Institutional Liquidity Costs, Internalized Retail Trade Imbalances, and the Cross-Section of Stock Returns*

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Abstract

Order flow segmentation prevents direct interactions between U.S. retail and institutional investors. Using the imbalance in observable internalized retail trades, we show wholesalers use retail flow to provide liquidity to institutional investors, espe-cially when *liquidity is scarce*. Our institutional liquidity cost (ILC) measures average absolute retail trade imbalances, positing that institutions holding stocks with greater such averages more often resort to the expensive wholesaler-provided liquidity. ILC is correlated with expected institutional price impacts. Unlike existing illiquidity measures, ILC has economically-meaningful relations with institutional holding horizons, and yields annualized liquidity premia of 2.7–3.2% post-2010, even after excluding micro-cap stocks.

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

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I. Introduction

Theory predicts that expected security returns are increasing in investors' expected costs of entering or exiting positions, i.e., investors demand liquidity premia (Amihud and Mendelson (1986)). While relevant to all participants, in today's U.S. equity markets such premia should reflect expected liquidity costs of institutional investors who account for over 70% of holdings (Blume and Keim (2012)). In fact, institutions still incur significant liquidity costs that vary substantially in the cross-section.[1] However, liquidity premia derived from *existing* liquidity measures largely have vanished in recent years, and some studies attribute this disappearance to reductions in liquidity costs that reduced investor's demand for liquidity premia.[2]

We argue that the constantly evolving market microstructure has rendered once-useful liquidity measures unable to capture institutional liquidity costs, biasing liquidity premia estimates toward zero.[3] We develop easy-to-construct institutional liquidity cost measures that reflect modern U.S. equity market structure. Our measures reveal that economically-significant liquidity premia still exist in stock returns. Importantly, we rely on publicly available data to

[1]Di Maggio, Egan, and Franzoni (2022) report institutional price impacts exhibit a mean and standard deviation of 32 and 64bps, respectively, in recent years. These heterogeneous price impacts should lead investors to demand liquidity premia. With quarterly re-balancing and a 50% turnover ratio, annualized round-trip execution costs rise by $4 \times 2 \times 0.5 \times 64\text{bps} = 2.56\%$ as price impacts rise by one standard deviation.

[2]See, e.g., Ben-Rephael, Kadan, and Wohl (2015), Asparouhova, Bessembinder, and Kalcheva (2010), Drienko, Smith, and von Reibnitz (2019), Harris and Amato (2019), and Amihud (2019).

[3]Indeed, a recent literature cautions against using spread-based measures or those aggregating information over calendar-time intervals to proxy for institutional trading costs (see Goyenko, Holden, and Trzcinka (2009), Chordia, Roll, and Subrahmanyan (2011), Holden and Jacobsen (2014), Angel, Harris, and Spatt (2011), O'Hara (2015), Barardehi, Bernhardt, and Davies (2019), and Eaton, Irvine, and Liu (2021)).

capture the liquidity concerns of institutional investors, mitigating the absence of direct proprietary data on institutional trading costs (e.g., ANcerno) that are no longer broadly available.

Our measures exploit the order flow segmentation in U.S. equity markets, which precludes direct interactions between retail and institutional investors but allows wholesalers—high-frequency market makers—to interact with both groups. Retail brokers outsource "handling" of retail orders exclusively to wholesalers, whose choices often determine execution outcomes of marketable retail orders.[4] Wholesalers have two options. One option is to execute these orders against their own inventory, "internalizing" the orders. Internalization often involves offering price improvements (PI) relative to national best bid and offer prices (NBBO) that lead to transaction prices with sub-penny increments. Alternatively, wholesalers can "externalize" orders, re-routing them to trading venues such as exchanges, where sub-penny execution prices are unavailable.[5] We use this fact to provide evidence of wholesalers intermediating between institutional and retail investors. Our evidence suggests that when institutional liquidity costs are high, wholesalers provide liquidity to institutions with pressing liquidity needs on one side of the market while internalizing disproportionately more retail orders on the opposite side to mitigate unwanted inventory accumulation. This intermediation's footprint in publicly-available data allows the construction of proxies for institutional liquidity costs.

Wholesaler trade data are difficult to obtain. However, Boehmer, Jones, Zhang, and Zhang (2021) (henceforth, BJZZ) propose an algorithm that identifies a subset of trades internalized by

[4]Non-marketable retail limit orders are normally routed to exchanges.

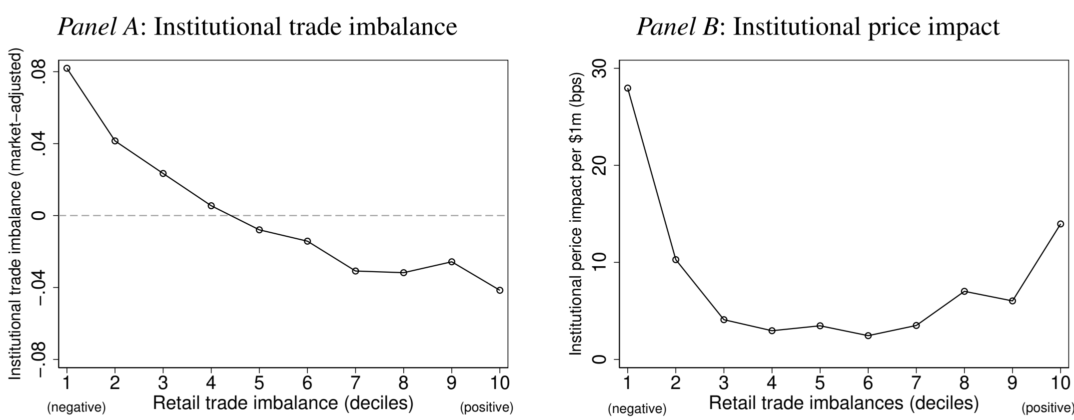
[5]Section II details a third possibility where best execution practices require wholesalers to internalize orders at the quote mid-point. This possibility cannot alter our conclusions since it indicates the presence of abundant liquidity and our analysis focuses on conditions with scarce liquidity.

wholesalers in TAQ data from regular-hours trading and classifies them into buyer- and seller-initiated retail trades using the sizes of sub-penny price increments. BJZZ then calculate standardized imbalances in buy and sell volumes, which they term $Mroib$—see equation (1). Our first contribution is to relate $Mroib$ to institutional trading activity. Figure 1 provides preliminary evidence of our proposed intermediation mechanism. Panel A reveals a negative relation between $Mroib$ and institutional order imbalances in ANcerno data, linking wholesaler trade imbalances in the retail segment to opposing order flow in the institutional segment. Panel B confirms that both more negative and more positive $Mroib$ are associated with scarcer liquidity as reflected by larger institutional price impacts calculated from ANcerno data.

FIGURE 1

Wholesaler Retail-Trade 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 market-adjusted institutional trade imbalances, defined for each stock-week as its institutional trade imbalance minus the corresponding weekly cross-section average, 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.



A host of stock-level and cross-sectional evidence support this intermediation mechanism—Internet Appendix II formalizes this mechanism using a stylized model and provides empirical support for its core assumptions. First, we show that more unbalanced $Mroib$ is associated with lower off-exchange midpoint liquidity (institutional investors' preferred source of liquidity), as well as wider quoted spreads and lower order-book depth—this scarce liquidity also manifests itself in higher institutional price impacts. Second, we establish that trade imbalances of short sellers, as well as those of mutual funds, are inversely related to $Mroib$. Third, we find that intraday returns move in the *opposite* direction of $Mroib$ imbalances but in the *same* direction as institutional trade imbalances, consistent with institutional price pressure. Further, these price pressures subsequently reverse as institutional trade imbalances level off, suggesting that $Mroib$'s return predictability reflect price reversals that follow institutional liquidity demand (Campbell, Grossman, and Wang (1993), Kaniel, Saar, and Titman (2008)).

Additional analyses suggest that $Mroib$ captures wholesaler choices to selectively internalize retail orders, but not forces such as retail trading motivated by stock-specific fundamental information. Importantly, (1) $Mroib$ imbalances reflect *increased* internalized retail volume on one side of the market, and (2) PI relative to NBBO is *larger* on the side with higher internalized volume. It is implausible that wholesalers offer larger PI when directional retail demand for liquidity increases, especially if this retail flow is informed as BJZZ posit. Rather, our collective evidence is consistent with wholesalers responding to increased demand for liquidity from liquidity-constrained institutional investors by internalizing additional, costlier retail flow. That is, we find evidence that wholesalers choose to exercise their *option* to internalize costlier retail order flow to manage inventory driven by filling unusually profitable institutional orders received in less liquid markets.

These findings suggest that, over a given period, e.g., a month, substantially positive or negative $Mroib$ occur more frequently in stocks with higher institutional liquidity costs where institutions must resort to expensive wholesaler-provided liquidity more often. This motivates us to investigate average daily $|Mroib|$ as a stock-level institutional liquidity cost (ILC) measure. We compare ILC's ability to capture institutional liquidity concerns with those of existing liquidity measures.[6] First, we document that ILC and several existing liquidity measures are correlated with future institutional price impacts obtained from ANcerno, indicating that the measures co-vary with expected institutional liquidity costs. Importantly, monthly ILC strongly persist over time, indicating that it capture cross-sectional variation in expected liquidity costs of institutions with long holding horizons.

Second, we provide direct evidence that ILC captures 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 *expected* holding horizon. As Amihud and Mendelson (1986) observe, investors with longer holding horizons should be more willing to invest in illiquid stocks; and we find that ILC produces a more monotone positive relationship between the illiquidity of a fund manager's equity holdings and their holding horizon than do existing measures. This finding is consistent with institutions who trade more frequently being reluctant to hold stocks that require them to turn to expensive wholesaler-provided liquidity. Similar evidence obtains from stock level analyses of the relation between illiquidity measures and holding horizon. Importantly, ILC is the only liquidity measures with an economically meaningful relation with holding horizons at *both* the investor and stock levels.

Third, we establish that ILC explains expected stock returns in the 2010–2019 period, but

[6]We observe that "illiquidity has a number of dimensions that are hard to capture in a single measure" (Amihud (2019), p. 214), and that existing measures are not specifically designed to capture *institutional* liquidity costs. Our focus on these costs reflects the economic significance of institutions in U.S. equity markets.

existing measures do not. Fama-MacBeth (1973) specifications regress stock returns in month m on (il)liquidity in month $m-2$ as well as an array of stock characteristic controls. We conservatively skip month $m-1$ to ensure that returns in month m are not confounded by short-term reversals after liquidity-demanding trades. Like the literature, we find existing liquidity measures are not priced (or have negative liquidity "premia"). In contrast, ILC is priced with economically-significant liquidity premia: a one standard deviation increase in ILC 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.[7]

Portfolio sorts confirm the economic magnitudes of the liquidity premia associated with ILC. Moreover, all results survive a battery of robustness tests that use alternative estimation approaches, weight observations unequally, apply various stock-inclusion criteria, and control for the momentum anomaly. Our robust results indicate that liquidity premia conditional on ILC hold among stocks that are the most likely to be held by institutions. Moreover, they validate our proposed economic mechanism underlying the variation in $Mroib$.

We also address the importance of BJZZ algorithm's errors in identifying retail trades. Type I errors occur when institutional trades with sub-penny execution prices are flagged as retail (Battalio, Jennings, Salgam, and Wu (2024)). If anything, removing such sub-penny institutional trades from the construction of $Mroib$ *reinforces* our findings. Type II errors refer to retail trades not identified by BJZZ, including (a) on-exchange executions where sub-penny trades are unavailable and (b) off-exchange trades executed near or at quote midpoints (Barber, Huang,

[7]ANcerno data became unavailable in 2015, preventing liquidity premia estimates using these data.

Jorion, Odean, and Schwarz (2022); Battalio et al. (2024)). As Section II discusses, the former component reflects wholesaler *choices* and is a core driver of $Mroib$ variations. We proxy the latter component using small off-exchange near-midpoint trades and show that our results robustly extend with a modified $Mroib$ that incorporates these trades. Our findings are also robust to correcting for BJZZ algorithm's errors in classifying sub-penny trades into buyer- and seller-initiated (Barber et al. (2022)).

Our paper adds to the work on the return predictability of retail order flow.[8] Our explanation for return predictability of $Mroib$ is consistent with Kaniel et al. (2008) who posit retail order flow reflects opposing institutional liquidity demand as institutional investors offer "price concessions" to "entice" large groups of retail investors to provide liquidity. However, Dyhrberg, Shkilko, and Werner (2023) find that retail investors do not seem to actively "time" liquidity consumption, suggesting that they do not respond to institutional price concessions. The economic mechanism we identify does not rely on retail investors strategically choosing to provide liquidity, but rather on wholesalers choosing to use retail order flow to provide liquidity to institutional investors when liquidity is scarce. This mechanism aligns with Barrot et al. (2016)'s notion of unintentional liquidity provision by retail investors. Most importantly, we uncover a new channel for the return predictability of retail order flow by showing that *average* $|Mroib|$ robustly explains the cross-section of expected returns over extended horizons.[9]

[8]E.g., Barber and Odean (2000), Barber and Odean (2008), Kumar and Lee (2006), Foucault, Sraer, and Thesmar (2011), Barrot, Kaniel, and Sraer (2016), Kaniel, Liu, Saar, and Titman (2012).

[9]It is important to note that we average $|Mroib|$ to arrive at a measure of institutional liquidity costs. Large $|Mroib|$ on a given stock-day can reflect idiosyncratic forces other than just high institutional trading costs. Averaging $|Mroib|$ across trading days offsets the effects of any idiosyncratic forces.

We also contribute to the literature that designs measures of stock liquidity or examines their asset-pricing implications.[10] After the adoption of Regulation National Market System, spreads often fell to a few pennies and depth became negligible, leading institutional investors to employ dynamic multi-venue trading strategies. This increased complexity made institutional liquidity costs empirically challenging to capture, which likely underlies why existing measures now only capture illiquidity in "penny stocks." We exploit order flow segmentation in modern U.S. equity markets to identify stocks where institutional investors rely more on costly, wholesaler-intermediated liquidity provision. Emphasizing this contrast, our measures robustly identify liquidity premia when we exclude micro-cap stocks, consistent witht institutional investors trading larger-cap stocks more heavily.

Our use of observable retail trades distinguishes our analysis from recent research. For example, Barardehi et al. (2019) develop trade-time liquidity measures, reflecting endogenous responses of investors to time-varying liquidity. Bogousslavsky and Collin-Dufresne (2023) use weekly volatility in total 5-minute order to measure liquidity *risk*, and show it predicts return in the next few days. Our findings indicate that BJZZ-identified retail trades capture important endogenous choices of wholesalers when providing liquidity in the segmented U.S. equity markets, facilitating the construction of useful institutional trading cost measures.

[10]See 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 (2023), among others.

II. Institutional Details and Hypothesis Development

Orders of retail investors in U.S. equity markets are "handled" almost exclusively by wholesalers, a group of sophisticated market makers, on the behalf of retail brokers. As a result, wholesaler choices shape execution outcomes for retail orders. Wholesalers, who are subject to best execution requirements,[11] compete to attract order flow from brokers. Wholesalers have two options to provide executions to marketable retail orders (market orders or limit orders that can cross the best available quoted price on the opposite side of the market). Specifically, wholesalers can (1) execute the orders against their own inventory, i.e., internalize orders; or (2) reroute the orders to trading venues such as exchanges, i.e., externalize orders. SEC (2022) reports wholesalers internalize 80% of retail orders and externalize the other 20%.

Competition and best execution requirements lead wholesalers to provide PI to internalized orders: they fill the vast majority of internalized orders at prices better than the NBBO (Battalio and Jennings (2024)). Crucially, wholesalers can provide PI by internalizing orders at sub-penny prices—which is not generally available for externalized orders filled on exchanges that must enforce the minimum 1¢-tick requirement. As a result, internalized retail trades that receive execution prices at sub-penny increments can be traced in TAQ data. This led BJZZ to propose an algorithm that uses TAQ data to flag trades with sub-penny price increments as retail, signing them as buyer- and seller-initiated using the size of the sub-penny increment.

About half of internalized retail orders receive PI at prices with round pennies or 0.5¢ increments. Most of these trades reflect best execution requirements: if wholesalers identify

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

inside-quote odd-lot or hidden midpoint liquidity using their superior data feeds or when "pinging" Alternative Trading Systems (ATSs) then they must fill marketable retail orders from the opposing side at these inside-quote round-penny or midpoint prices (the Manning rule).[12] By excluding these trades, which tend to occur when mid-point liquidity is abundant, the BJZZ algorithm facilitates our analysis of instances where liquidity is scarce.

For the remaining internalized orders, wholesalers *choose* the sizes of PI, leading to sub-penny price increments that are not concentrated at 0.5¢. BJZZ's algorithm flags these retail trades in TAQ data. Put differently, the algorithm identifies a select set of internalized trades that reflect wholesaler internalization choices over which retail orders to internalize, rather than internalization driven by best execution requirements.

A wholesaler also interacts with institutional investors through market making on exchanges, ATSs, and their own Single-Dealer platform (SDP). This allows wholesalers to intermediate between retail and institutional investors, clienteles that rarely interact otherwise. Direct retail-institutional flow interactions only occur on exchange in Retail Liquidity Programs; less than 5% of retail trades use this mechanism reflecting that such retail orders are typically viewed as highly toxic by institutions (Ernst, Spatt, and Sun (2024)).

The first hypothesis that we test is that the *imbalances* between BJZZ-identified buy and sell trades are driven by wholesaler choices to intermediate between institutional and retail flow,

[12]This outcome is akin to wholesalers using institutional flow to provide liquidity to retail investors. To see this, suppose a wholesaler receives 2,000 shares of marketable retail buy orders and 3,000 shares of sell orders; and 10,000 shares of sell interest is at the midpoint on ATS X and 20,000 shares of buy interest is at the midpoint on ATS Y. If the wholesaler "pings" both ATSs, the Manning rule requires the wholesaler to internalize *all* retail orders at the mid-point.

especially when limited mid-point liquidity is available. For multiple reasons, we expect this intermediation to concentrate in states with scarce liquidity. First, by turning to a wholesaler for immediacy, a revealed-preference cost logic indicates that liquidity-demanding institutional investors have trouble locating cheaper, midpoint liquidity, which endows a wholesaler with market power (Hu and Murphy (2022); Houang, Jorion, Lee, and Schwarz (2023)). Second, a revealed-preference information logic reinforces the absence of dark pool liquidity—seeking liquidity on SDPs or exchanges hinders institutions' ability to conceal their trading intentions from other market participants and results in price impacts (Zhu (2014)). Third, internalized retail orders are themselves a costly inventory management resource for wholesalers as they pay at least \$1 to internalize 100 shares of retail orders.[13] Institutions' willingness to compensate liquidity-providing wholesalers for these costs signifies scarce liquidity.

Wholesalers can offset the impacts on their inventories from filling large institutional orders on one side of the market by internalizing more retail orders on the opposite side. Thus, we expect institutional order flow to be inversely related to the imbalance in retail trades that wholesalers *choose* to internalize upon receiving large institutional orders—which tends to happen precisely when institutional liquidity costs are high due to limited midpoint liquidity.

Together these observations imply that BJZZ algorithm identifies imbalances in internalized retail trades used by wholesalers to provide liquidity to institutions, and we provide stock-level and cross-sectional evidence of this. The link between higher institutional trading costs and our intermediation mechanism suggests that such intermediation is more likely in stocks

[13]Panel A in Table B.1 shows that three major retail brokers charge between 9¢ to 20¢ in PFOF to allow a wholesaler handle 100 shares of their customer's marketable orders, and Battalio and Jennings (2024) report that wholesalers pay an average PI of 85¢ to internalize 100 shares.

where institutional investors face higher average costs of establishing and unwinding positions. This leads us to test our second hypothesis that the absolute value of BJZZ trade imbalances, as a proxy of expected institutional trading costs, captures institutional liquidity concerns in the cross-section. We find extensive evidence of this, corroborating our proposed mechanism.

III. *Mroib* and *ILC*

This section describes our main empirical measures. Appendix A provides detailed descriptions of additional data and variables. Table A.1 provides cross-references between each variable definition and relevant empirical findings. We use the BJZZ algorithm to construct measures of internalized retail order flow. From TAQ data, we obtain regular-hours round-lot off-exchange trades with sub-penny prices,[14] classifying them as retail buy orders if the sub-penny increments exceed 0.6¢ and as sell orders if the increments are below 0.4¢—Barber et al. (2022) and Battalio et al. (2024) identify three types errors in the BJZZ algorithm, which we address in Section VI. For stock j on day t, $Mroibvol_{jt}$ divides the difference between the volumes of internalized retail buy and internalized retail sell orders, denoted $Mrbvol$ and $Mrsvol$, respectively, by their sum. Similarly, $Mroibtrd_{jt}$ divides the difference between the number of internalized retail buy and internalized retail sell orders, denoted $Mrbtrd$ and $Mrstrd$, respectively, by their sum. That it,

$$(1) \qquad Mroibvol_{jt} = \frac{Mrbvol_{jt} - Mrsvol_{jt}}{Mrbvol_{jt} + Mrsvol_{jt}} \quad \text{and} \quad Mroibtrd_{jt} = \frac{Mrbtrd_{jt} - Mrstrd_{jt}}{Mrbtrd_{jt} + Mrstrd_{jt}}.$$

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

Panel B in Table B.1 reports summary statistics for these measures closely match those in BJZZ.[15] Our main analysis relies on $Mroibvol$, which we will refer to as $Mroib$ for simplicity, but our findings are robust to using $Mroibtrd$ as shown in the Internet Appendix. Our analysis of the economic mechanism, which relates $Mroib$ to institutional demand for liquidity, uses the sample of NMS-listed common shares from January 2010 to December 2014. We use this time period because (1) it maximizes overlap with BJZZ's sample of 2010–2015; and (2) our access to ANcerno institutional trade information only extends to December 2014.

We extend the sample through December, 2019 for analyses that relate institutional liquidity costs to investor holding horizons and the cross-section of stock returns, for which ANcerno data is not necessary. Our institutional liquidity cost measures (ILCs) for stock j in the period M ending in month m are defined as

$$(2) \qquad ILCV_{jm} = \frac{1}{n_M^j} \sum_{t \in M} |Mroibvol|_{jt} \quad \text{and} \quad ILCT_{jm} = \frac{1}{n_M^j} \sum_{t \in M} |Mroibtrd|_{jt},$$

where n_M^j is stock j's number of trading days with non-zero BJZZ volume in period M. Our main analysis is based on period M being identical to a given calendar month m. The Internet Appendix establishes robustness to expanding M to a three-month period ending in month m. We use $ILCV$ in our main analysis, referring to it as ILC for simplicity. The Internet Appendix establishes that our qualitative findings extend if we instead use $ILCT$.

[15] 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)).

IV. Institutional Liquidity Demand and BJZZ Imbalances

This section highlights the role of wholesaler internalization choices in driving $Mroib$. Our findings explain the robust predictive power of $Mroib$ for future returns without resorting to retail investors being informed. They also motivate our institutional liquidity cost measures.

IV. A. *Mroib* and Opposing Institutional Price Pressure

We first document evidence consistent with substantially unbalanced $Mroib$ signifying excess institutional liquidity demand on the opposite side of the market. To do this we analyze price dynamics and institutional trade imbalances at the *individual stock* level around positive or negative spikes (events) in $Mroib$. Day t^* in stock j is flagged as a positive $Mroib$ event day if $\frac{1}{5}\sum_{n=0}^{5} Mroib_{j,t^*-n} > \overline{|Mroib|}_{j,q-1}$; and it is flagged as a negative $Mroib$ event if $\frac{1}{5}\sum_{n=0}^{5} Mroib_{j,t^*-n} < -1 \times \overline{|Mroib|}_{j,q-1}$, where $\overline{|Mroib|}_{j,q-1}$ is the daily average from the preceding calendar quarter. We use $|Mroib|$ as the benchmark reflecting that average $Mroib$ is very close to zero (see Panel B in Table B.1). The 5-day moving average provides consistency with BJZZ's design, allowing us to relate our findings to theirs.[16]

For each stock j, event windows span the five trading days leading up to day t^*, labeled

[16] If there are clusters of qualifying 5-day moving average $Mroib$ within a 5-day interval, we define an event based on the first qualifying observation. This conservative design allows the positive autocorrelation in $Mroib$ to attenuate the post-event effects that we document. We also require that the $\frac{1}{5}\sum_{n=0}^{5}[Mrbtrd_{j,t-n} + Mrstrd_{j,t-n}]$ associated with an $Mroib$ event exceed the first quartile of daily $Mrbtrd_j + Mrstrd_j$ from the previous quarter. This ensures that highly unbalanced $Mroib$ observations driven by very few sub-penny trades do not drive our findings. Despite these restrictions, we identify almost 100,000 $Mroib$ events. This means our findings are not driven by rare liquidity or information arrival events.

-4 through 0 (pre-event), and five days after t^*, labeled 1 through 5 (post-event). We construct cumulative market-adjusted outcomes *separately* for pre-event (days $t^* - 5$ through t^*) and post-event (days $t^* + 1$ through $t^* + 5$) intervals. Of the 2,739,560 stock-day observations in our five-year sample, we identify 97,554 $Mroib$ events, 33,531 of which are positive events and 64,023 of which are negative events. The 10-day event windows encompass 940,937 stock-day observations or 34.3% of the sample.

Figure 2 summarizes our findings. The discontinuity at t^* reflects the separate constructions of pre- and post-event cumulative outcomes. Panel A shows abnormally unbalanced $Mroib$ prior to "events" followed by relatively balanced $Mroib$ post event, indicating that our empirical design effectively detects stock-specific $Mroib$ spikes. Panel B shows the dynamics of institutional trade. Abnormal institutional trade imbalance for each stock day is the ratio of buy minus sell institutional volume to total institutional volume, centered at its cross-sectional mean. Pre-event, cumulative abnormal institutional trade imbalances appear on the *opposite* side of $Mroib$, while post-event, institutional flows are largely balanced. These findings suggest that pre-event, pressing institutional liquidity demands induce wholesalers to internalize disproportionately more retail orders on the opposite side.

Panel C plots the corresponding cumulative abnormal 24-hour returns. The positive association between pre-event abnormal $Mroib$ (Panel A) and post-event returns is consistent with $Mroib$'s positive predictive power for future returns found by BJZZ. However, pre-event abnormal returns have the *opposite* sign of $Mroib$: prices move in the *opposite* direction of internalized retail flow (Panel A) but in the *same* direction as institutional order flow (Panel B), suggesting that *institutional liquidity demand drives prices, and not BJZZ flow.*

Decomposing returns into intraday (open-to-close) and overnight (close-to-open) components, as defined in Table A.1, reinforces this conclusion and reveals why price reversals begin to appear on day -2. Panel D shows that the pre-event price pressure associated with institutional flow is *only* realized during regular trading hours, i.e., when institutional investors are active (also recall that BJZZ's algorithm only uses *regular-hour* transactions). That intraday cumulative returns move in the same direction as cumulative institutional flow pre-event suggests a continuing buildup of price pressure from institutional investors. Panel E shows that post-event price reversals are *solely* attributable to price movements after-hours when institutional investors are largely inactive. Thus, even on a daily basis, both pre- and post-event, (1) intraday prices co-move with institutional flow, while (2) overnight, with no institutional demand, prices reverse. We next provide evidence consistent with overnight reversals reflecting compensation for the overnight inventory risk exposures of wholesalers.

Our results suggest increased wholesaler inventory imbalances pre-event. To see this, note first the strong pre-event price pressure (Figure 2, Panel D) is associated with persistent institutional liquidity demand (Figure 2, Panel B). We will show that wholesalers do not appear to offset increased institutional liquidity demand by internalizing fewer retail trades on the same side of the market. In contrast, they internalize more retail trades on the opposite side, trades for which wholesalers pay more to handle. Collectively these findings suggest that wholesaler inventory imbalances rise despite increased internalized retail flow on the opposite side of the institutional demand and reduced internalization on the same side. Consistent with this, Hendershott, Menkveld, Praz, and Seasholes (2022) observe that market makers (here, wholesalers) build up inventory as they provide liquidity to institutional investors.

As wholesalers carry more unwanted inventory overnight, they are exposed to increased overnight volatility risk for which they require compensation in the form of better prices near close. This risk drops once trading resumes at open, consistent with the reversion in overnight prices found. That overnight reversals more than offset the preceding intraday returns in the two days prior to an event suggests that wholesaler inventories grow increasingly out-of-balance due to persistent institutional liquidity demand, resulting in ever greater reversals.

Comparisons of the price improvements offered by wholesalers to internalized buy and sell trades around $Mroib$ events reinforce the salience of this mechanism. For each BJZZ-identified transaction, we define the size of effective price improvement (PI) for buy and sell orders as the distance between the execution price and the corresponding NBO and NBB, divided by the NBBO midpoint. We then construct volume-weighted averages of effective PIs for buy and sell trades per stock-day and analyze their evolution around $Mroib$ events.

Figure 3 shows wholesalers pay *more* effective PI on the side that they internalize disproportionately *more* retail orders. Panel A shows that internalized buy trades receive higher PI than sell trades prior to positive events, but lower PI than sell trades post-event. Panel B shows that prior to negative events, sell trades receive abnormally higher PI than buy trades relative to post-event.[17] Higher effective PI in the direction of $Mroib$ imbalances is consistent with (1) increased wholesaler profits from providing liquidity to institutional investors on the other side who have pressing liquidity needs; and (2) increased wholesaler inventory risk that justifies the internalization of more expensive retail orders that help balance inventory.[18]

[17]Note that we do not use cumulative outcomes over the pre- and post-event periods in this analysis. The relatively higher PI received by retail sell trades after *both* positive and negative $Mroib$ events may reflect that retail investors are net buyers, making sell retail orders more scarce from a wholesaler's perspective.

[18]These asymmetries in PI offered to retail trades underlying $Mroib$ imbalances are also consistent with wholesalers competing for retail order flow through execution quality. That is, wholesalers use increased revenue

Importantly, the asymmetries are at odds with two alternative explanations. First, they are inconsistent with these retail trades being informed, as it is not plausible that wholesalers would willingly pay *more* to fill "toxic" orders. Second, they imply that $Mroib$ imbalances cannot reflect excess liquidity demand from retail investors, as it is not plausible for a wholesaler to offer better prices to retail traders when retail liquidity demand rises, especially when prices move in the opposite direction.

Overall, these findings align with the literature on short-term institutional price pressure (Campbell et al. (1993), Hendershott and Menkveld (2014)). The findings suggest that minus $Mroib$ captures the pressing liquidity demand by the marginal institutional investor whose trading exerts temporary price pressure, inducing wholesalers to meet this demand by internalizing more retail orders on the opposite side.

IV. B. *Mroib*, Institutional Trading, and Liquidity

We next analyze the cross-sectional implications of the link between large positive or negative $Mroib$ and institutional liquidity costs. We posit that institutional investors are more likely to have to turn to wholesalers for liquidity in less liquid stocks; and, as a result, wholesalers are more likely to use internalized retail trades to offset this institutional liquidity demand. In turn, it follows that substantially positive or negative $Mroib$s are more likely in these stocks. All variables used in this analysis are defined in Table A.1.

Table 1 summarizes our cross-sectional findings. Our semi-parametric analysis examines the variation in each outcome variable across deciles of $Mroib$, constructed for each weekly

from providing liquidity to profitable institutional orders on one side of the market to improve execution quality of internalized retail orders on the opposite side.

cross-section, allowing for flexible functional forms that link levels of these outcomes to $Mroib$ imbalances. As the caption of Table 1 details, we use panel regressions with fixed effects to obtain averages and 95% confidence intervals of different outcomes by $Mroib$ decile. Non-overlapping confidence intervals for a given outcome variable obtained at different $Mroib$ deciles signify statistically significant differences.

Large positive or negative values of $Mroib$ are associated with less liquidity, consistent with wholesalers turning to internalized retail flow for inventory management as they provide liquidity to institutions that seek out wholesalers when cheaper liquidity is scarce. To show this, we first construct a stock-specific measure of abnormal realized off-exchange midpoint liquidity. For each stock-day, we divide the volume of large off-exchange mid-point executions[19] by the average of this quantity over the sample period for that stock. Higher values of this measure indicate greater midpoint liquidity. Table 1 shows abnormally low levels midpoint liquidity when $Mroib$ is more unbalanced, linking $Mroib$ to institutional investors' inability to find trading counter-parties at the midpoint. On-exchange liquidity is also scarcer—as indicated by the wider quoted spreads and reduced depth at the NBBO—when $Mroib$ is more unbalanced. For example, average relative quoted spreads in the lowest and highest $Mroib$ deciles are about 30% larger than those when $Mroib$ is more balanced. This scarce liquidity manifests itself in higher implicit institutional trading costs: the average institutional price impact per \$1m transaction for the average stock are 66.4 and 66.1bps for the lowest and highest $Mroib$ deciles, respectively, over double the 25bps found when $Mroib$ is balanced.

Table 1 reveals that more unbalanced $Mroib$ is associated with larger *opposing* trade

[19]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 quote midpoint.

imbalances from both long-only institutional investors and short sellers. Average raw (market-adjusted) institutional flow falls from 29% (0.05%) in the bottom decile to 18% (-0.06%) in the top decile. Short selling activity also occurs on the opposite side of $Mroib$ imbalances: increased short interest is associated with larger positive internalized retail order flow imbalances. Of note, directional (as opposed to liquidity-providing) short sellers, whose 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)), further reinforcing that the opposing internalized retail trade is not.

Table 1 summarizes the relationships between $Mroib$ and returns that link our cross-sectional analysis to our findings in Section IV. A. Close-to-close returns rise monotonically from 1.8bps in the bottom $Mroibvol$ decile to 29bps in the top decile. Importantly, as noted earlier, this pattern is *not* due to price pressure from retail order flow. Decomposing daily returns into intraday and overnight components reveals that the intraday returns that correspond to the trading activity underlying $Mroib$ *fall* from 7.3bps in the bottom $Mroib$ decile to -11bps in the top decile. In sharp contrast to intraday returns, overnight returns are *positively* related to $Mroib$. The signs of average intraday and overnight returns differ for most $Mroib$ deciles, exhibiting generally greater differences at more unbalanced $Mroib$ deciles. Collectively, these cross-sectional analyses indicate that institutional liquidity demand in less liquid markets drives intraday price pressure and wholesalers respond by internalizing more retail trades on the opposite side. Consistent with the findings in Section IV. A, institutional price pressure unwinds overnight reflecting the absence of institutional activity together with the reconciliation of marker-maker-inventory risk.

These findings complement the stock-level evidence provided in Section IV. A that

$Mroib$'s predictive power for near-term returns reflects reversals that follow institutional price pressure. Importantly, these findings also link the level of $|Mroib|$ to institutional liquidity costs. We next reinforce this link by analyzing $|Mroib|$'s return predictability for future returns.

IV. C. Return Predictability of *Mroib*

We now analyze $Mroib$'s return predictability, uncovering a strong link to liquidity premia. Panel B in Table B.1 provides summary statistics that closely match those in Table I of BJZZ, confirming that our construction of $Mroib$ parallel theirs.[20] We use portfolio sorts to study $Mroib$'s return predictability without imposing specific functional forms, examining both raw and market-adjusted future returns associated with weekly portfolios of past $Mroib$. We sort cross-sections based on $Mroib$ in week $w-1$ to examine average future returns in weeks $w+i$ with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36\}$.

Table 2 shows that, consistent with BJZZ, future returns in weeks w through $w+2$ rise in $Mroib$ from week $w-1$. The analyses in Sections IV. A and IV. B suggest that these patterns are due to price reversals that follow institutional price pressure in week $w-1$. Past negative $Mroib$ is a symptom of positive institutional flow faced by wholesalers with positive price pressure; as this price pressure reverses in future weeks, it tilts future returns downward. Conversely, past positive $Mroib$ signifies negative institutional flow with negative price pressure, with subsequent reversals that tilt future returns upward. This mechanism underlies the positive association between $Mroib$ and short-term future returns, and this process can take weeks due to the persistence in institutional order flow (Campbell, Ramadorai, and Schwartz (2009)). Table 2

[20]Differences arise since our sample period spans 2010–2014 and requires a \$2 share price, while BJZZ's spans 2010–2015 and requires a \$1 share price. All our qualitative findings extend for a \$1 price filter.

shows that the positive link between $Mroib$ and future returns begins to weaken in week $w+1$, turning to a ∪-shaped relation by week $w+6$. This ∪-shaped pattern persists past week $w+36$.[21]

The strong association between $|Mroib|$ and institutional liquidity costs established earlier suggests that the ∪-shaped pattern in longer-term future returns reflects liquidity premia. That is, institutional investors require higher returns on stocks with higher expected costs of entering or exiting positions (Amihud and Mendelson (1986)).

V. *ILC*s as Institutional Liquidity Cost Measures

We next provide evidence that our institutional liquidity cost measures capture liquidity concerns of institutional investors. We compare our ILC to existing liquidity measures (detailed in Appendix A) along different dimensions. Due to the substantive differences between liquidity measures in their constructions and the aspect of liquidity they aim to capture, we structure comparisons by dividing liquidity measures into three categories.[22]

Category 1 measures capture the *expected* costs of trading associated with individual transactions, but not the cumulative trading costs of institutional child orders that realize over many trades due to dynamic order splitting. These measures are directly obtained from limit order book data. Our analysis considers quoted spreads and quoted depth at the NBBO.

Category 2 measures estimate the *realized* trading costs of individual trades and involve estimations that follow specific economic aspects of trading costs. For example, effective spreads compare transaction prices to the NBBO midpoint in effect just prior to the transaction to measure

[21]Findings are robust to using the exact specification used by BJZZ that include controls.

[22]We thank an anonymous referee for suggesting this decomposition.

the margin from the fair asset value—the "benchmark"—associated with execution of a marketable order. Such measures are subject to estimation errors, largely driven by (1) calculation of the benchmark and (2) endogenous order type choices. Category 2 measures in our analysis include institutional price impacts (from ANcerno), effective spreads, general price impact estimates, i.e., post-trade quote mid-point drift, and realized spreads.

Category 3 measures, which include our institutional liquidity cost measures, proxy the cross-sectional differences in liquidity costs based on some footprint in the data. For example, ILC, defined in equation (2), uses a subset of wholesaler-retail trades to arrive at institutional liquidity costs. Similarly, the idea behind Roll's measure is that liquidity consumption leads to a temporary deviation of prices from fundamentals, leading to stronger short-term negatively auto-correlated returns in less liquid stocks. The other common feature of category 3 measures is that, unlike the other two categories, they aggregate information across individual trades. In addition to ILC, category 3 measures include Amvist, Roll, Kyle's lambda, Amihud, and trade-time measures of liquidity. We focus on comparing ILC with these peer measures, but some analyses assess all measures for completeness.

V. A. Liquidity Measures & Institutional Price Impacts

Any liquidity measure that is expected to capture the liquidity concerns of institutional investors should be positively associated with institutional price impacts. Reflecting dynamic order-splitting, estimating institutional liquidity costs from market data requires some aggregation across individual trades, a common feature of category 3 measures. We investigate this expected association between each category 3 measure and the expected institutional price impacts obtained from ANcerno. For less liquid stocks, most liquidity measures meet this expectation—lower measured liquidity in month $m - 2$ is associated with higher realized post-trade institutional price impacts in month m. However, for more liquid stocks, only Kyle's lambda, Amihud, trade-time measures, and ILC deliver this basic monotone relationship.

To show this, we sort each month-m cross-section into deciles of a given liquidity measure, constructed in $m - 2$, with deciles 1 and 10 containing the most and the least liquid stocks, respectively. We then calculate a time-series average of the institutional price impacts of the median stock in each decile.[23] In Figure 4, Panel A shows that for more liquid stocks (deciles 1–5), future institutional price impacts rise monotonically with "improved" liquidity only when measured by Kyle's lambda, Amihud measures, trade-time liquidity measures, and ILC. Panel B shows that for less liquid stocks (deciles 6–10), worsened liquidity according to all liquidity measures (movements from decile 6 to 10) is associated with increased future institutional price impacts. In sum, most liquidity measures can proxy institutional trading costs for less liquid stocks, and hence are correlated with the same phenomenon. However, only a few, including ILC, do so for more liquid stocks.

[23]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 cover 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.

V. B. *ILC*s are Stock Characteristics

We next document the temporal persistence in ILC, establishing that it reflects a stock characteristic.[24] This persistence is important because persistent trading costs should enter the decision making of institutional investors, justifying the existence of liquidity premia in stock returns. To examine their persistence, we fit Fama-MacBeth regressions of ILC on its lags from the six preceding months, correcting for auto-correlated error terms using Newey-West standard errors based on six lags, as in the rest of our regression analyses. We exclude stocks priced below $2 before estimating equally-weighted and value-weighted regressions (with weights computed using market capitalizations at the previous month's end). Table 3 shows that past ILC levels strongly predict future levels. That is, stocks with high ILCs in one month tend to have high ILCs in future months.

V. C. Liquidity and Institutional Holding Horizon

We next investigate Amihud and Mendelson (1986)'s prediction that (a) at the investor level, investors with longer holding horizons should hold less liquid stocks, and (b) at the stock level, less liquid stocks should be held by institutional investors with longer holding horizons.

V. C. 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 fund

[24]Table B.2 shows that high-ILC stocks, i.e., stocks identified as less liquid by the ILC, tend to be small growth stocks with relatively poor recent returns and low CAPM betas.

managers i in quarter q, denoted $mgrLIQ_q^i$, weighting observations by the fraction of the manager's total dollar-denominated portfolio value in a stock. Other EUM characteristics, including volatility ($mgrVolat$), market capitalization $mgrM$, and institutional ownership ($mgrIOShr$), are computed using a similar methodology in the previous quarter. We follow Gaspar, Massa, and Matos (2005) and Cella, Ellul, and Giannetti (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. Figure 5's caption provides details on these calculations.

We estimate the relation between an investor's EUM liquidity and expected holding horizons, defined as one minus churn percentiles, after controlling for other EUM characteristics. Each quarter, we obtain regression residuals from

$$mgrLIQ_{j,q} = a + b \times mgrVolat_{j,q} + c \times mgrM_{j,q} + d \times mgrIOShr_{j,q} + u_{j,q}. \tag{3}$$

We then sort each quarterly cross-section into percentile statistics of the previous quarter's residual EUM liquidity and current 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 summarizes results for all liquidity measures. Residual 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 strong $\cap$-shaped patterns with respect to holding horizon, contrary to the prediction that investors with longer holding horizons should hold less liquid stocks. In contrast, ILC-based EUM illiquidity displays a more monotonically increasing pattern in holding horizon that flattens for the longest holding horizons, consistent with investors who trade more frequently avoiding holding stocks where taking or leaving positions is more likely to require tapping into retail-sourced liquidity.

V. C. 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, institutional investors with longer expected holding horizons should hold less liquid stocks.

We test whether different illiquidity measures yield estimates consistent with this prediction. Following 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 churn ratio moving averages over the four *preceding* quarters, $q-4$ through $q-1$, to estimate institutional turnover $\overline{CR}_{j,q}$. Finally, we estimate

$$LIQ_{j,q} = \alpha + \beta HHpctl_{j,q} + \delta \times Volat_{j,q} + \lambda \times M_{j,q} + \eta \times IOShr_{j,q} + v_{j,q}, \tag{4}$$

where $HHpctl_{j,q}$ is stock j's holding horizon percentile (1 minus churn ratio percentile) in quarter q, Fama-MacBeth regressions with Newey-West standard errors based on 6 lags. Other stock characteristics are described in Appendix A.

Panel A in Table 4 reports that the coefficients on institutional holding horizon percentile have the expected sign for most liquidity measures. However, *striking* differences show up in R^2 magnitudes. The R^2s associated with ILC is 0.63, indicating that holding horizon explains most of the variation in investor-level portfolio liquidity based on ILC. In contrast, for existing liquidity measures, the next highest R^2 is 0.44 and most are far lower, with some only marginally greater than zero.

To emphasize that ILC better captures the concerns of institutional investors, we next orthogonalize the ILC measure with respect to the other liquidity measures. To do this, we first regress ILC on an alternative liquidity measure LIQ in each quarter q, denoting the respective residuals by Z_{ILCT}. We similarly regress each existing liquidity measure, separately, on ILC, denoting the residuals Y_{ILC}. Finally, to examine the ability of holding horizon to explain variation in these residuals, we estimate

$$(5) \qquad R_{j,q} = \alpha + \beta HHpctl_{j,q} + \delta \times Volat_{j,q} + \lambda \times M_{j,q} + \eta \times IOShr_{j,q} + v_{j,q},$$

where $R \in \{Z_{ILC}, Y_{ILC}\}$ using Fama-MacBeth regressions with Newey-West standard errors based on 6 lags.

In Table 4, the top three rows of Panel B report that relative to every existing liquidity measure ILC has incremental liquidity-related implications for institutional investors. In contrast, the bottom three rows in Panel B of Table 4 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_{ILC} residuals explained by holding horizon (and stock characteristics) is less than one-twentieth of the variation in the Z_{ILC} residuals explained by holding horizon (and stock characteristics). That is, institutional holding horizons better explain ILC residuals than they explain residuals of existing liquidity measures. In sum, ILC has incremental implications for investors relative to existing liquidity measures, but the converse is not true.

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

V. D. Liquidity Premia

We next contrast ILC and existing liquidity measures (see Appendix A) in their ability to predict the cross-section of expected returns. Unlike existing measures, ILC robustly predicts the cross-section of stock returns and captures economically-significant liquidity premia. We estimate the following Fama-MacBeth regression with Newey-West-corrected standard errors using six lags

$$RET_{j,m} = \gamma_m^0 + \gamma_m^{LIQ}\left(LIQ_{j,m-2}\right) + \Gamma^\top \text{CONT}_{j,m-1} + u_{j,m}, \tag{6}$$

where the dependent variable $RET_{j,m}$ is stock j's return in month m in excess of the corresponding 1-month T-Bill rate. $LIQ_{j,m-2}$ denotes one of the liquidity measures obtained at the end of month $m-2$ for stock j—adding a one-month gap between the construction of each liquidity measure and monthly returns ensures that short-term price reversals do not contaminate our inferences. $\text{CONT}_{j,m-1}$ is a vector of control variables that includes 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 falls sharply after 2003. It is therefore unlikely that controlling for more stock characteristics would qualitatively change our results, as our sample starts in 2010.

Panel A in Table 5 reports that unlike existing liquidity measures, measures based on institutional liquidity costs explain the cross-section of expected returns. We find estimated liquidity premia for InPrIm and ILC. Of note, most researchers lack access to the proprietary Ancerno data required to construct InPrIm—Ancerno data are only available to a subset of academics pre-2015, after which the data vendor terminated academic access (Hu et al. (2018)). Our ILC also captures institutional trading costs *and*, in important contrast, are easily constructed using publicly-available TAQ data.

The coefficients on the institutional price impacts (InPrIM) and ILC, are 0.029 and 1.27, respectively. Multiplying these coefficients by their respective standard deviations (of 0.109 and 0.21) yields monthly liquidity premia of 31.6 bps and 26.7bps, respectively. Thus, one standard deviation reductions in liquidity as measured by ILCs are associated with 26.7bps increases in expected monthly returns, or 3.20% increases in annual returns.[25] The analogous annual liquidity premium attributable to realized institutional price impacts is 3.8%. These results based on institutional trading costs comprise strong evidence that investors demand economically-significant liquidity premia.

Internet Appendix II documents robustness to $1 and $5 minimum share price requirements. Consistent with Barardehi et al. (2019) and Barardehi, Bernhardt, Ruchti, and Weidemier (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

[25]Using the trade-based ILC, denoted $ILCT$ in equation (2), yields annual liquidity premium of 2.74%.

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 is priced with a \$5 minimum price filter. Internet Appendix V confirms the robustness of the liquidity premia when liquidity measures are constructed over 3-month or 12-month rolling windows. These alternative constructions result in monthly liquidity premia of 25–31bps, with associated annual liquidity premia of 3.07–3.74%.

Panel B in Table 5 presents the significant incremental information content of ILC vis à vis (1) each existing liquidity measure and (2) the collection of all existing measures. Each ILC measure is first regressed on an alternative liquidity (price impact) measure using Fama-MacBeth regressions. The residuals from such regressions are then used, one at a time, as $LIQ_{j,m-2}$ in equation (6). The ILC residuals, except that orthogonalized to realized institutional price impacts (InPrIm), explain the cross-section of expected returns. Untabulated results verify that the residuals of existing liquidity measures orthogonalized with respect to our ILC all fail to explain the cross-section of returns. The last column in Panel B of Table 5 shows that the residuals from regressing ILC on *all* standard liquidity proxies, excluding InPrIm, still explain the cross-section of expected returns, underscoring the significant incremental information content of ILC.

Our results suggest that conclusions that liquidity premia have vanished post-decimalization (e.g., Asparouhova et al. (2010); Ben-Rephael et al. (2015)) reflect the use of liquidity measures that no longer capture the institutional features of modern equity markets. In particular, institutions employ complicated dynamic trade execution strategies in response to tight spreads (often binding at a penny tick) and limited depth at the NBBO in a fragmented marketplace, compromising existing measures. In contrast, ILC is motivated by the revealed preferences of investors who turn to wholesalers in the face of scarce liquidity. The ILC measure reveals that the average investor accounts for cross-stock heterogeneity in trading costs when pricing stocks.[26] That ILC do not outperform InPrIm in these residual analyses reflect that both measures capture institutional trading costs. However, only ILC is available for recent years.

Internet Appendix III shows that our main asset pricing result is robust to alternative empirical specifications, including (1) the use of panel regressions with fixed effects; (2) correcting for market microstructure noise, as in Asparouhova et al. (2010); (3) excluding the smallest 20% of stocks; (4) excluding stocks in the bottom 10% of sub-penny trade volume ($SPVS$); (5) weighting observations by firm size; and (6) estimating the model by listing exchange. The appendix provides evidence that liquidity premia based on ILC grows larger as institutional ownership ($IOShr$) falls, consistent with the economic mechanism underlying ILC. That is, with lower $IOShr$, institutional investors with pressing liquidity demand are less likely to find institutional trading counterparties, so they must turn more frequently to more expensive wholesaler-provided liquidity.

Finally, we confirm the economic magnitudes of liquidity premia based on ILC in portfolio sorts. Internet Appendix IV reveals economically significant equally-weighted 3- and 4-factor alphas in portfolio sorts based on CRSP breakpoints or value-weighted alphas in portfolios sorts based on NYSE breakpoints that exclude stocks in the smallest quintile of market-caps. We also apply three different minimum share price filters that remove stocks whose month-end closing price in the prior month is below $p_{min} \in \{\$1, \$2, \$5\}$. These analyses reveal significant risk-adjusted return spreads between the least liquid and most liquid portfolios

[26] 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.

according to ILC. Annualized portfolio return spreads range between 4.08–15.24%, with the larger estimates found for samples that include small, low-priced stocks.

Internet Appendix VI repeats the portfolio sorting exercise for alternative liquidity measures using the three minimum price filters. It confirms that ILC is the only measures for which the long-short portfolio risk-adjusted return spreads reflect liquidity premia close to 1% or higher. Internet Appendix VII shows that alphas associated with ILC survive double sorts that control for key stock characteristics. We form an array of 5×5 portfolios that first condition on a stock characteristic (one of market beta, market capitalization, book-to-market ratios, momentum, institutional ownership, and the share of sub-penny volume), and then on ILC. 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 literature (e.g., Lesmond, Schill, and Zhou (2004); Korajczyk and Sadka (2004)), we find that momentum profits do not survive institutional trading costs.

VI. Implications of BJZZ Algorithm's Errors

In this section, we address the importance of different types of errors that affect the outcomes of the BJZZ algorithm, and hence, $Mroib$ and ILC. The literature identifies three types of errors: (a) Type I errors in which the algorithm incorrectly flags non-retail trades associated with sub-penny execution prices as retail trades (Battalio et al. (2024)); (b) Type II errors, where the algorithm fails to flag actual retail trades that do not feature sub-penny prices (Barber et al.

(2022) and Battalio et al. (2024)); and (c) the use of the sub-penny increment sizes to sign flagged trades into buyer- and seller-initiated trades when quoted spreads exceed 1¢ may lead to *trade signing errors* (Barber et al. (2022)). We first show that such errors cannot explain the inverse relationship between $Mroib$ and institutional trade imbalances or the ∪-shaped relationship between $Mroib$ and institutional price impacts. We then show that they cannot affect the pricing of our institutional liquidity cost measures.

Battalio et al. (2024) report that the BJZZ algorithm flags some institutional trades as retail. Importantly, they also find that the algorithm systematically mis-classifies these institutional trades, flagging 80% institutional buy (sell) trades as retail sell (buy) trades (Battalio et al. (2024), p.42). To investigate whether these mis-classified institutional trades underlie the variation in $Mroib$, we use ANcerno data to identify known institutional trades with sub-penny prices and use the BJZZ algorithm to re-classify them into buy and sell *retail* trades based on the sub-penny price increments. Put differently, we apply the BJZZ algorithm to ANcerno data and dub the resulting trade imbalances "BJZZ-implied" institutional flow. If $Mroib$ from the TAQ data is largely driven by Type I error, then it must be positively correlated with "BJZZ-implied" institutional flow. Panel A in Table 6 shows no evidence of a systematic relationship between $Mroib$ and BJZZ-implied institutional trade imbalances, indicating that Type I errors do not drive the variation in $Mroib$.

Barber et al. (2022) and Battalio et al. (2024) report that the BJZZ algorithm misses some retail trades, especially those filled near NBBO midpoints. Ideally, one would use proprietary data on retail trades to test whether these Type II errors, reflecting near-midpoint fills, drive the variation in $Mroib$. In the absence of such data, we employ a simple proxy for this error. From TAQ data, we flag *off-exchange* transactions of (i) 100 shares or less occurring at (ii) the midpoint or at transaction prices with sub-penny increments between 0.4¢ and 0.6¢. The trade size screen reflects that institutional trades tend to be larger (e.g., Campbell et al. (2009)), especially for off-exchange transactions. We dub the daily volume of these trades—which are difficult to sign into buy and sell trades—in each stock $mpSmall$, and then adjust $Mroib$ as $(Mrbvol - Mrsvol)/(Mrbvol + Mrsvol + mpSmall)$. Panel B in Table 6 shows that this adjustment for Type II errors does not alter either the inverse relation between $Mroib$ and institutional imbalances or the $\cup$-shaped pattern of institutional price impacts in $Mroib$. These findings support our hypothesis that the variation in $Mroib$ attributable to round-penny fills reflects wholesaler discretion to selectively *externalize* some retail orders to exchanges where sub-penny execution is unavailable.

Barber et al. (2022) show that signing BJZZ trades into buy and sell trades by comparing transaction prices with the corresponding NBBO significantly reduces signing errors of the BJZZ algorithm. We follow them by reconstructing $Mroib$ after making this adjustment in trade signing. Panel C in Table 6 shows that the inverse relation between $Mroib$ and institutional imbalances as well as the $\cup$-shaped pattern of institutional price impacts in $Mroib$ extend when we implement this correction.

We next investigate the relevance of these errors for ILC's cross-sectional return predictability. Applying the BJZZ algorithm to "re-classify" ANcerno trades into "retail" buy and sell trades lets us decompose each trading day's BJZZ-identified trades into those reflecting institutional trades filled at sub-penny prices, which we observe in ANcerno data, and those reflecting the remaining trades. Hence, we construct three versions of 1-month and 3-month ILC using: (1) all BJZZ trades; (2) non-ANcerno trades and (3) ANcerno-only trades—of note, this analysis is only feasible for the 2010-2014 period as it requires ANcerno data. We also reconstruct 1-month and 3-month ILCs using $|Mroib|$ that adjust for Type II and signing errors as discussed earlier. We then use each of these modified ILCs from two months earlier as $LIQ_{j,m-2}$ in equation (6) to investigate the effects of different errors associated with the BJZZ algorithm on the pricing of our institutional liquidity cost measures.

Panel A in Table 7 suggests that Type I errors likely attenuate (rather than drive) the ability of ILC to capture liquidity premia. Specifically, the ILC constructed using non-ANcerno sub-penny trades always load with the expected *positive* coefficients. In sharp contrast, the ILC incorrectly based on ANcerno-only sub-penny trades always load with *negative* coefficients. Thus, the BJZZ algorithm's Type I errors do not underlie the pricing of our institutional liquidity cost measures. Panels B and C in Table 7 show that the pricing of ILC is also not driven by Type II or signing errors.

VII. Conclusion

We use observable imbalances in wholesaler-retail trades to provide evidence of wholesalers intermediating between institutional and retail investors in segmented U.S. equity markets. When liquidity is scarce, institutional investors with pressing liquidity needs turn to expensive wholesaler-provided liquidity. Wholesalers offset unwanted inventory imbalances driven by institutional liquidity consumption on one side of the market by internalizing disproportionately more retail orders from the opposite side, creating imbalances in trades flagged and signed in TAQ data using the BJZZ algorithm, i.e., $Mroib$. Reflecting that more unbalanced $Mroib$ signifies scarcer institutional liquidity, we find unbalanced $Mroib$ is associated with (i) opposing institutional price pressure followed by (ii) price reversals that underlie the positive correlation between $Mroib$ and future returns (BJZZ).

We find that stocks with higher institutional liquidity costs feature greater $|Mroib|$ reflecting that institutional investors holding these stocks must resort more frequently to expensive wholesaler-provided liquidity. We exploit this observation to propose institutional liquidity cost (ILC) measures that average daily $|Mroib|$ observations. We show that ILC is, in fact, correlated with expected institutional price impacts.

Unlike existing liquidity measures, ILC robustly yields annualized liquidity premia of 2.7–3.2% post-2010. These findings matter for many reasons: (1) they show that stock returns still reflect liquidity premia, consistent with nontrivial institutional trading costs and institutions holding over 70% of all U.S. equity; (2) they indicate that recent failures of researchers to find significant liquidity premia are due to the use of existing measures that no longer capture institutional trading costs; (3) they uncover a new channel for the return predictability of retail order flow; and (4) they provide researchers with easy-to-construct measures that capture institutional investors' liquidity concerns without requiring difficult-to-obtain proprietary institutional trade data.

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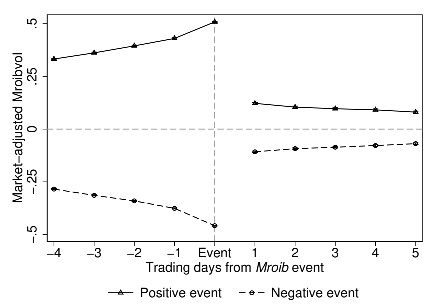
Figures and Tables

FIGURE 2

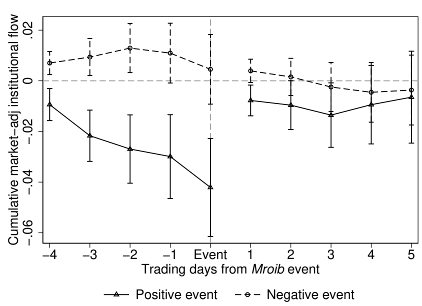
***Mroib*, Institutional Price Pressure, and Subsequent Price Reversals**

This figure plots average daily $Mroib$s, cumulative returns, and cumulative institutional order imbalances around $Mroib$ events. An event window starts at the open of day -4 and ends at the close of day 5. To construct market-adjusted outcomes, daily observations are adjusted relative the corresponding daily cross-sectional averages of the respective outcome. The daily cross-section of each market adjusted outcome is winsorized at the 1% and 99% cutoffs. All cumulative outcomes are constructed separately for pre-event windows (days -4 through 0) and post-event windows (days 1 through 5). Cumulative market-adjusted returns reflect compounded daily observations of 24-hour, intraday, or overnight returns. Cumulative institutional flow reflects the cumulative sums of daily market-adjusted institutional trade imbalances. The figures plot the average and the 95% confidence intervals over the event window. Estimates account for firm and date fixed effects.

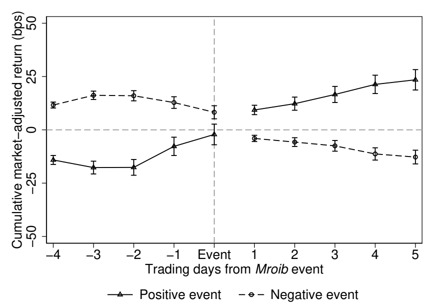
Panel A: Internalized retail flow imbalance ($Mroib$)



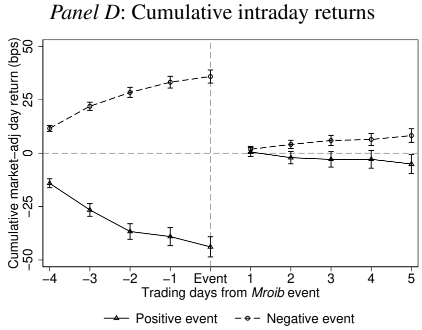
Panel B: Cumulative institutional trade imbalance



Panel C: Cumulative 24-hour returns



Panel D: Cumulative intraday returns



Panel E: Cumulative overnight returns

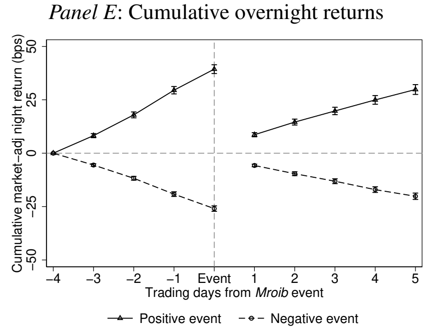


FIGURE 3

***Mroib*, Sub-penny Price Improvements, and Internalized Trade Volume**

This figure plots average daily volume-weighted mean PI as well as the trading volume for BJZZ-identified buy and sell trades around $Mroib$ events. An event window starts at the open of day -4 and ends at the close of day 5. For a buy (sell) transaction featuring sup-penny price increments, effective price improvement is the difference between transaction price and NBO (NBB), respectively, and divided by the quote midpoint in effect at the time of transaction. Volume-weighted average price improvements are calculated by stock-day and separately for buy and sell trades. Calculations exclude incorrectly signed individual transactions, i.e., transaction executed at a price above (below) the midpoint and classified as sell (buy) trades by BJZZ algorithm. Panel A compares average PI around positive $Mroib$ events. Panel B provides the analogue for negative $Mroib$ events. Panels C and D reports the evolution of the volumes associated with BJZZ-identified internalized buy and sell trade for positive and negative $Mroib$ events, respectively. The figures plot the average and the 95% confidence intervals over the event window. Estimates account for firm and date fixed effects.

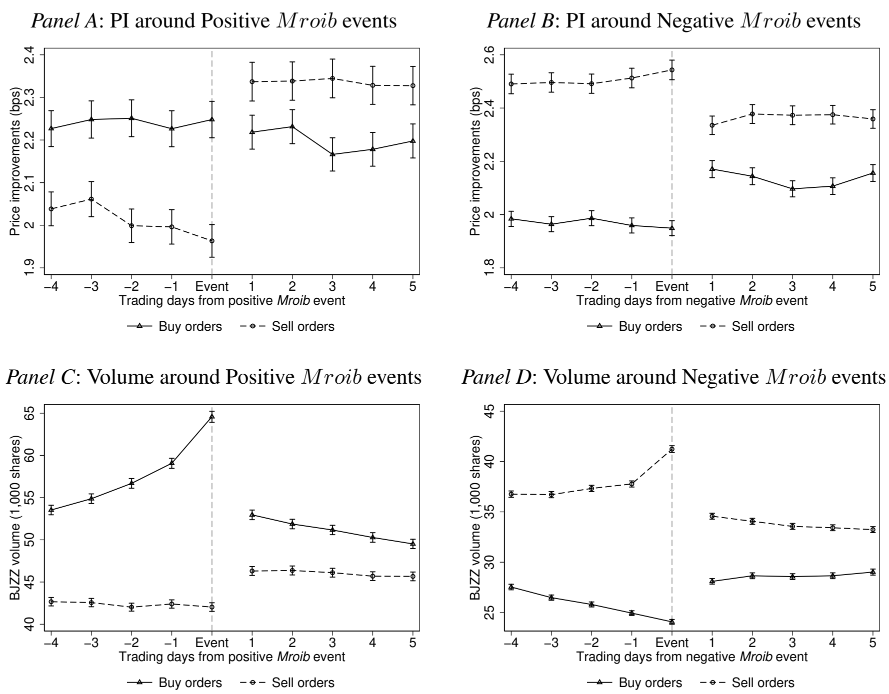
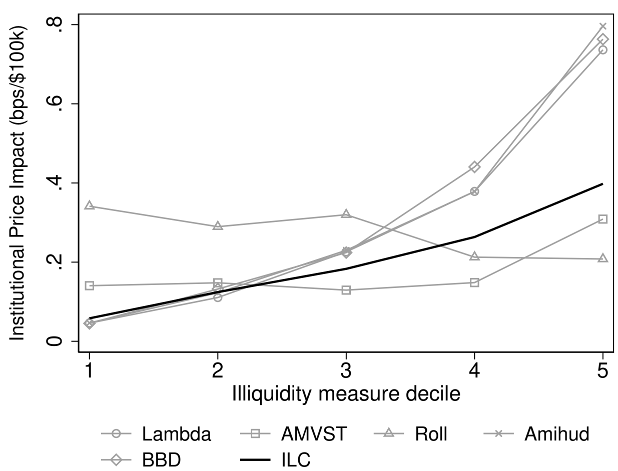


FIGURE 4

***ILC*, Standard Liquidity Measures, and Future Institutional Price Impacts**

The table reports on the cross-sectional relation between various category-3 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) Kyle's lambda estimates (Lambda); (2) Amvist illiquidity measure (AMVST); (3) Roll measure of realized spreads (Roll); (4) open-to-close Amihud measures (Amihud); (5) trade-time liquidity measures (BBD); (6 & 7) trade- and volume-based institutional liquidity measures (ILC). 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 2014, excluding stocks whose previous month-end's closing price is below \$2.

Panel A: Illiquidity deciles 1–5



Panel B: Illiquidity deciles 6–10

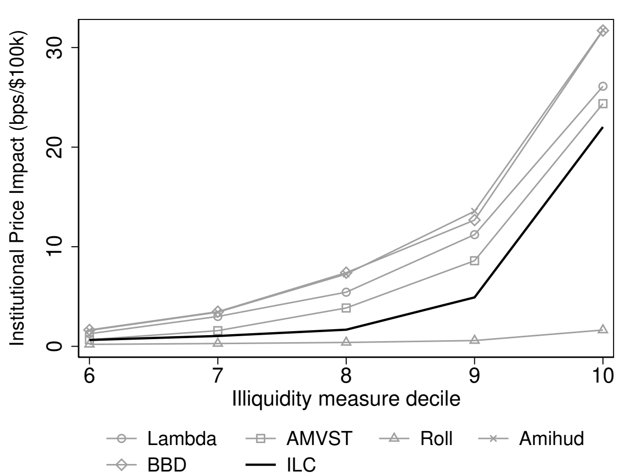


FIGURE 5

EUM Liquidity and Holding Horizon

This figure provides local polynomial estimates of equity under management (EUM) liquidity as a function of holding horizon. Holding horizon for manager i holding stocks $j \in \{1, \ldots, J_i\}$ in quarter q is

$$mgrCR_q^i = \frac{\sum_{j=1}^{J_i} \left| (Val_q^{ij} - Val_{q-1}^{ij}) - Shr_{q-1}^{ij}(p_q^j - p_{q-1}^j) \right|}{\sum_{j=1}^{J_i} \left(\dfrac{Val_q^{ij} + Val_{q-1}^{ij}}{2} \right)},$$

where Val denotes dollar-value of holdings, Shr is the number of shares held, and p is the price per share. Stock j's holding weighted EUM characteristic Y, including liquidity (LIQ), volatility ($Volat$), market capitalization (M), and institutional ownership ($IOShr$) in quarter q are calculated for each manager as

$$mgrY_q^i = \frac{\sum_{j=1}^{J_i} (Val_q^{ij} \times Y_q^{ij})}{\sum_{j=1}^{J_i} Val_q^{ij}}.$$

Every quarter, observations are independently sorted inter percentiles preceding quarter's residuals from equation (3) and current quarter's inverse $mgrCR$. The figures present local polynomial estimates of the association between residual EUM liquidity percentile statistics and next quarter's 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.

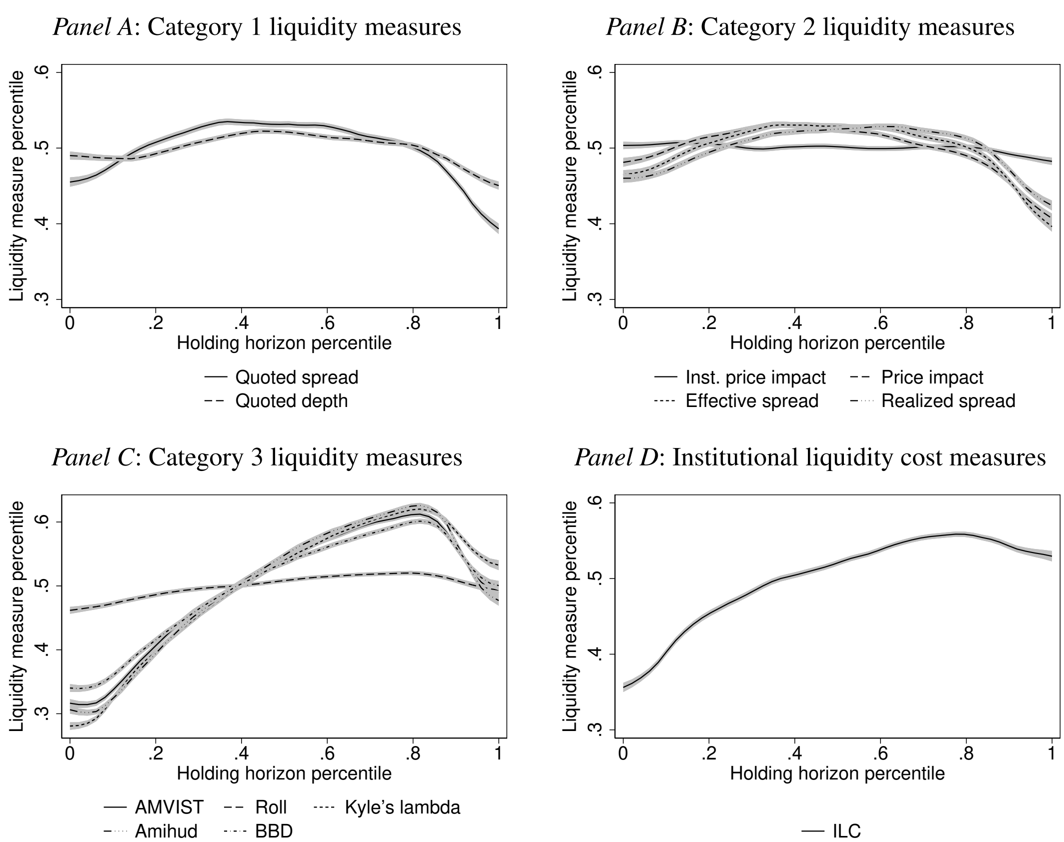


TABLE 1

Portfolios of *Mroib*: Contemporaneous Liquidity, Institutional Trading, Short Interest, and Return

The table presents the cross-sectional relationship between weekly $Mroib$ and the contemporaneous return, institutional trade, and liquidity outcomes. Outcome variables include (1) liquidity metrics including abnormal off-exchange midpoint executions of larger trades, relative quoted spreads, and average bid and ask quoted depth, in 100 shares, at national best prices; (2) institutional trading outcomes including actual trade imbalance $Inoibvol$, market-adjusted trade imbalances (defined as $Inoibvol$ minus its corresponding cross-sectional average), and institutional price impact (in bps/\$1m); (3) % changes in short interest; and (4) returns in percentage points (close-to-close, intraday, and overnight returns). Each weekly cross-section is sorted into deciles of $Mroib$. For each week ending on day t, $MroibDcl^k_{jt} = 1$ if stock j falls in decile k of $Mroib$, and $MroibDcl^k_{j,t} = 0$ otherwise, with $k \in \{1, \ldots, 10\}$. Average outcome variable Y_{jt} is then estimated using

$$Y_{jt} = \bar{Y}_1 + \sum_{k=2}^{10} \zeta^k MroibDcl^k_{jt} + u_{jt},$$

controlling for stock and date fixed effects and double-clustering standard errors. $\bar{Y}_k = \bar{Y}_1 + \hat{\zeta}^k$. For short interest, bi-weekly relative % changes in short interest are constructed and $Mroib$ is aggregated over two-week periods, before forming $Mroib$ portfolios, and the model is estimated using by-weekly data. All variables are winsorized at the top and bottom 5% on each date. The numbers in brackets are 95% confidence intervals.

	Liquidity			Institutional trading			Short selling	Return (%)		
$Mroib$ decile	Off-exchange midpoint	Relative spread (bps)	Average depth	Trade imbalance Raw	Trade imbalance Market-adjusted	Price impact	% change in short interest	close-to-close	Intraday	Overnight
Negative	.62	40.1	6.97	.29	.049	64.4	−.21	.018	.073	−.038
	[.62,.63]	[40.0,40.2]	[6.95,6.99]	[.28,.30]	[.042,.055]	[51.2,77.6]	[−1.14,.71]	[.0046,.032]	[.060,.086]	[−.044,−.032]
2	.67	34.3	7.21	.27	.033	36.4	.15	.10	.059	.061
	[.66,.67]	[34.2,34.4]	[7.20,7.23]	[.27,.28]	[.027,.039]	[24.0,48.8]	[−.23,.53]	[.092,.12]	[.047,.072]	[.055,.066]
3	.69	32.4	7.51	.27	.030	38.5	.93	.12	.036	.10
	[.69,.70]	[32.4,32.5]	[7.49,7.52]	[.27,.28]	[.024,.036]	[26.3,50.8]	[.54,1.33]	[.11,.14]	[.023,.049]	[.096,.11]
4	.71	31.3	7.73	.26	.021	21.3	1.43	.15	.021	.14
	[.71,.72]	[31.2,31.4]	[7.72,7.75]	[.26,.27]	[.015,.027]	[9.10,33.5]	[1.04,1.82]	[.14,.17]	[.0086,.034]	[.14,.15]
5	.73	30.9	7.91	.26	.016	33.3	1.84	.18	−.023	.21
	[.73,.73]	[30.8,31.0]	[7.89,7.93]	[.25,.26]	[.0099,.022]	[21.1,45.4]	[1.45,2.22]	[.16,.19]	[−.036,−.011]	[.21,.22]
6	.75	31.1	7.93	.25	.014	24.6	2.19	.19	−.071	.28
	[.75,.76]	[31.0,31.2]	[7.91,7.95]	[.25,.26]	[.0080,.020]	[12.4,36.9]	[1.26,3.12]	[.17,.20]	[−.084,−.058]	[.27,.28]
7	.77	30.8	8.00	.24	−.0050	35.8	2.35	.20	−.13	.34
	[.77,.78]	[30.7,30.9]	[7.99,8.02]	[.23,.24]	[−.011,.0010]	[23.6,48.0]	[1.89,2.80]	[.19,.22]	[−.15,−.12]	[.34,.35]
8	.77	31.2	7.86	.23	−.016	26.9	2.87	.22	−.17	.41
	[.77,.78]	[31.1,31.3]	[7.84,7.88]	[.22,.23]	[−.022,−.0097]	[14.6,39.1]	[2.41,3.33]	[.21,.24]	[−.19,−.16]	[.40,.41]
9	.77	33.2	7.59	.21	−.027	42.8	3.91	.22	−.19	.42
	[.76,.77]	[33.1,33.2]	[7.57,7.60]	[.21,.22]	[−.033,−.021]	[30.5,55.2]	[3.41,4.41]	[.21,.23]	[−.21,−.18]	[.42,.43]
Positive	.73	40.2	7.21	.18	−.058	66.1	6.81	.29	−.11	.40
	[.72,.73]	[40.1,40.3]	[7.19,7.23]	[.18,.19]	[−.064,−.051]	[53.0,79.2]	[6.06,7.55]	[.28,.31]	[−.12,−.093]	[.39,.40]

TABLE 2

Portfolios of *Mroib* and Future Weekly Returns

The table presents the cross-sectional relationships between $Mroib$ and future weekly (%) returns. Each cross-section is sorted into portfolios (deciles) of $Mroib_{w-1}$ to calculate portfolio-specific averages of future close-to-close returns in week $w+i$, with $i \in \{0, 1, 2, 3, 6, 9, 12, 24, 36\}$. Both raw and market-adjusted returns are used, with weekly market-adjusted return defined as raw return in a stock-week minus the corresponding week's equal-weighted average return across all stocks. The means of the time-series of portfolio future returns are presented by $Mroib$ decile.

$Mroib$ decile	Return measure	Future week w	$w+1$	$w+2$	$w+3$	$w+6$	$w+9$	$w+12$	$w+24$	$w+36$
Negative	raw	0.06	0.13	0.14	0.15	0.16	0.14	0.15	0.23	0.17
	market-adjusted	−0.10	−0.03	−0.03	−0.02	0.01	0.01	0.03	0.05	0.07
2	raw	0.12	0.14	0.16	0.17	0.14	0.15	0.14	0.19	0.16
	market-adjusted	−0.04	−0.02	−0.01	0.00	−0.02	0.01	0.02	0.01	0.05
3	raw	0.12	0.14	0.15	0.16	0.16	0.15	0.12	0.21	0.12
	market-adjusted	−0.04	−0.02	−0.01	0.00	0.01	0.02	0.00	0.02	0.02
4	raw	0.13	0.13	0.15	0.16	0.16	0.13	0.11	0.17	0.09
	market-adjusted	−0.03	−0.02	−0.02	−0.01	0.00	0.00	−0.01	−0.02	−0.01
5	raw	0.14	0.13	0.15	0.15	0.13	0.12	0.09	0.17	0.07
	market-adjusted	−0.02	−0.03	−0.02	−0.02	−0.03	−0.01	−0.03	−0.02	−0.03
6	raw	0.13	0.12	0.14	0.14	0.13	0.12	0.09	0.15	0.07
	market-adjusted	−0.03	−0.04	−0.02	−0.03	−0.03	−0.02	−0.03	−0.03	−0.04
7	raw	0.13	0.15	0.14	0.14	0.14	0.11	0.08	0.16	0.06
	market-adjusted	−0.03	−0.01	−0.03	−0.02	−0.02	−0.02	−0.03	−0.03	−0.04
8	raw	0.15	0.14	0.15	0.16	0.14	0.10	0.09	0.17	0.07
	market-adjusted	−0.01	−0.01	−0.01	−0.01	−0.02	−0.03	−0.02	−0.01	−0.04
9	raw	0.24	0.19	0.18	0.19	0.17	0.15	0.12	0.17	0.09
	market-adjusted	0.08	0.03	0.01	0.02	0.02	0.01	0.00	−0.01	−0.01
Positive	raw	0.37	0.30	0.30	0.26	0.24	0.17	0.18	0.22	0.12
	market-adjusted	0.21	0.15	0.13	0.09	0.08	0.03	0.06	0.04	0.02

TABLE 3

Persistence in the Institutional Liquidity Measures

The table reports on ILC's persistence. The following model is estimated using monthly observations and a Fama-MacBeth approach with Newey-West corrected standard errors with 6 lags:

$$ILC_{j,m} = c_0 + \sum_{i=1}^{6} c_i ILC_{j,m-i} + u_{j,m}.$$

Both equally-weighted and value-weighted 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% levels, respectively.

	Equal weighted	Value weighted
Constant	0.0096***	0.0045***
	[7.84]	[5.80]
ILC_{m-1}	0.43***	0.37***
	[83.17]	[49.29]
ILC_{m-2}	0.19***	0.18***
	[55.50]	[31.86]
ILC_{m-3}	0.13***	0.15***
	[47.16]	[31.93]
ILC_{m-4}	0.068***	0.084***
	[21.83]	[10.64]
ILC_{m-5}	0.060***	0.076***
	[23.77]	[15.89]
ILC_{m-6}	0.087***	0.10***
	[31.25]	[16.66]
Observations	310847	310847

TABLE 4

Stock Liquidity and Institutional Holding Horizon

This table reports on the relation between institutional holding horizons and liquidity. Churn ratio for stock j held by investors $i \in \{1, \ldots, I_j\}$ in quarter q is

$$CR_q^j = \frac{\sum_{i=1}^{I_j} \left| (Val_q^{ij} - Val_{q-1}^{ij}) - Shr_{q-1}^{ij}(p_q^j - p_{q-1}^j) \right|}{\sum_{i=1}^{I_j} \left(\dfrac{Val_q^{ij} + Val_{q-1}^{ij}}{2} \right)},$$

where Val is dollar-value of holdings, Shr is the number of shares held, and p is the price per share. Holding horizon is the minus backward-looking 4-quarter moving average of CR_q^j, denoted $\overline{CR}_q^j$. Panel A, report results from estimating equation (4). Panel B reports on the relations after orthogonalizing ILC with respect to existing liquidity measures and vice versa, as in equation (5). Models are fitted as Fama-MacBeth regressions with Newey-West standard errors of 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% levels, respectively.

Panel A: Stock liquidity and institutional turnover

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	ILC
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** **	**0.12*** **
	[−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]**	**[19.36]**
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**	**0.63**
Obs.	28,679†	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	91,541	71,952†	71,952†	91,541

† The number of observations reflects the largest ANcerno and BBD/WBBD samples

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

Residual	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD
Z_{ILC}	**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_{ILC}	−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 5

The Cross-Section of Expected Stock Returns and *ILC*

This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (6) 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 ILC with respect to each alternative liquidity measure with residuals calculated separately for each monthly cross-section. The last column in Panel B uses the residuals of ILC with respect to *all* alternative liquidity proxies (excluding InPrIm). 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% levels, 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	ILC
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**	**1.27*****
	[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]**	**[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	−0.043
	[−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]	[−0.23]
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	−0.12
	[−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]	[−0.98]
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	0.11
	[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]	[1.58]
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	0.0043
	[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]	[0.09]
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	0.12**
	[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]	[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	−0.11
	[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]	[−0.20]
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***	−0.21***
	[−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]	[−4.46]
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	−0.48
	[−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]	[−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	0.28*
	[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]	[1.81]
Observations	128,135†	340,227	340,227	340,227	340,227	340,227	339,681	340,225	340,227	340,225††	340,225††	277,750†††	277750†††	340,227

Panel B: Loadings of ILC 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	All measures
ILC 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**	1.35***
	[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]	[2.73]

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

†† The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

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

TABLE 6

Mroib versus Institutional Activity and Price Impacts: Robustness to BJZZ Algorithm's Errors

The table presents the cross-sectional relationship between weekly $Mroib$ and the contemporaneous institutional trade imbalances and institutional price impacts after controlling for the BJZZ algorithm's errors. Outcome variables include (1) market-adjusted actual institutional trade imbalance, market-adjusted BJZZ-implied institutional trade imbalance, and institutional price impact (in bps/\$1m). Each weekly cross-section is sorted into deciles of $Mroib$. For each week ending on day t, $MroibDcl^k_{jt} = 1$ if stock j falls in decile k of $Mroib$, and $MroibDcl^k_{j,t} = 0$ otherwise, with $k \in \{1, 2, \ldots, 10\}$. Average outcome variable Y_{jt} is then estimated using

$$Y_{jt} = \bar{Y}_1 + \sum_{k=2}^{10} \zeta^k MroibDcl^k_{jt} + u_{jt},$$

controlling for stock and date fixed effects and double-clustering standard errors. $\bar{Y}_k = \bar{Y}_1 + \hat{\zeta}^k$. In Panel A, $Mroib$ reflects the output of the baseline BJZZ algorithm. In Panel B, $Mroib$ reflects $\dfrac{Mrbvol - Mrsvol}{Mrbvol + Mrsvol + mpSmall}$, where $mpSmall$ is the volume of off-exchange trades that are at most 100 shares and are executed at the midpoint. In Panel C, $Mroib$ is based on selection of trades using BJZZ algorithm but signing each trade into buy or sell using the position of the execution price relative to the NBBO midpoint. All variables are winsorized at the top and bottom 5% on each date. The numbers in brackets represent 95% confidence intervals.

Panel A: Type I error tests

$Mroib$ decile	Actual trade imbalance	BJZZ-implied trade imbalance	Price impact
Negative	.049	−.0109	64.4
	[0.042,.055]	[−.015,−.006]	[51.2,77.6]
2	.033	−.00170	36.4
	[0.027,.039]	[−.006,.003]	[24.0,48.8]
3	.030	−.00714	38.5
	[0.024,.036]	[−.01,−.003]	[26.3,50.8]
4	.021	−.00597	21.3
	[0.015,.027]	[−.01,−.001]	[9.10,33.5]
5	.016	−.00538	33.3
	[0.0099,.022]	[−.01,−.001]	[21.1,45.4]
6	.014	.00184	24.6
	[0.0080,.020]	[−.003,.006]	[12.4,36.9]
7	−.0050	.00161	35.8
	[−.01,.001]	[−.003,.006]	[23.6,48.0]
8	−.016	.00769	26.9
	[−.022,−.01]	[0.003,.012]	[14.6,39.1]
9	−.027	.00437	42.8
	[−.033,−.021]	[−.0001,.009]	[30.5,55.2]
Positive	−.058	−.00209	66.1
	[−.064,−.051]	[−.006,.0025]	[53.0,79.2]

Panel B: Type II error tests

$Mroib$ decile	Actual trade imbalance	Price impact
Negative	.059	118.7
	[0.053,.065]	[101.8,135.6]
2	.043	28.0
	[0.037,.049]	[12.8,43.3]
3	.020	34.3
	[0.014,.026]	[19.4,49.2]
4	.019	20.5
	[0.013,.025]	[5.73,35.3]
5	.011	15.7
	[0.0046,.017]	[0.91,30.5]
6	.0068	18.2
	[0.0007,.013]	[3.37,33.0]
7	−.00048	29.9
	[−.006,.006]	[15.1,44.7]
8	−.010	26.4
	[−.016,−.004]	[11.6,41.3]
9	−.022	6.78
	[−.028,−.016]	[−8.28,21.8]
Positive	−.061	93.6
	[−.067,−.055]	[77.1,110.1]

Panel C: Signing error tests

$Mroib$ decile	Actual trade imbalance	Price impact
Negative	.063	48.4
	[0.057,.070]	[35.4,61.4]
2	.038	30.8
	[0.032,.044]	[18.5,43.0]
3	.027	27.6
	[0.021,.033]	[15.5,39.7]
4	.028	26.7
	[0.022,.034]	[14.7,38.6]
5	.017	27.1
	[0.011,.023]	[15.2,39.1]
6	.0092	28.3
	[0.0032,.015]	[16.2,40.3]
7	−.0018	28.5
	[−.008,.004]	[16.4,40.5]
8	−.015	39.2
	[−.021,−.009]	[27.2,51.3]
9	−.035	26.4
	[−.04,−.03]	[14.3,38.6]
Positive	−.066	91.6
	[−.072,−.060]	[78.8,104.4]

TABLE 7

Cross-Section of Expected Stock Returns and *ILC*: Robustness to BJZZ Errors

This table reports on the robustness of the relation between our institutional liquidity cost measures and the cross-section of expected stock returns. Equation (6) is estimated when institutional institutional liquidity cost measures constructed over a 1-month horizon (denoted ILC) or a 3-month horizon (denoted $ILC3$), defined in equation (2), are used as liquidity measures ($LIQ_{j,m-2}$). Control variables, whose coefficients are not reported, 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 to exclusion of institutional trades with sub-penny execution prices, identified from ANcerno in the 2010-2014 period, from $Mroib$ before constructing ILC. Panel B reports on the robustness to adjusting ILC for retail trades excluded by BJZZ algorithm. To include these trades $Mroib$ is adjusted to $\dfrac{Mrbvol - Mrsvol}{Mrbvol + Mrsvol + mpSmall}$, with $mpSmall$ capturing the corresponding volume of small off-exchange trades executed near midpoint (excluded by BJZZ), before ILC is are calculated as the average $|Mroib|$. Panel C reports on the robustness to correction for signing errors in BJZZ algorithm following Barber et al. (2022), before constructing, before ILC is are calculated as the average $|Mroib|$. The sample excludes stocks with previous month-end's closing price is below \$2. 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 (January 2010 to December 2014 for Panel A). The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Type I errors			**Panel B**: Type II errors	**Panel C**: Signing errors
	Sub-penny trades used			Small mid-point trades included in ILC	BJZZ trades signed using NBBO midpoints
Liquidity measure	All	no Ancerno	only Ancerno		
ILC	0.84*	0.90**	−0.21	1.00***	1.25***
	[1.83]	[2.60]	[−0.69]	[2.91]	[3.07]
$ILC3$	1.06*	0.98*	−1.56**	1.13***	1.60***
	[1.80]	[1.86]	[−2.45]	[2.89]	[3.26]

Appendix

A. Variable Definitions

This section describes the data and provides variable definitions. To analyze wholesaler intermediation between retail and institutional investors, we construct a sample of NYSE-, AMEX-, and NASDAQ-listed common shares following BJZZ for the period January, 2010 to December, 2014. We first aggregate daily $Mroibvol$ observations into overlapping 5-day rolling windows, constructing daily cross-sections of 5-day (weekly) internalized retail order flow imbalances. We use daily open and close prices from CRSP to calculate daily close-to-close, intraday open-to-close, and overnight, close-to-open returns, accounting for overnight adjustments and dividend distributions. To minimize the impact of bid-ask bounce, returns are based on quote midpoints at close. We aggregate (compound) daily 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 \$2.[27]

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);[28] (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;[29] (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 et al. (2021)'s open-to-close measure (ILLIQ_OC); (11 & 12) trade-time

[27]Unreported results verify the robustness of our findings to a \$1 share price requirement, as employed by BJZZ, or the inclusion of 2015 for the analyses that do not require ANcerno data.

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

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

liquidity measures of Barardehi et al. (2019) (BBD and WBBD);[30] (13) our trade-based institutional trading cost measure ($ILCT$), which averages $|Mroibtrd|$; (14) our volume-based trading cost measure measure ($ILCV$), 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 $ILCT$ and $ILCV$), 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 ILC measure, we also calculate corresponding daily averages of the share of volume occurring at sub-penny prices to total daily trading volume. These measures, denoted SPVS, help identify stocks with ILC magnitudes based on excessively-infrequent sub-penny trading. We use 13F data to calculate the share of institutional ownership (IOShr) for each stock as the number of institutionally held shares divided by the number of shares outstanding at the end of each quarter; we match each IOShr it with monthly stock observations in the following quarter.

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 $RET_{j,m-2}^{m-12}$, respectively, capture compound returns over the preceding month and the 11 months prior; $M_{j,m-12}$ is market-capitalization based on the closing price 12 months earlier; $DYD_{j,m-1}$ is dividend yield, i.e., the ratio of total dividend distributions over the 12 months ending in month $m-1$ divided by the closing price at the end of month $m-1$. 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 $m-1$.[31] We

[30]These measures reflect 1-month or 3-month average per-dollar absolute returns constructed over trade-time intervals. Each stock's trade times in a given month are defined as successive mutually exclusive intraday intervals that correspond to 0.04% of the stock's previous-month-end market-cap (Barardehi et al. (2019). The sample period for these measures is 2010 to 2017 rather than 2010-2019.

[31]Book value is defined as Compustat's shareholder equity value (seq) plus deferred taxes (txdb). We use the "linktable" from WRDS to match stocks across CRSP and Compustat, dropping stocks without links.

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 manager in quarter q, the churn ratio for stocks in her portfolio is defined as the sum of changes in the values of that stocks in the manager's portfolio relative to that in quarter $q-1$ that are not attributable to variation in its price, divided by the sum of average values of the manager's holdings of each 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 of the stock held by the manager. For each stock-quarter, we measure a manager's holding horizon by the moving average of these weighted mean churn ratios over the preceding four quarters. 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 the rank statistics of their churn ratios, using one minus churn ratio percentile statistics in a quarter to measure institutional holding horizons.

TABLE A.1

Variable Definitions

This table contains definitions of the variables used in the paper. For each variable the frequency of construction, a detailed description of the construction, underlying data sources, as well as the table or figure whose results are based on the variable are provided.

Notation	Frequency	Description	Source	Figure/Table
$Mrstrd$	Daily	Daily number of off-exchange trades with sub-penny price increments in $(0¢, 0.4¢)$	TAQ	Table B.1
$Mrsvol$	Daily	Daily sahre volume of off-exchange trades with sub-penny price increments in $(0¢, 0.4¢)$	TAQ	Table B.1, Figure 3
$Mrbtrd$	Daily	Daily number of off-exchange trades with sub-penny price increments in $(0.6¢, 1¢)$	TAQ	Table B.1

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TABLE A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
$Mrbvol$	Daily	Daily sahre volume of off-exchange trades with sub-penny price increments in $(0.6¢, 1¢)$	TAQ	Table B.1, Figure 3
$Mroibtrd$	Daily, Weekly	Daily: $Mroibtrd = (Mrbtrd - Mrstrd)/(Mrbtrd + Mrstrd)$; Weekly: Backward-looking rolling 5-day sum of $Mroibtrd$	TAQ	Table B.1
$Mroibvol$	Daily, Weekly	Daily: $Mroibvol = (Mrbvol - Mrsvol)/(Mrbvol + Mrsvvol)$; Weekly: Backward-looking rolling 5-day sum of $Mroibvol$; Bi-weekly: sum $Mroibvol$ across trading days between two successive FINRA short interest disclosure dates	TAQ	Figure 1, Table B.1, Table 1, Table 2
PI	Daily	Effective price improvement of a sub-penny trade is the difference between the relevant best quoted price and the transaction price, divided by the quote midpoint at the time of transaction. For each stock-day, PI reflects the volume-weighted average price improvement (in bps). Averages are calculated for buy and sell trades separately.	TAQ	Figure 3
$Inoibvol$	Daily, Weekly	For each stock-day, the difference between buy and sell institutional trading volume is divided by the total institutional trading volume. To construct weekly observations, daily imbalance ratios are aggregated using backward-looking 5-day sums for each stock-day.	ANcerno	Figure 3, Figure 2, Table 1
Institutional price impacts	Daily, Weekly	For each stock-day, volume-weighted average execution price across all investors are separately calculated for institutional buy and sell trades; for institutional buy (sell) trades, the price impact is the average execution price minus open price (open price minus the average execution price), divided by the open price, and scaled by the corresponding aggregate dollar value, in $million, of institutional trades. Daily observations are aggregated into weekly frequency using backward-looking rolling 5-day averages.	ANcerno	Figure 3, Figure 2, Table 1
Dollar quoted spread (QSP)	Weekly, Monthly	For each stock, daily time-weighted dollar quoted spreads from WRDS are averaged over (1) backward-looking rolling 5-day windows; (2) monthly windows and rolling 3-month windows updated every month.	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5, Table 1
Relative quoted spread	Weekly	For each stock, daily time-weighted relative quoted spreads from WRDS are averaged over backward-looking rolling 5-day windows.	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5, Table 1
Share depth (ShrDepth)	Weekly, Monthly	For each stock, daily time-weighted share depth at the National Best Bid and Offer (NBB and NBO) from WRDS are averaged over (1) backward-looking rolling 5-day windows, sperately for bid and ask side; (2) monthly windows and rolling 3-month windows updated every month	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5, Table 1
Large midpoint executions	Weekly	For each stock-day the trading volume associated with off-exchange midpoint transactions exceeding 1,000 shares in volume and $50k in value is divided by the mean of this variable in the entire sample period of the respective stock.	TAQ	Table 1
Changes in short interest	Bi-Weekly	Bi-weekly percentage change in the short interest, scaled by the number of shares outstanding.	FINRA, CRSP	Table 1
Close-to-close return	Daily, Weekly	$R^m_{jt} = \left(\frac{1+r_{jt}}{Prc_{jt}/Prc_{jt-1}} \times \frac{Prc^m_{jt}}{Prc^m_{jt-1}}\right) - 1$ is stock j's daily returns based on quote midpoints that adjusts for dividend distributions and other overnight adjustments. r_{jt} is the daily holding period return from CRSP, Prc is the closing price, and Prc^m is the quote midpoint at close. Daily returns are compounded over backward-looking rolling 5-day windows to produce weekly returns.	CRSP	Figure 2, Table 1

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TABLE A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
Intraday return	Daily, Weekly	Daily intraday return for stock j and day t is defined as $IDR_{jt} = Prc^m_{jt}/OpenPrc_{jt} - 1$, where Prc^m_{jt} and $OpenPrc_{jt}$ are the daily closing (based on quote mid-points) and opening prices from CRSP, respectively. Intraday returns are compounded over backward-looking rolling 5-day windows.	CRSP	Figure 2, Table 1
Overnight return	Daily, Weekly	Daily overnight return for stock j and day t is defined as $ONR_{jt} = (1 + R^m_{jt})/(1 + IDR_{jt}) - 1$, where R^m_{jt} and IDR_{jt} are the close-to-close and intraday returns, respectively. Overnight returns are compounded over backward-looking rolling 5-day windows.	CRSP	Figure 2, Table 1
Dollar effective spread (EFSP)	Monthly	For each stock, daily size-weighted dollar effective spreads from WRDS are averaged over monthly windows and rolling 3-month windows updated every month.	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5
Dollar realized spread (EFSP)	Monthly	For each stock, daily size-weighted dollar realized spreads from WRDS are averaged over monthly windows and rolling 3-month windows updated every month.	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5
Dollar price impacts (PIMP)	Monthly	For each stock, daily size-weighted dollar price impacts, defined as the difference between effective and realized spreads obtained from WRDS, are averaged over monthly windows and rolling 3-month windows updated every month.	WRDS Intraday Indicators	Figure 4, Figure 5, Table 4, Table 5
Kyle's Lambda (Lambda)	Monthly	For each stock, individual trades are classified into buyer- vs. seller-initiated using the Lee-Ready algorithm to construct order flow measures over 5-minute intervals. Lambda is the slope coefficient of a Regression of 5-minute returns on the corresponding order flow measures each month. Rolling 3-month Lambda estimates, updated every month, are also constructed.	TAQ	Figure 4, Figure 5, Table 4, Table 5
Amvist (AMVST)	Monthly	For each stock-day, absolute return is divided by turnover. This daily ratio is averaged across days monthly and over rolling 3-month windows updated every month	CRSP	Figure 4, Figure 5, Table 4, Table 5
Roll	Monthly	For each stock-month, daily return auto-correlations are constructed following Goyenko et al. (2009) to estimate effective spreads. Rolling 3-month Roll estimates, updated every month, are also constructed.	CRSP	Figure 4, Figure 5, Table 4, Table 5
Amihud (ILLIQ)	Monthly	For each stock-month, the ratio of absolute daily return to daily dollar volume is averaged across days. Rolling 3-month ILLIQ estimates, updated every month, are also constructed.	CRSP	Figure 4, Figure 5, Table 4, Table 5
Intraday Amihud (ILLIQ_OC)	Monthly	For each stock-month, the ratio of absolute daily open-to-close return to daily dollar volume is averaged across days. Rolling 3-month ILLIQ_ estimates, updated every month, are also constructed.	CRSP	Figure 4, Figure 5, Table 4, Table 5
Trade-time liquidity measures (BBD,WBBD)	Monthly	For each stock-month, the ratio of absolute return (or VWAP return) to dollar volume from trade-time intervals is averaged across intervals. Rolling 3-month BBD and WBBD estimates, updated every month, are also constructed.	CRSP, TAQ	Figure 4, Figure 5, Table 4, Table 5
Institutional Price Impacts (InPrIm)	Monthly	Average daily institutional price impacts, per $100k, that weight each institutional trade by its share volume are calculated across buy and sell institutional trades. Rolling 3-month InPrIm estimates, updated every month, are also constructed.	ANcerno	Figure 4, Figure 5, Table 4, Table 5

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TABLE A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
$ILCT$	Weekly, Monthly	Daily $\|Mroibtrd\|$ observations are averaged weekly and monthly. Rolling 3-month $ILCT$ estimates, updated every month, are also constructed.	TAQ	Figure 4, Figure 5, Table B.2, Table 3, Table 4, Table 5, Table III.1, Table III.2, Table IV.1
$ILCV$	Weekly, Monthly	Daily $\|Mroibvol\|$ observations are averaged weekly and monthly. Rolling 3-month $ILCV$ estimates, updated every month, are also constructed.	TAQ	Figure 4, Figure 5, Table B.2, Table 3, Table 4, Table 5, Table III.1, Table III.2, Table IV.1
Share of BJZZ volume (SPVS)	Monthly	For each stock-day, the fraction of BJZZ-identified trade volume is divided by the total regular-hour trading volume. Monthly averages of the fractions are then calculated for each stock. Rolling 3-month SPVS estimates, updated every month, are also constructed.	TAQ	Table III.2
Share of institutional ownership (IOShr)	Quarterly	At the end of each quarter, the total number of shares held by institutional investors is divided by the number of shares outstanding.	13F, CRSP	Table III.2
Monthly excess return (RET_m)	Monthly	Holding period monthly return minus the corresponding 1-month T-Bill rate.	CRSP	able 4, Table 5, Table III.1, Table III.2, Table IV.1
Last month's return (RET_{m-1})	Monthly	Holding period return from the previous month	CRSP	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1
Last year return, excluding last month (RET_{m-2}^{m-12})	Monthly	Compound holding period returns over the 11-month period ending at the beginning of the previous month	CRSP	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1
Market-capitalization (M_{m-12})	Monthly	The product of closing price and the number of shares outstanding 12 months earlier.	CRSP	Table B.2, Table 4, Table 5, Table III.1, Table III.2, Table IV.1
Dividend yield (DYD_{m-1})	Monthly	The ratio of aggregate dividend distribution over the preceding 12 months to the closing price at the end of the prior month.	CRSP	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1
Book-to-market ratio (BM_{m-1})	Monthly	Book value is defined as shareholder equity value plus deferred taxes. Book-to-market ratio is the most recent book value observation divided by market-capitalization at the end of prior month	Compustat, CRSP	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1
Three-factor Fama-French Betas (β^{mkt}, β^{hml}, β^{smb})	Monthly	Betas at the end of each month of a given stock are estimated using a three factor model that takes weekly stock and factor returns from the preceding 104 weeks of observations, requiring a minimum of 52 weeks of data.	Beta Suite by WRDS	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1
Idiosyncratic volatility (Id. Vol.)	Monthly	The standard deviation of the residuals from a market model fitted for each stock-month using daily stock and market return observations.	CRSP	Table B.2, Table 5, Table III.1, Table III.2, Table IV.1

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TABLE A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
Manager churn ratio	Quarterly	$\frac{\sum_{j=1}^{J_i} \left\|(Val_q^{ij} - Val_{q-1}^{ij}) - Shr_{q-1}^{ij}(p_q^j - p_{q-1}^j)\right\|}{\sum_{j=1}^{J_i} \left(\frac{Val_q^{ij} + Val_{q-1}^{ij}}{2}\right)}$, denoted CR_q^i, is the churn ratio for investor i holding stocks $j \in \{1, \ldots, J_i\}$ in quarter q, where Val is the value of holdings, Shr is the number of shares held, and p is the price per share. Holding horizon reflects 1 minus percentile rank statistics of CR_q^i defined each quarter across managers.	13F, CRSP	Figure 5
Stock churn ratio	Quarterly	$\frac{\sum_{i=1}^{I_j} \left\|(Val_q^{ij} - Val_{q-1}^{ij}) - Shr_{q-1}^{ij}(p_q^j - p_{q-1}^j)\right\|}{\sum_{i=1}^{I_j} \left(\frac{Val_q^{ij} + Val_{q-1}^{ij}}{2}\right)}$, denoted CR_q^j, is the churn ratio for stock j held by investors $i \in \{1, \ldots, I_j\}$ in quarter q, where Val is the value of holdings, Shr is the number of shares held, and p is the price per share. To proxy holding horizon in quarter q, the moving average of CR_q^i over quarter $q-4$ through $q-1$, denoted $\overline{CR}_q^j$ is used. Holding horizon reflects 1 minus percentile rank statistics of $\overline{CR}_q^j$ define each quarter across stocks.	13F, CRSP	Table 4

B. Basic Summary Statistics

This section first provides basic summary statistics for payment for order flow, $Mroibtrd$ and $Mroibvol$. Panel A in Table B.1 reports average Rule 606 figures from three major retail brokers based on interactions of each broker with their top-5 associated wholesalers. Panel B in Table B.1 provides basic summary statistics for $Mroibtrd$ and $Mroibvol$ and their underlying components. Our results closely match the summary statistics reported by BJZZ for a similar sample, indicating that we adopt the BJZZ algorithm as originally intended.

Table B.2 shows the association between ILCs and key stock characteristics. We match monthly ILC observations with stock characteristics constructed at the end of the preceding calendar month (see Section III). After excluding stocks whose previous month's closing price are below \$2, we sort each monthly cross-section into deciles of $ILC \in \{ILCT, ILCV\}$. We then calculate stock characteristic averages by ILC decile and date before computing the time-series averages of these averages across dates by ILC deciles. Table B.2 shows that high-ILC stocks, i.e., stocks identified as less liquid by the ILCs, tend to be small growth stocks with relatively poor recent returns and low CAPM betas.

TABLE B.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: Summary statistics of BJZZ-identified trades

	N	Mean	Std	Skewness	Median	Q1	Q3
$Mrbvol$	3,689,697	43,826	262,813	46	4,900	1,075	20,577
$Mrsvol$	3,689,697	44,049	253,247	41	5,424	1,291	21,708
$Mrbtrd$	3,689,697	108	390	22	21	5	77
$Mrstrd$	3,689,697	105	345	16	23	6	79
$Mroibvol$	3,689,697	−0.048	0.482	0.044	−0.035	−0.333	0.226
$Mrioibtrd$	3,689,697	−0.036	0.459	0.002	−0.014	−0.306	0.228
$Mroibvol > 0$	1,690,653	0.354	0.304	0.934	0.257	0.111	0.517
$Mroibvol < 0$	1,982,696	−0.390	0.313	−0.734	−0.302	−0.591	−0.132
$Mroibtrd > 0$	1,664,767	0.347	0.289	1.058	0.262	0.125	0.493
$Mroibtrd < 0$	1,873,021	−0.380	0.301	−0.865	−0.300	−0.543	−0.143

TABLE B.2

Institutional Liquidity Cost Measures and Stock Characteristics

The table reports on the cross-sectional relation between ILCs and (1) three-factor Fama-French betas, (2) book-to-market ratios (BM), (3) natural log of market capitalizations ($\ln(\text{Mcap})$), (4) dividend yields (DYD), (5) idiosyncratic volatilities, in percentage points, (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 cross-section is sorted into ILC deciles. The average outcome variable is calculated by $ILCT$ decile in each cross-section before the average of the time-series is calculated. Panels A and B report the results for $ILCT$ and $ILCV$, 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 Cost Measures ($ILCT$s) versus stock characteristics

	Monthly $ILCT$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.13	1.11	1.11	1.09	1.07	1.05	0.99	0.89	0.71	0.43
β^{hml}	−0.07	0.04	0.12	0.16	0.19	0.24	0.28	0.32	0.33	0.25
β^{smb}	0.27	0.48	0.63	0.76	0.87	0.96	1.01	1.00	0.84	0.48
BM	0.47	0.54	0.57	0.60	0.63	0.67	0.72	0.79	0.92	1.11
$\ln(\text{Mcap})$	23.28	22.25	21.70	21.25	20.82	20.41	19.98	19.47	18.85	18.23
DYD	0.017	0.017	0.017	0.018	0.016	0.014	0.014	0.014	0.015	0.015
Id. Vol.	1.604	1.751	1.863	1.960	2.050	2.147	2.237	2.318	2.310	2.267
$RET_{(-1)}$	0.012	0.012	0.013	0.013	0.015	0.017	0.018	0.021	0.020	0.017
$RET_{(-12,-2)}$	0.28	0.25	0.22	0.21	0.19	0.16	0.14	0.12	0.11	0.11

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

	Monthly $ILCV$ deciles									
	1	2	3	4	5	6	7	8	9	10
Stock Characteristics:										
β^{mkt}	1.20	1.13	1.11	1.08	1.06	1.02	0.97	0.88	0.69	0.43
β^{hml}	−0.02	0.05	0.08	0.12	0.16	0.22	0.29	0.35	0.35	0.26
β^{smb}	0.45	0.54	0.63	0.72	0.82	0.91	0.97	0.96	0.82	0.48
BM	0.55	0.57	0.58	0.58	0.61	0.64	0.69	0.77	0.91	1.12
$\ln(\text{Mcap})$	23.02	22.11	21.63	21.27	20.90	20.52	20.09	19.57	18.89	18.24
DYD	0.017	0.018	0.017	0.016	0.015	0.015	0.013	0.014	0.015	0.015
Id. Vol.	1.969	1.927	1.919	1.917	1.976	2.012	2.095	2.191	2.235	2.268
$RET_{(-1)}$	0.010	0.013	0.012	0.016	0.016	0.017	0.018	0.019	0.019	0.017
$RET_{(-12,-2)}$	0.30	0.23	0.21	0.19	0.17	0.16	0.15	0.13	0.12	0.11

Institutional Liquidity Costs, Internalized Retail Trade Imbalances, and the Cross-Section of Stock Returns: Internet Appendix

by Yashar H. Barardehi, Dan Bernhardt, Zhi Da, and Mitch Warachka

I. Wholesalers as Intermediaries

In this section, we first discuss the different relevant institutional details that shape the interactions among wholesalers, retail investors, and institutional investors. We also discuss the relevance of these institutional details for the output of the BJZZ algorithm, highlighting the reasons why this algorithm serves the purposes of our study well. We then provide a stylized theoretical framework to formally link institutional details to $Mroib$. Finally, we test the predictions of this framework use exogenous variations driven by the SEC's Tick Size Pilot program.

I. Institutional Details

I. 1. Retail Trade Execution

Executions of retail orders in U.S. equity markets are subject to "best execution" principles.[32] Wholesalers, e.g., Virtu and Citadel, handle the vast majority of 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 (2024)), ensuring best execution principles are met in addition to providing payment for order flow (PFOF) to certain brokers.[33]

Retail orders handled by wholesalers are executed in two ways. According to SEC (2022) nearly 20% of marketable retail orders are "externalized," where a wholesaler quotes an identical

[32] 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.

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

order on exchanges/ATSs and fills the retail order once that proprietary order is executed.[34] The remaining 80% of marketable retail order executions are internalized, a process by which wholesalers execute retail order flow against their own inventory.[35] 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 B.1 reports the distribution of order types across all non-directed orders[36] 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 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. Unreported calculations using BJZZ-identified trades that compare each execution price with the corresponding NBBO suggest

[34] 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.

[35] 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)).

[36] 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.

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 inside the NBBO by over 1¢ (see Battalio and Jennings (2024)).

Institutional details suggest two channels underlie these large PIs. Most importantly, the Manning rule requires wholesalers, who have 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.[37] Internalizing such non-marketable limit orders is very costly, even when executed at minimal PI because non-marketable orders receive much higher PFOF.[38]

[37]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.

[38]See, e.g., Bryzgalova, Pavlova, and Sikorskaya (2023) for institutional details of retail trade executions in U.S. option markets.

I. 2. Implications for BJZZ's Algorithm

Wholesalers internalize about 80% of the marketable retail orders received (SEC (2022)),[39] and BJZZ's algorithm identifies only a select subset of these trades. The algorithm's systematic selection of a subset of retail trades is *key* to our analysis for at least three reasons.

First, the algorithm excludes retail trades filled at the NBBO. Wholesalers have three main options when handling retail orders: (1) internalize them; (2) externalize them by rerouting orders to exchanges/ATSs, where non-midpoint sub-penny execution prices are banned; 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. (2024)). 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.[40]

[39] 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.

[40] Alternatively, Battalio and Jennings (2024) suggest that midpoint trades may reflect wholesaler competition to provide execution quality. 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.

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.[41] 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.

Battalio et al. (2024) find that BJZZ'z algorithm picks up some institutional trades. In unreported robustness analysis we verify such errors do not underlie our findings. We exploit another key finding of Battalio et al. (2024), that about 80% of institutional trades picked up by BJZZ are also incorrectly signed by the algorithm, to device our robustness test. TAQ data contain ANcerno-reported institutional trades, including those with sub-penny price increments that the algorithm picks up. 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 $Mroib$. Of note, if the mis-classification of institutional trades by BJZZ underlies our findings, then the positive relationship between BJZZ-implied institutional imbalance and $Mroibvol$ must also be stronger that the negative relationship between the actual institutional imbalance and $Mroibvol$. We find this imbalance is negative on average, while the analogue for actual institutional imbalance is positive, consistent with Battalio et al. (2024)'s finding that the algorithm signs most institutional trades incorrectly. More importantly BJZZ-implied institutional trade imbalances is nearly flat in $Mroib$, establishing that $Mroib$'s negative link to ANcerno institutional trade imbalances, reported in Table 1, is a robust feature.

[41] 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.

I. 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 brokers trade against the wholesaler.[42] 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.[43] 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.[44] 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

[42] 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.

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

[44] 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.

leads to a positive relation between $|Mroib|$ and the intensity with which these high-cost retail orders are internalized (see Figure 3).

II. Economics of Retail Order Internalization

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

We next 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.[45] The broker-dealer obtains $PFOF_j$ in return for outsourcing the execution of a type j order to the wholesaler.

Price improvement of $PI_M > 0$ 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).[46] 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 et al. (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

[45] 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.

[46] 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.

- 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 $\$(V+2t)$

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 $n^s_{-2}+n^s_{-1}-(n^b_2+n^b_1)>q^*$, 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[47] at $\$V$ to exchanges. Thus, absent institutional liquidity demand, for $n^s_{-2}+n^s_{-1}\leq n^b_2+n^b_1+q^*$, internalization order imbalances identified by the BJZZ algorithm equal

$$|Mroibvol|=\frac{(n^s_2+\alpha_{NM}n^s_1)-(n^b_{-2}+\alpha_{NM}n^b_{-1})}{n^b_2+\alpha_{NM}n^b_1+n^s_{-2}+\alpha_{NM}n^s_{-1}}=\frac{\Delta_2+\alpha_{NM}\Delta_1}{n^b_2+n^s_{-2}+\alpha_{NM}(n^b_1+n^s_{-1})}.$$

$|Mroibvol|$ reaches a maximum at $n^s_{-2}+n^s_{-1}=n^b_2+n^b_1+q^*$, where substituting for $\Delta_1=q^*-\Delta_2$ yields

$$|Mroibvol|=\frac{\alpha_{NM}q^*+(1-\alpha_{NM})\Delta_2}{2(n^b_2+\alpha_{NM}n^b_1)+\alpha_{NM}q^*+(1-\alpha_{NM})\Delta_2}.$$

For $n^s_{-2}+n^s_{-1}>n^b_2+n^b_1+q^*$, $|Mroibvol|$ 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

[47] That is, the n^s_0 limit sell orders, and the $n^b_0-q^*-(n^s_{-2}+n^s_{-1}-(n^b_2+n^b_1))$ remaining limit buy orders.

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 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, $\dfrac{\sum_j \Delta_j}{\sum_j (n_j^b + n_{-j}^s)} < 0$.

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

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

II. 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)).[48]

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.[49] 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 "$Z_{jt}^5 = 20 * \text{mod}(P_{jt}, 0.05)$", where Z_{jt}^5 is

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

[49]In unreported analysis we confirm the binding nature of this constraint for test Group 2 stocks; the distribution of PI indicates 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 (also see BJZZ).

the *sub-tick* execution price (P_{jt}) increment for a 5¢ tick size. With this scaling, $Z_{it}^5 \in [0, 1]$ and transactions can be classified into retail buy and retail sell trades as in Section III.

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:

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

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.[50] $X_{j,d}$ is stock j's outcome variable on trading day d; Post$_d$ is an indicator variable that equals 0 if $d < 0$ and 1 if $d \geq 0$. Treatment$_j^g$ is an indicator variable that equals 0 if stock j is in the control group and 1 if stock j is in the treatment group for Test Group $g \in \{1, 2\}$. The coefficient b_3^g captures the treatment effects associated with Test Group g. To ensure that estimated treatment effects are unaffected by outliers, we use both OLS and quantile (median) regressions to estimate equation (II. 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.[51] From Daily TAQ's Trades, Quotes, and NBBO files, we obtain trade and quote information to match

[50]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 303 stocks on 10/17/2016.

[51]Implementation consists of three phase-ins with different subsets of control stocks experiencing tick size

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.

Panel A in Table I.1 presents estimation results for the quote rule. A larger tick size given the same minimum PI raises the average and median volume of sub-penny-executed trades in low-spread stocks, where the new 5¢-tick tend to be binding.[52] This result, which obtains independent of share prices, indicates that the quote rule causes wholesalers to internalize retail orders more aggressively. Consider a low spread stock for which the 5¢ minimum spread reflects an endogenously-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 quoted spread increases the profitability of off-exchange liquidity provision at the midpoint, increasing the willingness of wholesalers to internalize order flow, since the variable cost of internalization, i.e., PI, can still be chosen by the wholesaler when Manning rule is not binding. In contrast, the quote rule restrictions does not alter the absolute values of $Mroibvol$ and $Mroibtrd$ in a systematical way, suggesting that a wider spread has a similar impact on internalization choices on both bid and ask sides.

Panel B in Table I.1 presents estimation results for Test Group 2 that introduced a 0.5¢ minimum PI in addition to the 5¢ pricing increment. In sharp contrast to the quote-rule treatment,

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.

[52]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.

TABLE I.1

Retail Order Internalization and the Tick Size Pilot

This table reports OLS and median (50^{th} quantile) regression estimates of b_3^g, with $g \in \{1, 2\}$, in equation (II. 2), comparing stocks in Test Group 1 to control stocks in Panel A and comparing Test Group 2 to control stocks in Panel B. Estimation is carried at using all qualifying stocks, low-priced (below median) stocks, and high-priced (above-median) stocks. In each of the these samples, stocks are split into low-spread vs. high-spread sotcks based on the median quoted bid-ask spreads calculated observed on August, 2016. 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. 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 trades executed at sub-penny prices. Numbers in brackets reflect t-statistics, and symbols ***, **, and * identify statistical significance at the 1%, 5%, and 10% type one errors, respectively.

Panel A: increased tick size, fixed minimum PI requirement (the Quote Rule)

	Low-spread stocks						High-spread stocks					
Share price	Median regression			OLS			Median regression			OLS		
category	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol
All stocks	.014**	.011	3057***	.0034	.0015	1360.3*	−.023**	−.0075	927***	−.019**	−.010	−334.1
	[2.04]	[1.18]	[10.87]	[.54]	[.21]	[1.70]	[−2.44]	[−.61]	[4.85]	[−2.46]	[−1.25]	[−.49]
Low-priced	.0053	.0065	2661***	−.00072	−.0033	−1691.5	−.035*	.0060	1371***	−.019	−.0087	−798.7
	[.44]	[.49]	[5.92]	[−.08]	[−.34]	[−1.44]	[−1.74]	[.28]	[3.84]	[−1.46]	[−.64]	[−.67]
High-priced	.0074	.0011	3725***	.0048	−.00084	5881.8***	.0095	.015	519**	−.0037	.0081	−153.1
	[.91]	[.09]	[10.67]	[.56]	[−.08]	[5.67]	[1.12]	[1.13]	[2.43]	[−.41]	[.82]	[−.19]

Panel B: increased tick size *and* increased minimum PI requirement (the Trade Rule)

	Low-spread stocks						High-spread stocks					
Share price	Median regression			OLS			Median regression			OLS		
category	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol	$\|Mroibtrd\|$	$\|Mroibvol\|$	BJZZ vol
All stocks	.027***	.091***	−2326***	.032***	.076***	−3277.9***	.028***	.092***	120	.042***	.052***	591.6
	[3.71]	[9.32]	[−8.13]	[5.13]	[10.79]	[−4.07]	[2.75]	[7.45]	[.64]	[5.44]	[6.27]	[.88]
Low-priced	.046***	.094***	−1632***	.041***	.078***	−1787.4	.062***	.028	431	.026**	.013	892.2
	[3.95]	[6.91]	[−3.45]	[4.61]	[7.96]	[−1.49]	[3.15]	[1.31]	[1.26]	[2.06]	[1.04]	[.81]
High-priced	.027***	.085***	−2746***	.030***	.082***	−4425.2***	.032***	.11***	−238	.052***	.076***	508.1
	[3.38]	[7.07]	[−8.23]	[3.54]	[8.29]	[−4.41]	[3.32]	[8.02]	[1.10]	[5.56]	[7.37]	[.62]

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. This result is stronger in low-spread stocks but does not to systematically vary share price. Notably, 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.[53] We posit that these effects manifest

[53]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

themselves in 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.

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.

II. Liquidity and Expected Returns: $1 and $5 Share Price Requirements

This section presents estimation results for equation (6) when low-priced stocks are excluded from the sample based on alternative cutoffs for prior month's share prices. Tables II.1 and II.2 (Panel A) report 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 II.1, in a more inclusive sample with a less strict (under $1) definition of penny stocks, ILCs 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

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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 in more unbalanced $Mroib$.

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, likely due to including stocks that institutional investors are reluctant or unable to hold.

In contrast, Table II.2 reports that with a stricter (under $5) definition of penny stocks, which still excludes stocks held in limited amounts by institutional investors, ILCs 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.

Panel B in Tables II.1 and II.2 highlights the incremental information content of $ILCT$ and $ILCV$ with respect to each alternative liquidity measure. First, the residuals of each ILC with respected an alternative measure are calculated using Fama-MacBeth regressions. These residuals are then used as LIQ in equation (6). For both minimum price filters, with the exception of realized institutional price impacts (InPrIM), ILC 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 ILCs outperform all existing liquidity measures in explaining the cross-section of expected returns.[54]

III. *ILC*s and Expected Returns: Robustness to Empirical Specifications

Table III.1 summarizes the results of extensive robustness tests that confirm the liquidity premia captured by our liquidity measures. These tests are implemented separately after imposing minimum share price requirements of $1, $2, and $5. First, estimating equation (6) using panel regressions that include date and stock fixed effects and double-cluster standard errors by date and

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

TABLE II.1

Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILCs

This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (6) 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 $ILCT$ and $ILCV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. The last column in Panel B use the residuals of $ILCT$ and $ILCV$ with respect to *all* alternative liquidity proxies (not including institutional price impacts). 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	ILCT	ILCV
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[†]	360,626	360,626	360,626	360,626	360,626	360,066	360,624	360,626	360,624[††]	360,624[††]	294,284[†††]	294,284[†††]	360626	360626

Panel B: Loadings of ILCs 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	All measures
ILCT 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	0.59
	[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]	(1.12)
ILCV 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	0.75
	[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]	(1.47)

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

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

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

TABLE II.2

Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILCs

This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (6) 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 $ILCT$ and $ILCV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. The last column in Panel B use the residuals of $ILCT$ and $ILCV$ with respect to *all* alternative liquidity proxies (not including institutional price impacts). 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	ILCT	ILCV
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]
$\ln(\text{Mcap})$	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†	297337	297337	297337	297337	297337	296805	297335	297337	297,335††	297,335††	242442	242442	297,337†††	297,337†††

Panel B: Loadings of ILCs 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	All measures
ILCT 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***	0.95**
	[−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]	(2.53)
ILCV 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***	0.99***
	[−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]	(2.82)

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

†† The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

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

stock leaves our qualitative findings unaffected. Second, correcting for market microstructure noise, as in Asparouhova et al. (2010), does not affect the economic significance of the liquidity premia. Third, qualitative findings are robust to excluding the smallest 20% of stocks, indicating that the liquidity premia are not a small-stock phenomena. Intuitively, this reflects the relevance of ILCs 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 ILCs of stocks with low sub-penny volume likely have higher measurement error. Fifth, weighting observations by firm size improves statistical significance of liquidity premia estimates for $ILCT$, but reduces it for $ILCV$. Sixth, excluding the top and bottom 10% of each ILC 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 ILC distributions. Indeed, down-weighting (censoring) extreme ILC observations strengthens our results. Seventh, motivated by Asparouhova et al. (2010) and Ben-Rephael et al. (2015), who find liquidity premia vary by listing exchange, we document robustness of liquidity premia across listing exchanges.

We next address the relevance of institutional/retail investor participation. The abundance of institutional liquidity, i.e., availability of institutional counterparties willing to trade at the midpoint, is endogenously determined with the level of institutional ownership. Thus, even though the marginal investors in stocks with high institutional ownership levels ($IOShr$) may still resort to wholesalers who can use retail flow to provide liquidity, they should do so less often. In turn, stocks predominantly held by institutions should also display lower shares of sub-penny trading volume ($SPVS$). We account for these observations by augmenting the set of control variables in equation (6) by either (1) monthly $IOShr$ percentile statistics and their interaction with the ILC measure or (2) monthly $SPVS$ percentile statistics and their interaction with the ILC measure. Thus, we allow the relationship between expected returns and ILCs to take nonlinear forms conditional on $IOShr$ and $SPVS$.

Table III.2 shows that ILCs remain significant predictors of expected stock returns with this non-linear specification. The baseline coefficients on "Liquidity" reflect the relation between an ILC measure and expected return when $IOShr$ and $SPVS$, respectively, are at their lowest levels observed in the sample. Hence, we report the "marginal effect" of illiquidity on expected returns for stocks with median $IOShr$ or $SPVS$. That is, in Panels A and B we plug 0.5 for $IOShr$ percentile and $SPVS$ percentile, respectively, in the first derivative with respect to "Liquidity." We see that the predictive power of ILCs is stronger among stocks with lower institutional ownership and higher shares of sub-penny trading volume. In sum, these results comprise strong evidence that ILCs predict expected stock returns and are associated with economically significant liquidity premia.

IV. Portfolio Sorts

This section reports that long-short portfolios based on ILC generate abnormal (risk-adjusted) monthly returns. For each monthly cross-section, we form 10 liquidity portfolios using $ILCT$ and separately using $ILCV$. These portfolios are formed by first sorting the cross-section of stocks into deciles based on the entire CRSP common-share universe before calculating equally-weighted portfolio returns. In robustness tests, we first remove stocks in the bottom 20% of market capitalization, and then specify portfolio breakpoints using ILCs of NYSE-listed stocks before calculating value-weighted portfolio returns.[55] Portfolio returns are calculated as the average return of the stocks assigned to the respective portfolio net of the contemporaneous 1-month T-bill rate. The monthly long-short portfolio return equals the return difference between the least and 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 (plus the momentum factor). 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 IV.1 reports significant risk-adjusted return spreads between the least liquid and most liquid portfolios according to both $ILCT$ and $ILCV$. The portfolio risk-adjusted returns display roughly monotonic patterns, increasing from the most liquid portfolio to the least liquid one. The associated return spreads are economically significant, ranging between 0.93% and 1.20% per month in our main sample (Panel B in Table IV.1) and between 0.41% and 1.27% per

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

month across all specifications. Overall, estimates imply that annualized portfolio return spreads based on ILC range between 4.08–15.24%, with the larger estimates found for samples that include small, low-priced stocks.

ANcerno data suggest that our liquidity premium estimates are plausible manifestations of expected implicit trading costs. Figure 4 indicates a 20bp difference in expected institutional price impacts between stocks in the top and bottom ILCs deciles for a $2 price filter. Institutional price impacts estimates (InPrIm) can be re-scaled to reflect costs per $100k of institutional trade size—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 IV.1, 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 did not use Abel Noser’s execution quality assessment services—so their trades do not enter ANcerno data.

TABLE III.1

The Cross-Section of Expected Stock Returns and ILC: 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 (6) 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 ($\text{BM}_{j,m-1}$), 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 ILC. 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 (6) to listing exchange. Observations are weighted according to Asparouhova et al. (2010) after excluding stocks whose previous month-end's closing price is below $2 and stocks falling in the bottom 10% of the ratio of sub-penny volume in total volume. Estimates are from Fama-MacBeth estimates of equation (6) 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	$ILCT$			$ILCV$		
	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 ILC excluded	[2.92]	[3.29]	[2.72]	[2.96]	[2.93]	[2.92]

Panel B: Robustness to estimation by listing exchange

	$ILCT$		$ILCV$	
	NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
Asparouhova et al. (2010)	0.83	1.11**	1.17**	1.25**
+ Price $>$ \$2	[1.57]	[2.14]	[2.15]	[2.55]
Asparouhova et al. (2010) + Price $>$ \$2	1.04*	1.20**	1.43**	1.36***
+ low sub-penny volume stocks excluded	[1.90]	[2.29]	[2.48]	[2.73]

This table reports on the robustness of the relation between between our institutional liquidity measures and the cross-section of expected stock returns. Equation (6) is estimated using institutional liquidity measures ($LIQ_{j,m-2}$) constructed over 1-month horizons. Panel A reports results when the set of control variables are augmented with (1) percentile statistics of the share of institutionally held shares at the end of the previous quarter, $IOShr$ percentile, and (2) the interaction of $IOShr$ percentile with the respective ILM measure. The marginal effect of Liquidity on expected returns is estimated for the stock with median $IOShr$. Panel B reports results when the set of control variables are augmented with (1) percentile statistics of the share of trading volume executed at sub-penny prices in month $m-2$, $SPVS$ percentile, and (2) the interaction of $SPVS$ percentile with the respective ILC measure. The marginal effect of Liquidity on expected returns is estimated for the stock with median $IOShr$. 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 $p_{min} \in \{\$1, \$2, \$5\}$. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: robustness to controlling for institutional ownership

	$ILCT$			$ILCV$		
Independent variable	Price $>$ \$1	Price $>$ \$2	Price $>$ \$5	Price $>$ \$1	Price $>$ \$2	Price $>$ \$5
Liquidity	1.67***	1.98***	1.24***	2.06***	2.21***	1.56***
	[2.68]	[3.57]	[2.91]	[3.51]	[4.20]	[3.65]
$IOShr$ percentile	1.01***	1.04***	0.59***	1.25***	1.26***	0.74***
	[3.51]	[3.92]	[2.69]	[4.09]	[4.54]	[3.43]
$IOShr$ percentile$\times$Liquidity	−0.64	−1.14**	−0.83*	−1.31**	−1.67***	−1.06**
	[−1.11]	[−2.03]	[−1.76]	[−2.35]	[−3.14]	[−2.35]
Marginal Liquidity effect	**1.35***	**1.41****	**0.82***	**1.41****	**1.38****	**1.04****
($IOShr$ percentile = 0.5)	**[1.97]**	**[2.27]**	**[1.70]**	**[2.17]**	**[2.33]**	**[2.14]**

Panel B: robustness to controlling for share of BJZZ volume

	$ILCT$			$ILCV$		
Independent variable	Price $>$ \$1	Price $>$ \$2	Price $>$ \$5	Price $>$ \$1	Price $>$ \$2	Price $>$ \$5
Liquidity	−0.51	−0.39	−0.26	−0.46	−0.41	−0.17
	[−1.27]	[−0.93]	[−0.61]	[−1.12]	[−0.99]	[−0.41]
$SPVS$ percentile	−1.80***	−1.87***	−1.48***	−1.94***	−1.94***	−1.56***
	[−5.44]	[−6.12]	[−5.51]	[−5.85]	[−6.53]	[−5.73]
$SPVS$ percentile$\times$Liquidity	3.36***	3.52***	2.55***	3.41***	3.41***	2.58***
	[6.59]	[7.87]	[5.16]	[7.39]	[8.78]	[5.52]
Marginal Liquidity effect	**1.17****	**1.37*****	**1.01****	**1.24****	**1.29*****	**1.12****
($SPVS$ percentile = 0.5)	**[2.44]**	**[2.90]**	**[2.04]**	**[2.61]**	**[2.83]**	**[2.31]**

TABLE IV.1

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. Panels G, H, and I augment estimates reported in Panels A, B, and C with the momentum factor. Stocks in each monthly cross-section are sorted into ten ILC 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 (plus momentum) 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 $p_{min} \in \{\$1, \$2, \$5\}$. 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
$ILCT$	−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]
$ILCV$	−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
$ILCT$	−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]
$ILCV$	−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]

Continued on next page

TABLE IV.1 – *continued from previous page*

Panel C: CRSP breakpoints, $5 minimum share price

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 − 1
$ILCT$	−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]
$ILCV$	−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]

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
$ILCT$	−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]
$ILCV$	−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
$ILCT$	−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]
$ILCV$	−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
$ILCT$	−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]
$ILCV$	−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]

Continued on next page

TABLE IV.1 – *continued from previous page*

Panel G: CRSP breakpoints, $1 minimum share price, FF-3 factors + momentum

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 − 1
$ILCT$	−0.31***	−0.31***	−0.16*	−0.13	−0.18**	−0.18	0.022	0.13	0.40**	0.64***	0.94***
	[−2.78]	[−3.45]	[−1.71]	[−1.09]	[−2.16]	[−1.37]	[0.21]	[0.92]	[2.57]	[4.28]	[4.47]
$ILCV$	−0.58***	−0.39***	−0.20**	−0.21***	−0.062	0.042	−0.0036	0.34***	0.35**	0.64***	1.21***
	[−4.07]	[−4.01]	[−2.03]	[−2.98]	[−0.57]	[0.53]	[−0.04]	[2.94]	[2.24]	[4.82]	[5.64]

Panel H: CRSP breakpoints, $2 minimum share price, FF-3 factors + momentum

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 − 1
$ILCT$	−0.29***	−0.30***	−0.18*	−0.024	−0.13*	−0.080	0.070	0.12	0.35**	0.62***	0.91***
	[−2.77]	[−3.61]	[−1.75]	[−0.29]	[−1.74]	[−0.81]	[0.78]	[1.07]	[2.55]	[4.46]	[4.47]
$ILCV$	−0.52***	−0.28***	−0.19**	−0.21***	−0.043	0.12	0.060	0.29***	0.32**	0.61***	1.13***
	[−3.79]	[−3.51]	[−2.00]	[−3.29]	[−0.43]	[1.58]	[0.84]	[3.35]	[2.23]	[4.96]	[5.15]

Panel I: CRSP breakpoints, $5 minimum share price, FF-3 factors + momentum

	Liquidity portfolios										
	1	2	3	4	5	6	7	8	9	10	10 − 1
$ILCT$	−0.28***	−0.21**	−0.12	0.079	0.059	0.038	0.15	0.28***	0.37***	0.64***	0.92***
	[−2.74]	[−2.62]	[−1.58]	[1.10]	[0.83]	[0.71]	[1.52]	[2.85]	[3.31]	[4.61]	[4.31]
$ILCV$	−0.38***	−0.17**	−0.11	−0.076	0.025	0.070	0.21***	0.37***	0.40***	0.66***	1.04***
	[−3.19]	[−2.30]	[−1.51]	[−1.05]	[0.29]	[1.54]	[3.09]	[4.55]	[3.76]	[5.19]	[4.79]

V. Three-month and twelve-month *ILC*s 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 5 using liquidity measures constructed over rolling 3-month and 12-month windows. Specifically, $LIQ_{j,m-2}$ averages daily stock j's observations from month $m-4$ through $m-2$ and from month $m-13$ through $m-2$. Tables V.1 and V.2 report that, with a $2 minimum price requirement, $ILCT$ and $ILCV$ explain the cross-section of stock returns in month m, unlike other liquidity measures. Sample standard deviations for 3-month $ILCT$ and $ILCV$ are 0.176 and 0.195, respectively. Thus, a one standard deviation increase in $ILCT$ 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 $ILCV$ is $0.195 \times 1.60 = 0.312\%$ per month or 3.74% per year.

VI. 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.[56]

Table VI.1 reports that ILCs are the only measures for which the traditional long-short strategy (4) consistently produces three-factor liquidity premia of nearly 1% or higher. In

[56]Note that the findings regarding $ILCT$ and $ILCV$ match those reported in Panels A–C in Table **??**.

TABLE V.1

Liquidity and the Cross-Section of Expected Stock Returns: 3-month liquidity measures

This table reports on the relation between an array of high-frequency liquidity measures and the cross-section of expected stock returns. Equation (6) 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 ($\text{BM}_{j,m-1}$), 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 ($RET_{(-12,-2)}$). 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	ILCT	ILCV
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[†]	327,842	327,842	327,842	327,842	327,842	332,943	337,181	337,185	334,134[††]	334,134[††]	271,641[†††]	271,641[†††]	327,842	327,842

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

†† The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

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

addition, $ILCV$ is the sole liquidity measure for which all four long-short strategies produce significant liquidity premia. This finding indicates that $ILCV$ identifies economically relevant differences in stock liquidity even for stocks with intermediate trading costs, highlighting the practical relevance of ILCs. 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

This table reports on the relation between an array of high-frequency liquidity measures and the cross-section of expected stock returns. Equation (6) is estimated using liquidity measures ($LIQ_{j,m-2}$) constructed over 12-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	ILCT	ILCV
Constant	1.56	0.51	0.60	0.54	0.63	0.55	1.74*	0.65	1.03	0.68	0.73	1.29	1.27	−2.67*	−3.67**
	[1.26]	[0.54]	[0.65]	[0.57]	[0.69]	[0.60]	[1.76]	[0.71]	[1.10]	[0.76]	[0.79]	[1.49]	[1.49]	[−1.81]	[−2.29]
Liquidity	**0.046**	**0.098**	**−0.00**	**0.12**	**−0.12**	**0.16**	**−0.22****	**−0.027**	**−6.61***	**−0.0072**	**−0.024**	**−0.090**	**−0.12**	**1.92*****	**2.14*****
	[1.11]	**[0.75]**	**[−1.15]**	**[0.78]**	**[−1.01]**	**[0.88]**	**[−2.05]**	**[−0.35]**	**[−1.86]**	**[−0.22]**	**[−0.27]**	**[−0.86]**	**[−0.66]**	**[3.60]**	**[3.94]**
β^{mkt}	−0.0096	−0.31	−0.31	−0.31	−0.32	−0.31	−0.32	−0.31	−0.30	−0.31	−0.31	−0.36	−0.36	−0.18	−0.13
	[−0.03]	[−1.59]	[−1.62]	[−1.62]	[−1.64]	[−1.62]	[−1.64]	[−1.59]	[−1.55]	[−1.59]	[−1.62]	[−1.61]	[−1.61]	[−0.95]	[−0.70]
β^{hml}	−0.11	−0.10	−0.10	−0.10	−0.10	−0.10	−0.099	−0.11	−0.12	−0.11	−0.11	−0.072	−0.072	−0.12	−0.14
	[−0.79]	[−0.82]	[−0.83]	[−0.82]	[−0.82]	[−0.82]	[−0.79]	[−0.85]	[−0.94]	[−0.85]	[−0.86]	[−0.49]	[−0.49]	[−0.98]	[−1.10]
β^{smb}	0.12	0.038	0.036	0.037	0.033	0.037	0.0092	0.036	0.029	0.031	0.030	0.028	0.029	0.093	0.11
	[1.37]	[0.49]	[0.47]	[0.48]	[0.43]	[0.49]	[0.12]	[0.46]	[0.38]	[0.39]	[0.38]	[0.30]	[0.32]	[1.23]	[1.47]
BM	0.19	−0.023	−0.023	−0.022	−0.023	−0.022	−0.022	−0.0085	−0.0051	−0.010	−0.0063	0.044	0.042	−0.024	−0.021
	[1.41]	[−0.46]	[−0.46]	[−0.44]	[−0.45]	[−0.44]	[−0.38]	[−0.16]	[−0.10]	[−0.20]	[−0.12]	[0.50]	[0.48]	[−0.47]	[−0.42]
$\ln(\mathrm{Mcap})$	−0.0039	0.046	0.044	0.045	0.042	0.045	−0.0082	0.041	0.025	0.039	0.037	0.016	0.017	0.17***	0.20***
	[−0.07]	[1.19]	[1.14]	[1.16]	[1.12]	[1.20]	[−0.20]	[1.10]	[0.67]	[1.07]	[0.98]	[0.46]	[0.50]	[2.87]	[3.24]
DYD	0.32	−0.11	−0.10	−0.11	−0.12	−0.11	−0.20	−0.096	−0.094	−0.089	−0.12	0.070	0.069	−0.15	−0.14
	[0.30]	[−0.21]	[−0.20]	[−0.22]	[−0.24]	[−0.22]	[−0.38]	[−0.19]	[−0.19]	[−0.18]	[−0.24]	[0.13]	[0.13]	[−0.29]	[−0.29]
Id. Vol.	−0.17***	−0.22***	−0.23***	−0.22***	−0.23***	−0.23***	−0.21***	−0.23***	−0.22***	−0.23***	−0.22***	−0.22***	−0.22***	−0.20***	−0.19***
	[−2.72]	[−4.27]	[−4.30]	[−4.29]	[−4.29]	[−4.28]	[−3.97]	[−4.30]	[−4.21]	[−4.19]	[−4.09]	[−3.65]	[−3.66]	[−3.96]	[−3.82]
RET_{-1}	−0.85	−0.28	−0.28	−0.28	−0.28	−0.27	−0.35	−0.34	−0.35	−0.33	−0.32	−0.40	−0.41	−0.39	−0.44
	[−1.21]	[−0.56]	[−0.55]	[−0.55]	[−0.54]	[−0.53]	[−0.65]	[−0.65]	[−0.69]	[−0.65]	[−0.62]	[−0.69]	[−0.70]	[−0.76]	[−0.86]
$RET_{(-12,-2)}$	0.40**	0.24	0.24	0.24	0.24	0.24	0.23	0.25	0.25	0.25	0.25	0.24	0.24	0.29*	0.31*
	[2.07]	[1.40]	[1.39]	[1.40]	[1.40]	[1.40]	[1.31]	[1.46]	[1.47]	[1.47]	[1.48]	[1.14]	[1.14]	[1.68]	[1.76]
Observations	132,985†	300,552	300,552	300,552	300,552	300,552	302,882	307,061††	307,082††	307,121	307,121	244,479†††	244,479†††	300,552	300,552

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

†† The number of observations reflects the largest sample available for ILLIQ and ILLIQ_OC.

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

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 5, II.1, and II.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 VI.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†	−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]
ILCT	−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]
ILCV	−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]

Continued on next page

TABLE VI.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†	−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]
ILCT	−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]
ILCV	−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]

Continued on next page

TABLE VI.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†	−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]
ILCT	−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]
ILCV	−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]

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

VII. Portfolio Double Sorts

This section provides return differences between stocks falling in different levels of ILC and stock characteristics. Double sorts based on ILCs 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 ILC.[57] 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 VII.1 documents liquidity premia for high- and low-beta, small and large, growth and value stocks, past losers and past winners, stocks with low and high institutional ownership, 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. Internet Appendix V establishes the robustness of these findings to constructing ILCs over 3-month rolling windows. Therefore, the liquidity premia associated with ILCs 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 ILC, and then on a stock characteristic. Table VII.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)).[58]

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[57] 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.

[58] Internet Appendix V confirms results are robust to constructing ILCs over 3-month rolling windows.

TABLE VII.1

Portfolio Alphas: Stock Characteristic and ILC Double-Sorts

table presents three-factor alphas using CRSP breakpoints. Stocks are first sorted into stock characteristic quintiles $X \in \{\beta^{mkt}$, Mcap, $RET_{(-12,-2)}$, BM, IOShr, SPVS$\}$. Within each characteristic quintile, stocks are further sorted into $LIQ \in \{ILCT, ILCV\}$ 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 ILC

		Portfolios of $ILCT$						Portfolios of $ILCV$					
		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 ILC

		Portfolios of $ILCT$						Portfolios of $ILCV$					
		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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TABLE VII.1 – *continued from previous page*

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

		Portfolios of $ILCT$						Portfolios of $ILCV$					
		Low	2	3	4	High	High−Low	Low	2	3	4	High	High−Low
Portfolios of book-to-market ratio	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 ILC

		Portfolios of $ILCT$						Portfolios of $ILCV$					
		Low	2	3	4	High	High−Low	Low	2	3	4	High	High−Low
Portfolios of past return	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 VII.1 – *continued from previous page*

Panel E: Sequential double sorts on institutional ownership and ILC

Portfolios of instl. ownership	Portfolios of $ILCT$: Low	2	3	4	High	High−Low	Portfolios of $ILCV$: Low	2	3	4	High	High−Low
Low	−0.96***	−0.28*	0.20	0.61***	0.71***	1.67***	−1.20***	−0.17	0.26*	0.63***	0.75***	1.96***
	[−5.10]	[−1.73]	[1.39]	[4.09]	[4.12]	[6.02]	[−5.24]	[−1.19]	[1.75]	[3.80]	[4.59]	[6.49]
2	−0.17	0.21*	0.38***	0.46**	0.60***	0.77***	−0.21**	0.097	0.43***	0.56***	0.60***	0.80***
	[−1.60]	[1.81]	[3.82]	[2.42]	[4.43]	[3.89]	[−2.22]	[0.77]	[3.48]	[4.33]	[4.49]	[4.38]
3	−0.015	−0.10	0.16	0.18*	0.32**	0.34*	−0.073	−0.032	0.086	0.12	0.44***	0.51***
	[−0.15]	[−0.86]	[1.55]	[1.67]	[2.45]	[1.92]	[−0.85]	[−0.29]	[0.94]	[1.52]	[3.24]	[2.94]
4	−0.080	−0.092	0.19**	0.11	0.30***	0.38**	−0.16	0.058	0.047	0.16**	0.31***	0.47***
	[−0.78]	[−1.05]	[2.19]	[1.29]	[3.23]	[2.62]	[−1.22]	[0.61]	[0.41]	[2.09]	[3.31]	[2.66]
High	−0.30**	−0.17	−0.084	−0.052	−0.058	0.24	−0.35**	−0.19	−0.23**	0.086	0.025	0.38**
	[−2.22]	[−1.61]	[−0.65]	[−0.43]	[−0.60]	[1.36]	[−2.10]	[−1.64]	[−2.32]	[0.97]	[0.27]	[2.00]

Panel F: Sequential double sorts on share of sub-penny trade volume and ILC

Portfolios of sub-penny volume	Portfolios of $ILCT$: Low	2	3	4	High	High−Low	Portfolios of $ILCV$: 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 VII.2

Portfolio Alphas: ILC and Stock Characteristic Double-Sorts

This table presents three-factor alphas using CRSP breakpoints. Stocks are sorted into liquidity quintiles based on $LIQ \in \{ILCT, ILCV\}$. Within each liquidity quintile, stocks are further sorted into stock characteristic quintiles $X \in \{\beta^{mkt}$, Mcap, $RET_{(-12,-2)}$, BM, $\}$. 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 $ILCT$ and stock characteristics

Portfolios of $ILCT$	Portfolios of beta: Low	2	3	4	High	High−Low
Low	0.048	0.031	−0.11	−0.41***	−0.87***	−0.92**
	[0.44]	[0.37]	[−1.27]	[−2.69]	[−3.01]	[−2.57]
2	0.32*	0.18**	0.034	−0.18*	−0.57***	−0.89***
	[1.76]	[2.15]	[0.35]	[−1.73]	[−2.79]	[−2.66]
3	0.14	0.26***	0.12	−0.051	−0.43**	−0.57**
	[1.34]	[2.68]	[1.07]	[−0.50]	[−2.17]	[−2.25]
4	0.26**	0.54***	0.36***	0.016	−0.18	−0.44**
	[2.07]	[5.28]	[3.47]	[0.12]	[−1.05]	[−1.99]
High	0.71***	0.81***	0.47***	0.44***	0.16	−0.56**
	[3.49]	[5.99]	[3.24]	[3.54]	[1.09]	[−2.21]

Portfolios of $ILCT$	Portfolios of market capitalization: Low	2	3	4	High	High−Low
Low	−0.85***	−0.37**	−0.053	−0.021	−0.030	0.82***
	[−3.99]	[−2.33]	[−0.43]	[−0.21]	[−0.72]	[3.77]
2	−0.33**	−0.14	0.029	0.012	0.20***	0.54***
	[−2.24]	[−1.17]	[0.24]	[0.11]	[2.95]	[3.05]
3	−0.34**	0.029	0.15	0.12	0.065	0.40**
	[−2.09]	[0.27]	[1.42]	[1.53]	[0.82]	[2.03]
4	−0.30	0.47***	0.30***	0.37***	0.16**	0.46*
	[−1.29]	[4.06]	[3.39]	[3.69]	[2.00]	[1.74]
High	0.29	0.80***	0.59***	0.45***	0.46***	0.18
	[1.41]	[4.23]	[4.11]	[2.74]	[3.44]	[0.71]

Portfolios of $ILCT$	Portfolios of book-to-market ratio: Low	2	3	4	High	High−Low
Low	−0.11	−0.23**	−0.32**	−0.27**	−0.39***	−0.28
	[−0.67]	[−2.06]	[−2.59]	[−2.52]	[−3.15]	[−1.42]
2	0.12	0.036	−0.019	−0.23*	−0.13	−0.26
	[0.68]	[0.41]	[−0.20]	[−1.95]	[−0.81]	[−0.94]
3	−0.059	−0.067	0.041	−0.019	0.13	0.19
	[−0.41]	[−0.60]	[0.37]	[−0.20]	[0.87]	[0.82]
4	0.16	0.18**	0.12	0.31***	0.22	0.068
	[1.04]	[2.09]	[1.06]	[2.94]	[1.21]	[0.35]
High	0.18	0.18	0.65***	0.84***	0.74***	0.56**
	[0.99]	[1.29]	[4.18]	[5.10]	[3.92]	[2.07]

Portfolios of $ILCT$	Portfolios of past return ($R_{(-12,-2)}$): Low	2	3	4	High	High−Low
Low	−0.84***	−0.017	−0.075	−0.090	−0.30	0.54
	[−3.33]	[−0.14]	[−1.05]	[−0.83]	[−1.54]	[1.56]
2	−0.60***	0.078	0.24**	0.22**	−0.17	0.43
	[−2.96]	[0.68]	[2.61]	[2.25]	[−0.79]	[1.27]
3	−0.35	0.083	0.19*	0.11	−0.012	0.34
	[−1.65]	[0.63]	[1.84]	[0.91]	[−0.08]	[1.09]
4	−0.24	0.14	0.37***	0.43***	0.29**	0.52*
	[−0.94]	[1.20]	[2.81]	[3.88]	[2.06]	[1.72]
High	−0.15	0.51***	0.90***	0.74***	0.59***	0.74***
	[−0.80]	[3.66]	[6.97]	[4.96]	[4.49]	[3.54]

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TABLE VII.2 – *continued from previous page*

Panel B: Sequential double sorts on $ILCV$ 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 $ILCV$	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 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 $ILCV$	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]