It is therefore unlikely that controlling for more stock characteristics would qualitatively change our results, as our sample starts in 2010. Consistent with this, our findings are robust to using panel regressions that control for unobserved heterogeneities using stock and date fixed effects.

Recall that we impose a $2 minimum price requirement to preclude the possibility that findings are driven by penny stocks. To further ensure that results are not spurious, we add a one-month lag between the construction of each liquidity measure and monthly returns.

Panel A in Table 8 reports that unlike other liquidity measures, both the institutional price impact measure (InPrIm) and the ILMs explain the cross-section of expected returns.[56] Specifically, InPrIM, $ILMT$, and $ILMV$ coefficients are 0.029, 1.20 and 1.27, respectively. Multiplying these coefficients by their respective standard deviations (of 0.109, 0.19, and 0.21) yields monthly liquidity premia of 31.6 bps, 22.8bps, and 26.7bps, respectively. Thus, one standard deviation increases in ILMs are associated with 22.8–26.7bps increases in expected monthly returns, with associated annualized increases of 2.74–3.20%. The analogous annual liquidity premium attributable to realized institutional price impacts is 3.8%. These results comprise strong evidence that investors demand economically-significant liquidity premia.

Online Appendix E documents robustness to \$1 and \$5 minimum share price requirements. Consistent with Barardehi et al. (2019) and Barardehi et al. (2021), quoted depth, $ILLIQ\_OC$, BBD, and $WBBD$ only explain the cross-section of stock returns when a \$1 minimum price filter is imposed, indicating that these measures are only priced in very illiquid stocks. Furthermore, consistent with low institutional trading in penny stocks, InPrIM is not priced with a \$1 minimum price filter, but it is priced with a \$5 minimum price filter.[57]

Panel B in Table 8 presents the significant incremental information content of $ILMT$ and $ILMV$ vis à vis each existing liquidity measures. Each ILM measure is first regressed on an alternative liquidity (price impact) measure using Fama-MacBeth regressions. The residual from such regressions are then used, one at a time, as $LIQ_{j,m\ \ 2}$ in equation (2). The $ILMT$ and $ILMV$ residuals, with the exception of those orthogonalized to realized institutional price impacts (InPrIm), explain the cross-section of expected returns. Untabulated results verify that the residuals of existing liquidity measures with respect to our measures fail to explain the cross-section of returns.

These results suggest that the literature's conclusion that liquidity premia have disappeared post-decimalization (e.g., Asparouhova et al. (2010); Ben-Rephael et al. (2015)) solely reflect the use of liquidity measures that no longer capture the institutional features of modern equity markets. In particular, tight spreads (often binding at a penny tick) combined with limited depth at the

[56] In unreported results, we compare ILMs to relative (percentage) quoted, effective, and realized spreads, and find ILMs outperform them in all the three dimensions examined.

[57] Online Appendix H establishes the robustness of these results to the construction of our liquidity measures over 3-month rolling windows. This alternative construction results in monthly liquidity premia of 25–31bps, with associated annual liquidity premia of 3.07–3.74%.

NBBO in a fragmented marketplace cannot capture the complicated trade execution strategies institutions adopted in response. In contrast, ILMs are motivated by the actual trading costs of institutional investors and the propensity with which they need to rely on retail-sourced liquidity through wholesalers. As a result, the use of ILMs reveals that institutions account for cross-stock heterogeneity in trading costs when pricing stocks.[58] That $ILMT$ and $ILMV$ do not outperform InPrIm in these residual analyses suggests that only liquidity measures based on proprietary data with limited availability, such as ANcerno data, can possibly compete with ILMs in capturing institutional trading costs.

Table 9 summarizes the results of several robustness tests that confirm the liquidity premia captured by our liquidity measures. First, estimating equation (2) using panel regressions that include date and stock fixed effects and double-cluster standard errors by date and stock leaves our qualitative findings largely unaffected. Second, correcting for market microstructure noise, as in Asparouhova et al. (2010), does not affect the economic significance of the liquidity premia. Third, excluding the smallest 20% of stocks (at the end of the previous month) leaves our qualitative findings unaffected, indicating that the liquidity premia are not a small-stock phenomena. Intuitively, this reflects the relevance of ILMs to institutional investors who tend to hold larger stocks. Fourth, excluding stocks in the bottom 10% of SPVS in each cross-section results in more efficient estimates of liquidity premia. This reflects that ILMs of stocks with low sub-penny volume tend to have higher measurement error. Fifth, weighting observations by stock-level market-capitalizations improves statistical significance of liquidity premia estimates for $ILMT$, but reduces it for $ILMV$. Sixth, excluding the top and bottom 10% of each ILM cross-section increases the precision of liquidity premia estimates and leaves our qualitative findings unaffected. This indicates that estimates are not driven by the tails of the ILM distributions. Indeed, down-weighting (censoring) extreme ILM observations strengthens our results. All robustness tests are implemented separately after imposing minimum share price requirements of \$1, \$2, and \$5. Seventh, we document robustness of liquidity premia across listing exchanges. This final robustness test is motivated by Asparouhova et al. (2010) and Ben-Rephael et al. (2015), who detect liquidity premia post decimalization for NASDAQ-listed firms, but not NYSE-listed firms. Online Appendix H confirms the robustness of

[58] Kyle's λ fails to explain the cross-section of expected returns. This suggests that the conclusions of Huh (2014) that Kyle's λ explained the cross-section of returns in the 1983–2009 period do not extend past 2010.

the liquidity premia when liquidity measures are constructed over 3-month rolling windows.

Overall, our empirical results provide compelling evidence that ILMs predict expected stock returns and are associated with economically significant liquidity premia.

8.2 Portfolio Sorts

This section reports that long-short portfolios based on ILM generate abnormal (risk-adjusted) monthly returns. For each monthly cross-section, we form 10 liquidity portfolios using $ILMT$ and separately using $ILMV$. These portfolios are first formed by sorting the cross-section of stocks into deciles based on the entire CRSP common-share universe before calculating equally-weighted portfolio returns. In additional robustness tests, we form portfolios breakpoints using ILMs of NYSE-listed stocks after removing stocks whose market capitalization is in the bottom 20% before calculating value-weighted portfolio returns.[59] Portfolio returns are calculated as the average return of the stocks assigned to the respective portfolio net of the contemporaneous 1-month Treasury-bill rate. The monthly long-short portfolio return equals the return difference between the least liquid and the most liquid portfolios. Finally, we regress the time-series of individual portfolio returns as well as the time-series of the long-short returns on the Fama-French three factors. The intercept of each time-series regression is the relevant risk-adjusted return (spread), whose significance is assessed using Newey-West standard errors with 6 lags. We apply three different minimum share price filters that remove stocks whose month-end closing price in the prior month is below $p_{min} \in \{\$1, \$2, \$5\}$.

Table 10 reports significant risk-adjusted return spreads between the least liquid portfolio and the most liquid portfolio according to both $ILMT$ and $ILMV$. The portfolio risk-adjusted returns display roughly monotonic patterns, increasing from the most liquid portfolio to the least liquid portfolio. The corresponding return spreads are economically significant, ranging between 0.93% and 1.20% per month in our main sample (Panel B in Table 10) and between 0.41% and 1.27% per month across all specifications. Online Appendix H establishes the robustness of findings to constructing ILMs over 3-month rolling windows, uncovering three-factor return spreads that range from 0.34% to 1.18% per month. Overall, our estimates imply that annualized portfolio return spreads based on ILM range between 4.08–15.24%, with the larger estimates attributable

[59] Conclusions are robust to alternative combinations of break-points, weights, and small-firm filters.

to samples involving involve small, low-priced stocks.

An investigation of ANcerno data suggests that our liquidity premium estimates are plausible manifestations of expected implicit trading costs. Figure 5 suggests a 20bp difference in expected institutional price impacts between stocks in the top and bottom ILMs deciles for a \$2 price filter. Our institutional price impacts estimates (InPrIm) are re-scaled to reflect costs per \$100k of institutional trade size—hence, the 20bp difference can be re-scaled to reflect the variation associated with alternative benchmark trade sizes. To match the 40-120pbs liquidity premia estimates in Table 10, true dollar values for monthly institutional trade volumes in a typical stock should be about \$200-600k , scaling up the benchmark trade size used in our estimates by factors of 2–6. ANcerno data suggest that these benchmarks are reasonable. The median and average dollar value of institutional trades per month in 2010 are about \$110k and \$1,200k, respectively, when we use a \$2 price filter. These values understate true institutional monthly trade volumes because larger institutional investors employ "in-house" trade execution algorithms and do not use Abel Noser's execution quality assessment services—so their trades are not reflected in ANcerno data.

Internet Appendix F repeats the portfolio sorting exercise for alternative liquidity measures using the three minimum price filters. It confirms that ILMs are the only measures for which the long-short portfolio risk-adjusted return spreads reflect liquidity premia close to 1% or higher.

We also find that alphas associated with ILMs survive double sorts that control for key stock characteristics. Internet Appendix G forms an array of 5×5 portfolios that first condition on a stock characteristic (one of market beta, market capitalization, book-to-market ratios, past returns, and the share of sub-penny volume), and then on an ILM. We document liquidity premia for high- and low-beta, small and large, growth and value stocks, past losers and past winners, and stocks with low and high sub-penny executed volume. We then investigate whether trading costs can explain the returns of anomalies based on stock characteristics by switching the order of the double sorts. Consistent with the existing literature (e.g., Lesmond, Schill, and Zhou (2004); Korajczyk and Sadka (2004)), we find that momentum profits do not survive institutional trading costs.

9 Conclusion

Our paper attributes the strong return predictability of the imbalance in retail buy vs. sell orders internalized at sub-penny prices (Boehmer et al. (2021)) to liquidity provision by retail investors to institutional investors (Kaniel et al. (2008)). Importantly, order flow segmentation in U.S. equity markets prevents retail liquidity provision through direct interactions between retail and institutional order flows. We provide the first evidence of wholesalers, a group of high-frequency market makers, intermediating between retail and institutional investors. Wholesalers' exclusive access to internalized retail orders equips them with a competitive advantage in providing liquidity to institutional investors when liquidity is scarce. When liquidity-constrained institutions access liquidity by interacting with a wholesaler on one side of the market, the wholesaler internalizes unequal amounts of retail buy and sell order flow to offset the inventory they would otherwise accumulate when providing liquidity to institutions. We show that such institutional liquidity consumption when liquidity is scarce is associated with institutional price pressure. The subsequent price reversals create a positive association between imbalances in a ***select subset*** of internalized retail flow that reflect wholesaler choices and future returns. Hence, this return predictability should not be attributed to informed retail trading.

These findings motivate our use of the absolute value of the imbalance in observable internalized retail flow as a stock-level proxy of institutional trading costs—higher such imbalances signify scarce liquidity from the perspectives of institutional investors. We show that, relative to existing measures, our stock-level institutional liquidity measures are more closely linked with realized institutional trading costs and institutional holding horizons. We also provide robust evidence that our liquidity measures are priced in the cross-section of stock returns and yield economically significant liquidity premia post 2010, when existing liquidity measures are no longer priced. This finding is important for three reasons: (1) consistent with nontrivial institutional trading costs, it shows that stock returns still contain liquidity premia, indicating that a recent literature did not find significant liquidity premia only because their measures no longer capture relative trading costs; (2) it uncovers a new channel for return predictability of retail order flow; and (3) it provides researchers with an easy-to-construct measure of stock liquidity that captures the institutional details of modern U.S. equity markets.

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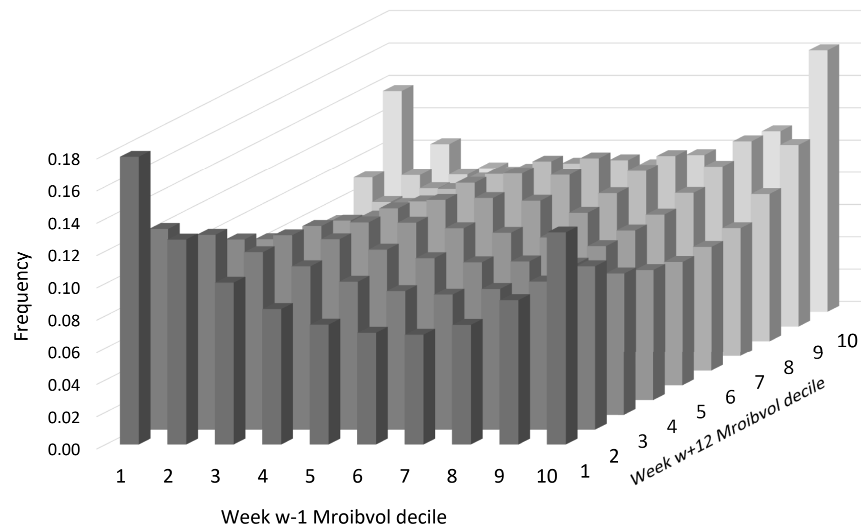
Figures and Tables

Figure 3. Dynamics of *Mroibvol*: A Conditional Distribution. Panel A illustrates conditional distributions of $Mroibvol$ in week $w+12$ given $Mroibvol$ deciles in week $w \quad 1$. Stocks are first sorted into deciles of $Mroibvol_{w \quad 1}$. Within each deciles, stocks are then sorted into deciles of $Mroibvol_{w+12}$. The figure plots the relative frequencies of different $Mroibvol_{w+12}$ deciles at any given $Mroibvol_{w \quad 1}$ decile. Panel B illustrates the analogous conditional distributions using simulated for a variable with $AR(1)$ structure $y_w = 0.8y_{w \quad 1} + \epsilon_w$, with $\epsilon_w \quad N(0,1)$ and $y_0 = \epsilon_0$.

Panel A: Empirical joint distribution of $Mribvol$



Panel B: Simulated joint distribution of y

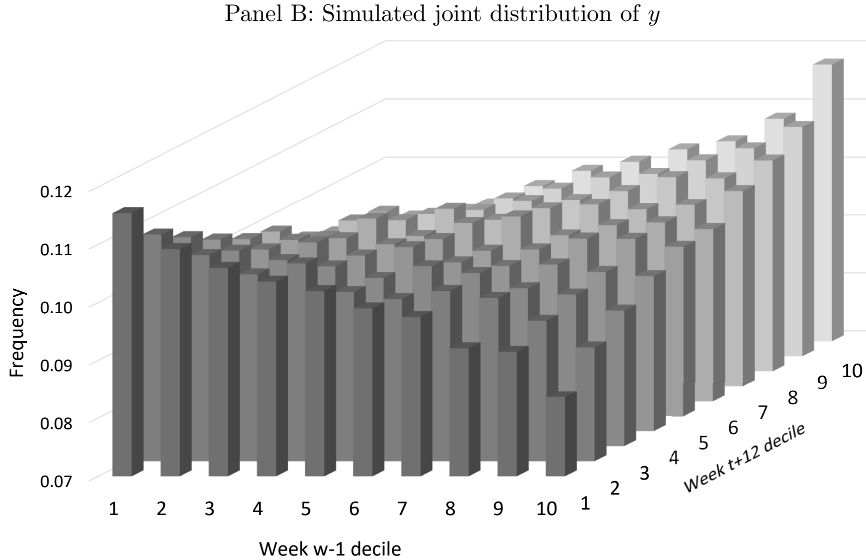
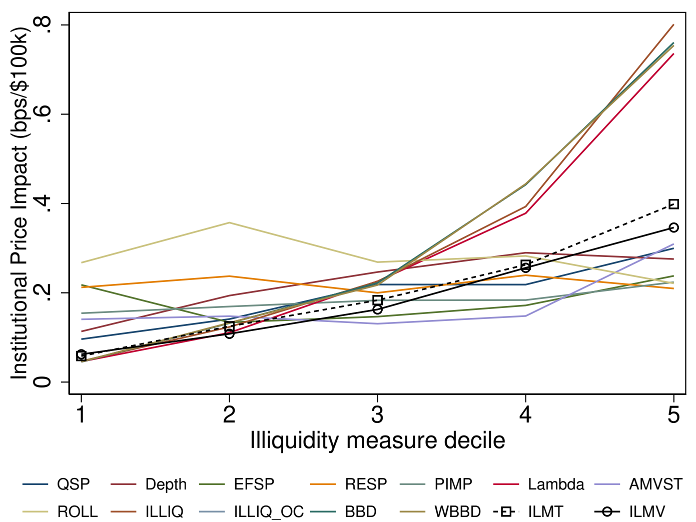


Figure 4. ***ILMs*, Standard Liquidity Measures, and Future Institutional Price Impacts.** The table reports on the cross-sectional relation between various liquidity measures constructed in month m 2 and realized, post-trade institutional price impacts, InPrIm, (in bps per $100k) constructed in month m. Liquidity measures include (1) quoted bid-ask spread (QSP); (2) quoted depth at best prices (Depth); (3) effective spreads (EFSP); (4) realized spreads (RESP); (5) price impacts (PIMP); (6) Kyle's lambda estimates (Lambda); (7) Amvist illiquidity measure (AMVST); (8) Roll measure of realized spreads (ROLL); (9 & 10) close-to-close and open-to-close Amihud measures (ILLIQ & ILLIQ_OC); (11 & 12) simple and volume-weighted trade-time liquidity measures (BBD & WBBD); (13 & 14) trade- and volume-based institutional liquidity measures (ILMT & ILMV). Each month, stocks are sorted into deciles of liquidity, with decile 1 (10) reflecting the most (least) liquid stocks, based on a given liquidity measure from month m 2. Month m InPrIm of the median stock in each liquidity decile is averaged across months by liquidity decile. This average is plotted against the respective liquidity decile. Panels A and B report results for liquidity deciles 1 through 5 and 6 through 10, respectively. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2.

Panel A: Illiquidity deciles 1–5



Panel B: Illiquidity deciles 6–10

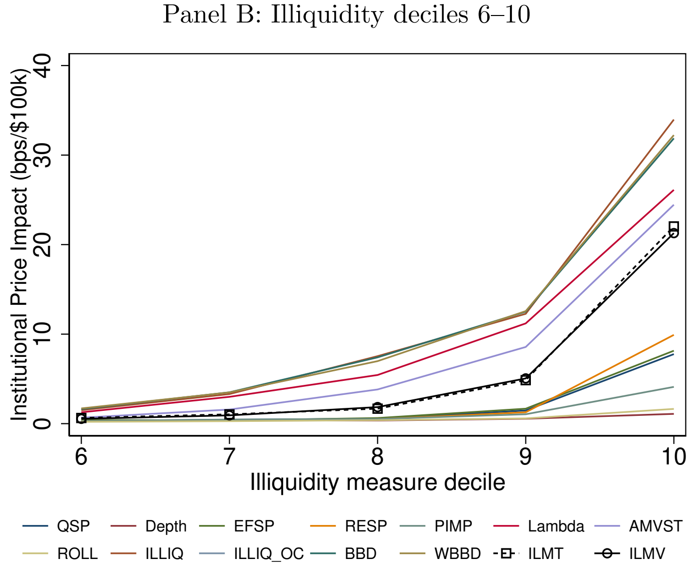


Figure 5. **EUM Liquidity and Holding Horizon.** This figure provides local polynomial estimates of equity under management (EUM) liquidity as a function of holding horizon. Holding weighted EUM liquidity, volatility, market capitalization, and institutional ownership are calculated for each manager. Every quarter, the residuals from regressing EUM liquidity on volatility, market capitalization, and institutional ownership are sorted into percentile statistics. Every quarter, manager-level holding horizons are calculated following Vovchak (2014) and sorted into percentile statistics. The figures present local polynomial estimates of residual EUM liquidity percentile statistics as functions of holding horizon percentile statistics. The sample includes all NMS common shares from January 2010 to December 2019. The sample for institutional price impacts (InPrIm) spans January 2010 through December 2019.

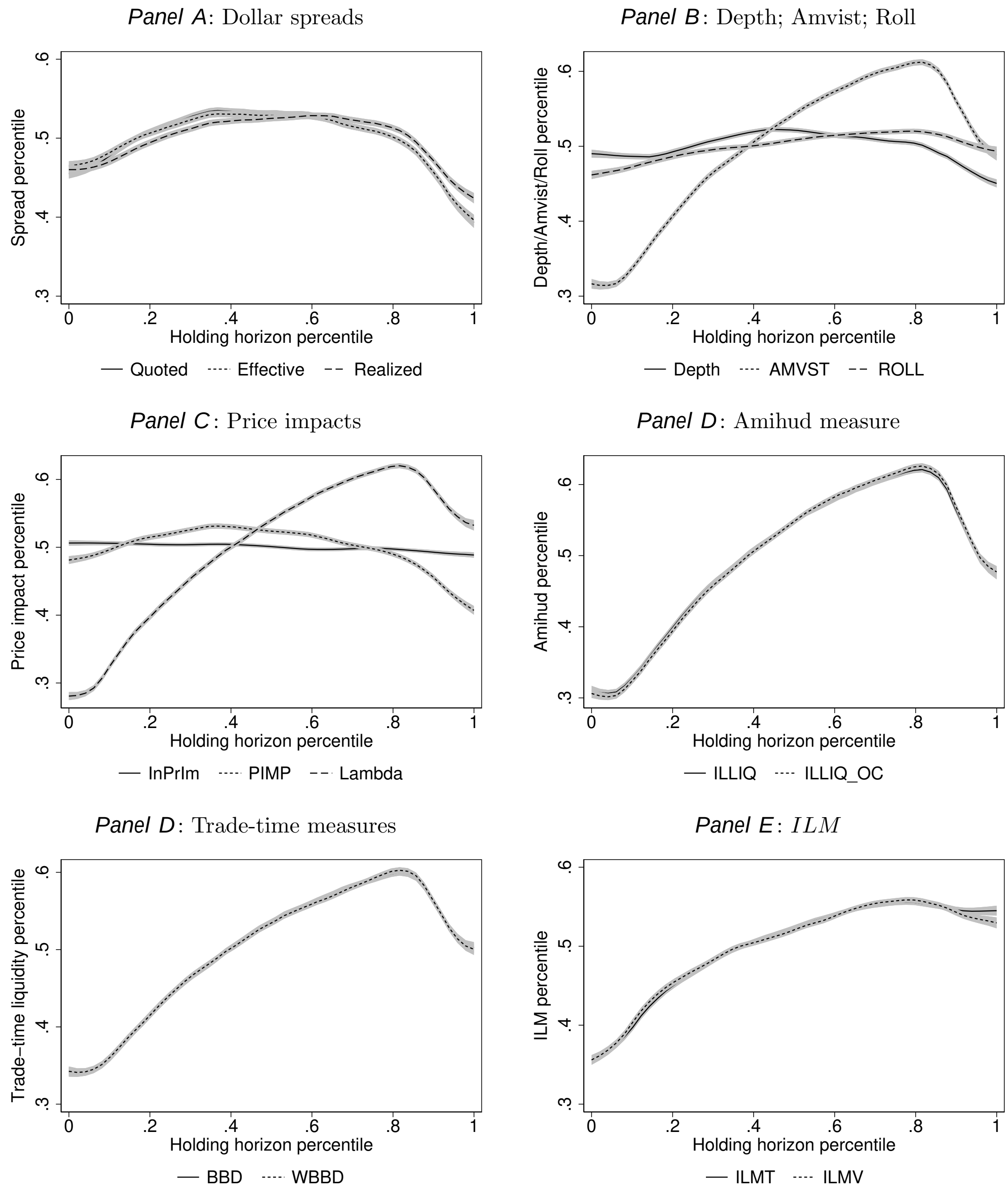


Table 1. Summary Statistics. Panel A reports (1) distributions of retail order types among all non-directed orders received by retail brokers; (2) distributions of retail order types, based on trade volume, among non-directed orders that are executed by wholesalers and receive PFOF; and (3) PFOF amount 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 (%)	Volume receiving PFOF (%)	PFOF (cents per 100 shares)	Non-directed orders (%)	Volume receiving PFOF (%)	PFOF (cents per 100 shares)	Non-directed orders (%)	Volume 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
$Mrbvol$	4,627,339	46,345	288,628	5,850	1,395	23,157
$Mrsvol$	4,627,339	46,249	270,718	6,333	1,559	24,346
$Mrbtrd$	4,627,339	108	389	23	6	79
$Mrstrd$	4,627,339	106	349	24	6	81
$Mroibvol$	4,627,339	-0.035	0.453	-0.025	-0.286	0.209
$Mrioibtrd$	4,627,339	-0.030	0.430	-0.008	-0.263	0.200
$Mroibvol > 0$	2,154,810	0.330	0.295	0.233	0.101	0.471
$Mroibvol < 0$	2,448,368	-0.357	0.301	-0.265	-0.522	-0.115
$Mroibtrd > 0$	2,088,865	0.321	0.282	0.232	0.111	0.435
$Mroibtrd < 0$	2,329,910	-0.347	0.290	-0.261	-0.500	-0.123

Table 2. 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 (actual trade imbalance, institutional price impact (in bps/$1m), and BJZZ-implied trade imbalance); and (4) short interest (% change in bi-weekly short interest). Each weekly cross-section is sorted into deciles of $Mroibvol$. 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 ($Mroibvol$)									
	1	2	3	4	5	6	7	8	9	10
Mroibvol	−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										
Actual trade imbalance	0.277	0.265	0.264	0.247	0.238	0.228	0.212	0.212	0.202	0.172
Price impact	19.57	7.13	3.48	3.10	3.25	2.96	4.04	7.25	7.60	22.50
BJZZ-implied trade imbalance	−0.243	−0.257	−0.266	−0.270	−0.267	−0.250	−0.256	−0.252	−0.245	−0.221
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	0.79	0.89	0.94	0.98	1.00	1.04	1.07	1.06	1.03	0.99

Table 3. 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 of each stock 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, denoted CCR_w, IDR_w,and ONR_w, respectively. According to equation (1), week w returns are regressed on week $w\quad 1$'s internalized order flows ($Mroibvol_{w\ \ 1}$) and control variables including last week's return ($CCR_{w\ \ 1}$), 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 on 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	CCR_w	ONR_w	IDR_w
Constant	0.0063	0.58***	−0.57**
	[0.02]	[4.58]	[−2.10]
$Mroibvol_{w\ \ 1}$	0.087***	0.12***	−0.029***
	[13.73]	[25.53]	[−4.41]
$R_{w\ \ 1}$	−0.021***	0.00090	−0.022***
	[−5.86]	[0.50]	[−7.07]
$RET_{(\ \ 1)}$	0.21	−0.19**	0.40**
	[1.14]	[−2.30]	[2.47]
$RET_{(\ \ 7,\ \ 2)}$	0.063	0.061**	0.0024
	[0.84]	[2.45]	[0.03]
ln(TO)	−0.037***	0.036***	−0.073***
	[−3.60]	[8.89]	[−8.16]
VOLAT	−6.44***	9.68***	−16.1***
	[−3.55]	[11.02]	[−10.03]
ln(Size)	0.020	−0.033***	0.053***
	[1.47]	[−5.31]	[4.39]
ln(BM)	0.058***	−0.038***	0.096***
	[2.73]	[−6.10]	[4.75]
Observations	3,330,408	3,330,408	3,330,408

Table 4. 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) returns in week $w + i$, with $i\ 2\ f0, 1, 2, 3, 6, 9, 12, 24, 36, 39, 42, 45, 48, 51, 54, 57, 60g$. The means of the time-series of portfolio future returns are presented by $Mroibvol$ decile.

	Deciles of $Mroibvol_{w\ \ 1}$									
Week	1	2	3	4	5	6	7	8	9	10
w	−0.02	0.09	0.13	0.18	0.22	0.25	0.27	0.29	0.27	0.32
$w + 1$	0.13	0.15	0.14	0.15	0.15	0.14	0.17	0.16	0.21	0.34
$w + 2$	0.14	0.16	0.17	0.16	0.16	0.15	0.16	0.17	0.21	0.31
$w + 3$	0.17	0.20	0.18	0.18	0.17	0.17	0.17	0.18	0.23	0.29
$w + 6$	0.19	0.17	0.19	0.18	0.16	0.16	0.18	0.18	0.21	0.26
$w + 9$	0.14	0.16	0.16	0.13	0.13	0.12	0.10	0.11	0.15	0.19
$w + 12$	0.15	0.12	0.11	0.10	0.08	0.07	0.07	0.09	0.12	0.18
$w + 24$	0.21	0.18	0.19	0.15	0.14	0.13	0.13	0.15	0.16	0.22
$w + 36$	0.22	0.21	0.20	0.17	0.15	0.13	0.14	0.15	0.17	0.20
$w + 39$	0.16	0.17	0.16	0.14	0.13	0.11	0.10	0.10	0.13	0.14
$w + 42$	0.18	0.15	0.13	0.13	0.12	0.11	0.09	0.08	0.12	0.15
$w + 45$	0.19	0.17	0.15	0.14	0.12	0.10	0.09	0.10	0.12	0.14
$w + 48$	0.14	0.13	0.11	0.09	0.07	0.05	0.06	0.04	0.06	0.10
$w + 51$	0.13	0.10	0.12	0.07	0.02	0.02	0.01	0.03	0.04	0.07
$w + 54$	0.08	0.10	0.08	0.08	0.04	0.01	0.00	-0.01	0.03	0.06
$w + 57$	0.07	0.03	0.04	0.01	-0.01	-0.01	-0.01	0.02	0.03	0.05
$W + 60$	0.08	0.07	0.04	0.01	0.00	0.00	-0.01	-0.02	0.00	0.00

Table 5. Institutional Liquidity Measures and Stock Characteristics. The table reports on the cross-sectional relation between $ILMs$ and (1) three-factor Fama-French betas, (2) book-to-market ratios (BM), (3) natural log of market capitalizations (ln(Mcap)), (4) dividend yields (DYD), (5) idiosyncratic volatilities (IdVol), (6) previous month's returns ($RET_{(\ 1)}$), and (7) preceding returns from the prior 11 months ($RET_{(\ 12,\ 2)}$). Stock characteristics are computed from the prior month. Each weekly cross-section is sorted into ILM deciles. The average outcome variable is calculated by $ILMT$ decile in each cross-section before the average of the time-series is calculated. Panels A and B report the results for $ILMT$ and $ILMV$, respectively. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2.

Panel A: Trade-based Institutional Liquidity Measures ($ILMT$s) versus stock characteristics

	Weekly $ILMT$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.02	1.02	1.02	1.01	1.00	0.99	0.97	0.93	0.88	0.82
β^{hml}	0.73	0.73	0.73	0.73	0.74	0.75	0.76	0.77	0.78	0.79
β^{smb}	0.15	0.15	0.16	0.16	0.17	0.17	0.18	0.20	0.22	0.24
BM	0.64	0.64	0.65	0.65	0.66	0.67	0.68	0.72	0.76	0.80
ln(Mcap)	20.99	20.98	20.95	20.91	20.85	20.76	20.64	20.38	20.05	19.71
DYD	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.015	0.015
Id. Vol.	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.022	0.022
$RET_{(\ 1)}$	0.016	0.018	0.016	0.017	0.016	0.015	0.014	0.015	0.015	0.016
$RET_{(\ 12,\ 2)}$	0.19	0.19	0.19	0.19	0.19	0.18	0.17	0.16	0.15	0.14

Panel B: Volume-based Institutional Liquidity Measures ($ILMT$s) versus stock characteristics

	Weekly $ILMV$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.07	1.07	1.06	1.04	1.02	1.00	0.94	0.94	0.89	0.73
β^{hml}	0.71	0.71	0.72	0.73	0.73	0.75	0.74	0.79	0.82	0.77
β^{smb}	0.12	0.12	0.13	0.14	0.15	0.17	0.19	0.21	0.25	0.29
BM	0.62	0.62	0.63	0.63	0.64	0.65	0.70	0.70	0.74	0.87
ln(Mcap)	21.29	21.26	21.19	21.10	20.97	20.81	20.45	20.36	20.01	19.26
DYD	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.015	0.015
Id. Vol.	0.022	0.022	0.022	0.021	0.021	0.021	0.021	0.020	0.021	0.021
$RET_{(\ 1)}$	0.019	0.018	0.017	0.016	0.016	0.015	0.014	0.014	0.014	0.015
$RET_{(\ 12,\ 2)}$	0.21	0.21	0.20	0.19	0.19	0.18	0.16	0.16	0.15	0.13

Table 6. Persistence in the Institutional Liquidity Measures. The table reports on ILM's persistence. For $LIQ \in \{ILMT, ILMV\}$, monthly observations are regressed on monthly lagged observations from the preceding six months. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. Both equally-weighted (EW) and value-weighted (VW) estimates, with weights being the previous month's market capitalization, are reported. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

	$ILMT$		$ILMV$	
	EW	VW	EW	VW
Constant	0.0080***	0.0091***	0.0096***	0.0045***
	[5.81]	[6.14]	[7.84]	[5.80]
LIQ_{m-1}	0.40***	0.39***	0.43***	0.37***
	[69.77]	[33.97]	[83.17]	[49.29]
LIQ_{m-2}	0.19***	0.15***	0.19***	0.18***
	[54.73]	[14.43]	[55.50]	[31.86]
LIQ_{m-3}	0.13***	0.13***	0.13***	0.15***
	[37.56]	[14.46]	[47.16]	[31.93]
LIQ_{m-4}	0.078***	0.085***	0.068***	0.084***
	[19.72]	[10.00]	[21.83]	[10.64]
LIQ_{m-5}	0.070***	0.070***	0.060***	0.076***
	[22.27]	[9.70]	[23.77]	[15.89]
LIQ_{m-6}	0.090***	0.092***	0.087***	0.10***
	[39.04]	[14.33]	[31.25]	[16.66]
Observations	310,847	310,847	310,847	310,847

Table 7. Stock Liquidity and Institutional Holding Horizon. This table reports on the relation between the holding horizons of institutional investors and stock liquidity using different liquidity measures. Institutional investor turnover measures are constructed by stock and quarter as the weighted averages of turnover across the institutional investors holding a stock. For each stock, the weight assigned to an investor's turnover is the fraction held by the investor relative to the total amount held by institutional investors. Each quarter, investor-level holding horizon percentile statistics, "HH pctile", are defined as 1 minus institutional turnover percentile statistics across all the stocks held by an investor. In Panel A, for each stock j in quarter q, liquidity measure $LIQ_{j,q}$ is regressed on the holding horizon percentile statistic, return volatility, natural log of market capitalization, and institutional ownership from quarter q 1. Panel B reports on the relation between institutional turnover and liquidity, after orthogonalizing $ILMT$ and $ILMV$ with respect to existing liquidity measures and vice versa. Z_{ILMT} and Z_{ILMV}, respectively, are the residuals from regressing quarterly cross-sections of $ILMT$ and $ILMV$ on existing liquidity measures. Y_{ILMT} and Y_{ILMV}, respectively, are the residuals from regressing quarterly cross-sections of individual existing liquidity measures on $ILMT$ and $ILMV$. Z_{ILMT}, Z_{ILMV}, Y_{ILMT}, and Y_{ILMV} from quarter q are then regressed on institutional turnover, return volatility, natural log of market capitalization, and institutional ownership from quarter q 1. Institutional turnover coefficients are reported. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock liquidity and institutional turnover

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
HH pctile	−7.07	0.12***	−7.82***	0.12***	0.11**	0.0082	0.14***	0.051***	−0.00029	0.15***	0.099***	0.25	0.092**	0.093***	0.12***
	[−0.81]	[7.52]	[−6.50]	[3.26]	[2.66]	[0.40]	[4.24]	[6.92]	[−0.43]	[4.12]	[5.16]	[1.61]	[2.13]	[11.63]	[19.36]
Volatility	435.6	−1.50***	239.9***	−0.26	−0.11	−0.23	5.61***	−0.25	0.19***	3.17***	2.15***	5.23***	2.79***	−2.73***	−3.60***
	[1.30]	[−7.40]	[3.94]	[−0.40]	[−0.15]	[−1.27]	[9.62]	[−1.49]	[17.36]	[3.75]	[4.54]	[4.85]	[6.17]	[−12.14]	[−19.65]
ln(Mcap)	0.88	−0.021***	3.94***	−0.015***	−0.0036	−0.011***	−0.15***	−0.020***	−0.0013***	−0.12***	−0.074***	−0.098***	−0.049***	−0.064***	−0.077***
	[1.13]	[−14.40]	[6.09]	[−10.84]	[−0.87]	[−2.79]	[11.19]	[−9.81]	[−17.40]	[13.03]	[13.62]	[−3.19]	[−5.11]	[−23.20]	[−46.22]
Ownership	−19.0	−0.089***	−18.0***	−0.095***	−0.13**	0.040	−0.56***	−0.12***	−0.0048***	−0.53***	−0.33***	−0.31***	−0.18***	−0.13***	−0.12***
	[−0.95]	[−7.55]	[−15.27]	[−4.37]	[−2.61]	[1.02]	[10.96]	[−8.17]	[−10.20]	[13.10]	[15.45]	[−9.81]	[−10.20]	[−27.37]	[−27.59]
R^2	0.0061	0.092	0.026	0.095	0.021	0.011	0.36	0.027	0.13	0.11	0.14	0.18	0.18	0.61	0.63
Obs.	28,679[y]	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	71,952[yy]	71,952[yy]	91,541	91,541

[y] The number of observations reflects the largest sample of ANcerno data available from 2010–2014.

[yy] The number of observations reflects the largest sample available for BBD and WBBD from 2010–2017.

Panel B: Stock liquidity and institutional turnover, ILM versus existing measures

Residual	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD
Z_{ILMT}	0.10***	0.053***	0.092***	0.055***	0.087***	0.090***	0.078***	0.089***	0.092***	0.086***	0.082***	0.090***	0.090***
	[9.56]	[10.18]	[12.25]	[9.47]	[8.28]	[10.02]	[13.96]	[11.08]	[13.39]	[11.52]	[12.15]	[12.56]	[12.96]
R^2	0.60	0.54	0.61	0.54	0.60	0.61	0.41	0.60	0.57	0.55	0.52	0.53	0.53
Z_{ILMV}	0.13***	0.080***	0.12***	0.082***	0.12***	0.12***	0.11***	0.12***	0.12***	0.12***	0.11***	0.12***	0.12***
	[17.39]	[18.49]	[19.91]	[17.90]	[13.18]	[15.80]	[22.54]	[18.22]	[22.28]	[18.87]	[19.82]	[18.58]	[18.97]
R^2	0.61	0.56	0.62	0.56	0.62	0.63	0.44	0.62	0.59	0.57	0.54	0.55	0.55
Y_{ILMT}	−5.60	0.080***	−7.17***	0.085**	0.072*	0.014	−0.047***	−0.0081	−0.0018***	−0.069***	−0.029**	0.12	0.024
	[−0.59]	[4.97]	[−4.82]	[2.44]	[1.86]	[0.97]	[−3.13]	[−1.15]	[−3.25]	[−3.13]	[−2.23]	[0.95]	[0.66]
R^2	0.0026	0.025	0.022	0.025	0.0096	0.0069	0.13	0.029	0.086	0.024	0.031	0.057	0.058
Y_{ILMV}	−4.39	0.070***	−6.36***	0.078**	0.069*	0.011	−0.082***	−0.013	−0.0018***	−0.099***	−0.049***	0.11	0.014
	[−0.47]	[4.82]	[−4.36]	[2.24]	[1.77]	[0.73]	[−4.52]	[−1.68]	[−3.46]	[−4.23]	[−3.51]	[0.85]	[0.41]
R^2	0.0026	0.025	0.020	0.025	0.0097	0.0065	0.14	0.022	0.092	0.030	0.038	0.065	0.065

Table 8. The Cross-Section of Expected Stock Returns and ILM. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (2) is estimated using liquidity measures ($LIQ_{j,m\ \ 2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m\ \ 1}$, $\beta^{hml}_{j,m\ \ 1}$, $\beta^{smb}_{j,m\ \ 1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m\ \ \ 1$, book-to-market ratio, ($\text{BM}_{j,m\ \ 1}$), natural log of market capitalization, ($\ln(\text{Mcap}_{j,m\ \ 1})$), dividend yield ($\text{DYD}_{j,m\ \ 1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m\ \ \ 1$, idiosyncratic volatility ($\text{IdVol}_{j,m\ \ 1}$), previous month's return ($RET_{(\ \ 1)}$), and preceding return from the prior 11 months ($RET_{(\ \ 12,\ \ 2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock liquidity and the cross-section of expected returns

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
Constant	1.38	1.00	0.99	0.95	0.99	1.00	1.45*	0.99	1.41	1.13	1.00	1.68*	1.63*	−0.99	−1.54
	[1.08]	[1.11]	[1.14]	[1.06]	[1.15]	[1.15]	[1.73]	[1.16]	[1.60]	[1.30]	[1.13]	[1.93]	[1.87]	[−0.77]	[−1.13]
Liquidity	**0.029***	**0.0057**	**−0.00**	**0.13**	**0.049**	**−0.034**	**−0.11**	**0.043**	**−8.24*****	**−0.015**	**0.050**	**−0.070**	**−0.055**	**1.20*****	**1.27*****
	[1.91]	**[0.05]**	**[−0.84]**	**[0.78]**	**[0.63]**	**[−0.33]**	**[−1.53]**	**[0.35]**	**[−3.47]**	**[−0.45]**	**[0.56]**	**[−0.56]**	**[−0.28]**	**[2.91]**	**[3.11]**
β^{mkt}	−0.023	−0.15	−0.15	−0.15	−0.15	−0.15	−0.16	−0.16	−0.15	−0.16	−0.15	−0.17	−0.17	−0.070	−0.043
	[−0.06]	[−0.75]	[−0.75]	[−0.74]	[−0.74]	[−0.75]	[−0.78]	[−0.75]	[−0.71]	[−0.76]	[−0.75]	[−0.71]	[−0.70]	[−0.36]	[−0.23]
β^{hml}	−0.15	−0.098	−0.097	−0.097	−0.098	−0.098	−0.096	−0.097	−0.10	−0.098	−0.096	−0.064	−0.064	−0.11	−0.12
	[−1.02]	[−0.83]	[−0.82]	[−0.82]	[−0.82]	[−0.82]	[−0.81]	[−0.82]	[−0.88]	[−0.82]	[−0.81]	[−0.47]	[−0.47]	[−0.92]	[−0.98]
β^{smb}	0.12	0.063	0.062	0.064	0.062	0.061	0.053	0.064	0.060	0.052	0.060	0.057	0.061	0.10	0.11
	[1.28]	[0.84]	[0.82]	[0.86]	[0.83]	[0.81]	[0.69]	[0.85]	[0.79]	[0.68]	[0.80]	[0.67]	[0.71]	[1.44]	[1.58]
BM	0.22	0.0056	0.0059	0.0058	0.0056	0.0052	−0.0015	0.0044	0.0088	0.0073	0.0023	0.055	0.054	0.0030	0.0043
	[1.52]	[0.11]	[0.12]	[0.12]	[0.11]	[0.11]	[−0.03]	[0.09]	[0.18]	[0.15]	[0.05]	[0.71]	[0.69]	[0.06]	[0.09]
ln(Mcap)	0.0048	0.022	0.023	0.023	0.023	0.022	0.0024	0.022	0.0055	0.016	0.022	−0.0054	−0.0030	0.097*	0.12**
	[0.09]	[0.59]	[0.62]	[0.62]	[0.63]	[0.61]	[0.07]	[0.62]	[0.15]	[0.44]	[0.59]	[−0.15]	[−0.08]	[1.89]	[2.15]
DYD	0.35	−0.049	−0.062	−0.050	−0.066	−0.075	−0.070	−0.053	−0.077	−0.088	−0.086	0.11	0.11	−0.13	−0.11
	[0.31]	[−0.09]	[−0.11]	[−0.09]	[−0.12]	[−0.13]	[−0.12]	[−0.09]	[−0.14]	[−0.15]	[−0.15]	[0.17]	[0.17]	[−0.23]	[−0.20]
Id. Vol.	−0.16**	−0.23***	−0.23***	−0.23***	−0.23***	−0.23***	−0.23***	−0.23***	−0.22***	−0.23***	−0.24***	−0.23***	−0.23***	−0.22***	−0.21***
	[−2.47]	[−4.75]	[−4.78]	[−4.75]	[−4.76]	[−4.75]	[−4.62]	[−4.77]	[−4.51]	[−4.69]	[−4.65]	[−4.01]	[−4.05]	[−4.54]	[−4.46]
$RET_{\ \ 1}$	−0.74	−0.38	−0.39	−0.38	−0.37	−0.36	−0.36	−0.37	−0.39	−0.33	−0.35	−0.42	−0.43	−0.44	−0.48
	[−1.04]	[−0.81]	[−0.82]	[−0.81]	[−0.78]	[−0.77]	[−0.75]	[−0.79]	[−0.82]	[−0.70]	[−0.74]	[−0.79]	[−0.80]	[−0.93]	[−1.02]
$RET_{(\ \ 12,\ \ 2)}$	0.35*	0.21	0.21	0.21	0.21	0.21	0.18	0.21	0.21	0.20	0.20	0.21	0.21	0.27*	0.28*
	[1.80]	[1.39]	[1.39]	[1.39]	[1.39]	[1.40]	[1.14]	[1.38]	[1.37]	[1.32]	[1.30]	[1.11]	[1.13]	[1.76]	[1.81]
Observations	128,135[y]	340,227	340,227	340,227	340,227	340,227	339,681	340,225	340,227	340,225[yy]	340,225[yy]	277,750[yyy]	277750[yyy]	340,227	340,227

Panel B: Loadings of ILMs in the cross-section of expected returns after orthogonlization relative to other liquidity measures

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
ILMT residual	0.10	1.22***	1.19***	1.15***	1.18***	1.20***	1.30***	1.20***	1.38***	1.27***	1.13**	1.14**	1.12**	-	-
	[0.19]	[3.51]	[2.92]	[3.27]	[2.85]	[2.90]	[2.85]	[2.77]	[3.35]	[2.90]	[2.48]	[2.18]	[2.17]		
ILMV residual	0.055	1.31***	1.24***	1.25***	1.25***	1.28***	1.34***	1.25***	1.40***	1.31***	1.19***	1.17**	1.15**	-	-
	[0.11]	[3.85]	[3.11]	[3.60]	[3.05]	[3.14]	[3.05]	[2.98]	[3.45]	[3.11]	[2.76]	[2.30]	[2.29]		

[y] The number of observations reflects the largest sample of ANcerno data available from 2010–2014.

[yy] The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

[yyy] The number of observations reflects the largest sample available for BBD and WBBD from 2010–2017.

Table 9. The Cross-Section of Expected Stock Returns and ILM: Robustness Tests. This table reports on the robustness of the relation between between our institutional liquidity measures and the cross-section of expected stock returns. Equation (2) is estimated using institutional liquidity measures ($LIQ_{j,m\ \ 2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m\ \ 1}$, $\beta^{hml}_{j,m\ \ 1}$, $\beta^{smb}_{j,m\ \ 1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m\ \ \ 1$, book-to-market ratio ($\mathrm{BM}_{j,m\ \ 1}$), natural log of market capitalization ($\ln(\mathrm{Mcap}_{j,m\ \ 1})$), dividend yield ($\mathrm{DYD}_{j,m\ \ 1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m\ \ \ 1$, idiosyncratic volatility ($\mathrm{IdVol}_{j,m\ \ 1}$), previous month's return ($RET_{(\ \ 1)}$), and preceding return from the prior 11 months ($RET_{(\ \ 12,\ \ 2)}$). Panel A reports on the robustness of the results to (1) estimating coefficients using panel regressions with date and stock fixed effects and date-stock double-clustered standard errors, (2) weighting observations (by size or according to Asparouhova et al. 2010) to correct for microstructure noise, (3) excluding firms with the smallest 20% market capitalization, (4) excluding stocks in the bottom 10% of the ratio of sub-penny volume in total volume; and (5) excluding stocks in the top or bottom 10% of the respective ILM. Stocks whose previous month-end's closing price is below p_{min} 2 f\$1, \$2, \$5g are excluded. Panel B reports on the robustness of the estimates in equation (2) to listing exchange. Observations are weighted according to Asparouhova et al. (2010) after excluding stocks whose previous month-end's closing price is below \$1 and stocks falling in the bottom 10% of the ratio of sub-penny volume in total volume. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Robustness to estimation method and sample selection

Robustness specification	*ILMT*			*ILMV*		
	Price > \$1	Price > \$2	Price > \$5	Price > \$1	Price > \$2	Price > \$5
Panel regressions + stock & date FEs	1.20**	1.17**	0.55	1.54***	1.27***	0.80*
+ double-clustered S.E.	[2.18]	[2.25]	[1.16]	[2.98]	[2.64]	[1.85]
Asparouhova et al. (2010)	1.19**	1.18***	0.66*	1.35***	1.24***	0.88**
	[2.45]	[2.72]	[1.88]	[2.80]	[2.83]	[2.43]
Asparouhova et al. (2010)	0.99**	0.95**	0.62*	1.10**	1.06**	0.84**
+ top 80% market capitalization	[2.38]	[2.41]	[1.74]	[2.52]	[2.57]	[2.30]
Asparouhova et al. (2010)	1.33***	1.34***	0.86**	1.51***	1.41***	1.09***
+ low sub-penny volume stocks excluded	[2.64]	[2.98]	[2.37]	[3.02]	[3.09]	[2.89]
Size-weighted estimation	1.50**	1.52**	1.53**	0.38	0.38	0.36
	[2.38]	[2.39]	[2.35]	[0.73]	[0.72]	[0.67]
Stocks in top and bottom	2.42***	2.35***	1.33***	1.77***	1.62***	1.35***
10% of *ILM* excluded	[2.92]	[3.29]	[2.72]	[2.96]	[2.93]	[2.92]

Panel B: Robustness to estimation by listing exchange

	ILMT		*ILMV*	
	NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
Asparouhova et al. (2010)	0.83	1.11**	1.17**	1.25**
+ Price > \$1	[1.57]	[2.14]	[2.15]	[2.55]
Asparouhova et al. (2010) + Price > \$1	1.04*	1.20**	1.43**	1.36***
+ low sub-penny volume stocks excluded	[1.90]	[2.29]	[2.48]	[2.73]

Table 10. Liquidity Alphas. This table presents three-factor alphas conditional on our liquidity measures. Panels A, B, and C report results based on NMS-listed common shares using CRSP breakpoints and equally-weighted portfolio returns. Panels D, E, and F report results based on the NMS-listed common shares, after removing stocks with the smallest 20% market capitalization at the end-of-last-month, using NYSE breakpoints and value-weighted portfolio returns. Stocks in each monthly cross-section are sorted into ten ILM portfolios (deciles). Monthly portfolio returns are averages of monthly stock returns in the portfolio. The time-series feature 118 months. The time-series returns of each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on Fama-French three factors. The resulting intercepts represent three-factor alphas. The sample period is from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below p_{min} 2 f\$1, \$2, \$5g. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: CRSP breakpoints, \$1 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.32***	0.34***	0.19**	0.17	0.23***	0.24*	0.032	0.089	0.38**	0.64***	0.96***
	[2.77]	[3.82]	[2.13]	[1.58]	[2.80]	[1.83]	[0.30]	[0.63]	[2.48]	[4.25]	[4.30]
$ILMV$	0.63***	0.44***	0.25***	0.25***	0.11	0.00096	0.027	0.32***	0.32**	0.64***	1.27***
	[4.28]	[4.40]	[2.88]	[3.56]	[1.07]	[0.01]	[0.28]	[2.85]	[2.10]	[4.76]	[5.49]

Panel B: CRSP breakpoints, \$2 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.30***	0.33***	0.21**	0.062	0.18**	0.14	0.023	0.11	0.34**	0.62***	0.93***
	[2.70]	[4.05]	[2.17]	[0.82]	[2.26]	[1.33]	[0.27]	[0.92]	[2.54]	[4.48]	[4.33]
$ILMV$	0.58***	0.33***	0.23***	0.25***	0.084	0.091	0.041	0.28***	0.31**	0.63***	1.20***
	[3.97]	[3.86]	[2.76]	[3.68]	[0.92]	[1.12]	[0.59]	[3.37]	[2.26]	[4.97]	[5.09]

Panel C: CRSP breakpoints, \$5 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.29***	0.24***	0.14*	0.053	0.019	0.0071	0.12	0.28***	0.38***	0.65***	0.95***
	[2.66]	[2.89]	[1.98]	[0.78]	[0.26]	[0.11]	[1.26]	[2.84]	[3.49]	[4.72]	[4.30]
$ILMV$	0.43***	0.21***	0.14**	0.11	0.0080	0.048	0.19***	0.37***	0.43***	0.68***	1.10***
	[3.35]	[2.64]	[2.16]	[1.54]	[0.10]	[1.01]	[2.86]	[4.65]	[4.02]	[5.32]	[4.82]

Continued on next page

Table 10 – *continued from previous page*

Panel D: NYSE breakpoints, largest 80% market capitalization, $1 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.10	0.0096	0.0039	0.0073	0.10	0.23**	0.19**	0.26*	0.15*	0.47***	0.58***
	[1.58]	[0.10]	[0.05]	[0.06]	[0.90]	[2.61]	[2.37]	[1.87]	[1.76]	[7.07]	[6.09]
ILMV	0.084	0.085	0.026	0.026	0.12	0.069	0.19*	0.25***	0.32**	0.32***	0.41***
	[1.41]	[1.20]	[0.29]	[0.29]	[1.17]	[0.65]	[1.87]	[3.40]	[2.42]	[3.12]	[4.05]

Panel E: NYSE breakpoints, largest 80% market capitalization, $2 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.099	0.017	0.015	0.0083	0.14	0.17	0.22**	0.24*	0.17*	0.48***	0.58***
	[1.51]	[0.18]	[0.20]	[0.06]	[1.29]	[1.64]	[2.51]	[1.77]	[1.93]	[7.12]	[6.15]
ILMV	0.086	0.086	0.016	0.030	0.11	0.071	0.17	0.26***	0.28**	0.37***	0.46***
	[1.43]	[1.18]	[0.19]	[0.32]	[1.12]	[0.67]	[1.64]	[3.33]	[2.24]	[3.63]	[4.69]

Panel F: NYSE breakpoints, largest 80% market capitalization, $5 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.10	0.041	0.024	0.0047	0.20**	0.082	0.33***	0.17	0.10	0.53***	0.63***
	[1.58]	[0.46]	[0.29]	[0.03]	[2.01]	[0.77]	[3.46]	[1.34]	[1.04]	[7.20]	[6.17]
ILMV	0.091	0.11	0.060	0.0087	0.11	0.086	0.22**	0.21**	0.28***	0.34***	0.43***
	[1.52]	[1.38]	[0.68]	[0.10]	[1.22]	[0.81]	[2.47]	[2.25]	[2.65]	[2.91]	[4.27]

Internet Appendix

A Economics of Retail Order Internalization

A.1 Wholesaler Incentives, *Mroib*, and Institutional Liquidity

In this section, we provide a setting to illustrate the economic incentives underlying a wholesaler's decisions about which retail orders to internalize, and the consequences for $Mroib$. We focus on a setting where the wholesaler faces variable costs of internalization due to the possibility of internalizing both marketable and non-marketable orders. Similar economic considerations arise in a framework where internalization of marketable orders is sometimes more costly as a result of inside quote hidden liquidity (due to the Manning rule).

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

- ${n^s}_2$ marketable sell orders at $\$(V-2t)$
- ${n^s}_1$ limit sell orders at $\$(V-t)$
- n^s_0 limit sell orders and n^b_0 limit buy orders at $\$V$
- n^b_1 limit buy orders at $\$(V+t)$
- n^b_2 marketable buy orders at $\$(V+2t)$

To illustrate the economics, suppose there is more retail sell interest than retail buy interest so that ${n^s}_j \geq n^b_j$, for $j = 0, 1, 2$, and we define $\Delta_j = {n^s}_j - n^b_j \geq 0$. To reduce the number of cases that we need to enumerate, we assume that (a) ${n^s}_2 \leq n^b_2 + n^b_1$, and (b) ${n^s}_2 + {n^s}_1 \leq n^b_2 + n^b_1 + n^b_0$. 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.[60] The broker-dealer obtains $PFOF_j$ in return for outsourcing the execution of a

[60] A 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.

type j order to the wholesaler.

Price improvement of $PI_M > 0$ is offered to marketable orders in order to satisfy best execution duties. For simplicity, we assume that fraction $\alpha_{NM} \geq 0$ of non-marketable orders receive price improvement of $PI_{NM} > 0$. As we show, a large share of trade executions 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. The notion that a market-maker has "preferred" inventory positions dates back to Amihud and Mendelson (1980).[61] We assume that these costs rise convexly in q, i.e., $c(q) - c(q-1)$ is strictly increasing in q, consistent with risk-averse liquidity providers as in Grossman and Miller (1988) or Campbell, Grossman, and Wang (1993), 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 $Mroib$ 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 $min\{n^s{}_2 + n^s{}_1, n^b_2 + n^b_1\} = n^b_2 + n^b_1$ 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 $2(n^b_2 + \alpha_{NM} n^b_1)$.

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

- 0 marketable sell orders at $\$(V - 2t)$
- $n^s{}_2 + n^s{}_1 - (n^b_2 + n^b_1)$ limit sell orders at $\$(V - t)$
- n^s_0 limit sell orders and n^b_0 limit buy orders at $\$V$
- 0 limit buy orders at $\$(V + t)$
- 0 marketable buy orders at $\$(V + 2t)$

[61] Other early studies suggesting or modeling the existence of such inventory positions include Smidt (1971), Barnea and Logue (1975), Stoll (1976), Ho and Stoll (1982), and Grossman and Miller (1988), among others.

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 $n^s{}_2+n^s{}_1-(n_2^b+n_1^b)>q$, the wholesaler fills the remaining limit sell orders at \$$(V-t)$ with limit buy orders at \$$V$. The dealer then submits all remaining limit orders[62] at \$$V$ to exchanges. Thus, absent institutional liquidity demand, for $n^s{}_2+n^s{}_1 \leq n_2^b+n_1^b+q$, internalization order imbalances identified by the BJZZ algorithm equal

$$|Mroibvol| = \frac{(n_2^s+\alpha_{NM}n_1^s)-(n^b{}_2+\alpha_{NM}n^b{}_1)}{n_2^b+\alpha_{NM}n_1^b+n^s{}_2+\alpha_{NM}n^s{}_1} = \frac{\Delta_2+\alpha_{NM}\Delta_1}{n_2^b+n^s{}_2+\alpha_{NM}(n_1^b+n^s{}_1)}.$$

$|Mroibvol|$ reaches a maximum at $n^s{}_2+n^s{}_1=n_2^b+n_1^b+q$, 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 $n^s{}_2+n^s{}_1>n_2^b+n_1^b+q$, $|Mroibvol|$ falls with further increases in $n^s{}_1$, 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

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

Thus, with no institutional liquidity demand, we predict that internalization of retail orders should

[62] That is, the n_0^s limit sell orders, and the $n_0^b \quad q \quad (n^s{}_2+n^s{}_1 \quad (n_2^b+n_1^b))$ remaining limit buy orders.

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, $\frac{\sum_j \Delta_j}{\sum_j (n_j^b + n^s{}_j)} < 0$.

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*.

A.2 Minimum Tick Sizes and Internalization

In this section, we exploit the design of the Tick Size Pilot to establish that variation in $Mroibtrd$ and $Mroibvol$ reflects the internalization decisions of wholesalers. We first examine the response in a wholesaler's appetite to internalize, proxied by the extent of off-exchange sub-penny BJZZ-identified trading volume, to a shock in the profitability of wholesaler liquidity provision. More importantly, we also analyze the effect of a shock to the cost of internalization on imbalances in $Mroibtrd$ and $Mroibvol$. This analysis allows us to link wholesaler cost-benefit considerations to their choices of which retail orders to internalize.

The SEC implemented the 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 of 400 stocks each. Treated stocks in Test Group 1 were subject to a minimum quoting requirement of 5¢ but could trade at price increments of 1¢—the ***quote rule*** (Rindi and Werner (2019)). Treated stocks in Test Groups 2 and 3 were subject to a minimum quoting requirement of 5¢ and had to trade at price increments of 5¢—the ***trade rule*** (Rindi and Werner (2019)). Test Group 3 stocks were also subject to a Trade-At Prohibition provision that effectively prevented sub-penny off-exchange execution prices, rendering test Group 3 irrelevant for our study (see Hu and Murphy (2022)).[63]

A key exception to the minimum tick size applied to retail trades. Although retail trades are quoted using the minimum tick size, they could be executed at sub-penny prices off-exchange. While TSP did not restrict the magnitudes of PI for test Group 1, the program imposed a minimum PI of 0.5¢ for off-exchange retail order executions of Test Group 2 stocks, raising the cost of internalizing orders in test Group 2 stocks above that for control and test Group 1 stocks.[64] This key difference provides an opportunity to examine the causal impacts of internalization costs on $Mroib$ imbalances.

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 do this for Test Group 2, after activation of the Trade Rule, we re-scale the algorithm's command that classifies trades according to small vs. large sub-penny increments by a factor of 5: in BJZZ's notation, we replace "$Z_{jt} = 100 * \text{mod}(P_{jt}, 0.01)$" by "$Z^5_{jt} = 20 * \text{mod}(P_{jt}, 0.05)$", where Z^5_{jt} is the ***sub-tick*** execution price (P_{jt}) increment for a 5¢ tick size. With this scaling, $Z^5_{it} \in [0, 1]$ and transactions can be classified into retail buy and retail sell trades as in Section 4.

The TPS provides an ideal setting to study the economics of retail flow internalization by wholesalers since the experiment raises (i) the profitability of off-exchange liquidity provision in all test groups (Rindi and Werner 2018); and (ii) the costs of internalization in test Group 2. 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 (DiD) methodology to examine the causal impact of a tick size change:

$$X_{j,d} = b^g_0 + b^g_1(\text{Post}_d) + b^g_2(\text{Treat}^g_j) + b^g_3(\text{Post}_j) \times (\text{Treat}^g_d) + u_{j,d}. \tag{3}$$

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.[65] $X_{j,d}$ is stock j's outcome variable on trading day d;

[63] Non-midpoint sub-penny trade executions remain available for Group 3 stocks through exchange retail liquidity programs. However, these executions do not involve wholesalers.

[64] Highlighting the binding nature of this constraint for test Group 2 stocks, Figure C.1 illustrates that absent the minimum 0.5¢ PI restrictions, wholesalers offer only 0.01¢ PI most of the time, implying that this restriction raised the PI-driven cost of internalization by a factor of 50 for most internalized trades.

[65] Our 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

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 (A.2). Following standard practice (see Rindi and Werner (2019), Griffith, Roseman, and Shang (2020), Albuquerque, Song, and Yao (2020), we condition estimates on quoted spread levels prior to the introduction of TSP.

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. For each stock, we construct daily observations over the 10 trading days prior to implementation of TSP on 10/03/2016 as well as the 10 trading days after full implementation on 10/17/2016.[66] 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.

Table A.1 presents estimation results for Test Group 1. Panels A-C in Figure A.1 provide complementary visual evidence. The quote rule raises the average and median volume of sub-penny-executed trades by 9% and 63% relative to the corresponding intercept, respectively.[67] This indicates that the quote rule causes wholesalers to internalize retail orders more aggressively. The effects are stronger for stocks with tighter pre-TSP quoted spreads—stocks that are more likely to

303 stocks on 10/17/2016.

[66] Implementation 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.

[67] Rindi and Werner (2019) 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.

have binding quote test restrictions.

Table A.1. Retail Order Internalization and Tick Size Pilot *Quote Rule*. This table reports OLS and Quantile (median) Regression (QR) estimates of equation (A.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 $Mroibvol$; and (3) the total share volume, in round lots, of trades receiving price improvement (PI shr vol). 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:	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol
Intercept	0.31***	0.39***	14517.1***	0.31***	0.39***	14517.1***
	[198.21]	[225.90]	[74.77]	[173.36]	[208.29]	[89.14]
PrePost	−0.047***	−0.047***	6277.4***	0.10***	0.12***	−8964.6***
	[−17.74]	[−16.08]	[18.90]	[32.11]	[34.77]	[−32.32]
Treat	−0.012***	−0.0099**	462.3	−0.012***	−0.0099**	462.3
	[−3.15]	[−2.33]	[0.97]	[−2.76]	[−2.15]	[1.16]
PrePost*Treat	0.0034	0.0015	1360.3*	−0.019**	−0.010	−334.1
	[0.54]	[0.21]	[1.70]	[−2.46]	[−1.25]	[−0.49]

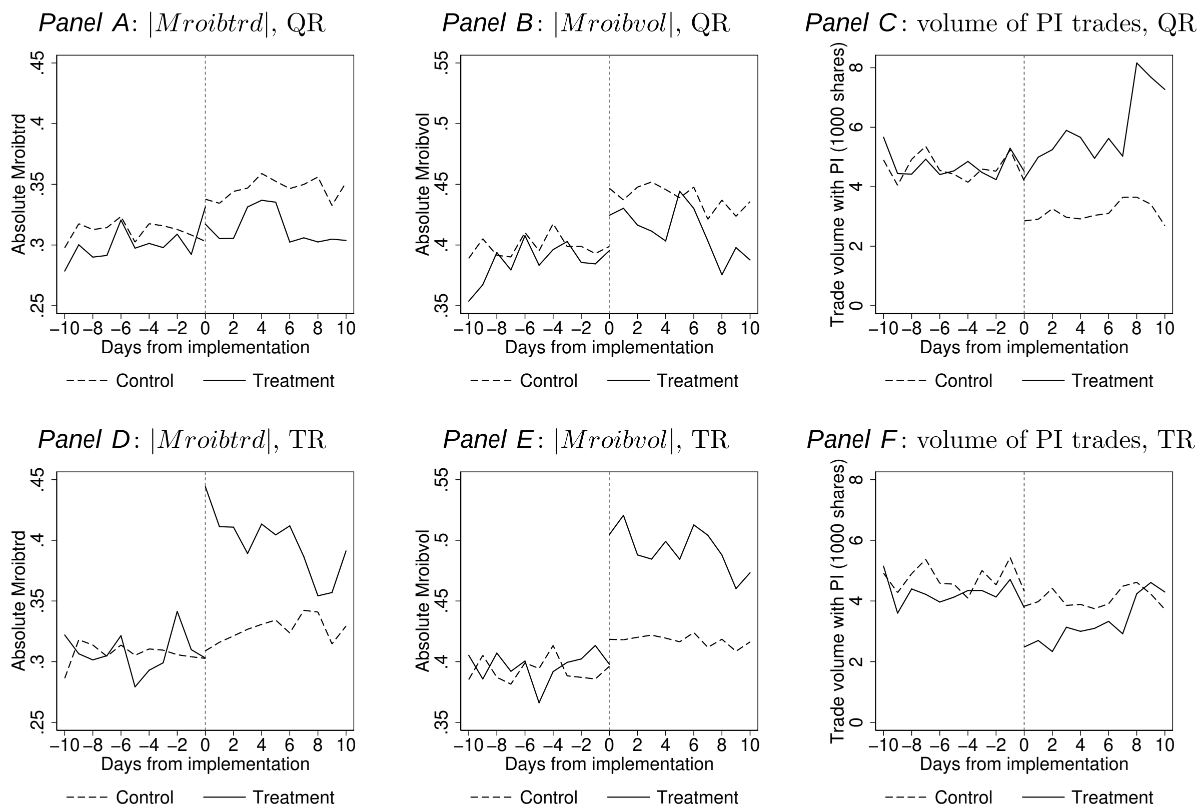
	Panel C: Low-spread stocks, QR			Panel D: High-spread stocks, QR		
Outcome variable:	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol
Intercept	0.23***	0.32***	4893***	0.23***	0.32***	4893***
	[132.83]	[136.29]	[71.81]	[102.92]	[112.02]	[107.96]
PrePost	−0.029***	−0.040***	4389***	0.097***	0.14***	−3506***
	[−9.81]	[−10.07]	[37.65]	[24.58]	[27.06]	[−45.42]
Treat	−0.014***	−0.015***	−86	−0.014***	−0.015**	−86
	[−3.40]	[−2.62]	[−0.52]	[−2.63]	[−2.15]	[−0.78]
PrePost*Treat	0.014**	0.011	3057***	−0.023**	−0.0075	927***
	[2.04]	[1.18]	[10.87]	[−2.44]	[−0.61]	[4.85]

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,[68] replacing the set of attractive non-marketable limit orders with marketable limit orders.[69] More importantly, widening the quoted spread increased the profitability of off-exchange liquidity provision at the midpoint, increasing the willingness of wholesalers to

[68] Werner 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.

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

Figure A.1. **Tick Size Pilot.** This figure provides visual evidence associated with the results of the Difference-in-Difference specification in equation (A.2) for Test Group 1 and 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: the absolute value of $Mroibtrd$; the absolute value of $Mroibvol$; and the total share volume of trades receiving price improvement. Panels A-C and D-F present findings associated with the Quote Rule (QR) and Trade Rule (TR), respectively.



internalize order flow.

Table A.1 reports that the intensity of sub-penny-executed retail trades—as measured by the total volume of price-improved trades—rises due to the minimum 5¢-spread. In contrast, the absolute values of $Mroibvol$ and $Mroibtrd$ fall, 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 internalization rather than retail trading per se.

Table A.2 presents estimation results for Test Group 2 that introduced a 0.5¢ minimum PI in addition to the 5¢ pricing increment. Panels D–F in Figure A.1 provide complementary visual evidence. In contrast to the quote-rule treatment, the trade-rule treatment caused the absolute values of $Mroibtrd$ and $Mroibvol$ to increase dramatically, even though the treatment ***reduced*** the volume of internalized (sub-penny) trades. For stocks with tight spreads, median internalized trade volume fell by 47%relative to the corresponding intercept, while trade volume is unchanged for stocks with wide spreads.[70]

Table A.2. **Retail Order Internalization and Tick Size Pilot *Trade Rule*.** This table reports OLS and quantile (median) regression estimates of equation (A.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 $Mroibvol$; and (3) the total share volume, in round lots, of trades receiving price improvement (PI shr vol). 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:	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol
Intercept	0.31***	0.39***	14695.6***	0.31***	0.39***	14695.6***
	[198.89]	[225.93]	[75.76]	[172.60]	[207.06]	[90.92]
PrePost	−0.056***	−0.065***	7917.6***	0.087***	0.10***	−8872.9***
	[−21.80]	[−22.28]	[23.91]	[27.91]	[31.63]	[−32.19]
Treat	0.0043	0.011**	−1382.4***	0.0043	0.011**	−1382.4***
	[1.13]	[2.53]	[−2.92]	[0.98]	[2.32]	[−3.51]
PrePost*Treat	0.032***	0.076***	−3277.9***	0.042***	0.052***	591.6
	[5.13]	[10.79]	[−4.07]	[5.44]	[6.27]	[0.88]

	Panel C: Low-spread stocks, QR			Panel D: High-spread stocks, QR		
Outcome variable:	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	PI shr vol
Intercept	0.22***	0.31***	4948***	0.22***	0.31***	4948***
	[125.61]	[131.66]	[71.84]	[97.95]	[111.11]	[109.61]
PrePost	−0.036***	−0.052***	5796***	0.075***	0.12***	−3296***
	[−11.86]	[−13.06]	[49.29]	[18.57]	[23.75]	[−42.81]
Treat	0.0058	0.0065	−546***	0.0058	0.0065	−546***
	[1.31]	[1.12]	[−3.25]	[1.03]	[0.94]	[−4.96]
PrePost*Treat	0.027***	0.091***	−2326***	0.028***	0.092***	120
	[3.71]	[9.32]	[−8.13]	[2.75]	[7.45]	[0.64]

In Group 2 stocks, the trade rule's minimum 0.5¢ PI requirement sharply raises the costs of internalizing retail orders. The increases in $|Mroibtrd|$ and $|Mroibvol|$ let us attribute the increased variation in $Mroib$ to this increased cost.[71] We posit that these effects manifest themselves in

[70] Our findings are robust to correcting for multiple-testing issues due to reusing natural experiments. Almost all t-statistics associated with the significant treatment effects in Tables A.1 and A.2 exceed the heuristic critical values of 2.5 and 3.0 proposed by Heath et al. (2022).

[71] The increased variation in $Mroib$ may also reflect the increased share of non-marketable limit orders in all internalized order flow. The trade rule 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 more than 1¢), retail traders would rely more on marketable limit orders in lieu of market orders. By the time a wholesaler handles orders flagged as marketable limit, some will have become non-marketable due to updates in the order book, increasing the share of non-marketable limit orders, and hence reducing internalization. Again, internalization is reduced by less when there is (more profitable) institutional demand on the other side than when are retail market orders, resulting

the increased sensitivity of $Mroib$ to institutional liquidity demand, as the orders that are more costly to internalize are the marginal retail orders used to provide liquidity to institutions through internalization. Section C.3 provides further support for this prediction when $Mroib$ is constructed from retail orders with price improvement levels that are relatively more likely to be associated with internalized orders executed at prices falling over 1¢ inside the NBBO.

These findings based on the TSP reinforce conclusions that variations in $Mroibtrd$ and $Mroibvol$ are largely not due to imbalances in the underlying retail order flow. Instead, these measures reflect wholesaler decisions of whether to internalize retail order flow. Our findings also indicate that $Mroib$ is unlikely to capture directional informed retail trading. Interpreting the higher $|Mroib|$ associated with Test group 2 stocks as due to increased informed retail trading would imply that wholesalers pay ***more*** PFOF + PI to internalize more toxic (informed) retail orders. This is hard to reconcile with any notion of profit-maximization by wholesalers. In contrast, the willingness to pay more for internalizing these marginal orders is consistent with wholesalers facilitating liquidity provision when institutional demand is high. Having established that wholesaler internalization choices are responsible for variation in $Mroib$, we now examine the cross-sectional variation in $Mroib$.

B Signed *Mroib*'s Return Predictability

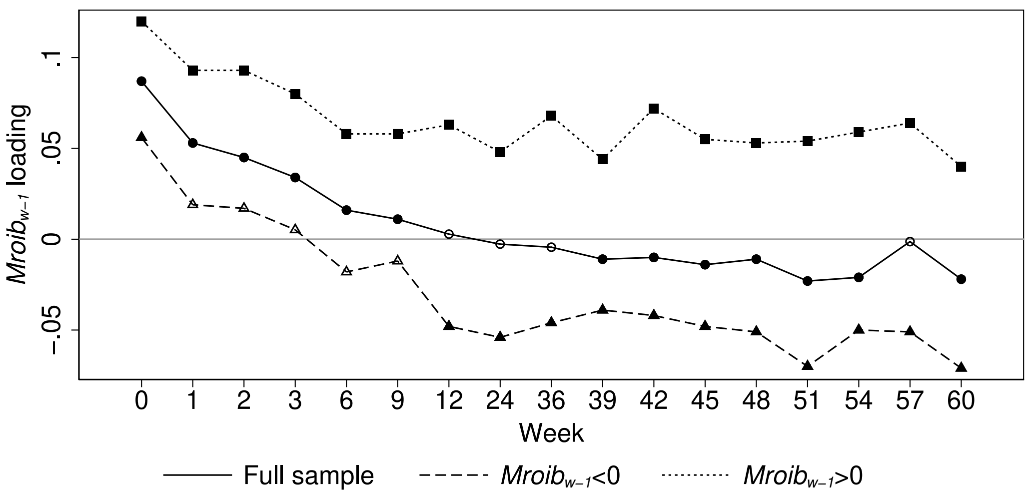
In this section, we examine the return predictability of $Mroib$ in more detail. Our findings are inconsistent with $Mroib$ capturing informed retail order flow. In contrast, near-term future weekly returns conditional on $Mroib$ are consistent with price reversals following liquidity consumption by institutional investors.

We estimate (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. As in BJZZ, we estimate equation (1) using Fama-Macbeth regressions, featuring Newey-West corrected standard errors with 6 lags. We extend their analysis in three ways. First, we estimate the weekly return predictability of $Mroibvol_{j,w\;1}$ for up to 60 weeks ahead (past the 12 weeks in BJZZ). Second, we estimate return predictability conditional on the sign of $Mroibvol_{j,w\;1}$. Third, we decompose returns entering the left-hand-side of equation (1) into intraday and overnight components.

Striking evidence obtains. Figure B.1 shows that the coefficients on $Mroibvol_{j,w\;1}$ become

in more unbalanced $Mroib$.

Figure B.1. Internalized Order Flow and the Cross-sections of Future Weekly Returns. This figure shows the associations between $Mroibvol_{w-1}$ 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 standard errors with 6 lags. Statistically significant and insignificant $Mroibvol_{w-1}$ loadings at the 10% type one error are identified by *filled* and *hollow* markers, respectively. 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.



uniformly negative after 39 weeks. This is inconsistent with informed retail trading, but consistent with return dynamics reflecting pricing errors (Hendershott, Menkveld, Praz, and Seasholes (2022)). The far-future return reversals are also consistent with the positive association between $Mroib$ and changes in short interest documented in Table 2. As established by the literature, increased short interest (associated with higher $Mroib$) predicts lower future returns, while decreased short interest (associated with lower $Mroib$) predicts higher future returns (Desai et al. (2002); Engelberg et al. (2012); Boehmer and Wu (2013)). 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 $w + 6$, contrary to retail sell orders being informed, as "retail sell order flow" realizes weekly losses due to persistent price appreciation after 6 weeks. In contrast, a positive $Mroibvol_{j,w-1}$ yields a positive coefficient for weekly returns across all horizons.

Decomposing returns into intraday and overnight components uncovers further asymmetries in the loadings conditional on the sign of $Mroibvol_{j,w-1}$. For overnight returns, $\hat{c}^1_w$ is positive after negative $Mroibvol_{j,w-1}$ (retail selling, institutional buying), but negative and insignificant after positive $Mroibvol_{j,w-1}$ (retail buying, institutional selling). Barclay and Hendershott (2003) and

Jiang, Likitapiwat, and T. McInish (2012) show that overnight price movements are information-driven; the insignificant negative relation between net retail buying imbalances and next week's overnight returns indicates that retail buys are not informed.[72] Moreover, informed retail trading cannot explain why $\hat{c}_w^1$ switches sign for intraday returns when $Mroibvol_{j,w-1}$ switches sign.[73]

C Why Does *Mroib* Predict Short-Term Returns?

In this section, we report how wholesaler liquidity provision to institutional investors is responsible for the return predictability of $Mroib$. Specifically, we attribute this return predictability to the unwinding of institutional price pressure.

C.1 Dynamics of Institutional and Retail Order Flows

In Section 5.2, we documented that overnight reversals exceeded intraday price pressure (in the same week). This section reconciles this phenomenon by showing that 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.

To show this, we estimate

$$\begin{aligned} X_{j,w} &= a^0 + \sum_{i=1}^{6} a_i^1 Inoibvol_{j,w-i} + \sum_{i=1}^{6} a_i^2 \left[I(Inoibvol_{j,w-i} < 0) \right] \\ &+ \sum_{i=1}^{6} a_i^3 \left[I(Inoibvol_{j,w-i} < 0) \times Inoibvol_{j,w-i} \right] + \epsilon_{j,w}, \end{aligned} \tag{4}$$

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.[74] To reduce the noise attributable to a lack of coverage we use the subset of stocks for which the share of ANcerno-

[72] Furthermore, 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.

[73] Table ?? 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.

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

reported volume relative to CRSP is above-average.

Columns (1)–(4) in Table C.1 present the AR(k) estimates for $Inoibvol$, showing that past positive and negative institutional trade imbalances, especially those for institutional buying, predict current institutional trade imbalances differently. The most recent week's positive and negative $Inoibvol$ predict current week's $Inoibvol$ 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 a literature that finds long-only fund managers accumulate long positions slowly, but sell quickly, largely to fund purchases.[75] 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 C.1 highlight how past institutional trade imbalances predict future 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.[76] Mirroring the weaker auto-correlation in institutional trade imbalances 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 2, 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 institutions' demand for retail sourced liquidity. The negative correlation between past positive institutional trade imbalances and current internalized retail order flow is consistent with institutions resorting to retail-sourced liquidity, provided by wholesalers, especially in less liquid markets.

[75] This asymmetry is consistent with institutional buying, but not selling, being motivated by a fund manager's best ideas (Akepanidtaworn et al. 2021). This leads managers to accumulate long positions more slowly to conceal their presence, prolonging the unwinding of price pressure. Hendershott and Seasholes (1994) also find that short positions of market makers, which are accumulated due to institutional buying, are associated with subsequent price reversals that last up to 11 trading days. In contrast, price reversals following the accumulation of long positions by market markers, which reflect institutional selling, only last for 7 trading days.

[76] The only exception to statistical significance appears in column (8) for $Inoibvol_{w\ \ 5}$.

Table C.1. Asymmetric Persistence in Institutional Trade Imbalances: Implications for Retail Flow Internalization. This table presents estimates of the predictive power of past institutional trade imbalance, conditional on its sign, for both current institutional trade imbalance and current internalized retail order flow. Columns (1)–(4) report estimation results of equation (4) for i 2 f3, 4, 5, 6g and $X = Inoibvol_w$. Columns (5)–(8) report estimation results of equation (4) for i 2 f3, 4, 5, 6g 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**	0.038	0.023	0.0088	−0.16***	−0.15***	−0.15***	−0.14***
	[2.46]	[1.42]	[0.86]	[0.32]	[−14.54]	[−13.32]	[−12.50]	[−11.77]
$Inoibvol_{w \; 1}$	0.33***	0.33***	0.33***	0.33***	−0.016***	−0.016***	−0.016***	−0.016***
	[58.36]	[59.42]	[58.50]	[58.00]	[−7.43]	[−7.86]	[−7.66]	[−7.58]
$I(Inoibvol_{w \; 1} < 0) \times Inoibvol_{w \; 1}$	0.020***	0.022***	0.022***	0.023***	0.0083***	0.0085***	0.0081**	0.0085***
	[2.71]	[2.98]	[3.03]	[3.24]	[2.63]	[2.69]	[2.56]	[2.65]
$Inoibvol_{w \; 2}$	0.075***	0.072***	0.071***	0.069***	−0.0067***	−0.0062***	−0.0060***	−0.0059***
	[17.07]	[16.60]	[16.60]	[15.35]	[−3.41]	[−3.06]	[−2.94]	[−2.90]
$I(Inoibvol_{w \; 2} < 0) \times Inoibvol_{w \; 2}$	−0.023***	−0.020***	−0.020***	−0.018**	0.0059*	0.0051	0.0046	0.0044
	[−3.06]	[−2.70]	[−2.68]	[−2.46]	[1.85]	[1.57]	[1.38]	[1.31]
$Inoibvol_{w \; 3}$	0.062***	0.048***	0.045***	0.043***	−0.0069***	−0.0054***	−0.0052**	−0.0050**
	[13.26]	[10.52]	[9.90]	[9.65]	[−3.40]	[−2.64]	[−2.53]	[−2.41]
$I(Inoibvol_{w \; 3} < 0) \times Inoibvol_{w \; 3}$	−0.017***	−0.014**	−0.012*	−0.011*	0.0091***	0.0079***	0.0078***	0.0077**
	[−2.63]	[−2.14]	[−1.86]	[−1.79]	[3.09]	[2.66]	[2.63]	[2.54]
$Inoibvol_{w \; 4}$		0.052***	0.040***	0.037***		−0.0055***	−0.0048**	−0.0050**
		[12.29]	[9.65]	[8.77]		[−2.64]	[−2.30]	[−2.40]
$I(Inoibvol_{w \; 4} < 0) \times Inoibvol_{w \; 4}$		−0.023***	−0.021***	−0.019***		0.0078**	0.0080***	0.0078***
		[−3.51]	[−3.20]	[−2.90]		[2.58]	[2.69]	[2.60]
$Inoibvol_{w \; 5}$			0.041***	0.031***			−0.0041**	−0.0028
			[10.22]	[7.73]			[−2.11]	[−1.38]
$I(Inoibvol_{w \; 5} < 0) \times Inoibvol_{w \; 5}$			−0.029***	−0.025***			0.00047	0.000084
			[−4.14]	[−3.78]			[0.16]	[0.03]
$Inoibvol_{w \; 6}$				0.037***				−0.0044**
				[9.35]				[−2.15]
$I(Inoibvol_{w \; 6} < 0) \times Inoibvol_{w \; 6}$				−0.026***				0.0019
				[−3.79]				[0.63]
Observations	976,110	976,110	976,110	976,110	976,110	976,110	976,110	976,110

C.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 liquidity demand, especially institutional buying, overnight price reversals associated with extreme $Mroibvol$ magnitudes extend into future weeks. This creates distinguishable differences between close-to-close returns that follow extremely negative and extremely positive internalized retail order flow imbalances.

To highlight the persistence of institutional liquidity demand, we estimate

$$\begin{aligned} Inoibvol_{j,w} &= c^0 + \sum_{i=1}^{6} c_i^1 Mroibvol_{j,w\ \ i} + \sum_{i=1}^{6} c_i^2 \left[I(Inoibvol_{j,w\ \ i} < 0) \right] \\ &+ \sum_{i=1}^{6} c_i^3 \left[I(Inoibvol_{j,w\ \ i} < 0) \times Mroibvol_{j,w\ \ i} \right] + \epsilon_{j,w}. \end{aligned} \tag{5}$$

Variable definitions and estimation approaches are identical to those in equation (4). Table C.2 shows that 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 buy pressure is higher, the greater internalization of retail sell orders relative to buy orders is associated with abnormally high institutional buy pressure for up to two weeks ahead. This persistence drives subsequent abnormally negative overnight returns, due to reversals after institutional price pressure that skew future weeks' close-to-close returns downward. Thus, while $Mroibvol$ seems to predict future close-to-close returns, this just reflects price reversals following institutional buy pressure.

C.3 Implications of the Size of Price Improvement

To provide further support for how wholesaler choices drive $Mroib$ imbalances, we now delve more deeply 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 stronger institutional demand for liquidity, as manifested by more extreme institutional trade imbalance and price impacts, is associated with more costly internalization, i.e., internalized retail orders not only with larger sub-penny price improvements but also a higher probability of execution at prices inside the NBBO by over 1¢.

Figure C.1 plots the histogram of sub-penny price improvements associated with internalized retail trades, as identified by BJZZ's algorithm. Over 80% of sub-penny PIs are at 0.01¢, 0.1¢, 0.2¢, 0.25¢, 0.3¢, or 0.4¢ increments, suggesting that simple informal agreements govern price improvement schedules. More importantly, we find that (1) the size of price improvement is positively related to the bid-ask spread; (2) the sub-penny increments of PIs are larger when internalized orders are executed inside the NBBO by over 1¢; and (3) more frequent such inside-quote internalization is associated with wider bid-ask spreads.

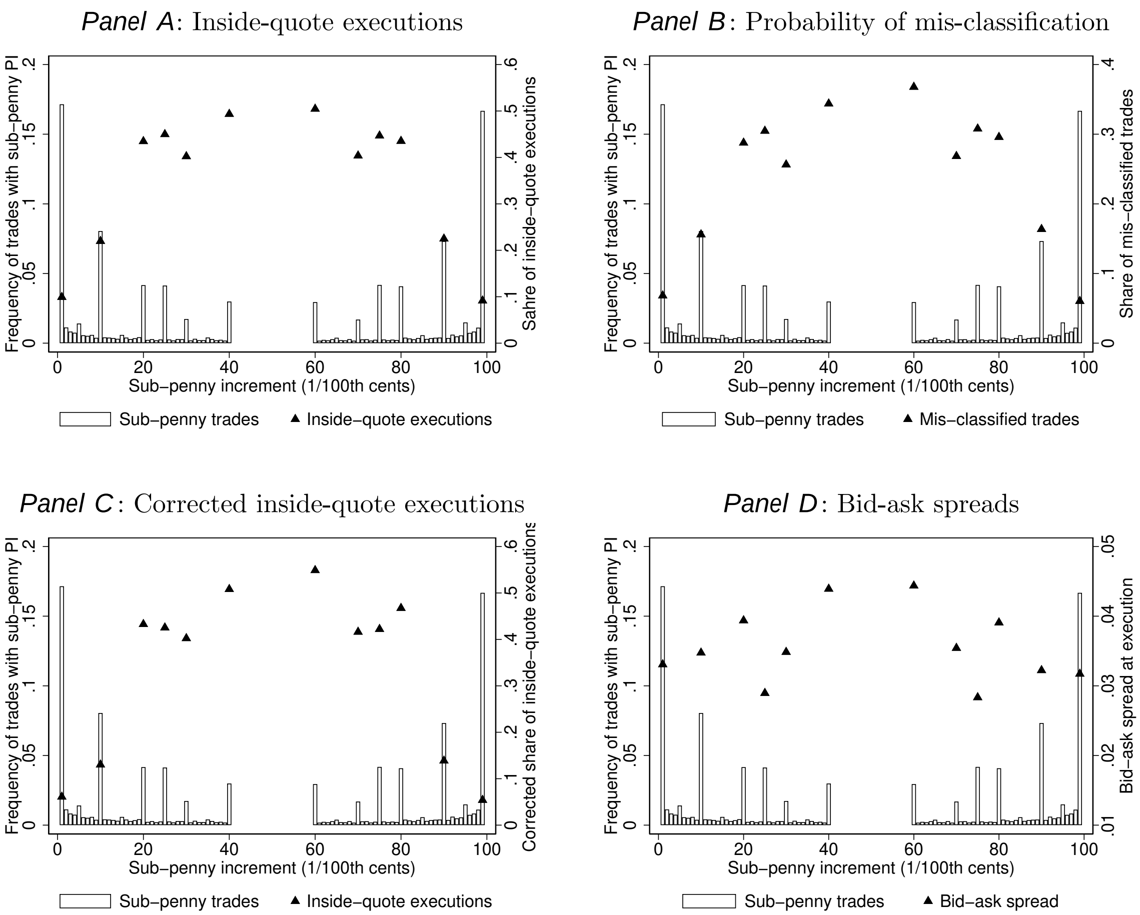
Table C.2. Predictability of Institutional Trade Imbalances Using Internalized Retail Trading Imbalance. This table presents estimates of the predictive power of past internalized order flow, conditional the sign the corresponding institutional trade imbalance, for current institutional trade imbalance. Equation (5) 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***	1.09***	1.14***	1.17***
	[39.71]	[40.99]	[41.98]	[43.14]
$Mroibvol_{w\ 1}$	−0.020***	−0.021***	−0.021***	−0.020***
	[−3.69]	[−3.74]	[−3.74]	[−3.57]
$I(Inoibvol_{w\ 1} < 0) \times Mroibvol_{w\ 1}$	0.021***	0.020***	0.020***	0.021***
	[2.85]	[2.78]	[2.81]	[2.79]
$Mroibvol_{w\ 2}$	−0.013**	−0.014**	−0.013**	−0.013**
	[−2.43]	[−2.56]	[−2.43]	[−2.38]
$I(Inroibvol_{w\ 2} < 0) \times Mroibvol_{w\ 2}$	0.025***	0.025***	0.025***	0.024***
	[3.41]	[3.39]	[3.42]	[3.30]
$Mroibvol_{w\ 3}$	−0.0043	−0.0063	−0.0054	−0.0067
	[−0.72]	[−1.13]	[−0.93]	[−1.14]
$I(Inoibvol_{w\ 3} < 0) \times Mroibvol_{w\ 3}$	0.017**	0.018***	0.019***	0.020***
	[2.38]	[2.59]	[2.59]	[2.72]
$Mroibvol_{w\ 4}$		0.0047	0.0054	0.0035
		[0.70]	[0.87]	[0.57]
$I(Inoibvol_{w\ 4} < 0) \times Mroibvol_{w\ 4}$		0.0017	0.0038	0.0038
		[0.23]	[0.51]	[0.52]
$Mroibvol_{w\ 5}$			−0.0058	−0.0065
			[−1.08]	[−1.20]
$I(Inoibvol_{w\ 5} < 0) \times Mroibvol_{w\ 5}$			−0.0036	−0.0018
			[−0.45]	[−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

We first observe that BJZZ's algorithm, which does not require the use of quote data, incorrectly signs some buy retail trades as sells, and vice versa. We describe the source of mis-classification with an example: suppose the NBB and NBO are $9.97 and $10.03, and a marketable buy order placed at $10.03 is executed at $10.013. BJZZ's algorithm observes the sub-penny increment of 0.3¢ and signs this transaction as a sell, but the trade is actually a buy receiving price improvement of 1.7¢. As Section 5.2 notes, Battalio et al. (2022) show that many trade mis-classifications reflect the algorithm's inclusion of some institutional trades.

Matching each transaction with the corresponding NBBO and comparing execution prices against quote midpoints yields estimates for the share of incorrectly-signed trades by sub-penny

Figure C.1. **Distributions of Sub-penny trades, Bid-Ask Spreads, and the Probability of Inside-Quotes Execution.** This figure plots a histogram of sub-penny price improvements (in $1/100^{th}$ cents) associated with transactions. For each stock-year, the frequency of trades associated with each of the 80 sub-penny increments, from 0.01¢ through 0.40¢ and from 0.60¢ through 0.99¢ is calculated. The mean frequency for a given increment, measured on the left axes of the for panels, is then averaged across stocks and years. The figure also reports, for the 12 most frequent sub-penny price improvement outcomes, (1) the share of corresponding transactions executed by at least 1¢ inside the NBBO (Panel A); (2) the share of transactions mis-classified by the BJZZ algorithm (Panel B); (3) the share of corresponding transactions executed by at least 1¢inside the NBBO after removing mis-classified trades from the sample (Panel C); and (4) average bid-ask spread at the time of execution (Panel D).



increment.[77] Panel B in Figure C.1 shows that this share rises sharply with the distance of the sub-penny increment from the nearest full penny. Importantly, an unreported robustness analysis reveals that all of our main findings continue to hold when we correct for the mis-classification of trades, likely because our aggregation to the weekly level mitigates the largely idiosyncratic nature of mis-classified buy and sell trades. Complementing our findings in Section 5.2, this robustness finding indicates that imbalances in sub-penny executed institutional trades not reported

[77] Barber et al. (2022) use a similar approach to identify signing errors in BJZZ's algorithm.

by ANcerno do not drive the variation in $Mroib$.

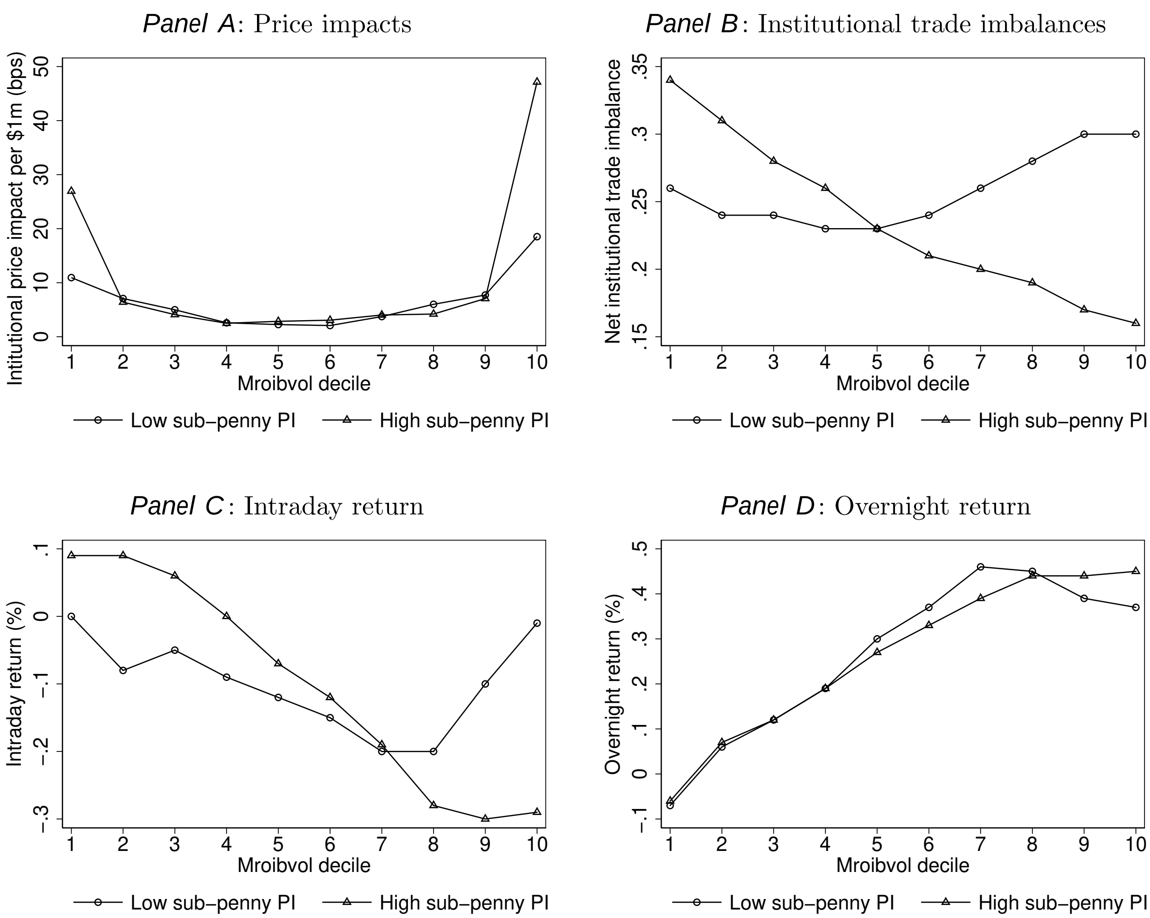
We next document a strong relation between the size of sub-penny increment of PIs and the likelihood that the corresponding execution takes place inside the NBBO by over 1¢. This finding is robust to removing mis-classified retail trades from the sample. As Panels A and C in Figure C.1 illustrate, the share of internalized retail orders whose execution price is at least 1¢ better than the NBBO at the time of transaction rises sharply with the size of sub-penny PI increment. For example, after removing mis-classified trades, this share goes from about 5% to over 50% as the sub-penny increment of PI goes from 0.01¢ (0.99¢) to 0.4¢ (0.6¢). Moreover, Panel D of Figure C.1 shows that both larger sub-penny PI increments and more frequent inside-quote executions are associated with wider bid-ask spreads. Overall, our findings suggest that wholesalers are willing to spend more PFOF+PI to internalize orders in less liquid markets. We next show that the imbalance in these more costly internalized orders is more strongly related to institutional trading costs than the imbalance in the less costly internalized orders, highlighting the economic motives that justify such costlier internalization.

Figure C.1 shows that the median sub-penny price improvement is 0.1¢. This leads us to construct two versions of $Mroibvol$, one for internalized retail orders with "small" sub-penny PI increments of less than 0.1¢ and one for "large" such increments of at least 0.1¢.[78] We then compare institutional trading outcomes, price impacts, institutional trade imbalances, intraday returns (proxy for institutional price pressure), and overnight return (proxy for the unwinding of institutional price pressure), across the two versions of $Mroibvol$.

Panel A in Figure C.2 shows that price impacts display far stronger ∪-shaped patterns for high-sub-penny $Mroibvol$ than for low-sub-penny $Mroibvol$. That is, the most extreme high-sub-penny $Mroibvol$ observations occur when institutional trading costs are highest. This result reinforces that the unbalanced internalization of retail orders that are more costly to internalize, due to large price improvements, occurs when wholesalers provide liquidity to institutions willing to incur larger price impacts to locate liquidity. Panel B provides further evidence of this mechanism, showing a sharp inverse relationship between institutional trade imbalances and high-sub-penny $Mroibvol$,

[78] Unreported results establish that the predictive power of $Mroib$ for short-term future returns is not affected by the size of sub-penny PI used to construct $Mroib$ with a 0.1¢ threshold. BJZZ classify transactions into those with small versus large price improvement using a 0.2¢ cutoff. The 0.2¢ threshold assigns over 75% of internalized retail trades to the "small" sub-penny group, resulting in a noisy $Mroib$ based on "large" PI.

Figure C.2. Price Impacts, Institutional Trade Imbalances, Intraday Returns, and Overnight Returns Conditional on the Magnitude of Price Improvement. This figure compares contemporaneous institutional price impacts, institutional net trade imbalance, intraday returns, and overnight returns when $Mroirbvol$ is constructed using retail trades with sub-penny price improvements that are low (< .01¢) versus high (.01¢). 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 price impacts (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.



highlighting how institutional liquidity demand drives the unbalanced and costly internalization of retail orders on the opposite side. In contrast, institutional trade imbalance is weakly ∪-shaped conditional on low-sub-penny $Mroibvol$. Building on these insights, Panels C and D show that as high-sub-penny $Mroibvol$ rises, intraday returns fall from 10bps to -30bps while overnight returns reverse in the opposite direction. That is, high-sub-penny $Mroibvol$ is associated with institutional price pressure followed by overnight reversals. In contrast, with small-sub-penny $Mroibvol$, returns mirror the weak ∪-shaped pattern in institutional trade imbalances.

D *ILM*s, Existing Liquidity Measures, and Institutional Price Impacts: Excluding Low Sub-Penny Volume Stocks

This section establishes that the findings documents by Figure 4 and Table 5 are not driven by stocks with low levels of trading volumes executed at sub-penny prices.

Table D.1. Institutional Liquidity Measures and Stock Characteristics. The table reports on the cross-sectional relation between ILMs and (1) three-factor Fama-French betas, (2) book-to-market ratios (BM), (3) natural log of market capitalizations (ln(Mcap)), (4) dividend yields (DYD), (5) idiosyncratic volatilities (IdVol), (6) previous month's returns ($RET_{(\ 1)}$), and (7) preceding returns from the prior 11 months ($RET_{(\ 12,\ 2)}$). Stock characteristics are computed from the prior month. Each weekly cross-section is sorted into ILM deciles. The average outcome variable is calculated by $ILMT$ decile in each cross-section before the average of the time-series is calculated. Panels A and B report the results for $ILMT$ and $ILMV$, respectively. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2 and stocks falling in the bottom 10% of the share of sub-penny executed volume in total volume.

Panel A: Trade-based Institutional Liquidity Measures ($ILMT$s) versus stock characteristics

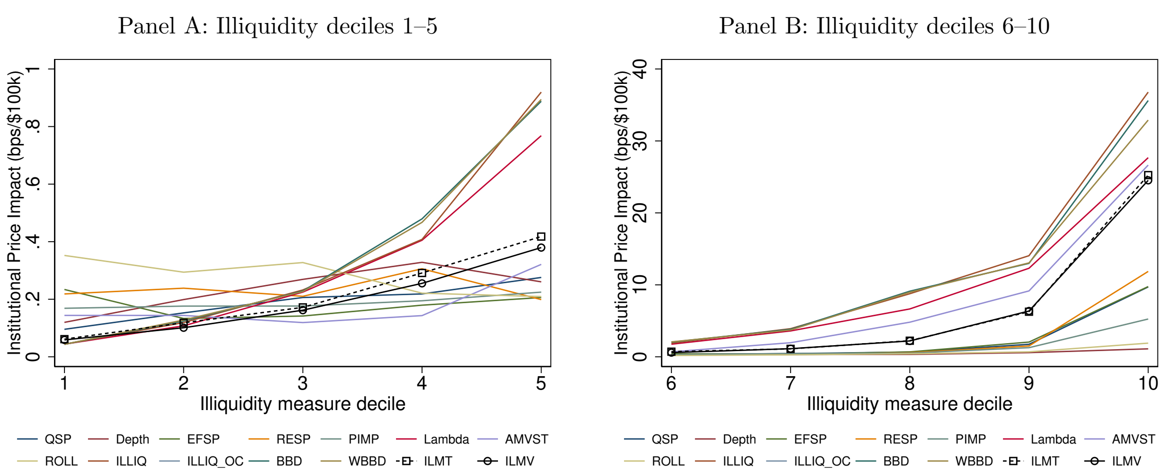
	Weekly $ILMT$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.02	1.02	1.02	1.01	1.00	0.99	0.97	0.93	0.88	0.82
β^{hml}	0.73	0.73	0.73	0.73	0.74	0.75	0.76	0.77	0.78	0.79
β^{smb}	0.15	0.15	0.16	0.16	0.17	0.17	0.18	0.20	0.22	0.24
BM	0.64	0.64	0.65	0.65	0.66	0.67	0.68	0.72	0.76	0.80
ln(Mcap)	20.99	20.98	20.95	20.91	20.85	20.76	20.64	20.38	20.05	19.71
DYD	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.015	0.015
Id. Vol.	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.022	0.022
$RET_{(\ 1)}$	0.016	0.018	0.016	0.017	0.016	0.015	0.014	0.015	0.015	0.016
$RET_{(\ 12,\ 2)}$	0.19	0.19	0.19	0.19	0.19	0.18	0.17	0.16	0.15	0.14

Panel B: Volume-based Institutional Liquidity Measures ($ILMT$s) versus stock characteristics

	Weekly $ILMV$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.07	1.07	1.06	1.04	1.02	1.00	0.94	0.94	0.89	0.73
β^{hml}	0.71	0.71	0.72	0.73	0.73	0.75	0.74	0.79	0.82	0.77
β^{smb}	0.12	0.12	0.13	0.14	0.15	0.17	0.19	0.21	0.25	0.29
BM	0.62	0.62	0.63	0.63	0.64	0.65	0.70	0.70	0.74	0.87
ln(Mcap)	21.29	21.26	21.19	21.10	20.97	20.81	20.45	20.36	20.01	19.26
DYD	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.015	0.015
Id. Vol.	0.022	0.022	0.022	0.021	0.021	0.021	0.021	0.020	0.021	0.021
$RET_{(\ 1)}$	0.019	0.018	0.017	0.016	0.016	0.015	0.014	0.014	0.014	0.015
$RET_{(\ 12,\ 2)}$	0.21	0.21	0.20	0.19	0.19	0.18	0.16	0.16	0.15	0.13

A potential concern with ILMs is that these measures do not account for the intensity of trade execution at sub-penny prices, allowing the effects of low sub-penny volume to be conflated with high imbalances in internalized retail orders. For example, suppose that 100,000 shares of both stocks A and B are traded on a given trading day. Also suppose that while stock A, on the same day, has 1,500 shares of buy retail trades and 1,000 shares of sell retail trades executed at sub-penny prices; stock B has 15,000 shares of buy and 10,000 shares of sell retail trades. For both stocks, $|Mroibvol| = 0.2$, even though retail trading in stock B is far higher than that in stock A. This leads us to examine the robustness of our results to excluding stocks whose share of sub-penny executed volume relative to total trading volume (SPVS) is low. Specifically, Table D.1 and Figure D.1 how that excluding stocks whose SPVS fall in the bottom 10% of each cross-section leaves our qualitative findings unaffected.

Figure D.1. ***ILMs*, Standard Liquidity Measures, and Future Institutional Price Impacts.** The table reports on the cross-sectional relation between various liquidity measures constructed in month m 2 and realized, post-trade institutional price impacts, InPrIm, (in bps per $100k) constructed in month m. Liquidity measures include (1) quoted bid-ask spread (QSP); (2) quoted depth at best prices (Depth); (3) effective spreads (EFSP); (4) realized spreads (RESP); (5) price impacts (PIMP); (6) Kyle's lambda estimates (Lambda); (7) Amvist illiquidity measure (AMVST); (8) Roll measure of realized spreads (ROLL); (9 & 10) close-to-close and open-to-close Amihud measures (ILLIQ & ILLIQ_OC); (11 & 12) simple and volume-weighted trade-time liquidity measures (BBD & WBBD); (13 & 14) trade- and volume-based institutional liquidity measures (ILMT & ILMV). Each month, stocks are sorted into deciles of liquidity, with decile 1 (10) reflecting the most (least) liquid stocks, based on a given liquidity measure from month m 2. Month m InPrIm of the median stock in each liquidity decile is averaged across months by liquidity decile. This average is plotted against the respective liquidity decile. Panels A and B report results for liquidity deciles 1 through 5 and 6 through 10, respectively. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2 and stocks falling in the bottom 10% of the share of sub-penny executed volume in total volume.



E Liquidity and Expected Returns: $1 and $5 Share Price Requirements

This section presents estimation results for equation (2) when low-priced stocks are excluded from the sample based on alternative cutoffs for prior month's share prices.

Panel A in Tables E.1 and E.2 reports estimation results when liquidity measures are constructed over one month using samples of stocks with previous month's minimum closing prices of $1 and $5, respectively. According to Table E.1, in a more inclusive sample with a less strict (under

Table E.1. Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILMs. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (2) is estimated using liquidity measures ($LIQ_{j,m\ \ 2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m\ \ 1}$, $\beta^{hml}_{j,m\ \ 1}$, $\beta^{smb}_{j,m\ \ 1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m\ \ 1$, book-to-market ratio, ($\text{BM}_{j,m\ \ 1}$), natural log of market capitalization, ($\ln(\text{Mcap}_{j,m\ \ 1})$), dividend yield ($\text{DYD}_{j,m\ \ 1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m\ \ 1$, idiosyncratic volatility ($\text{IdVol}_{j,m\ \ 1}$), previous month's return ($RET_{(\ \ 1)}$), and preceding return from the prior 11 months ($RET_{(\ \ 12,\ \ 2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $1. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock liquidity and the cross-section of expected returns

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
Constant	2.03	0.93	0.92	0.90	0.93	0.93	0.80	0.91	1.33	0.88	0.56	1.42	1.26	−0.87	−1.65
	[1.42]	[0.89]	[0.92]	[0.86]	[0.93]	[0.93]	[0.83]	[0.92]	[1.36]	[0.88]	[0.55]	[1.41]	[1.23]	[−0.58]	[−1.03]
Liquidity	**0.024**	**−0.023**	**−0.0000065**	**0.081**	**0.025**	**−0.068**	**0.034**	**0.10**	**−7.04*** **	**0.018**	**0.13** **	**0.18***	**0.39** **	**1.16** **	**1.36*** **
	[1.31]	**[−0.16]**	**[−1.51]**	**[0.41]**	**[0.32]**	**[−0.53]**	**[0.50]**	**[0.69]**	**[−3.27]**	**[0.68]**	**[2.20]**	**[1.75]**	**[2.07]**	**[2.57]**	**[3.04]**
β^{mkt}	−0.059	−0.25	−0.25	−0.25	−0.25	−0.25	−0.24	−0.25	−0.25	−0.25	−0.23	−0.26	−0.25	−0.17	−0.13
	[−0.15]	[−1.15]	[−1.13]	[−1.14]	[−1.13]	[−1.15]	[−1.11]	[−1.13]	[−1.14]	[−1.13]	[−1.06]	[−1.00]	[−0.97]	[−0.82]	[−0.66]
β^{hml}	−0.12	−0.080	−0.079	−0.080	−0.079	−0.079	−0.076	−0.079	−0.084	−0.081	−0.079	−0.045	−0.044	−0.091	−0.10
	[−0.83]	[−0.67]	[−0.66]	[−0.66]	[−0.66]	[−0.65]	[−0.63]	[−0.66]	[−0.70]	[−0.67]	[−0.66]	[−0.33]	[−0.32]	[−0.76]	[−0.84]
β^{smb}	0.046	0.033	0.034	0.034	0.033	0.032	0.036	0.035	0.028	0.033	0.052	0.061	0.067	0.066	0.079
	[0.44]	[0.44]	[0.45]	[0.46]	[0.44]	[0.43]	[0.49]	[0.47]	[0.38]	[0.45]	[0.74]	[0.77]	[0.85]	[0.91]	[1.09]
BM	0.19	0.046	0.046	0.046	0.046	0.045	0.036	0.045	0.049	0.049	0.034	0.065	0.062	0.043	0.043
	[1.27]	[1.08]	[1.10]	[1.09]	[1.08]	[1.06]	[0.84]	[1.06]	[1.18]	[1.13]	[0.82]	[1.29]	[1.21]	[1.02]	[1.03]
ln(Mcap)	−0.019	0.026	0.027	0.027	0.027	0.027	0.032	0.027	0.010	0.028	0.043	0.011	0.018	0.093	0.12*
	[−0.30]	[0.60]	[0.64]	[0.62]	[0.63]	[0.63]	[0.80]	[0.65]	[0.24]	[0.67]	[1.00]	[0.25]	[0.41]	[1.55]	[1.89]
DYD	0.16	−0.15	−0.17	−0.15	−0.17	−0.18	−0.18	−0.15	−0.17	−0.19	−0.18	−0.0020	0.0041	−0.23	−0.22
	[0.15]	[−0.28]	[−0.31]	[−0.29]	[−0.32]	[−0.34]	[−0.34]	[−0.28]	[−0.33]	[−0.35]	[−0.33]	[−0.00]	[0.01]	[−0.46]	[−0.44]
Id. Vol.	−0.19***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.19***	−0.20***	−0.21***	−0.25***	−0.25***	−0.19***	−0.18***
	[−2.82]	[−4.14]	[−4.14]	[−4.14]	[−4.14]	[−4.13]	[−4.23]	[−4.14]	[−3.93]	[−4.09]	[−4.21]	[−4.59]	[−4.59]	[−3.99]	[−3.84]
$RET_{\ \ 1}$	−0.69	−0.082	−0.084	−0.083	−0.068	−0.063	−0.070	−0.069	−0.11	−0.040	−0.080	−0.41	−0.44	−0.15	−0.21
	[−0.94]	[−0.16]	[−0.16]	[−0.16]	[−0.13]	[−0.12]	[−0.14]	[−0.13]	[−0.22]	[−0.08]	[−0.15]	[−0.72]	[−0.77]	[−0.29]	[−0.41]
$RET_{(\ \ 12,\ \ 2)}$	0.31*	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.19	0.19	0.21	0.21	0.23
	[1.87]	[1.04]	[1.01]	[1.03]	[1.04]	[1.04]	[1.06]	[1.03]	[1.01]	[1.02]	[1.26]	[1.08]	[1.18]	[1.29]	[1.40]
Observations	131,986[y]	360,626	360,626	360,626	360,626	360,626	360,066	360,624	360,626	360,624[yy]	360,624[yy]	294,284[yyy]	294,284[yyy]	360626	360626

Panel B: Loadings of ILMs in the cross-section of expected returns after orthogonalization relative to other liquidity measures

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
ILMT residual	0.18	1.22***	1.16**	1.17***	1.18**	1.18**	0.91*	1.16**	1.35***	1.06**	0.72	0.41	0.29	-	-
	[0.30]	[3.14]	[2.58]	[2.97]	[2.55]	[2.59]	[1.98]	[2.54]	[2.96]	[2.33]	[1.52]	[0.81]	[0.55]		
ILMV residual	0.26	1.45***	1.33***	1.40***	1.36***	1.38***	1.10**	1.34***	1.49***	1.25***	0.95**	0.59	0.48	-	-
	[0.42]	[3.79]	[3.03]	[3.60]	[3.00]	[3.09]	[2.43]	[2.97]	[3.32]	[2.82]	[2.05]	[1.16]	[0.92]		

[y] The number of observations reflects the largest sample of ANcerno data available from 2011-2014.
[yy] The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.
[yyy] The number of observations reflects the largest sample available for BBD and WBBD from 2010–2017.

$1) definition of penny stocks, ILMs continue to explain the cross-section of expected returns. However, reflecting the relevance of alternative liquidity measures for smaller firms, the open-to-close version of Amihud's liquidity measure, ILLIQ_OC, also explains expected stock returns in the 2010-2019 period, consistent with Barardehi et al. (2021). In addition, the trade-time liquidity measures, BBD and $WBBD$, explain expected stock returns in the 2010–2017 period, consistent with Barardehi et al. (2019). However, realized institutional price impacts (InPrIM) no longer explain expected returns, a possible consequence of including stocks that institutional investors are reluctant or unable to hold.

In contrast, Table E.2 reports that with a stricter (under $5) definition of penny stocks, which still excludes stocks held in limited amounts by institutional investors, ILMs and realized institutional price impacts explain the cross-section of returns. In addition, quoted depth has a negative coefficient, consistent with a characteristic liquidity premium, implying lower depth is associated with higher expected returns. In contrast, many standard liquidity measures, including spreads, Amihud, and trade-time measures, load with unexpected negative coefficients, indicating that such measures are unreliable liquidity measures for stocks more likely to be held by institutional investors. This reinforces the conclusion that standard liquidity measures are mostly relevant for small stocks.

Table E.2. Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILMs. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (2) is estimated using liquidity measures ($LIQ_{j,m\ \ 2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m\ \ 1}$, $\beta^{hml}_{j,m\ \ 1}$, $\beta^{smb}_{j,m\ \ 1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m\ \ 1$, book-to-market ratio, ($\mathrm{BM}_{j,m\ \ 1}$), natural log of market capitalization, ($\ln(\mathrm{Mcap}_{j,m\ \ 1})$), dividend yield ($\mathrm{DYD}_{j,m\ \ 1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m\ \ 1$, idiosyncratic volatility ($\mathrm{IdVol}_{j,m\ \ 1}$), previous month's return ($RET_{(\ \ 1)}$), and preceding return from the prior 11 months ($RET_{(\ \ 12,\ \ 2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $5. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock liquidity and the cross-section of expected returns

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
Constant	1.34	1.42	1.31	1.39	1.35	1.39	1.90**	1.37	1.70*	1.52*	1.66*	2.71***	2.64***	0.26	−0.46
	[1.22]	[1.64]	[1.55]	[1.59]	[1.61]	[1.64]	[2.18]	[1.61]	[1.98]	[1.76]	[1.84]	[3.01]	[2.93]	[0.23]	[−0.38]
Liquidity	**0.027****	**−0.068**	**−0.000011****	**−0.032**	**0.055**	**−0.070**	**−0.17****	**−0.024**	**−8.31*****	**−0.050**	**−0.25***	**−0.86*****	**−1.23*****	**0.67***	**0.88****
	[2.11]	**[−0.72]**	**[−2.06]**	**[−0.22]**	**[0.69]**	**[−0.68]**	**[−2.37]**	**[−0.33]**	**[−3.80]**	**[−0.91]**	**[−1.88]**	**[−3.62]**	**[−3.21]**	**[1.94]**	**[2.49]**
β^{mkt}	−0.0056	−0.11	−0.10	−0.11	−0.10	−0.10	−0.12	−0.11	−0.099	−0.11	−0.12	−0.13	−0.13	−0.055	−0.026
	[−0.01]	[−0.51]	[−0.49]	[−0.50]	[−0.48]	[−0.49]	[−0.56]	[−0.50]	[−0.46]	[−0.54]	[−0.58]	[−0.52]	[−0.50]	[−0.27]	[−0.13]
β^{hml}	−0.11	−0.11	−0.10	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.057	−0.056	−0.11	−0.12
	[−0.74]	[−0.81]	[−0.78]	[−0.81]	[−0.81]	[−0.81]	[−0.80]	[−0.81]	[−0.87]	[−0.81]	[−0.82]	[−0.38]	[−0.37]	[−0.85]	[−0.92]
β^{smb}	0.12	0.036	0.035	0.037	0.038	0.036	0.023	0.038	0.039	0.026	0.016	0.00	0.0052	0.065	0.076
	[1.21]	[0.46]	[0.45]	[0.47]	[0.48]	[0.45]	[0.29]	[0.48]	[0.49]	[0.34]	[0.21]	[0.00]	[0.06]	[0.85]	[1.01]
BM	0.12	−0.0050	−0.0045	−0.0048	−0.0047	−0.0060	−0.012	−0.0053	−0.00030	0.000071	0.0013	0.054	0.050	−0.0071	−0.0045
	[0.94]	[−0.16]	[−0.14]	[−0.15]	[−0.15]	[−0.19]	[−0.37]	[−0.17]	[−0.01]	[0.00]	[0.04]	[1.09]	[1.02]	[−0.23]	[−0.14]
ln(Mcap)	0.0049	−0.0015	0.0040	−0.00	0.0015	0.00	−0.022	0.00075	−0.012	−0.0056	−0.012	−0.058	−0.054	0.043	0.069
	[0.11]	[−0.04]	[0.11]	[−0.01]	[0.04]	[0.00]	[−0.61]	[0.02]	[−0.34]	[−0.16]	[−0.31]	[−1.54]	[−1.45]	[0.97]	[1.43]
DYD	0.68	0.24	0.23	0.24	0.22	0.22	0.25	0.22	0.21	0.20	0.20	0.53	0.53	0.19	0.20
	[0.61]	[0.42]	[0.40]	[0.42]	[0.39]	[0.40]	[0.44]	[0.39]	[0.38]	[0.35]	[0.35]	[0.82]	[0.83]	[0.34]	[0.37]
Id. Vol.	−0.11	−0.18***	−0.18***	−0.18***	−0.18***	−0.18***	−0.17***	−0.18***	−0.17***	−0.18***	−0.17***	−0.14**	−0.14**	−0.17***	−0.17***
	[−1.52]	[−3.47]	[−3.48]	[−3.47]	[−3.48]	[−3.47]	[−3.21]	[−3.44]	[−3.34]	[−3.30]	[−3.18]	[−2.22]	[−2.26]	[−3.47]	[−3.44]
$RET_{\ \ 1}$	−0.80	−0.88	−0.87	−0.88	−0.87	−0.87	−0.86	−0.89	−0.89	−0.87	−0.85	−0.84	−0.85	−0.90	−0.92
	[−1.12]	[−1.49]	[−1.47]	[−1.49]	[−1.46]	[−1.46]	[−1.46]	[−1.49]	[−1.52]	[−1.47]	[−1.44]	[−1.24]	[−1.26]	[−1.50]	[−1.54]
$RET_{(\ \ 12,\ \ 2)}$	0.38*	0.17	0.17	0.17	0.17	0.17	0.15	0.17	0.18	0.17	0.16	0.13	0.13	0.21	0.23
	[1.89]	[1.10]	[1.10]	[1.09]	[1.09]	[1.11]	[1.00]	[1.10]	[1.16]	[1.07]	[1.02]	[0.68]	[0.68]	[1.34]	[1.45]
Observations	115,759[y]	297337	297337	297337	297337	297337	296805	297335	297337	297,335[yy]	297,335[yy]	242442	242442	297,337[yyy]	297,337[yyy]

Panel B: Loadings of ILMs in the cross-section of expected returns after orthogonalization relative to other liquidity measures

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
ILMT residual	−0.27	0.73**	0.64*	0.69**	0.64*	0.69**	0.88***	0.68*	0.84**	0.81**	0.93***	1.19***	1.14***	-	-
	[−0.54]	[2.55]	[1.90]	[2.46]	[1.93]	[2.04]	[2.70]	[1.92]	[2.46]	[2.50]	[2.90]	[3.02]	[2.97]		
ILMV residual	−0.22	0.96***	0.84**	0.92***	0.85**	0.90**	1.03***	0.88**	1.00***	0.97***	1.06***	1.23***	1.18***	-	-
	[−0.47]	[3.28]	[2.41]	[3.20]	[2.51]	[2.62]	[3.14]	[2.44]	[2.82]	[3.04]	[3.45]	[3.23]	[3.20]		

[y] The number of observations reflects the largest sample of ANcerno data available from 2011-2014.

[yy] The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

[yyy] The number of observations reflects the largest sample available for BBD and WBBD from 2010–2017.

Panel B in Tables E.1 and E.2 highlights the incremental information content of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure. First, the residuals of each ILM with respected an alternative measure are calculated using Fama-MacBeth regressions. These residuals are then used as LIQ in equation (2). For both minimum price filters, with the exception of realized institutional price impacts (InPrIM), ILM residuals explain the cross-section of two-months-ahead returns whenever the liquidity measure against which these residuals are calculated does not explain the cross-section of these returns (with expected sign) in Panel A. As such, our findings provide unambiguous evidence that ILMs outperform all existing liquidity measures in explaining the cross-section of expected returns.[79]

F Portfolio Sorts: Alternative Liquidity Measures

This section employs simple portfolio sorts to compare the economic magnitudes of the premia associated with all liquidity measures used in our study. We sort each monthly cross-section into ten portfolios (deciles) of each liquidity measure (LIQ). We then calculate average monthly stock returns of each portfolio as well as monthly returns associated with four long-short strategies that buy illiquid stocks and sell liquid stocks. Strategy (1) in long on decile 7 and short on decile 4; strategy (2) is long on decile 8 and short on decile 3; strategy (3) is long on decile 9 and short on decile 2; and the "traditional" strategy (4) is long on decile 10 and short on decile (1). Examining these four strategies reveals whether liquidity premia are only attributable to the tails of the distributions. We obtain three-factor alphas by regressing the time series of portfolio returns as well as those of the long-short strategies on Fama-French three factors. We conduct three versions of these analyses based on samples with minimum previous month's end share price filters of \$1, \$2, and \$5.[80]

Table F.1 reports that ILMs are the only measures for which the traditional long-short strategy (4) consistently produces three-factor liquidity premia of nearly 1% or higher. In addition, $ILMV$ is the sole liquidity measure for which all four long-short strategies produce significant liquidity premia. This finding indicates that $ILMV$ identifies economically relevant differences in stock liquidity even for stocks with intermediate trading costs, highlighting the practical relevance of

[79] In untabulated results, we verify that the converse is not true.

[80] Note that the findings regarding $ILMT$ and $ILMV$ match those reported in Panels A–C in Table 10.

$ILMs$. Long-short strategies based on dollar quoted, effective, and realized spreads also produce relatively consistent liquidity premia. However, these measures are impacted by variations in share price: ceteris paribus, higher share price is associated with wider spreads measures. This observation is consistent with the finding that long-short strategies based on percentage (relative) quoted, effective, and realized spreads do ***not*** produce significant three-factor alphas. That is, when adjusted for share price, these spreads-based measures fail to capture liquidity. This interpretation is reinforced by the regression analyses reported in Tables 8, E.1, and E.2 where controlling for other stock characteristics, including book-to-market ratio and market-capitalization, renders all spread-based measures insignificant predictors of expected returns.

Table F.1. **Liquidity Alphas:** This table presents three-factor alphas of liquidity measures ($LIQ_{j,m\ \ 2}$) from 1-month horizons. Every month, stocks are sorted into deciles of the respective LIQ. Alphas for four long-short strategies are reported: long decile 7, short decile 4; long decile 8, short decile 3; long decile 9, short decile 2; and long decile 10, short decile 1. The 118-month time-series of monthly average portfolio returns for each portfolio (net of 1-month T-bill rate) and the long-short strategies are regressed on the Fama-French three factors to obtain alphas. The sample period is from 2010–2019, excluding stocks with previous month-end's closing price below $1, $2, and $5, in Panels A, B, and C, respectively. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: $1 minimum share price

	Liquidity portfolios								Long-short strategies			
LIQ	1	2	3	4	7	8	9	10	7 4	8 3	9 2	10 1
InPrIm	0.14	0.082	0.058	0.042	0.064	0.17	0.072	0.014	0.11	0.11	0.0098	0.15
	[0.58]	[0.63]	[0.48]	[0.23]	[0.54]	[1.40]	[0.64]	[0.07]	[0.47]	[0.53]	[0.06]	[0.91]
QSP	0.45***	0.48***	0.24*	0.16*	0.10	0.13	0.37***	0.40***	0.26**	0.37***	0.85***	0.85***
	[3.17]	[3.73]	[1.94]	[1.80]	[1.24]	[1.44]	[3.87]	[3.44]	[2.00]	[3.72]	[5.39]	[4.00]
ShrDepth^{y}	0.15*	0.21***	0.13	0.21***	0.041	0.28*	0.32*	0.78***	0.25*	0.41**	0.53**	0.93***
	[1.79]	[2.83]	[1.59]	[3.26]	[0.34]	[1.89]	[1.78]	[4.07]	[1.76]	[2.11]	[2.52]	[4.03]
EFSP	0.57***	0.28***	0.39***	0.23***	0.13	0.16*	0.27**	0.47***	0.35***	0.56***	0.56***	1.05***
	[3.29]	[2.66]	[4.03]	[3.76]	[1.36]	[1.74]	[2.59]	[4.40]	[3.59]	[5.47]	[4.19]	[4.54]
RESP	0.14	0.28***	0.23***	0.31***	0.082	0.11	0.30***	0.37***	0.23*	0.34***	0.58***	0.51***
	[1.03]	[2.90]	[3.07]	[2.99]	[0.86]	[1.18]	[2.68]	[3.14]	[1.94]	[3.14]	[4.02]	[2.80]
PIMP	0.62***	0.33***	0.32***	0.27***	0.16**	0.17**	0.33***	0.32***	0.43***	0.49***	0.66***	0.94***
	[3.21]	[2.66]	[3.26]	[3.65]	[2.39]	[2.50]	[3.65]	[3.34]	[4.91]	[4.50]	[4.31]	[4.87]
Lambda	0.14**	0.016	0.12*	0.075	0.021	0.046	0.32*	0.34	0.054	0.17	0.30	0.49
	[2.61]	[0.18]	[1.79]	[1.15]	[0.25]	[0.44]	[1.78]	[1.15]	[0.58]	[1.20]	[1.52]	[1.60]
AMVST	0.36***	0.20***	0.11**	0.17***	0.013	0.13	0.29*	0.41**	0.19**	0.015	0.49***	0.77***
	[3.16]	[2.83]	[2.17]	[2.99]	[0.17]	[1.10]	[1.91]	[2.11]	[2.25]	[0.13]	[3.06]	[3.76]
ROLL	0.16*	0.12	0.18**	0.085	0.22***	0.082	0.20	0.69***	0.14	0.26**	0.075	0.53**
	[1.70]	[1.35]	[2.44]	[1.09]	[3.64]	[0.76]	[1.57]	[2.83]	[1.28]	[2.28]	[0.55]	[2.45]
ILLIQ	0.040	0.081	0.11	0.031	0.11	0.26**	0.16	0.32	0.14	0.15	0.078	0.28
	[0.82]	[0.88]	[1.34]	[0.52]	[1.28]	[2.24]	[0.85]	[1.17]	[1.43]	[1.02]	[0.38]	[1.03]
ILLIQ_OC	0.048	0.099	0.089	0.00036	0.100	0.25**	0.065	0.21	0.099	0.16	0.034	0.16
	[0.94]	[1.09]	[1.03]	[0.01]	[1.08]	[2.31]	[0.36]	[0.75]	[0.92]	[1.12]	[0.16]	[0.57]
BBD	0.049	0.026	0.13	0.067	0.021	0.063	0.013	0.011	0.046	0.065	0.038	0.059
	[1.14]	[0.25]	[1.59]	[1.38]	[0.21]	[0.51]	[0.08]	[0.03]	[0.41]	[0.39]	[0.20]	[0.18]
WBBD	0.036	0.030	0.13*	0.097*	0.015	0.0040	0.048	0.0014	0.081	0.14	0.078	0.035
	[0.80]	[0.29]	[1.70]	[1.86]	[0.16]	[0.03]	[0.28]	[0.00]	[0.73]	[0.80]	[0.40]	[0.11]
ILMT	0.32***	0.34***	0.19**	0.17	0.032	0.089	0.38**	0.64***	0.14	0.28	0.72***	0.96***
	[2.77]	[3.82]	[2.13]	[1.58]	[0.30]	[0.63]	[2.48]	[4.25]	[0.86]	[1.62]	[3.72]	[4.30]
ILMV	0.63***	0.44***	0.25***	0.25***	0.027	0.32***	0.32**	0.64***	0.22**	0.57***	0.77***	1.27***
	[4.28]	[4.40]	[2.88]	[3.56]	[0.28]	[2.85]	[2.10]	[4.76]	[2.15]	[4.17]	[4.28]	[5.49]

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Table F.1 – *continued from previous page*

Panel B: $2 minimum share price

	Liquidity portfolios								Long-short strategies			
LIQ	1	2	3	4	7	8	9	10	7 4	8 3	9 2	10 1
InPrIm	0.092	0.066	0.12	0.055	0.053	0.13	0.078	0.23	0.11	0.0077	0.013	0.32**
	[0.42]	[0.51]	[1.22]	[0.32]	[0.44]	[1.13]	[0.65]	[1.10]	[0.51]	[0.05]	[0.08]	[2.31]
QSP	0.41***	0.26**	0.21**	0.21***	0.098	0.14	0.34***	0.41***	0.30**	0.35***	0.60***	0.82***
	[3.41]	[2.47]	[1.99]	[2.63]	[1.15]	[1.64]	[3.48]	[3.83]	[2.54]	[3.51]	[3.71]	[4.28]
ShrDepth^{y}	0.15*	0.19***	0.14*	0.22***	0.0090	0.24*	0.29**	0.56***	0.23	0.38**	0.48***	0.71***
	[1.72]	[2.72]	[1.68]	[3.00]	[0.07]	[1.74]	[2.25]	[4.19]	[1.52]	[2.17]	[2.90]	[3.92]
EFSP	0.47***	0.21**	0.33***	0.11*	0.061	0.21**	0.29***	0.42***	0.17	0.54***	0.51***	0.89***
	[3.16]	[2.06]	[4.44]	[1.70]	[0.70]	[2.33]	[2.99]	[3.87]	[1.53]	[5.71]	[3.52]	[4.08]
RESP	0.18	0.23**	0.23***	0.19**	0.075	0.097	0.33***	0.42***	0.12	0.33***	0.56***	0.60***
	[1.51]	[2.57]	[3.12]	[2.59]	[0.98]	[1.09]	[3.11]	[3.54]	[1.24]	[2.91]	[4.07]	[3.15]
PIMP	0.42***	0.28**	0.24***	0.13*	0.15**	0.24***	0.29***	0.26***	0.28***	0.48***	0.57***	0.68***
	[2.68]	[2.57]	[2.68]	[1.72]	[2.48]	[3.20]	[3.15]	[2.81]	[2.84]	[4.44]	[3.85]	[3.63]
Lambda	0.13**	0.016	0.14*	0.027	0.090	0.17*	0.20	0.28	0.063	0.31**	0.18	0.41
	[2.42]	[0.20]	[1.92]	[0.36]	[1.17]	[1.81]	[1.55]	[1.10]	[0.67]	[2.17]	[1.11]	[1.54]
AMVST	0.37***	0.20**	0.048	0.18***	0.058	0.0034	0.22**	0.43**	0.24**	0.052	0.42***	0.80***
	[3.12]	[2.57]	[1.05]	[3.33]	[0.63]	[0.04]	[2.10]	[2.45]	[2.34]	[0.55]	[3.13]	[4.22]
ROLL	0.12	0.12	0.19**	0.099	0.31***	0.14*	0.055	0.76***	0.21*	0.33***	0.063	0.64***
	[1.34]	[1.54]	[2.58]	[1.13]	[4.36]	[1.90]	[0.50]	[3.91]	[1.70]	[3.71]	[0.59]	[3.20]
ILLIQ	0.040	0.058	0.15*	0.030	0.013	0.073	0.050	0.20	0.043	0.076	0.0081	0.16
	[0.81]	[0.67]	[1.85]	[0.49]	[0.17]	[0.62]	[0.31]	[0.88]	[0.53]	[0.47]	[0.04]	[0.69]
ILLIQ_OC	0.041	0.071	0.095	0.036	0.0036	0.10	0.023	0.14	0.040	0.0085	0.094	0.10
	[0.83]	[0.76]	[1.19]	[0.62]	[0.04]	[0.93]	[0.16]	[0.61]	[0.42]	[0.06]	[0.51]	[0.43]
BBD	0.040	0.057	0.15*	0.10	0.072	0.13	0.051	0.062	0.18	0.28	0.0052	0.10
	[0.91]	[0.55]	[1.77]	[1.56]	[0.83]	[0.91]	[0.44]	[0.23]	[1.41]	[1.45]	[0.03]	[0.38]
WBBD	0.047	0.053	0.16*	0.090	0.052	0.16	0.093	0.11	0.14	0.31	0.040	0.16
	[1.07]	[0.52]	[1.78]	[1.40]	[0.59]	[1.10]	[0.82]	[0.39]	[1.19]	[1.64]	[0.22]	[0.55]
ILMT	0.30***	0.33***	0.21**	0.062	0.023	0.11	0.34**	0.62***	0.085	0.31*	0.67***	0.93***
	[2.70]	[4.05]	[2.17]	[0.82]	[0.27]	[0.92]	[2.54]	[4.48]	[0.72]	[1.81]	[4.32]	[4.33]
ILMV	0.58***	0.33***	0.23***	0.25***	0.041	0.28***	0.31**	0.63***	0.30***	0.50***	0.65***	1.20***
	[3.97]	[3.86]	[2.76]	[3.68]	[0.59]	[3.37]	[2.26]	[4.97]	[3.10]	[4.27]	[3.72]	[5.09]

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Table F.1 – *continued from previous page*

Panel C: $5 minimum share price

	Liquidity portfolios								Long-short strategies			
LIQ	1	2	3	4	7	8	9	10	7 4	8 3	9 2	10 1
InPrIm	0.080	0.21*	0.017	0.060	0.041	0.17	0.11	0.28**	0.10	0.19	0.095	0.20
	[0.40]	[1.77]	[0.14]	[0.33]	[0.34]	[1.37]	[1.01]	[2.09]	[0.50]	[1.00]	[0.58]	[1.35]
QSP	0.23***	0.13	0.056	0.019	0.071	0.21**	0.39***	0.41***	0.090	0.27**	0.52***	0.65***
	[2.73]	[1.58]	[0.61]	[0.31]	[0.82]	[2.55]	[4.13]	[3.92]	[0.86]	[2.36]	[3.49]	[3.98]
ShrDepth[y]	0.13	0.23***	0.18**	0.13**	0.20***	0.036	0.11	0.18**	0.069	0.14	0.34**	0.31*
	[1.31]	[3.04]	[2.03]	[2.00]	[3.06]	[0.32]	[1.06]	[1.99]	[0.72]	[0.99]	[2.39]	[1.88]
EFSP	0.24**	0.11	0.15**	0.026	0.15*	0.22***	0.31***	0.48***	0.13	0.37***	0.41***	0.72***
	[2.12]	[1.30]	[2.58]	[0.44]	[1.81]	[2.74]	[3.27]	[4.36]	[1.26]	[3.66]	[2.93]	[3.79]
RESP	0.10	0.063	0.17**	0.080	0.047	0.21**	0.39***	0.52***	0.13	0.38***	0.46***	0.62***
	[0.95]	[0.96]	[2.57]	[1.25]	[0.69]	[2.41]	[3.53]	[4.38]	[1.38]	[3.26]	[3.17]	[3.12]
PIMP	0.079	0.19**	0.044	0.039	0.15**	0.20***	0.31***	0.33***	0.19*	0.25**	0.50***	0.41**
	[0.84]	[2.03]	[0.67]	[0.50]	[2.31]	[2.66]	[3.69]	[3.16]	[1.81]	[2.52]	[3.87]	[2.56]
Lambda	0.14***	0.0072	0.15*	0.025	0.15**	0.13	0.32***	0.011	0.18*	0.28**	0.31**	0.13
	[2.71]	[0.09]	[1.67]	[0.33]	[2.43]	[1.60]	[3.03]	[0.06]	[1.85]	[2.04]	[2.00]	[0.66]
AMVST	0.30**	0.13*	0.043	0.036	0.057	0.28***	0.30***	0.55***	0.093	0.24**	0.43***	0.85***
	[2.32]	[1.84]	[0.73]	[0.65]	[0.86]	[3.79]	[2.75]	[4.69]	[1.11]	[2.48]	[3.26]	[4.11]
ROLL	0.058	0.072	0.00013	0.13**	0.26***	0.27***	0.049	0.46***	0.13	0.27***	0.023	0.40***
	[0.82]	[1.10]	[0.00]	[2.12]	[4.20]	[5.24]	[0.55]	[3.61]	[1.41]	[2.73]	[0.21]	[3.23]
ILLIQ	0.045	0.039	0.11	0.048	0.085	0.12	0.26**	0.44***	0.13	0.23*	0.30*	0.39**
	[0.92]	[0.43]	[1.48]	[0.71]	[1.13]	[1.31]	[2.08]	[2.73]	[1.23]	[1.69]	[1.67]	[2.13]
ILLIQ_OC	0.045	0.036	0.093	0.059	0.11	0.12	0.25**	0.45***	0.16	0.21	0.28	0.40**
	[0.90]	[0.48]	[1.04]	[0.88]	[1.28]	[1.55]	[2.01]	[2.74]	[1.43]	[1.62]	[1.65]	[2.16]
BBD	0.071*	0.045	0.12	0.030	0.12	0.11	0.31**	0.39**	0.15	0.23	0.26	0.32*
	[1.67]	[0.51]	[1.20]	[0.40]	[1.66]	[1.20]	[2.21]	[2.55]	[1.27]	[1.38]	[1.34]	[1.96]
WBBD	0.062	0.050	0.14	0.015	0.13*	0.16	0.27*	0.42***	0.14	0.30*	0.22	0.36**
	[1.44]	[0.56]	[1.38]	[0.21]	[1.74]	[1.53]	[1.91]	[2.80]	[1.26]	[1.67]	[1.11]	[2.23]
ILMT	0.29***	0.24***	0.14*	0.053	0.12	0.28***	0.38***	0.65***	0.067	0.42***	0.62***	0.95***
	[2.66]	[2.89]	[1.98]	[0.78]	[1.25]	[2.84]	[3.49]	[4.73]	[0.56]	[3.25]	[4.39]	[4.30]
ILMV	0.43***	0.21***	0.14**	0.11	0.19***	0.37***	0.43***	0.68***	0.30***	0.51***	0.64***	1.10***
	[3.35]	[2.64]	[2.16]	[1.54]	[2.86]	[4.65]	[4.02]	[5.32]	[3.64]	[4.44]	[3.92]	[4.82]

[y] For consistency, returns to long-short strategies based on quoted depth (ShrDepth) are multiplied by 1.

G Portfolio double-sorts

This section provides return differences between stocks falling in different levels of ILM and stock characteristics. Double sorts based on ILMs and other stock characteristics provide additional evidence that the 3-factor risk-adjusted portfolio return spreads associated with our liquidity measures are not concentrated in specific subsets of stocks. These double sorts control for market beta, market capitalization, book-to-market ratios, past returns, and the share of sub-penny volume. After excluding stocks priced below $5 at the end of the preceding month, we form an array of 5×5 portfolios that first condition on a stock characteristic, and then on an ILM.[81] Next, we estimate monthly portfolio returns as well as return spreads between the most and least liquid stock portfolios, conditional on the level of each stock characteristic.

Table G.1 documents liquidity premia for high- and low-beta, small and large, growth and value stocks, past losers and past winners, and stocks with low and high sub-penny executed volume. A slightly smaller liquidity premia is apparent among large stocks, past winners, and value stocks. However, reflecting lowered measurement error, the significant liquidity premia grows by nearly six times as the share of sub-penny executed volume rises from its bottom to its top quintile. Online Appendix H establishes the robustness of these findings to constructing ILMs over 3-month rolling windows. Therefore, the liquidity premia associated with ILMs are largely orthogonal to stock characteristics known to influence expected returns.

Finally, we investigate whether trading costs can explain the returns of anomalies based on stock characteristics by changing the order of the double sorts—first conditioning on a ILM, and then on a stock characteristic. Table G.2 reports evidence that low-beta and value premia are present in both liquid and illiquid stocks. In contrast, momentum's alpha is only significant among the 20% least liquid stocks, suggesting that momentum profits do not survive institutional trading costs (Lesmond et al. (2004); Korajczyk and Sadka (2004)).[82]

[81] Our choice of the $5 minimum share price precludes effects attributable to penny stocks, leading to conservative estimates. Qualitative findings are unaffected by using $1 and $2 share price filters.

[82] Online Appendix H confirms results are robust to constructing ILMs over 3-month rolling windows.

Table G.1. **Portfolio Alphas: Stock Characteristic and ILM Double-Sorts.** This table presents three-factor alphas using CRSP breakpoints. Stocks are first sorted into stock characteristic quintiles X 2 fβ^{mkt}, Mcap, $RET_{(12, 2)}$, BM, SPVSg. Within each characteristic quintile, stocks are further sorted into LIQ 2 f$ILMT$, $ILMV$g quintiles. Monthly 5 5 portfolio returns are equally-weighted averages of monthly stock returns in the portfolio. The time-series returns of each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on Fama-French three factors. The resulting intercepts are three-factor alphas. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $5. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Sequential double sorts on market beta and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of market beta	Low	0.23	0.011	0.41**	0.75***	0.82***	0.59***	0.069	0.19	0.50***	0.74***	0.82***	0.89***
		[1.47]	[0.09]	[2.58]	[5.07]	[4.90]	[2.74]	[0.41]	[1.52]	[4.20]	[4.58]	[5.01]	[3.94]
	2	0.021	0.32**	0.57***	0.47***	0.47***	0.44***	0.13	0.32***	0.45***	0.47***	0.49***	0.37**
		[0.20]	[2.61]	[6.30]	[4.91]	[3.58]	[2.91]	[1.11]	[3.15]	[5.05]	[4.40]	[3.74]	[2.12]
	3	0.059	0.066	0.073	0.30***	0.30**	0.24	0.12	0.038	0.079	0.27**	0.39***	0.50***
		[1.08]	[0.72]	[0.70]	[2.80]	[2.40]	[1.60]	[1.62]	[0.47]	[0.84]	[2.61]	[3.79]	[3.90]
	4	0.19*	0.15	0.011	0.13	0.14	0.33**	0.34***	0.10	0.19*	0.12	0.18	0.52***
		[1.90]	[1.50]	[0.10]	[1.02]	[0.84]	[1.99]	[3.94]	[1.07]	[1.69]	[1.07]	[1.08]	[3.56]
	High	0.78***	0.54**	0.39**	0.38**	0.22	0.57**	0.86***	0.39**	0.59***	0.31**	0.16	0.70**
		[2.99]	[2.55]	[2.39]	[2.23]	[1.34]	[2.03]	[2.86]	[2.21]	[2.81]	[2.31]	[1.03]	[2.51]

Panel B: Sequential double sorts on market capitalization and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of market capitalization	Low	0.69***	0.0053	0.42***	0.70***	0.76***	1.45***	0.87***	0.20	0.37**	0.68***	0.79***	1.67***
		[2.96]	[0.03]	[2.82]	[4.08]	[4.45]	[5.23]	[3.90]	[1.07]	[2.32]	[4.23]	[4.61]	[6.06]
	2	0.76***	0.093	0.33***	0.50***	0.46***	1.22***	0.90***	0.025	0.31***	0.54***	0.51***	1.41***
		[4.73]	[0.66]	[3.16]	[3.94]	[2.72]	[4.92]	[4.85]	[0.18]	[3.08]	[3.73]	[3.18]	[5.29]
	3	0.35***	0.14	0.091	0.25***	0.28**	0.63***	0.33**	0.079	0.24**	0.23**	0.35***	0.68***
		[3.56]	[1.41]	[0.85]	[2.65]	[2.48]	[3.90]	[2.49]	[0.91]	[2.37]	[2.14]	[3.15]	[3.32]
	4	0.35*	0.14	0.14	0.052	0.10	0.45**	0.52**	0.055	0.054	0.059	0.27***	0.79***
		[1.92]	[1.05]	[1.47]	[0.55]	[1.45]	[2.36]	[2.53]	[0.45]	[0.65]	[0.62]	[3.62]	[3.82]
	High	0.28***	0.024	0.10*	0.13	0.23***	0.50***	0.25**	0.075	0.11	0.052	0.22***	0.47***
		[2.86]	[0.34]	[1.71]	[1.51]	[3.92]	[4.78]	[1.98]	[1.29]	[1.45]	[0.50]	[2.71]	[3.52]

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Panel C: Sequential double sorts on book-to-market ratio and ILM

	Portfolios of $ILMT$						Portfolios of $ILMV$					
Portfolios of book-to-market ratio	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.13	0.14	0.065	0.012	0.26	0.38	0.32*	0.029	0.063	0.14	0.34*	0.65***
	[0.98]	[0.98]	[0.40]	[0.08]	[1.19]	[1.52]	[1.92]	[0.25]	[0.53]	[0.83]	[1.78]	[3.27]
2	0.29**	0.15	0.12	0.080	0.13	0.42*	0.37***	0.016	0.16	0.075	0.19	0.56***
	[2.10]	[1.39]	[0.96]	[0.63]	[0.94]	[1.95]	[2.65]	[0.14]	[1.36]	[0.65]	[1.58]	[2.89]
3	0.22**	0.057	0.043	0.11	0.088	0.31*	0.31**	0.13	0.013	0.15	0.15	0.46**
	[2.22]	[0.49]	[0.55]	[0.94]	[0.62]	[1.68]	[2.60]	[1.20]	[0.17]	[1.12]	[1.15]	[2.41]
4	0.36***	0.053	0.15	0.34**	0.66***	1.02***	0.43***	0.017	0.18**	0.46***	0.65***	1.08***
	[3.22]	[0.45]	[1.35]	[2.47]	[4.27]	[4.48]	[3.36]	[0.13]	[2.08]	[3.09]	[4.21]	[4.63]
High	0.32*	0.020	0.26	0.69***	0.88***	1.20***	0.43**	0.11	0.24	0.75***	0.87***	1.29***
	[1.90]	[0.13]	[1.45]	[4.41]	[5.35]	[4.15]	[2.04]	[0.76]	[1.61]	[5.38]	[5.33]	[4.18]

Panel D: Sequential double sorts on past 11-month return and ILM

	Portfolios of $ILMT$						Portfolios of $ILMV$					
Portfolios of past return	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.93***	0.56***	0.27	0.18	0.038	0.89***	1.00***	0.61***	0.26	0.025	0.075	0.93**
	[3.55]	[2.82]	[1.25]	[0.95]	[0.21]	[2.70]	[3.22]	[3.14]	[1.60]	[0.15]	[0.40]	[2.37]
2	0.056	0.12	0.14	0.25*	0.57***	0.63***	0.17	0.036	0.11	0.23*	0.57***	0.74***
	[0.44]	[0.96]	[1.05]	[1.96]	[4.26]	[3.22]	[1.46]	[0.33]	[0.86]	[1.87]	[4.16]	[3.83]
3	0.081	0.22**	0.30***	0.34***	0.93***	1.01***	0.085	0.16*	0.15	0.53***	0.94***	1.02***
	[1.16]	[2.24]	[2.77]	[2.67]	[6.61]	[5.81]	[1.08]	[1.76]	[1.39]	[4.18]	[6.64]	[6.16]
4	0.022	0.15	0.088	0.35***	0.74***	0.76***	0.013	0.042	0.14	0.44***	0.68***	0.67***
	[0.24]	[1.51]	[0.78]	[3.14]	[5.23]	[4.54]	[0.13]	[0.34]	[1.42]	[4.31]	[4.59]	[3.45]
High	0.21	0.21	0.0078	0.23	0.40**	0.61***	0.40*	0.10	0.18	0.27*	0.63***	1.03***
	[1.03]	[1.06]	[0.05]	[1.64]	[2.44]	[2.90]	[1.92]	[0.53]	[1.08]	[1.86]	[3.84]	[4.21]

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Table G.1 – *continued from previous page*

Panel E: Sequential double sorts on share of sub-penny trade volume and ILM

Portfolios of sub-penny volume	Portfolios of $ILMT$						Portfolios of $ILMV$					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.033	0.037	0.20**	0.17*	0.38***	0.35*	0.058	0.029	0.18**	0.14*	0.42***	0.36**
	[0.32]	[0.43]	[2.39]	[1.73]	[3.19]	[1.98]	[0.56]	[0.33]	[2.36]	[1.71]	[3.62]	[2.01]
2	0.051	0.10	0.11	0.17***	0.38***	0.33*	0.013	0.18*	0.087	0.15**	0.41***	0.42***
	[0.59]	[0.96]	[1.18]	[2.65]	[3.46]	[1.94]	[0.17]	[1.88]	[1.00]	[2.05]	[3.25]	[2.65]
3	0.11	0.084	0.070	0.10	0.46***	0.57***	0.12	0.11	0.11	0.15	0.48***	0.60***
	[1.17]	[0.87]	[0.73]	[0.81]	[3.70]	[3.44]	[1.11]	[1.12]	[1.15]	[1.52]	[3.92]	[3.25]
4	0.12	0.15	0.010	0.27**	0.58***	0.70***	0.15	0.10	0.0014	0.23*	0.59***	0.75***
	[1.27]	[1.11]	[0.07]	[2.11]	[3.14]	[2.94]	[1.27]	[0.84]	[0.01]	[1.67]	[3.81]	[3.26]
High	1.17***	0.64***	0.053	0.56***	0.82***	1.99***	1.15***	0.81***	0.093	0.57***	0.83***	1.98***
	[5.07]	[3.55]	[0.32]	[2.93]	[4.87]	[6.20]	[4.94]	[4.91]	[0.49]	[2.75]	[4.88]	[6.01]

Table G.2. **Portfolio Alphas: ILM and Stock Characteristic Double-Sorts.** This table presents three-factor alphas using CRSP breakpoints. Stocks are sorted into liquidity quintiles based on LIQ 2 f$ILMT, ILMV$g. Within each liquidity quintile, stocks are further sorted into stock characteristic quintiles X 2 fβ^{mkt}, Mcap, $RET_{(\ 12,\ 2)}$, BM, g. Monthly 5 5 portfolio returns are equally-weighted averages of monthly stock returns in the portfolio. The time-series returns of each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on Fama-French three factors. The resulting intercepts are three-factor alphas. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $5. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Sequential double sorts on $ILMT$ and stock characteristics

Portfolios of $ILMT$		Portfolios of beta						Portfolios of market capitalization					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
	Low	0.048	0.031	0.11	0.41***	0.87***	0.92**	0.85***	0.37**	0.053	0.021	0.030	0.82***
		[0.44]	[0.37]	[1.27]	[2.69]	[3.01]	[2.57]	[3.99]	[2.33]	[0.43]	[0.21]	[0.72]	[3.77]
	2	0.32*	0.18**	0.034	0.18*	0.57***	0.89***	0.33**	0.14	0.029	0.012	0.20***	0.54***
		[1.76]	[2.15]	[0.35]	[1.73]	[2.79]	[2.66]	[2.24]	[1.17]	[0.24]	[0.11]	[2.95]	[3.05]
	3	0.14	0.26***	0.12	0.051	0.43**	0.57**	0.34**	0.029	0.15	0.12	0.065	0.40**
		[1.34]	[2.68]	[1.07]	[0.50]	[2.17]	[2.25]	[2.09]	[0.27]	[1.42]	[1.53]	[0.82]	[2.03]
	4	0.26**	0.54***	0.36***	0.016	0.18	0.44**	0.30	0.47***	0.30***	0.37***	0.16**	0.46*
		[2.07]	[5.28]	[3.47]	[0.12]	[1.05]	[1.99]	[1.29]	[4.06]	[3.39]	[3.69]	[2.00]	[1.74]
	High	0.71***	0.81***	0.47***	0.44***	0.16	0.56**	0.29	0.80***	0.59***	0.45***	0.46***	0.18
		[3.49]	[5.99]	[3.24]	[3.54]	[1.09]	[2.21]	[1.41]	[4.23]	[4.11]	[2.74]	[3.44]	[0.71]

Portfolios of $ILMT$		Portfolios of book-to-market ratio						Portfolios of past return ($R_{(\ 12,\ 2)}$)					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
	Low	0.11	0.23**	0.32**	0.27**	0.39***	0.28	0.84***	0.017	0.075	0.090	0.30	0.54
		[0.67]	[2.06]	[2.59]	[2.52]	[3.15]	[1.42]	[3.33]	[0.14]	[1.05]	[0.83]	[1.54]	[1.56]
	2	0.12	0.036	0.019	0.23*	0.13	0.26	0.60***	0.078	0.24**	0.22**	0.17	0.43
		[0.68]	[0.41]	[0.20]	[1.95]	[0.81]	[0.94]	[2.96]	[0.68]	[2.61]	[2.25]	[0.79]	[1.27]
	3	0.059	0.067	0.041	0.019	0.13	0.19	0.35	0.083	0.19*	0.11	0.012	0.34
		[0.41]	[0.60]	[0.37]	[0.20]	[0.87]	[0.82]	[1.65]	[0.63]	[1.84]	[0.91]	[0.08]	[1.09]
	4	0.16	0.18**	0.12	0.31***	0.22	0.068	0.24	0.14	0.37***	0.43***	0.29**	0.52*
		[1.04]	[2.09]	[1.06]	[2.94]	[1.21]	[0.35]	[0.94]	[1.20]	[2.81]	[3.88]	[2.06]	[1.72]
	High	0.18	0.18	0.65***	0.84***	0.74***	0.56**	0.15	0.51***	0.90***	0.74***	0.59***	0.74***
		[0.99]	[1.29]	[4.18]	[5.10]	[3.92]	[2.07]	[0.80]	[3.66]	[6.97]	[4.96]	[4.49]	[3.54]

Continued on next page

Table G.2 – *continued from previous page*

Panel B: Sequential double sorts on $ILMV$ and stock characteristics

Portfolios of $ILMV$	Portfolios of beta						Portfolios of market capitalization					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.0089	0.050	0.29***	0.35**	0.90***	0.89**	1.02***	0.49***	0.039	0.057	0.0071	1.03***
	[0.06]	[0.69]	[3.68]	[2.57]	[2.79]	[2.12]	[4.23]	[2.85]	[0.31]	[0.69]	[0.19]	[4.06]
2	0.19	0.099	0.12	0.17	0.63***	0.82***	0.65***	0.13	0.047	0.032	0.071	0.72***
	[1.31]	[1.55]	[1.18]	[1.32]	[3.65]	[3.08]	[3.86]	[1.18]	[0.43]	[0.32]	[0.87]	[3.41]
3	0.10	0.23**	0.15	0.11	0.45***	0.55**	0.32**	0.11	0.12*	0.064	0.17*	0.48***
	[0.92]	[2.07]	[1.64]	[1.03]	[2.73]	[2.45]	[2.60]	[1.00]	[1.77]	[0.72]	[1.83]	[2.91]
4	0.47***	0.50***	0.45***	0.13	0.14	0.61***	0.035	0.40***	0.42***	0.38***	0.23**	0.26
	[4.84]	[5.30]	[3.76]	[1.09]	[1.02]	[3.57]	[0.16]	[3.18]	[3.56]	[3.89]	[2.31]	[0.96]
High	0.75***	0.77***	0.50***	0.43***	0.30**	0.45*	0.33*	0.77***	0.65***	0.56***	0.46***	0.13
	[3.78]	[5.70]	[3.14]	[3.43]	[2.25]	[1.88]	[1.78]	[4.05]	[4.62]	[3.65]	[2.80]	[0.51]

Portfolios of $ILMV$	Portfolios of book-to-market ratio						Portfolios of past return ($R_{(\ 12,\ 2)}$)					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.12	0.31***	0.33**	0.38***	0.46**	0.34	0.99***	0.11	0.14**	0.048	0.40**	0.59
	[0.64]	[2.78]	[2.59]	[3.07]	[2.27]	[1.18]	[3.05]	[1.00]	[2.10]	[0.40]	[1.99]	[1.40]
2	0.12	0.022	0.064	0.28**	0.13	0.0098	0.66***	0.072	0.20*	0.049	0.19	0.48
	[0.98]	[0.23]	[0.66]	[2.23]	[0.87]	[0.04]	[3.48]	[0.62]	[1.93]	[0.45]	[1.14]	[1.55]
3	0.085	0.053	0.040	0.043	0.11	0.024	0.24	0.14	0.045	0.21*	0.014	0.23
	[0.52]	[0.50]	[0.45]	[0.39]	[0.98]	[0.11]	[1.33]	[1.09]	[0.48]	[1.90]	[0.08]	[0.72]
4	0.44***	0.10	0.15	0.38***	0.33**	0.11	0.11	0.11	0.47***	0.54***	0.40***	0.51**
	[2.69]	[0.97]	[1.29]	[3.21]	[2.37]	[0.52]	[0.65]	[0.82]	[4.09]	[4.53]	[3.57]	[2.29]
High	0.21	0.30**	0.58***	0.86***	0.80***	0.58**	0.070	0.59***	0.88***	0.73***	0.63***	0.70***
	[1.43]	[2.34]	[3.54]	[5.21]	[4.54]	[2.49]	[0.42]	[4.23]	[6.60]	[4.98]	[4.46]	[3.69]

H Three-month ILMs and Expected Returns

This section establishes the robustness of our main asset pricing findings to constructing liquidity measures over rolling 3-month windows. We first uncover results similar to those in Table 8 using liquidity measures constructed over rolling 3-month windows. Specifically, $LIQ_{j,m\ \ 2}$ averages daily stock j's observations from month $m-4$ through $m-2$. Table H.1 reports that, with a \$2 minimum price requirement, $ILMT$ and $ILMV$ explain the cross-section of stock returns in month m, unlike other liquidity measures. Sample standard deviations for $ILMT$ and $ILMV$ are 0.176 and 0.195, respectively. Thus, a one standard deviation increase in $ILMT$ is associated with estimated monthly liquidity premium of $0.176 \times 1.45\% = 0.255\%$, or 3.06% per year. Similarly, the liquidity premium associated with a one standard deviation increase in $ILMV$ is $0.195 \times 1.60 = 0.312\%$ per month or 3.74% per year.

Table H.1. **Liquidity and the Cross-Section of Expected Stock Returns: 3-month ILMs.** This table reports on the relation between an array of high-frequency liquidity measures and the cross-section of expected stock returns. Equation (2) is estimated using liquidity measures ($LIQ_{j,m\ \ 2}$) constructed over 3-month horizons. Control variables include three Fama-French betas ($\beta^{mkt}_{j,m\ \ 1}$, $\beta^{hml}_{j,m\ \ 1}$, $\beta^{smb}_{j,m\ \ 1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m\ \ 1$, book-to-market ratio ($\mathrm{BM}_{j,m\ \ 1}$), natural log of market capitalization ($\ln(\mathrm{Mcap}_{j,m\ \ 1})$), dividend yield ($\mathrm{DYD}_{j,m\ \ 1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m\ \ 1$, idiosyncratic volatility ($\mathrm{IdVol}_{j,m\ \ 1}$), previous month's return ($RET_{(\ \ 1)}$), and preceding return from the prior 11 months ($RET_{(\ \ 12,\ \ 2)}$). Estimates 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 2019, excluding stocks whose previous month-end's closing price is below \$2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILMT	ILMV
Constant	1.47	0.70	0.71	0.68	0.75	0.71	1.53*	0.96	1.53*	0.92	0.90	1.51*	1.51*	−1.62	−2.40
	[1.17]	[0.76]	[0.79]	[0.73]	[0.84]	[0.79]	[1.71]	[1.12]	[1.70]	[1.06]	[1.00]	[1.73]	[1.75]	[−1.17]	[−1.58]
Liquidity	**0.060**	**0.042**	**−0.00**	**0.11**	**−0.095**	**0.091**	**−0.18****	**−0.038**	**−10.8*****	**−0.041**	**−0.057**	**−0.13**	**−0.19**	**1.45*****	**1.60*****
	[1.28]	**[0.34]**	**[−1.07]**	**[0.64]**	**[−0.77]**	**[0.72]**	**[−2.13]**	**[−0.37]**	**[−4.26]**	**[−1.25]**	**[−0.65]**	**[−0.88]**	**[−0.72]**	**[2.95]**	**[3.26]**
β^{mkt}	−0.039	−0.21	−0.21	−0.21	−0.22	−0.21	−0.23	−0.18	−0.18	−0.22	−0.22	−0.24	−0.24	−0.12	−0.082
	[−0.11]	[−1.04]	[−1.04]	[−1.03]	[−1.05]	[−1.04]	[−1.08]	[−0.89]	[−0.86]	[−1.05]	[−1.06]	[−1.00]	[−0.99]	[−0.62]	[−0.44]
β^{hml}	−0.10	−0.13	−0.13	−0.13	−0.13	−0.13	−0.13	−0.12	−0.12	−0.13	−0.13	−0.10	−0.10	−0.14	−0.16
	[−0.69]	[−1.07]	[−1.06]	[−1.07]	[−1.06]	[−1.06]	[−1.05]	[−0.97]	[−1.03]	[−1.06]	[−1.06]	[−0.72]	[−0.73]	[−1.19]	[−1.27]
β^{smb}	0.12	0.039	0.037	0.039	0.034	0.036	0.015	0.048	0.044	0.023	0.024	0.022	0.022	0.080	0.093
	[1.27]	[0.53]	[0.50]	[0.53]	[0.47]	[0.49]	[0.20]	[0.65]	[0.60]	[0.31]	[0.32]	[0.25]	[0.25]	[1.12]	[1.31]
BM	0.19	−0.026	−0.026	−0.026	−0.027	−0.027	−0.025	0.00040	0.0057	−0.0095	−0.0100	0.026	0.027	−0.029	−0.027
	[1.43]	[−0.54]	[−0.53]	[−0.53]	[−0.56]	[−0.56]	[−0.45]	[0.01]	[0.12]	[−0.19]	[−0.20]	[0.32]	[0.33]	[−0.59]	[−0.55]
ln(Mcap)	0.0010	0.036	0.036	0.037	0.034	0.036	−0.00043	0.023	−0.00017	0.026	0.027	0.0028	0.0028	0.12**	0.15**
	[0.02]	[0.96]	[0.99]	[0.98]	[0.93]	[0.98]	[−0.01]	[0.65]	[−0.00]	[0.74]	[0.74]	[0.08]	[0.08]	[2.24]	[2.54]
DYD	0.34	−0.096	−0.099	−0.091	−0.10	−0.10	−0.034	−0.067	−0.092	−0.065	−0.084	0.12	0.12	−0.14	−0.14
	[0.31]	[−0.17]	[−0.17]	[−0.16]	[−0.18]	[−0.18]	[−0.06]	[−0.12]	[−0.16]	[−0.11]	[−0.15]	[0.18]	[0.18]	[−0.26]	[−0.25]
Id. Vol.	−0.16**	−0.23***	−0.23***	−0.23***	−0.23***	−0.23***	−0.22***	−0.23***	−0.22***	−0.23***	−0.23***	−0.22***	−0.23***	−0.21***	−0.20***
	[−2.57]	[−4.66]	[−4.68]	[−4.66]	[−4.64]	[−4.65]	[−4.43]	[−4.73]	[−4.47]	[−4.51]	[−4.37]	[−3.82]	[−3.82]	[−4.44]	[−4.31]
$RET_{\ \ 1}$	−0.84	−0.33	−0.34	−0.34	−0.33	−0.32	−0.29	−0.34	−0.38	−0.35	−0.34	−0.43	−0.43	−0.41	−0.46
	[−1.16]	[−0.69]	[−0.70]	[−0.70]	[−0.68]	[−0.67]	[−0.61]	[−0.71]	[−0.80]	[−0.72]	[−0.70]	[−0.80]	[−0.80]	[−0.86]	[−0.96]
$RET_{(\ \ 12,\ \ 2)}$	0.37*	0.21	0.21	0.21	0.21	0.21	0.18	0.21	0.21	0.21	0.21	0.21	0.21	0.28*	0.29*
	[1.96]	[1.35]	[1.34]	[1.35]	[1.35]	[1.35]	[1.12]	[1.39]	[1.35]	[1.35]	[1.30]	[1.07]	[1.07]	[1.71]	[1.81]
Observations	131,828[y]	327,842	327,842	327,842	327,842	327,842	332,943	337,181	337,185	334,134[yy]	334,134[yy]	271,641[yyy]	271,641[yyy]	327,842	327,842

[y] The number of observations reflects the largest sample available in ANcerno data from 2010–2014.

[yy] The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

[yyy] The number of observations reflects the largest sample available for BBD and WBBD from 2010–2017.

Second, we present results from various robustness tests when our institutional liquidity measures are constructed over 3-month rolling windows. Table H.2 reports results similar to those in Table 9 using ILMs constructed over 3-month rolling windows. While our conclusions otherwise remain unchanged, the ILM coefficients in value-weighted regressions do become insignificant.

Table H.2. The Cross-Section of Expected Stock Returns and ILM: Robustness Tests. This table reports on the robustness of the relation between between our institutional liquidity measures and the cross-section of expected stock returns. Equation (2) is estimated using institutional liquidity measures ($LIQ_{j,m-2}$) constructed over 3-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m-1}$, $\beta^{hml}_{j,m-1}$, $\beta^{smb}_{j,m-1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m-1$, book-to-market ratio ($\text{BM}_{j,m-1}$), natural log of market capitalization ($\ln(\text{Mcap}_{j,m-1})$), dividend yield ($\text{DYD}_{j,m-1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m-1$, idiosyncratic volatility ($\text{IdVol}_{j,m-1}$), previous month's return ($RET_{(-1)}$), and preceding return from the prior 11 months ($RET_{(-12,-2)}$). Panel A reports on the robustness of the results to (1) estimating coefficients using panel regressions with date and stock fixed effects and date-stock double-clustered standard errors, (2) weighting observations (by size or according to Asparouhova et al. 2010) to correct for microstructure noise, (3) excluding firms with the smallest 20% market capitalization, (4) excluding stocks in the bottom 10% of the ratio of sub-penny volume in total volume; and (5) excluding stocks in the top or bottom 10% of the respective ILM. Stocks whose previous month-end's closing price is below $p_{min} \in \{\$1, \$2, \$5\}$ are excluded. Panel B reports on the robustness of the estimates in equation (2) to listing exchange. Observations are weighted according to Asparouhova et al. (2010) after excluding stocks whose previous month-end's closing price is below $1 and stocks falling in the bottom 10% of the ratio of sub-penny volume in total volume. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Robustness to estimation method and sample selection

Robustness specification	*ILMT*			*ILMV*		
	Price > $1	Price > $2	Price > $5	Price > $1	Price > $2	Price > $5
Panel regressions + stock & date FEs	1.77**	1.56**	0.61	2.24***	1.89***	1.04*
+ double-clustered S.E.	[2.45]	[2.24]	[0.90]	[3.33]	[2.99]	[1.78]
Asparouhova et al. (2010)	1.54***	1.43***	0.85*	1.74***	1.57***	1.14**
	[2.77]	[2.77]	[1.96]	[3.10]	[3.00]	[2.60]
Asparouhova et al. (2010)	1.21**	1.15**	0.83*	1.43***	1.36***	1.10**
+ top 80% market capitalization	[2.46]	[2.40]	[1.87]	[2.76]	[2.77]	[2.50]
Asparouhova et al. (2010)	1.68***	1.62***	1.07**	1.90***	1.77***	1.37***
+ low sub-penny volume stocks excluded	[2.96]	[3.02]	[2.40]	[3.32]	[3.28]	[3.03]
Size-weighted estimation	1.16	1.18	1.20	0.24	0.24	0.22
	[1.52]	[1.54]	[1.51]	[0.39]	[0.38]	[0.34]
Stocks in top and bottom	3.22***	2.86***	2.03***	2.35***	2.21***	1.88***
10% of ILM excluded	[3.51]	[3.78]	[3.32]	[3.18]	[3.32]	[3.38]

Panel B: Robustness to estimation by listing exchange

	NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
Asparouhova et al. (2010)	0.81	1.48**	1.35**	1.61***
+ Price > $1	[1.35]	[2.45]	[2.13]	[2.81]
Asparouhova et al. (2010) + Price > $1	1.04	1.57**	1.59**	1.71***
+ low sub-penny volume stocks excluded	[1.65]	[2.58]	[2.43]	[2.97]

Third, we report three-factor alphas for long-short trading strategies conditional on ILMs constructed over 3-month ($m-4$ to $m-2$) rolling windows. Table H.3 presents results similar to those in Table 10. Panel A reports that equal-weighed long-short strategies conditional on 3-month ILMs are associated with monthly three-factor alphas that range from 0.82% to 1.1% depending on minimum share price requirements of \$1, \$2, and \$5. Panel B reports three-factor alphas from long-short strategies based on value-weighted returns calculated after removing stocks with the smallest 20% market capitalization. Alphas range from 0.29% to 0.63% per month, which correspond to annualized three-factor alphas of 3.48% and 7.56%. These results confirm the robustness of liquidity premia to constructing ILMs over 3-month rolling windows.

Tables H.4 and H.5 demonstrate the robustness of our double-sort results to the use of ILMs constructed over 3-month ($m-4$ to $m-2$) rolling windows. We find significant liquidity premia in all subsamples (quintiles) of stock characteristics. In contrast, the momentum anomaly becomes insignificant after controlling for institutional liquidity. The value premium is also more salient among less liquid stocks.

Table H.3. *ILM* **Liquidity Alphas: CRSP and NYSE Breakpoints, Equal- and Value-Weighted Returns.** This table presents three-factor alphas conditional on ILM. Panels A, B, and C report results based on NMS-listed common shares using CRSP breakpoints and equally-weighted portfolio returns. Panels D, E, F report results based on NMS-listed common shares, after first removing stocks with the smallest 20% market capitalization in the prior month, using NYSE breakpoints and value-weighted portfolio returns. Stocks in each monthly cross-section are sorted into ten portfolios (deciles) conditional on one ILM. Monthly portfolio returns are averages of monthly stock returns in the portfolio. The time-series features 116 months. The time-series of returns for each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on the Fama-French three factors. The resulting intercepts are three-factor alphas. The sample period is from January 2010 to December 2019, excluding stock's whose previous month-end's closing price is below p_{min} 2 f$1, $2, $5g. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: CRSP breakpoints, $1 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.61***	0.43***	0.34***	0.24***	0.15	0.054	0.020	0.22**	0.33**	0.57***	1.18***
	[3.68]	[5.13]	[3.31]	[2.67]	[1.51]	[0.57]	[0.24]	[2.14]	[2.57]	[4.02]	[4.79]
ILMV	0.32**	0.37***	0.21**	0.20**	0.13	0.25*	0.15	0.093	0.28*	0.58***	0.90***
	[2.34]	[3.80]	[2.60]	[2.22]	[1.18]	[1.91]	[1.21]	[0.79]	[1.96]	[4.11]	[3.97]

Panel B: CRSP breakpoints, $2 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.54***	0.38***	0.32***	0.17*	0.058	0.012	0.033	0.31***	0.27**	0.54***	1.09***
	[3.49]	[4.78]	[3.59]	[1.92]	[0.65]	[0.16]	[0.49]	[3.05]	[2.53]	[3.94]	[4.41]
ILMV	0.30**	0.35***	0.23***	0.11	0.041	0.14	0.032	0.073	0.29**	0.55***	0.86***
	[2.27]	[4.05]	[2.74]	[1.55]	[0.53]	[1.33]	[0.37]	[0.67]	[2.18]	[4.23]	[3.94]

Panel C: CRSP breakpoints, $5 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
ILMT	0.45***	0.26***	0.15*	0.068	0.025	0.11*	0.15**	0.37***	0.40***	0.64***	1.09***
	[3.23]	[3.59]	[1.77]	[0.71]	[0.36]	[1.68]	[2.16]	[3.71]	[4.02]	[5.20]	[4.74]
ILMV	0.28**	0.24***	0.17**	0.032	0.073	0.11	0.075	0.22**	0.42***	0.61***	0.89***
	[2.19]	[2.83]	[2.48]	[0.39]	[0.96]	[1.33]	[1.04]	[2.25]	[3.75]	[5.02]	[4.24]

Continued on next page

Table H.3 – *continued from previous page*

Panel D: NYSE breakpoints, largest 80% market capitalization, $1 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.15***	0.088	0.16*	0.085	0.11	0.26**	0.13	0.19	0.23**	0.48***	0.63***
	[2.72]	[1.08]	[1.81]	[1.00]	[1.05]	[2.31]	[1.15]	[1.59]	[2.59]	[4.14]	[5.06]
$ILMV$	0.078	0.0055	0.061	0.17**	0.067	0.063	0.24***	0.32***	0.33***	0.29**	0.37***
	[1.39]	[0.07]	[0.90]	[2.01]	[0.74]	[0.64]	[3.79]	[5.13]	[2.74]	[2.07]	[2.62]

Panel E: NYSE breakpoints, largest 80% market capitalization, $2 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.16***	0.10	0.16*	0.070	0.11	0.30**	0.12	0.20*	0.25***	0.46***	0.62***
	[2.86]	[1.31]	[1.85]	[0.83]	[0.97]	[2.57]	[1.11]	[1.77]	[2.71]	[3.97]	[4.95]
$ILMV$	0.076	0.017	0.064	0.19**	0.057	0.071	0.24***	0.34***	0.34***	0.27*	0.34**
	[1.33]	[0.20]	[0.97]	[2.23]	[0.65]	[0.76]	[3.57]	[5.67]	[3.03]	[1.87]	[2.44]

Panel F: NYSE breakpoints, largest 80% market capitalization, $5 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 1
$ILMT$	0.15***	0.098	0.13*	0.080	0.095	0.28**	0.15	0.14	0.36***	0.44***	0.58***
	[2.66]	[1.31]	[1.68]	[0.96]	[0.90]	[2.61]	[1.37]	[0.99]	[2.92]	[4.39]	[5.23]
$ILMV$	0.065	0.039	0.073	0.18**	0.092	0.065	0.25***	0.33***	0.31***	0.30**	0.36**
	[1.14]	[0.46]	[1.08]	[2.18]	[0.98]	[0.70]	[3.27]	[4.64]	[2.86]	[2.02]	[2.54]

Table H.4. **Liquidity Alphas: Stock Characteristic and ILM Double-Sorts.** This table presents three-factor alphas to ILM using CRSP breakpoints for stock characteristic quintiles. Stocks are sorted into quintiles of characteristic $X \in \{\beta^{mkt}, \text{Mcap}, RET_{(-12,-2)}, \text{BM}, \text{SPVS}\}$. Within each quintile of characteristic X, stocks are further sorted into quintiles of $LIQ \in \{ILMT, ILMV\}$. Monthly 5 × 5 portfolio returns are equally-weighted averages of monthly stock returns in the portfolio. The time-series of returns for each portfolio (net of 1-month Treasury-bill rate) including the long-short portfolio are then regressed on the Fama-French three factors. The resulting intercepts are three-factor alphas. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $5. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Sequential double sorts on market beta and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of market beta	Low	0.075	0.15	0.34**	0.67***	0.75***	0.68***	0.054	0.088	0.50***	0.68***	0.77***	0.83***
		[0.42]	[0.97]	[2.33]	[4.95]	[4.31]	[2.88]	[0.32]	[0.61]	[4.24]	[4.82]	[4.25]	[3.55]
	2	0.056	0.34***	0.50***	0.48***	0.52***	0.46***	0.14	0.34**	0.43***	0.44***	0.55***	0.41**
		[0.57]	[2.87]	[5.06]	[4.03]	[4.17]	[3.04]	[1.30]	[2.60]	[4.60]	[3.98]	[4.23]	[2.49]
	3	0.11	0.023	0.23**	0.33***	0.34***	0.45***	0.18**	0.042	0.15	0.36***	0.39***	0.57***
		[1.62]	[0.26]	[2.29]	[3.88]	[3.32]	[3.43]	[2.42]	[0.41]	[1.33]	[4.82]	[3.43]	[3.81]
	4	0.17*	0.19*	0.0089	0.089	0.13	0.30	0.31***	0.19*	0.059	0.096	0.14	0.45***
		[1.80]	[1.80]	[0.09]	[0.86]	[0.70]	[1.48]	[2.83]	[1.80]	[0.44]	[0.86]	[0.95]	[2.97]
	High	0.78***	0.45**	0.41**	0.40**	0.23	0.56*	0.85***	0.54***	0.27	0.48***	0.14	0.71***
		[2.75]	[2.22]	[2.24]	[2.51]	[1.25]	[1.78]	[3.10]	[2.80]	[1.52]	[2.70]	[0.85]	[2.66]

Panel B: Sequential double sorts on market capitalization and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of market capitalization	Low	0.70***	0.20	0.49***	0.65***	0.65***	1.35***	0.93***	0.11	0.36**	0.65***	0.69***	1.62***
		[3.31]	[0.89]	[3.80]	[4.64]	[3.39]	[4.83]	[3.98]	[0.47]	[2.61]	[4.66]	[3.72]	[5.71]
	2	0.69***	0.018	0.23*	0.54***	0.50***	1.19***	0.79***	0.064	0.31***	0.53***	0.56***	1.34***
		[3.72]	[0.16]	[1.86]	[4.39]	[2.80]	[4.47]	[3.82]	[0.59]	[2.71]	[4.05]	[3.11]	[4.63]
	3	0.33**	0.13	0.19**	0.18**	0.35***	0.68***	0.44***	0.11	0.17	0.31***	0.36***	0.79***
		[2.36]	[1.23]	[2.08]	[2.09]	[3.01]	[3.81]	[3.00]	[1.11]	[1.60]	[2.93]	[3.12]	[3.99]
	4	0.37*	0.18*	0.011	0.13*	0.23**	0.60**	0.52**	0.093	0.013	0.17*	0.26***	0.77***
		[1.75]	[1.93]	[0.10]	[1.92]	[2.52]	[2.62]	[2.36]	[0.80]	[0.16]	[1.94]	[3.24]	[3.30]
	High	0.26**	0.00081	0.021	0.17**	0.27***	0.53***	0.17	0.041	0.017	0.19**	0.21**	0.38***
		[2.48]	[0.01]	[0.29]	[2.18]	[4.21]	[4.34]	[1.27]	[0.57]	[0.21]	[2.27]	[2.19]	[2.94]

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Table H.4 – *continued from previous page*

Panel C: Sequential double sorts on book-to-market ratio and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of book-to-market ratio	Low	0.14	0.21*	0.040	0.17	0.20	0.34	0.33*	0.21*	0.13	0.26*	0.21	0.54**
		[0.92]	[1.75]	[0.34]	[0.99]	[0.97]	[1.45]	[1.70]	[1.80]	[1.16]	[1.66]	[1.06]	[2.44]
	2	0.25*	0.25**	0.020	0.13	0.13	0.38*	0.37***	0.17*	0.0020	0.059	0.26	0.63***
		[1.85]	[2.48]	[0.20]	[1.09]	[0.74]	[1.68]	[2.75]	[1.74]	[0.01]	[0.54]	[1.63]	[2.92]
	3	0.22*	0.047	0.071	0.028	0.12	0.34*	0.23*	0.11	0.063	0.035	0.20*	0.43**
		[1.97]	[0.45]	[0.93]	[0.23]	[0.94]	[1.71]	[1.73]	[0.91]	[0.87]	[0.27]	[1.68]	[2.03]
	4	0.29**	0.040	0.13	0.36***	0.72***	1.01***	0.36***	0.12	0.19*	0.41***	0.77***	1.13***
		[2.19]	[0.34]	[0.93]	[2.87]	[4.82]	[4.35]	[2.68]	[0.87]	[1.77]	[3.12]	[4.88]	[4.47]
	High	0.36**	0.037	0.22	0.58***	0.81***	1.17***	0.48**	0.074	0.25*	0.61***	0.82***	1.29***
		[2.00]	[0.21]	[1.28]	[3.63]	[5.07]	[4.00]	[2.19]	[0.45]	[1.70]	[4.19]	[5.44]	[4.06]

Panel D: Sequential double sorts on past 11-month return and ILM

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of past return	Low	0.99***	0.48**	0.072	0.20	0.069	0.92***	0.92***	0.65***	0.25	0.065	0.071	0.84**
		[3.57]	[2.05]	[0.32]	[1.18]	[0.37]	[2.66]	[2.85]	[3.11]	[1.23]	[0.35]	[0.44]	[2.30]
	2	0.11	0.037	0.17	0.27**	0.50***	0.61***	0.13	0.022	0.11	0.34**	0.51***	0.64***
		[0.88]	[0.31]	[1.39]	[2.06]	[3.46]	[3.08]	[0.89]	[0.17]	[0.91]	[2.57]	[3.52]	[2.79]
	3	0.037	0.088	0.34***	0.38***	0.95***	0.98***	0.11	0.21*	0.19*	0.44***	0.98***	1.09***
		[0.49]	[0.76]	[3.19]	[2.63]	[6.65]	[5.79]	[1.28]	[1.86]	[1.74]	[3.08]	[6.78]	[6.65]
	4	0.046	0.15	0.16	0.27**	0.72***	0.77***	0.12	0.088	0.24**	0.32***	0.73***	0.84***
		[0.57]	[1.16]	[1.50]	[2.37]	[5.00]	[4.36]	[1.27]	[0.82]	[1.99]	[2.95]	[4.90]	[4.44]
	High	0.34*	0.23	0.028	0.096	0.44***	0.78***	0.48**	0.16	0.087	0.24	0.48***	0.96***
		[1.68]	[1.15]	[0.16]	[0.55]	[2.86]	[3.47]	[2.03]	[0.89]	[0.52]	[1.42]	[3.07]	[3.63]

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Table H.4 – *continued from previous page*

Panel E: Sequential double sorts on share of sub-penny trade volume and ILM

Portfolios of sub-penny volume	Portfolios of $ILMT$						Portfolios of $ILMV$					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.078	0.072	0.29***	0.12	0.46***	0.38**	0.046	0.0051	0.18**	0.18**	0.48***	0.43**
	[0.78]	[0.67]	[3.52]	[1.29]	[3.62]	[2.12]	[0.51]	[0.05]	[2.03]	[2.17]	[3.55]	[2.26]
2	0.011	0.041	0.22**	0.23***	0.38***	0.39**	0.096	0.12	0.19**	0.30***	0.35***	0.45***
	[0.11]	[0.50]	[2.57]	[3.12]	[3.41]	[2.54]	[1.07]	[1.12]	[2.28]	[3.66]	[3.16]	[2.93]
3	0.13	0.10	0.055	0.0026	0.54***	0.67***	0.11	0.21**	0.0068	0.13	0.55***	0.66***
	[1.29]	[1.28]	[0.58]	[0.02]	[4.20]	[4.16]	[0.88]	[2.30]	[0.08]	[0.97]	[3.52]	[3.15]
4	0.19	0.034	0.057	0.17	0.61***	0.80***	0.14	0.13	0.012	0.27**	0.64***	0.78***
	[1.64]	[0.26]	[0.37]	[1.54]	[3.51]	[3.27]	[1.12]	[0.91]	[0.07]	[2.33]	[4.04]	[3.20]
High	1.28***	0.64***	0.21	0.43***	0.77***	2.05***	1.25***	0.86***	0.068	0.44***	0.81***	2.05***
	[5.00]	[3.82]	[0.92]	[2.89]	[4.18]	[5.98]	[4.62]	[4.66]	[0.32]	[2.75]	[4.19]	[5.54]

Table H.5. **Liquidity Alphas:** ILM **and Stock Characteristic Double-Sorts.** This table presents three-factor alphas associated with ILMs and stock characteristics using CRSP breakpoints. Stocks are sorted into quintiles of LIQ 2 f$ILMT, ILMV$g constructed over three-month rolling windows. Within each LIQ quintile, stocks are further sorted into quintiles of characteristic X 2 fβ^{mkt}, Mcap, $RET_{(\ 12,\ 2)}$, BMg. Monthly 5 5 portfolio returns are equally-weighted averages of monthly stock returns in the portfolio. The time-series of returns for each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on the Fama-French three factors. The resulting intercepts are three-factor alphas. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $5. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Sequential double sorts on $ILMT3$ and stock characteristics

Portfolios of $ILMT$	Portfolios of beta						Portfolios of market capitalization					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.11	0.013	0.19*	0.32**	0.79**	0.90**	0.86***	0.25	0.096	0.013	0.027	0.88***
	[0.94]	[0.16]	[1.80]	[2.10]	[2.51]	[2.39]	[3.38]	[1.63]	[0.72]	[0.14]	[0.71]	[3.48]
2	0.061	0.093	0.19	0.35*	0.83***	0.89***	0.74**	0.33	0.26	0.16	0.072	0.81***
	[0.30]	[0.55]	[1.21]	[1.79]	[3.03]	[3.18]	[2.56]	[1.64]	[1.64]	[1.07]	[0.51]	[3.64]
3	0.036	0.17	0.12	0.38	0.64	0.68**	0.54	0.35	0.10	0.19	0.034	0.57**
	[0.14]	[0.75]	[0.54]	[1.36]	[1.62]	[2.36]	[1.39]	[1.37]	[0.41]	[0.81]	[0.15]	[2.18]
4	0.016	0.30	0.085	0.28	0.77**	0.79***	0.62*	0.071	0.027	0.068	0.062	0.56**
	[0.06]	[1.20]	[0.35]	[1.09]	[2.11]	[3.55]	[1.75]	[0.24]	[0.11]	[0.26]	[0.25]	[2.18]
High	0.51*	0.46	0.30	0.17	0.13	0.64**	0.022	0.44	0.35	0.28	0.26	0.28
	[1.69]	[1.61]	[0.99]	[0.60]	[0.39]	[2.54]	[0.07]	[1.30]	[1.29]	[0.92]	[0.88]	[1.14]

Portfolios of $ILMT$	Portfolios of book-to-market ratio						Portfolios of past return ($R_{(\ 12,\ 2)}$)					
	Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Low	0.14	0.26**	0.26*	0.17	0.36**	0.22	0.77***	0.0068	0.052	0.074	0.28	0.50
	[0.79]	[2.41]	[1.84]	[1.41]	[2.31]	[1.02]	[2.99]	[0.05]	[0.62]	[0.63]	[1.33]	[1.51]
2	0.10	0.29	0.35*	0.31	0.36*	0.26	0.79***	0.13	0.046	0.061	0.48	0.31
	[0.53]	[1.60]	[1.89]	[1.52]	[1.75]	[1.31]	[3.06]	[0.68]	[0.29]	[0.30]	[1.64]	[0.86]
3	0.049	0.17	0.17	0.34	0.22	0.17	0.54*	0.069	0.0096	0.099	0.25	0.28
	[0.17]	[0.78]	[0.63]	[1.09]	[0.68]	[0.81]	[1.67]	[0.29]	[0.04]	[0.37]	[0.68]	[0.85]
4	0.14	0.15	0.20	0.066	0.096	0.040	0.55*	0.13	0.099	0.044	0.12	0.43
	[0.46]	[0.63]	[0.79]	[0.22]	[0.32]	[0.21]	[1.82]	[0.54]	[0.36]	[0.15]	[0.39]	[1.61]
High	0.034	0.0019	0.33	0.51	0.43	0.40	0.42	0.19	0.63**	0.53*	0.38	0.80***
	[0.11]	[0.01]	[1.06]	[1.60]	[1.13]	[1.29]	[1.36]	[0.63]	[2.27]	[1.78]	[1.22]	[4.68]

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Table H.5 – *continued from previous page*

Panel B: Sequential double sorts on $ILMV3$ and stock characteristics

		Portfolios of beta						Portfolios of market capitalization					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of $ILMV$	Low	0.024	0.070	0.31***	0.39***	0.90***	0.87**	1.08***	0.55***	0.077	0.0088	0.011	1.09***
		[0.17]	[0.95]	[3.10]	[2.74]	[2.91]	[2.22]	[4.50]	[2.88]	[0.64]	[0.10]	[0.33]	[4.41]
	2	0.077	0.050	0.28*	0.50**	0.76***	0.84***	0.81***	0.40*	0.18	0.085	0.051	0.87***
		[0.37]	[0.30]	[1.81]	[2.54]	[2.95]	[2.96]	[3.00]	[1.92]	[1.19]	[0.54]	[0.33]	[3.93]
	3	0.012	0.076	0.093	0.20	0.81**	0.79***	0.70*	0.20	0.025	0.12	0.0046	0.70***
		[0.05]	[0.32]	[0.44]	[0.66]	[2.25]	[2.85]	[1.87]	[0.73]	[0.11]	[0.52]	[0.02]	[3.21]
	4	0.18	0.31	0.060	0.12	0.51	0.69***	0.42	0.12	0.11	0.17	0.064	0.35
		[0.69]	[1.26]	[0.23]	[0.44]	[1.45]	[3.66]	[1.06]	[0.42]	[0.46]	[0.64]	[0.25]	[1.21]
	High	0.52*	0.43	0.24	0.21	0.067	0.59**	0.012	0.40	0.38	0.31	0.23	0.22
		[1.73]	[1.57]	[0.81]	[0.77]	[0.21]	[2.53]	[0.03]	[1.26]	[1.50]	[1.01]	[0.77]	[0.89]

		Portfolios of book-to-market ratio						Portfolios of past return ($R_{(\; 12, \; 2)}$)					
		Low	2	3	4	High	High Low	Low	2	3	4	High	High Low
Portfolios of $ILMV$	Low	0.28	0.34***	0.30*	0.23*	0.54***	0.25	1.00***	0.061	0.040	0.077	0.52**	0.49
		[1.42]	[3.09]	[1.95]	[1.76]	[2.71]	[0.88]	[3.20]	[0.47]	[0.54]	[0.63]	[2.15]	[1.14]
	2	0.010	0.40**	0.26	0.45**	0.32	0.33*	0.81***	0.15	0.030	0.11	0.33	0.48
		[0.06]	[2.33]	[1.39]	[2.33]	[1.47]	[1.70]	[3.46]	[0.79]	[0.18]	[0.57]	[1.25]	[1.59]
	3	0.039	0.15	0.23	0.45	0.24	0.28	0.62**	0.023	0.11	0.027	0.26	0.36
		[0.14]	[0.71]	[0.85]	[1.54]	[0.82]	[1.42]	[2.05]	[0.10]	[0.47]	[0.10]	[0.74]	[1.30]
	4	0.035	0.13	0.16	0.047	0.13	0.092	0.24	0.055	0.13	0.093	0.016	0.22
		[0.11]	[0.56]	[0.60]	[0.15]	[0.42]	[0.54]	[0.76]	[0.22]	[0.50]	[0.32]	[0.05]	[0.73]
	High	0.047	0.029	0.37	0.47	0.41	0.36	0.45	0.23	0.68**	0.50*	0.38	0.83***
		[0.19]	[0.12]	[1.19]	[1.49]	[1.14]	[1.41]	[1.48]	[0.79]	[2.47]	[1.70]	[1.30]	[5.17]