Uncovering the Liquidity Premium in Stock Returns Using Sub-Penny Trade Executions*

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Abstract

Order flow segmentation prevents direct interactions between retail and institutional investors. However, U.S. wholesalers interact with both groups and can use one group's order flow to help meet the other's liquidity demands. Readily-observable large wholesaler-retail trade imbalances reflect such intermediation when *liquidity is scarce.* We use imbalances in these trades to measure stock-specific liquidity, exploiting larger average absolute imbalances in less liquid stocks. Our ILM measures are correlated with expected institutional price impacts. Unlike existing illiquidity measures, ILMs have economically-meaningful stock- and investor-level relations with institutional holding horizons, and yield annualized liquidity premia of 2.7–3.2% post-2010, even after excluding micro-cap stocks.

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

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1 Introduction

The literature that bridged market microstructure and asset pricing by documenting a positive association between illiquidity and expected stock returns dates back to Amihud and Mendelson (1986). However, the past two decades have witnessed radical changes in the market microstructure of U.S. equity markets. Contemporaneously, liquidity premia derived from *existing* microstructure-based liquidity measures have largely vanished.[1] One might posit that this disappearance is evidence that markets became so liquid that investors no longer demand liquidity premia as compensation for the costs of entering and exiting stock positions. However, such reasoning is at odds with institutional investors, who collectively hold about 70% of publicly-traded equity in the U.S. (Blume and Keim (2012)), still incurring economically significant trading costs that vary substantially in the cross-section.[2] The more plausible explanation is that market microstructure changes have rendered existing liquidity measures unable to capture institutional trading costs.[3] We develop novel, easy-to-construct measures of liquidity that reflect modern U.S. equity market structure. These measures reveal that economically-significant liquidity premia still exist in stock returns. Even one year forward, our measures continue to predict future returns. Our measures use publicly-available data to 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 liquidity measures reflect 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. When liquidity is scarce and one of these groups has pressing liquidity needs, wholesalers can act as liquidity providers. Although such liquidity provision may result in wholesalers accumulating unwanted inventory, wholesalers' access to both retail and institutional flows enables them to use order flow from one group to partially offset accumulated inventory from providing liquidity to the other group.

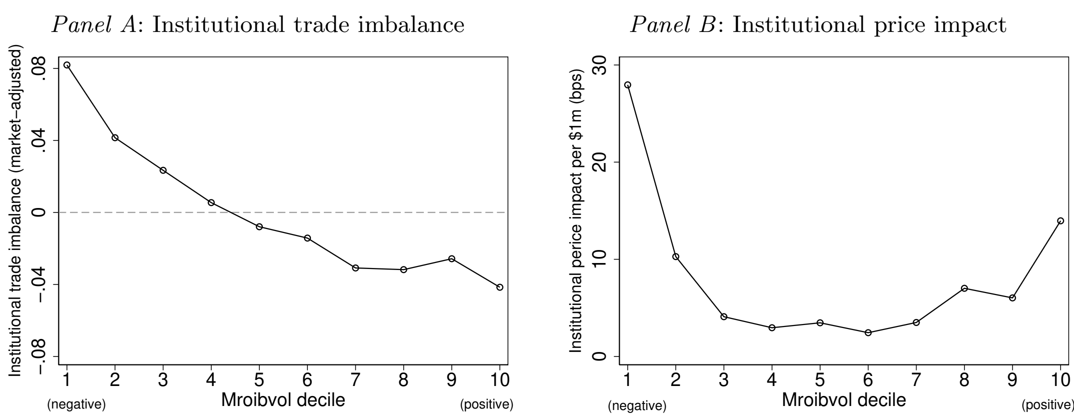
[1] See, e.g., Asparouhova, Bessembinder, and Kalcheva (2010), Ben-Rephael, Kadan, and Wohl (2015), Drienko, Smith, and von Reibnitz (2019), Harris and Amato (2019), and Amihud (2019).

[2] Di Maggio, Egan, and Franzoni (2022) report institutional price impacts exhibit a mean and standard deviation of 32 and 64bps, respectively, in recent years. This heterogeneity implies investors should demand a premium as compensation for institutional price impacts. 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.

[3] Indeed, a recent literature cautions against using these liquidity measures to proxy for institutional trading costs. See, e.g., Goyenko, Holden, and Trzcinka (2009), Chordia, Roll, and Subrahmanyan (2011), Kim and Murphy (2013), Holden and Jacobsen (2014), Angel, Harris, and Spatt (2011), O'Hara (2015), Barardehi, Bernhardt, and Davies (2019), and most recently Eaton, Irvine, and Liu (2021).

While data on wholesaler trades are difficult to obtain, Boehmer, Jones, Zhang, and Zhang (2021) (henceforth, BJZZ) propose an algorithm that identifies a subset of (primarily retail) trades executed by wholesalers in TAQ data and classifies them into buyer- and seller-initiated trades. As in BJZZ, we denote standardized imbalances in these trades by $Mroib$. Barber, Huang, Jorion, Odean, and Schwarz (2022) and Battalio, Jennings, Salgam, and Wu (2023) find that $Mroib$ measures overall retail order flow with large errors. However, we show that one can use $|Mroib|$ to proxy the intensity with which wholesalers provide liquidity in less liquid conditions. Panel A of Figure 1 reveals the negative association 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 of Figure 1 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 (Section 6 provides evidence on economic foundations of the variation in $Mroib$).

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.



These observations suggest that substantially positive and negative $Mroib$ manifest themselves more frequently in less liquid stocks. This leads us to investigate average daily $|Mroib|$ as a stock-level illiquidity measure (ILM) and test its implications for the cross-section of stock returns. We construct two versions of ILM: $ILMT$ is based on the number of trades, and $ILMV$ is based on trading volumes. Stocks that are less liquidity according to our ILM measures tend to have smaller market-capitalizations, smaller market betas, higher book-to-market ratios and lower recent returns. We contrast the abilities of ILMs to capture institutional trading costs with those of traditional liquidity measures. First, we document that both ILMs and several existing liquidity measures are correlated with future institutional price impacts obtained from ANcerno. These findings indicate that liquidity measures co-vary with expected trading costs.

Second, we provide direct evidence that ILMs capture the liquidity concerns of institutional investors better than existing measures by linking the liquidity of fund manager holdings based on different liquidity measures to their holding horizon. As Amihud and Mendelson (1986) observe, managers with longer holding horizons should be more willing to invest in illiquid stocks, implying a positive relation between a manager's holding horizon and the measured illiquidity of their equity holdings. ILMs produce a more monotone positive relationship between the illiquidity of a fund manager's equity holdings and their holding horizon than does any of the traditional measures. This finding is consistent with institutions who trade more frequently being reluctant to hold stocks that are likely to require them to turn to wholesalers as the ultimate liquidity providers. We find similar evidence when we analyze the relationship between illiquidity measures and holding horizon at the stock level. ILMs are the only liquidity measures that have economically meaningful relations with holding horizon at *both* the investor and stock levels.

Third, we establish that ILMs explain expected stock returns in the 2010–2019 period, but 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.[4] Conservatively skipping month $m-1$ ensures that returns in month m are not confounded by short-term reversals after liquidity-demanding trades. As in the prior literature, we find existing liquidity measures are not priced (or have negative liquidity "premia"). In contrast, ILMs are priced with economically-significant liquidity premia: a one standard deviation increase in $ILMT$ ($ILMV$) is associated with an annualized liquidity premium of 2.74% (3.20%), comparable to the institutional price impacts computed from ANcerno data that are priced with an annualized premium of 3.8% over 2010-2014.[5]

Portfolio sorts confirm the economic magnitudes of the liquidity premia associated with ILMs. We sort stocks into deciles based on their $ILMT$s or $ILMV$s in month $m-2$, skip month $m-1$,

[4] Internet Appendix C demonstrates robustness to constructing ILMs over three months, $m-4$ to $m-2$, or twelve months, $m-13$ to $m-2$.

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

and examine portfolio returns in month m. The high-minus-low return spreads involving deciles 1 and 10, after a Fama-French three-factor adjustment, are 0.86% and 1.06% per month for $ILMT$ and $ILMV$, respectively. Value-weighting returns after removing stocks with smallest 20% market-capitalizations, reduces these risk-adjusted returns to 0.58% and 0.46%, respectively. Robustness tests confirm that risk-adjusted return spreads associated with ILMs exceed those based on existing liquidity measures. Moreover, unlike with existing liquidity measures, significant risk-adjusted return spreads are associated with ILMs between intermediate deciles, such as spreads between decile 2 vs. 9, decile 3 vs. 8, and even decile 4 vs. 7.

The regression and portfolio results are confirmed by a battery of robustness tests that use alternative estimation approaches, weight observations unequally, apply various filters that remove micro-cap stocks from the sample, construct ILMs after excluding institutional trades filled at sub-penny prices (Battalio et al. (2023)), and control for the momentum anomaly. Our robust results enable us to conclude that liquidity premia conditional on ILMs hold among stocks that are the most likely to be held by institutional investors.

After documenting the superior performance of ILMs in capturing institutional trading costs and explaining expected stock returns, we highlight one economic mechanism that can explain the variation in $Mroib$, and hence ILMs. Our analysis suggests ILMs work because the underlying $|Mroib|$ components capture instances where wholesalers endogenously internalize unequal amounts of retail buy and sell orders to offset directional institutional flow, especially when liquidity is scarce. BJZZ show that $Mroib$ positively predicts future returns, suggesting that institutional order flow on the other side cannot be informed, but leaving open the possibility that some retail trades might be (Kelley and Tetlock (2013), Fong, Gallagher, and Lee (2014)). However, we show that $Mroib$ is associated with contemporaneous price movements in the *opposite* direction of BJZZ-identified retail trade imbalances, with minus $Mroib$ reflecting institutional liquidity demand and associated price pressure as suggested by Kaniel, Saar, and Titman (2008). This pattern is consistent with institutions not being willing to trade against informed retail flow. We find that the subsequent unwinding of this institutional price pressure manifests itself in price reversals that underlie the positive return predictability of $Mroib$.

We next observe that (1) almost all retail orders are handled by wholesalers (SEC (2022)); (2) the vast majority of trades underlying $Mroib$ are wholesaler trades (Battalio et al. (2023)); and (3)

BJZZ-identified trades reflect less than 40% of all retail trades (Barber et al. (2022)). These observations indicate that variation in $Mroib$ captures wholesaler internalization *choices* and not overall retail order flow. Our evidence indicates that these choices play a central role in driving $Mroib$'s variation and help explain why $Mroib$ positively predicts return. At the stock level, we show $Mroib$'s return predictability is attributable to short-term price reversals that follow institutional price pressure (Campbell, Grossman, and Wang (1993)). Consistent with excess institutional—but not retail—liquidity demand, abnormal $Mroib$ is inversely associated with abnormal institutional trade imbalances and returns contemporaneously. These abnormal returns realize intraday when institutional investors are active, suggesting the accumulation of price pressure that induces market makers to fill institutional liquidity demand. Reflective of wholesalers' motives to offset inventory to the extent possible, abnormal $Mroib$ is positively associated with increased execution quality of internalized retail trades, i.e., wholesalers pay greater price improvements to internalize retail trades on the opposite side of institutional demand shocks. Institutional price pressures later reverse, with reversals realized overnight, consistent with the reconciliation of risk borne by wholesalers carrying inventory overnight (Bogousslavsky (2021)) acquired from institutional traders.

To conclude, we connect these results back to our findings of cross-sectional links between ILMs and stock liquidity. Consistent with scarce liquidity, a large $|Mroib|$ is associated with abnormally low quote-midpoint liquidity, wider quoted spreads and lower quoted depth. Finally, while weekly $Mroib$ positively predicts near-term returns, the relation between $Mroib$ and future returns turns ∪-shaped after 6 weeks. This ∪-shaped pattern persists for months, consistent with $|Mroib|$ capturing liquidity premia in expected returns.

We contribute to the literatures that design measures of stock liquidity or examines their asset-pricing implications.[6] According to Amihud (2019), "illiquidity has a number of dimensions that are hard to capture in a single measure, including fixed costs, variable costs—price impact costs that increase in the traded quantity—and opportunity costs." The multifaceted nature of liquidity grew even more complicated after the adoption of Regulation National Market System where spreads are often a few pennies and depth is negligible, causing institutional investors to employ dynamic trading strategies and compromising the accuracy of traditional friction-based liquidity

[6]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 many others.

measures in capturing trading costs. This increased complexity likely underlies why existing measures can now only capture illiquidity in "penny stocks." Rather than use market friction metrics, our liquidity measures 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 with institutional investors not trading heavily in these stocks.

Our use of observable retail trades distinguishes our approach from other recent approaches. 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 the volatility in total 5-minute order flow over a week 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. This selection enables us to construct useful liquidity measures.

Our paper also contributes to work on the relationship between retail order flow and future returns.[7] Our explanation is consistent with Kaniel et al. (2008) who posit retail order flow reflects opposing institutional liquidity demand. However, we relax their premise that institutional investors offer "price concessions" to "entice" large groups of retail investors to provide liquidity. Based on a recent sample, Dyhrberg, Shkilko, and Werner (2023) find average retail investor does not actively "time" liquidity consumption, which suggests that most retail investors do not provide liquidity in response to institutional price concessions. Our proposed economic mechanism 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 $|Mroib|$ robustly explains the cross-section of expected returns over a year forward.

[7] 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).

2 Data

We follow BJZZ to construct measures of observable internalized retail order flow based on the selected sample identified by their algorithm. Using TAQ data, we focus on round-lot off-exchange trades with sub-penny prices.[8] Transactions are classified as retail buy and sell orders if the sub-penny increments exceed 0.6¢ and are below 0.4¢, respectively.[9] We construct daily, normalized measures of imbalance in internalized retail trade frequency and trade volume. $Mroibtrd = (Mrbtrd - Mrstrd)/(Mrbtrd + Mrstrd)$ divides the difference between the number of internalized retail buy and internalized retail sell orders by their sum, while $Mroibvol = (Mrbvol - Mrsvol)/(Mrbvol + Mrsvol)$ is the normalized difference in internalized trade volume. Panel B in Table 8 reports these measures' summary statistics, which closely match those in BJZZ.[10]

To analyze liquidity premia, we construct a sample spanning January 2010 through December 2019 of common shares listed on the NYSE, AMEX, and NASDAQ. We construct two daily institutional liquidity proxies as $|Mroibtrd|$ and $|Mroibvol|$. We use WRDS Daily Indicators, TAQ, and CRSP data to construct the following liquidity measures: (1) time-weighted dollar quoted spreads (QSP); (2) time-weighted share depth (ShrDepth); (3) size-weighted dollar effective spread (EFSP); (4) size-weighted dollar realized spread (RESP); (5) size-weighted price impacts (PIMP);[11] (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;[12] (7) Amvist liquidity measure, defined as the daily ratio of absolute return to turnover; (8) Roll (1984)'s measure of effective spreads; (9) Amihud (2002)'s measure (ILLIQ); (10) Barardehi, Bernhardt, Ruchti, and Weidemier (2021)'s open-to-close measure (ILLIQ_OC); (11 & 12) Barardehi et al. (2019)'s trade-time liquidity measures (BBD and WBBD);[13] (13) our trade-based illiquidity measure ($ILMT$), which averages $|Mroibtrd|$; (14)

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

[9] Barber et al. (2022) show the algorithm mis-classifies some buy and sell orders. In an unreported analysis, we verify that correcting for this mis-classification using quote midpoints marginally reinforces our qualitative findings.

[10] 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)).

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

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

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

our volume-based illiquidity measure ($ILMV$), which averages $|Mroibvol|$. We also construct a stock-specific institutional price impact measure (InPrIm) using ANcerno data from 2010–2014 to directly capture post-trade institutional trading costs per \$100k of trade. For each stock-month, we calculate a size-weighted average of institutional price impacts (defined above) associated with individual institutional trades reported by ANcerno.

For all liquidity measures (including $IMLT$ and $IMLV$), we construct two versions; one over a 1-month-horizon that averages daily liquidity proxies and another that averages daily liquidity proxies over rolling three-month windows with monthly updates. For each ILM measure, we also 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 ILM 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 $m-1$.[14] We obtain three-factor Fama-French betas for each stock from Beta Suite by WRDS. Our approach employs weekly data from rolling horizons that span the preceding 104 weeks, requiring a minimum of 52 weeks. For each stock month, the set of betas represent estimates from the estimation horizon ending in the last week of that month. As in Ang, Hodrick, Zhing, and Zhang (2006), we use a CAPM regression using daily observations in each month to construct monthly idiosyncratic volatility measures.

We construct measures of holding horizon using institutional ownership (13F filings data). Following Gaspar, Massa, and Matos (2005) and Cella, Ellul, and Giannetti (2013), for each institu-

[14] 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.

tional 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.

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 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 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 on based 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.[15]

From TAQ data, we match each identified internalized retail transaction with the National Best Bid and Offer prices (NBBO) at the same millisecond. NBBO are used for two purposes: (1) following Barber et al. (2022), we conduct robustness analyses that use NBBO midpoints to reclassify sub-penny trades into buy and sell retail trades before constructing $Mroibtrd$ and $Mroibvol$; (2) for

[15] 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.

each internalized trade signed based on NBBO midpoints, we calculate the effective price improvement (PI) as the difference between the relevant best quote and the transaction price, divided by the quote midpoint. We then separately calculate volume-weighted average PI for buy and sell trades.

ANcerno data from 2010-2014 provide institutional trade sizes, buy versus sell indicators, execution prices, and stock identifiers. We aggregate institutional buy and sell trades separately at the stock-day level to construct the institutional analogue of $Mroibvol$ denoted $Inoibvol$. To construct institutional price impact measures we calculate volume-weighted average buy and sell execution prices across institutional investors for each stock-day. The price impact of a typical institutional buy trade equals the average execution price minus the open price divided by the open price and scaled by the trade's dollar value in millions. Similarly, the price impact of a typical institutional sell trade equals open price minus the average execution price divided by the open price and scaled by the trade's dollar value in millions. We then aggregate institutional trading outcomes over 5-day rolling windows to construct daily cross-sections of 5-day (weekly) institutional trading outcomes.

3 Retail-Based Iliquidity Measures, *ILM*s

This section highlights characteristics of ILMs and contrasts them with existing liquidity measures.

3.1 *ILM*s, Existing Liquidity Measures, and Institutional Price Impacts

We first investigate how ILMs are related to key stock characteristics. We then examine how ILMs compare with existing liquidity measures in exhibiting correlations with future post-trade institutional price impacts. We construct weekly $ILMT$ and $ILMV$ for each stock by averaging $|Mroibtrd|$ and $|Mroibvol|$, respectively, over 5-day rolling windows to obtain weekly observations. We then match these weekly observations with stock characteristics constructed at the end of the preceding calendar month (see Section 2). After excluding stocks whose previous month's closing price are below \$2 (results are robust to excluding stocks with closing prices below \$5), we sort each weekly cross-section into deciles of $ILM \in \{ILMT, ILMV\}$. We then calculate stock characteristic averages by ILM decile and date before computing the time-series averages of these averages across dates by ILM deciles. Table 1 shows that high-ILM stocks, i.e., stocks identified as less liquid by the ILMs, tend to be small growth stocks with relatively poor recent returns and low CAPM betas.

A minimal requirement of a reasonable liquidity measure is that lower measured liquidity should be associated with higher institutional price impacts. We investigate this for each of our liquidity measures. For less liquid stocks, most liquidity measures, including ILMs meet this requirement—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 a handful of liquidity measures, including ILMs, 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.[16] Panel A in Figure 2 shows that for more liquid stocks (deciles 1–5), future institutional price impacts only rise monotonically with "improved" liquidity as measured by Kyle's lambda, Amihud measures, trade-time liquidity measures, and ILMs. Panel B in Figure 2 shows that for less liquid stocks (deciles 6–10), worsened liquidity according to most standard liquidity measures (movements from decile 6 to 10) is associated with increased future institutional price impacts. The bottom line is that 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 ILMs, do so for more liquid stocks. In unreported analyses, we verify that excluding stocks for which sub-penny volume comprises less than 10% of total volume leaves our qualitative findings unaffected.

3.2 Persistence of ILMs

We next document the temporal persistence in ILMs, establishing that they reflect a stock characteristic. The illiquidity measures $ILMT$ and $ILMV$ used in our asset pricing tests average daily $|Mroibtrd|$ and $|Mroibvol|$ observations over one month.[17] To examine the persistence in these measures, we regress $ILMT$ and $ILMV$ on their lags from the six preceding months. These Fama-MacBeth regressions correct for auto-correlated error terms using Newey-West standard er-

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

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

rors based on 6 lags, as do the rest of our regression analyses. We exclude stocks priced below \$2, before estimating equally-weighted and value-weighted regressions (with weights computed using market capitalizations at the previous month's end).

Table 2 documents strong persistence in ILMs: past ILM levels strongly predict future levels. That is, stocks with high ILMs in one month tend to have high ILMs in future months. This holds even when we weight observations by market capitalization, indicating that persistence is not attributable to the illiquidity of small stocks. This persistence indicates that our liquidity measures represent a stock characteristic that is sufficiently persistent to impact institutional investors with extended holding horizons and hence justify the existence of a liquidity premium in stock returns.

4 Liquidity and Institutional Holding Horizon

Our next analyses are motivated by the predictions in Amihud and Mendelson (1986) 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.

4.1 Investor-Level Analysis

To calculate the liquidity of an institutional investor's Equity Under Management (EUM), we first calculate the weighted average of each liquidity measure across all stocks held by individual fund managers. We weight observations by the fraction of an investor's total dollar-denominated portfolio value in a stock. Other EUM characteristics, including volatility, market capitalization, and institutional ownership, are computed using a similar methodology in the previous quarter. We follow Gaspar et al. (2005) and Cella et al. (2013) to construct investor-level churn ratios in the previous quarter. The churn ratio captures the frequency at which a fund enters and exits positions, and hence is inversely related to its holding horizon. The churn ratio is calculated at the stock-quarter level, and then weighted by holdings at the manager-quarter level (see Section 2).

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

Figure 3 illustrates that 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 a strong ∩-shaped pattern with respect to holding horizon, contrary to the prediction that investors with longer holding horizons should hold less liquid stocks. In contrast, ILM-based EUM illiquidity displays a more monotonically increasing pattern with the holding horizon despite flattening for the longest holding horizons, consistent with investors who trade more frequently, i.e., who have shorter holding horizons, avoiding holding stocks where taking or leaving positions more likely requires tapping into retail-sourced liquidity.

4.2 Stock-Level Analysis

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

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

Panel A in Table 3 reports that for most liquidity measures, the institutional holding horizon percentile has a coefficient with the expected sign. However, striking differences show up in R^2 magnitudes. The R^2s associated with $ILMT$ and $ILMV$ are 0.61 and 0.63, respectively, indicating that holding horizon explains a large amount of the variation in investor-level portfolio liquidity based on ILMs. In contrast, the R^2s associated with existing liquidity measures are notably smaller—the next highest R^2 is 0.44 and most are far lower, with some only marginally different from zero.

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

The top four rows in Panel B of Table 3 report that, relative to every existing liquidity measure, $ILMT$ and $ILMV$ have incremental liquidity-related implications for institutional investors. In contrast, the bottom four rows in Panel B of Table 3 report that the coefficients for holding horizon have their expected sign *only* for dollar quoted/effective spread, relative effective spread, and quoted depth. Moreover, the R^2s in these specifications indicate that for these four liquidity measures, the variation in the Y_{ILMT} and Y_{ILMV} residuals explained by holding horizon (and stock characteristics) is less than one-twentieth of the variation in the Z_{ILMT} and Z_{ILMV} residuals explained by holding horizon (and stock characteristics). That is, institutional holding horizons better explain ILM residuals than they explain residuals of existing liquidity measures. In sum, ILMs have incremental implications for investors relative to existing liquidity measures, but the converse is not true.

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

5 Liquidity Premia

We next contrast ILMs and existing liquidity measures in their ability to predict the cross-section of expected returns. Unlike existing measures, ILMs robustly predict the cross-section of stock returns and capture economically-significant liquidity premia. Long-short portfolios reinforce these findings.

5.1 Regression Analysis

To examine the abilities of ILMs and the other liquidity measures described in Section 2 to predict future monthly returns, we first estimate the following Fama-MacBeth regression with Newey-West-corrected standard errors using 6 lags

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

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.[18] $\mathrm{CONT}_{j,m-1}$ denotes a vector of control variables containing betas from the three-factor Fama-French model, book-to-market ratio, market capitalization, dividend yield, idiosyncratic volatility, and the previous month's return as well as the return from the prior 11 months. Green, Hand, and Zhang (2017) examine the return predictability of a comprehensive list of 94 stock characteristics and find their predictive power 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 4 reports that unlike liquidity measures based on market microstructure frictions, measures based on institutional trading costs explain the cross-section of expected returns.[19] We find estimated liquidity premia for InPrIm, $ILMT$ and $ILMV$. Of note, most researchers do not have 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)). A key contribution of our paper is that our ILMs capture institutional trading costs and are easily constructed using publicly-available TAQ data.

The coefficients on the institutional price impacts (InPrIM), $ILMT$, and $ILMV$, are 0.029, 1.20 and 1.27, respectively. Multiplying these coefficients by their respective standard deviations (of 0.109, 0.19, and 0.21) yields monthly liquidity premia of 31.6 bps, 22.8bps, and 26.7bps, respectively. Thus, one standard deviation reductions in liquidity as measured by ILMs are associated

[18]Our qualitative findings are robust to the use of liquidity measures from month $m-1$ or skipping more than one month (even up to *twelve*), reflecting the stock-specific temporal persistence in liquidity. Table 10 results show that a positive link between current week's $|Mroib|$ and future weekly return emerges after two weeks, but this relationship largely reflects a positive relation only between *positive* $Mroib$ and returns. Indeed, the relationship between $Mroib$ and returns evolves increasingly toward a $\cup$-shaped relationship by week $w+6$, i.e., more extreme negative *or* positive $Mroib$ tends to predict higher future returns. Thus, a positive association between month m returns and month $m-1$ ILMs is expected since the underlying return and $|Mroib|$ observations are up to nine weeks apart in this setting.

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

with 22.8–26.7bps increases in expected monthly returns, or 2.74–3.20% increases in annual returns. 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 B documents robustness to \$1 and \$5 minimum share price requirements. Consistent with Barardehi et al. (2019) and Barardehi et al. (2021), quoted depth, $ILLIQ\_OC$, BBD, and $WBBD$ only explain the cross-section of stock returns when a \$1 minimum price filter is imposed, indicating that these measures are only priced in very illiquid stocks. Furthermore, consistent with low institutional trading in penny stocks, InPrIM is not priced with a \$1 minimum price filter, but it is priced with a \$5 minimum price filter.[20]

Panel B in Table 4 presents the significant incremental information content of $ILMT$ and $ILMV$ vis à vis (1) each existing liquidity measure and (2) the collection of all existing measures. Each ILM measure is first regressed on an alternative liquidity (price impact) measure using Fama-MacBeth regressions. The residual from such regressions are then used, one at a time, as $LIQ_{j,m-2}$ in equation (1). The $ILMT$ and $ILMV$ residuals, except those orthogonalized to realized institutional price impacts (InPrIm), explain the cross-section of expected returns. Untabulated results verify that the residuals of existing liquidity measures orthogonalized with respect to our measures all fail to explain the cross-section of returns. The last column in Panel B of Table 4 shows that the residuals from regressing ILMs on *all* standard liquidity proxies still explain the cross-section of expected returns, underscoring the significant incremental information content of ILMs.

These results suggest that the literature's conclusion that liquidity premia have disappeared post-decimalization (e.g., Asparouhova et al. (2010); Ben-Rephael et al. (2015)) reflects the use of liquidity measures that no longer capture the institutional features of modern equity markets. In particular, tight spreads (often binding at a penny tick) combined with limited depth at the NBBO in a fragmented marketplace cannot capture the complicated dynamic trade execution strategies institutions adopted in response. In contrast, ILMs are motivated by the actual trading costs of investors and the propensity with which they need to rely on liquidity provided by wholesalers. The ILMs reveal that the average investor accounts for cross-stock heterogeneity in trading costs

[20] Internet Appendix C establishes the robustness of these results to the construction of our liquidity measures 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%.

when pricing stocks.[21] That $ILMT$ and $ILMV$ do not outperform InPrIm in these residual analyses reflect that these measures all capture institutional trading costs. However, only our ILM measures are available in recent years.

Table 5 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 (1) using panel regressions that include date and stock fixed effects and double-cluster standard errors by date and 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 ILMs to institutional investors who tend to hold larger stocks. Fourth, excluding stocks in the bottom 10% of SPVS in each cross-section results in more efficient estimates of liquidity premia. This reflects that ILMs of stocks with low sub-penny volume likely have higher measurement error. Fifth, weighting observations by firm size improves statistical significance of liquidity premia estimates for $ILMT$, but reduces it for $ILMV$. Sixth, excluding the top and bottom 10% of each ILM cross-section increases the precision of liquidity premia estimates and leaves our qualitative findings unaffected. This indicates that estimates are not driven by the tails of the ILM distributions. Indeed, down-weighting (censoring) extreme ILM observations strengthens our results. 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. Internet Appendix C confirms the robustness of the liquidity premia when liquidity measures are constructed over 3-month or 12-month rolling windows.[22] Our focus on a 1-month aggregation horizon for our main analysis reflects the longer time-series per stock and hence greater statistical power for this horizon.

Finally, Panel C in Table 5 shows that ILMs' abilities to explain expected returns do not reflect the inclusion of institutional trades that are picked up by the BJZZ algorithm. Battalio et al. (2023) show the BJZZ algorithm incorrectly flags institutional trades with sub-penny execution

[21]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.

[22]Internet Appendix C reports robustness for our baseline regression results. However, in unreported analysis we verify that results of virtually all the main tests presented throughout the paper are robust to using ILMs constructed over 3-month or 12-month windows.

prices as retail, i.e., the algorithm produces false positives. We investigate the relevance of such errors for our findings by decomposing each trading day's imbalances in the number and volume of 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 two versions of each ILM measure using: (1) non-ANcerno trades and (2) ANcerno-only trades. Panel C in Table 5 shows that, for the 2010-2014 period where ANcerno data is available, ILMs' abilities to explain expected returns *improve* when we exclude sub-penny institutional trades from the construction of measures. Moreover, ILMs solely based on imbalances in sub-penny institutional trades predict future returns with a negative coefficient, inconsistent with BJZZ's false positives driving our liquidity premium results. Our analysis suggests that, if anything, the false positives add noise to ILMs and attenuate our findings.

We conclude our cross-sectional analysis of liquidity premia based on ILMs by observing 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 (1) by either (1) monthly $IOShr$ percentile statistics and their interaction with the ILM measure or (2) monthly $SPVS$ percentile statistics and their interaction with the ILM measure. Thus, we allow the relationship between expected returns and ILMs to take nonlinear forms conditional on $IOShr$ and $SPVS$.

Table 6 shows that ILMs remain significant predictors of expected stock returns with this non-linear specification.[23] The baseline coefficients on "Liquidity" reflect the relation between an ILM 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 ILMs is stronger among stocks with lower institutional ownership and higher

[23]Unreported analysis verifies robustness to controlling for $IOShr$ or $SPVS$, without an interaction term.

shares of sub-penny trading volume. In sum, these results comprise strong evidence that $ILMs$ predict expected stock returns and are associated with economically significant liquidity premia.

5.2 Portfolio Sorts

This section reports that long-short portfolios based on ILM generate abnormal (risk-adjusted) monthly returns. For each monthly cross-section, we form 10 liquidity portfolios using $ILMT$ and separately using $ILMV$. These portfolios are 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 $ILMs$ of NYSE-listed stocks before calculating value-weighted portfolio returns.[24] 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 7 reports significant risk-adjusted return spreads between the least liquid and most liquid portfolios according to both $ILMT$ and $ILMV$. The portfolio risk-adjusted returns display roughly monotonic patterns, increasing from the most liquid portfolio to the least liquid 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 7) and between 0.41% and 1.27% per month across all specifications. Overall, estimates imply that annualized portfolio return spreads based on ILM 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 2 indicates a 20bp difference in expected institutional price impacts between stocks in the top and bottom $ILMs$ deciles for a \$2 price filter. Institutional price impacts estimates (InPrIm) can be re-scaled to reflect costs per \$100k of institutional trade size—

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

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 7, 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.

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

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

6 Price Pressure, *Mroib*'s Return Predictability, and Illiquidity

We have established that ILMs capture institutional trading costs and that, unlike existing friction-based liquidity measures, they have robust asset pricing implications. We had posited that ILMs capture illiquidity and trading costs by identifying stocks where wholesalers more often face difficulty managing their inventory. We now address whether institutional investors or retail investors are the primary source of excess liquidity demand faced by wholesalers when $|Mroib|$ is large, providing evidence on the economic mechanism that drives variation in $Mroib$, and hence the ILMs.

Our analysis highlights the role of internalization choices by wholesalers in driving the variation in $Mroib$. We provide evidence that substantially positive and substantially negative $Mroib$ signify wholesalers endogenously internalizing unequal amounts retail buy and sell orders in an effort to offset inventory pressure due to opposing institutional liquidity demand when liquidity is scarce. This means that wholesalers accumulate some unbalanced inventory that results in the accumulation of price pressure that subsequently reverses. Wholesalers then reroute the remaining ("exhaust") retail orders to other trading venues, e.g., exchanges, for execution—as detailed in Internet Appendix F.1, $Mroib$ does not pick up executions of these rerouted orders that comprise about one in every ten retail trades. We discuss institutional details and provide several empirical findings consistent with key elements of our proposed economic mechanism.

6.1 Order Flow Segmentation and Wholesaler Internalization Choices

Order flow segmentation in the U.S. equity markets prevents direct interactions between retail and institutional orders; however, wholesalers can interact with both sources of order flow. In fact, wholesalers exclusively "handle" all retail orders (see Internet Appendix F.1 for institutional details). Consequently, wholesalers *choose* whether to interact with these orders, i.e., internalize them, or to reroute them to other trading venues, i.e., externalize them. This means that should a wholesaler's inventory grow unbalanced as a result of absorbing directional institutional flow she can endogenously internalize unequal amounts of retail buy and sell orders to offset inventory pressure to the extent possible. Internet Appendix F.2.1 analyzes a stylized framework of wholesaler internalization choices when facing directional institutional liquidity demand.

This mechanism is especially pronounced when liquidity is scarce as suggested by at least three reasons. First, by turning to a wholesaler for immediacy, liquidity-demanding institutional investors signal that they have trouble locating less expensive sources of liquidity such as dark-pool midpoint trading that gives them access to liquidity provided by other institutions that do not need to be compensated. This gives the wholesaler market power (Hu and Murphy (2022); Houang, Jorion, Lee, and Schwarz (2023)). Second, institutions value the ability to conceal their trading intentions in dark pools, whereas interacting with wholesalers on their Single-Dealer Platforms (SDPs) or on exchanges can disclose institutional trading intentions to other market participants and result in price impacts (Zhu (2014)). Third, internalized retail orders are themselves a costly inventory management resource for wholesalers as they often have to pay for order flow (PFOF) or offer price improvements relative to best national quotes (PI) on internalized orders. Panel A in Table 8 shows that three major retail brokers charge between 9¢ to 20¢ in PFOF to allow a wholesaler to handle 100 shares of their customer's marketable orders, and Battalio and Jennings (2022) report that wholesalers pay an average PI of 85¢ to internalize every 100 shares. Thus, all else constant, using 100 shares of internalized retail flow as a source for institutional liquidity costs wholesalers at least \$1. This means that liquidity-demanding institutions must be prepared to pay wholesalers high enough to cover internalization costs, and such high willingness to pay signifies scarce liquidity.

Wholesalers may also use institutional order flow to provide liquidity to retail customers. However, such outcomes require excess supply of institutional liquidity that most likely occurs at the mid-point. In such conditions, Best Execution principles along with wholesaler competition over retail execution quality leads internalized retail orders to fill at the mid-point. The BJZZ algorithm excludes such fills, so they do not affect the variation in $Mroib$ (see Internet Appendix F.1 for details). More important for our analysis, these trades are most likely when liquidity is abundant, and hence their exclusion means that ILMs better identify low liquidity.

6.2 *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. We examine the dynamics of prices and institutional trade imbalances in event time. We define $Mroib$ events at the *individual stock* level. An event occurs when the absolute value of the backward-looking 5-day moving average of $Mroib$ exceeds the stock's average daily $|Mroib|$ in the previous calendar quarter. We use $|Mroib|$ as the benchmark reflecting that average $Mroib$ is very close to zero (see Panel B in Table 8). The 5-day moving average provides consistency with BJZZ's empirical design, allowing us to relate our findings to theirs. A positive (negative) $Mroib$ event reflects above-average net internalized retail buying (selling) in the past 5 days.[25]

[25] 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 the 5-day moving average of the number of BJZZ-identified trades associated with an $Mroib$ event exceed the first quartile of daily number of BJZZ-identified trades from the previous quarter. This ensures that highly unbalanced $Mroib$ observations driven by very few sub-penny trades do not drive our findings. Unreported analyses verify the robustness of our findings to removing this requirement.

This empirical design is conservative in that it yields a large sample of events that cannot be dominated by "special" outliers (e.g., with substantial information arrival or extreme liquidity events). Event windows span the five trading days leading up to each $Mroib$ event, labeled -4 through 0, and five days after the event, labeled 1 through 5. Of the 2,739,560 stock-day observations (for stocks with data for the preceding quarter) in our April 2010 through December 2014 sample, we identify 97,554 $Mroib$ events that split to 33,531 positive events and 64,023 negative events. The 10-day event windows encompass 940,937 stock-day observations or 34.3% of the sample.

Figure 4 summarizes our findings. Panel A shows abnormally unbalanced $Mroib$ observations leading up to "events" that are followed by more balanced $Mroib$ post event, indicating that our empirical design effectively detects stock-specific $Mroib$ spikes. Panel B illustrates the dynamics of institutional trade: pre-event cumulative abnormal institutional trade imbalances appear on the opposite side of $Mroib$, while post-event, institutional flows do not display economically-meaningful imbalances. These findings support the notion that pre-event, pressing institutional liquidity demands induce wholesalers to internalize disproportionately more retail orders on the opposite side.

Panel C plots the corresponding pre- and post-event 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 documented by BJZZ. However, we note that pre-event abnormal returns oppose the corresponding $Mroib$ signs. That is, prices move in the *opposite* direction of internalized retail flow (Panel A) but in the *same* direction as institutional order flow (Panel B), suggesting price pressure from pressing institutional liquidity demand.

Decomposing returns into intraday and overnight components reinforces this interpretation and reveals why price reversals appear to begin as of day -2. Panel D in Figure 4 shows that the pre-event price pressure associated with institutional flow is *only* realized during regular trading hours when institutional investors are active—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 the 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. Even on a daily basis, both pre- and post-event, (1) intraday prices co-move with institutional flow, while (2) overnight prices reverse in the absence of institutional liquidity demand. We next provide evidence consistent with overnight reversals reflecting compensation for overnight inventory risk exposures of wholesalers.

Wholesaler inventory imbalances appear to increase pre-event. Of note, the strong pre-event price pressure (Panel D in Figure 4) is associated with persistent institutional liquidity demand (Panel B in Figure 4). Panel C in Figure 5 documents that the volume of internalized buy trades rises sharply prior to events associated with institutional selling pressure, i.e., positive $Mroib$ events, with a corresponding modest decline in the volume of internalized sell trades. Panel D in Figure 5 documents the opposite patterns prior to events with institutional buying pressure. 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. In fact, Hendershott, Menkveld, Praz, and Seasholes (2022) observe that market makers (here, wholesalers) build up inventory as they provide liquidity to institutional investors.

As a result, wholesalers must carry more unwanted inventory overnight, exposing their holdings to increased risk for which they require compensation in the form of better prices near close. This inventory risk declines once trading resumes at the open of the next trading session, leading to a revision of prices that is manifested in an overnight price reversion.[26] That overnight reversals more than offset the preceding intraday returns in the two days prior to an event is consistent with wholesaler inventories growing increasingly out-of-balance due to persistent institutional liquidity demand, resulting in greater overnight inventory risk exposure, and hence greater reversals.

Comparisons of the price improvements offered by wholesalers to internalized buy and sell trades around $Mroib$ events reinforce the salience of this economic mechanism. For each BJZZ-identified transaction, we calculate the sizes of effective price improvement (PI) for buy and sell orders as the distance between the execution price and the associated NBO and NBB in effect at the time of the transactions, divided by the midpoint of NBBO. We then construct volume-weighted averages of PIs for buy and sell trades per stock-day before analyzing their evolution around $Mroib$ events.

Our findings reveal wholesalers' higher willingness to pay PI on the side from which they internalize disproportionately more retail orders. Panel A in Figure 5 shows that internalized buy trades receive significantly 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

[26]Our discussion of overnight reversals reflects insightful comments from Albert Menkveld and Terry Hendershott.

higher PI than buy trades relative to post-event.[27] Higher PI in the direction of $Mroib$ imbalances is consistent with (1) increased wholesaler profits associated with providing liquidity to institutional investors with pressing liquidity needs relative to less expensive liquidity, i.e., at the midpoint, which is otherwise available to institutional investors; and (2) increased wholesaler inventory risk that justifies the internalization of more expensive retail orders that help balance inventory.

These asymmetries in PI offered to retail trades underlying $Mroib$ imbalances are at odds with two alternative explanations. First, they are inconsistent with these 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 of this increased liquidity demand.

Overall, our findings are consistent with the literature on short-term institutional price pressure (Campbell et al. (1993), Hendershott and Menkveld (2014)). These 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.

6.3 *Mroib*, Institutional Trading, and Liquidity

We next analyze the cross-sectional implications of the link between large positive or negative $Mroib$ and stock liquidity. We posit that institutional investors need to turn to wholesalers for liquidity more often in less liquid stocks, so that wholesalers are more likely to use internalized retail trades to offset this institutional liquidity demand. As a result, substantially positive or negative $Mroib$s are more likely in these stocks—leading to larger ILMs.

Table 9 shows that large positive or negative values of $Mroibvol$ are associated with less liquidity, consistent with wholesalers turning to internalized retail flow for inventory management as they provide liquidity to institutions when less expensive liquidity is scarce. To document this, we first construct a stock-specific measure of abnormal realized off-exchange institutional liquidity. For each stock-day, we divide the volume of large off-exchange mid-point executions[28] by the aver-

[27] The relatively higher PI received by sell trades after *both* positive and negative $Mroib$ events may reflect that sell retail orders are more scarce from a wholesaler's perspective consistent with retail investors being net buyers.

[28] TAQ data transactions with trade venue flag 'D' that are at least 1,000 shares, worth at least \$50k, and executed

age of this quantity over the sample period for that stock. Higher values of this measure indicate greater midpoint liquidity. Table 9 shows abnormally low levels of block trades receive off-exchange midpoint execution when $Mroibvol$ is more unbalanced, suggesting a link between $Mroib$ and institutional investors' ability to find counter-parties with whom to trade at the midpoint. Liquidity is also scarce on exchanges when $Mroibvol$ is more unbalanced. Table 9 shows that spreads are widest and depth at the NBBO is lowest for the extreme deciles of $Mroibvol$: average dollar and relative quoted spreads in the lowest and highest $Mroibvol$ deciles are roughly *double* those when $Mroibvol$ is more balanced. The relevance of this scarce liquidity for institutions manifests itself in implicit institutional trading costs: median institutional price impact per \$1m transaction for the average stock are 28 and 14bps for the lowest and highest $Mroibvol$ deciles, respectively, while balanced $Mroibvol$ is associated with only 3bps of such costs.

Consistent with higher institutional liquidity demand in less liquid markets, more unbalanced $Mroib$ is associated with larger *opposing* trade imbalances from both long-only institutional investors and short sellers. Table 9 shows that average raw (market-adjusted) institutional flow falls from 34.5% (0.08%) in the bottom decile to 22.1% (-0.04%) in the top decile. Short selling activity also occurs on the opposite side of $Mroib$ imalances: 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)), suggesting that the opposing internalized retail trade is not.

Table 9 summarizes the relationships between $Mroibvol$ and returns that link our cross-sectional analysis to our findings in Section 6.2. Close-to-close returns rise monotonically from -15bps in the bottom $Mroibvol$ decile to 11.4bps in the top decile. Importantly, this pattern is *not* due to price pressure from retail order flow. Decomposing daily returns into intraday and overnight components reveals that intraday returns, that correspond to the trading activity underlying $Mroib$, *fall* from 18.7bps in the bottom $Mroibvol$ decile to -4.5bps in the top decile. In sharp contrast to intraday returns, overnight returns are *positively* related to $Mroibvol$. The signs of intraday and overnight returns differ for all the ten $Mroibvol$ deciles, exhibiting generally greater differences at more unbalanced $Mroibvol$ deciles. As such, our cross-sectional analysis indicates that institutional

at a price within 0.1¢ of the corresponding quote midpoint.

liquidity demand in less liquid markets drives intraday price pressure and encourages wholesalers to internalize more retail trades on the opposite side. This price pressure then unwinds overnight due to a lack of institutional activity together with the conciliation of marker-maker-inventory risk.

Our collective findings corroborate the stock-level evidence provided in Section 6.2 that $Mroib$'s predictive power for near-term future returns is driven by price reversals that follow institutional price pressure. Importantly, these findings also link the level of $|Mroib|$ to stock illiquidity. We next reinforce this link by analyzing $|Mroib|$'s return predictability for future returns.

6.4 Long-term Return Predictability of *Mroib*

We now analyze $Mroibvol$'s long-term return predictability, linking this predictability to liquidity premia. Panel B in Table 8 provides summary statistics that closely match those in Table I of BJZZ, confirming that our constructions of $Mroibtrd$ and $Mroibvol$ parallel theirs.[29] We employ portfolio sorts to study $Mroib$'s return predictability that do not impose a specific functional form, examining both raw and market-adjusted future returns associated with weekly portfolios of past $Mroibvol$. We sort cross-sections based on $Mroibvol$ 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 10 shows that, consistent with BJZZ, future returns in weeks w through $w+2$ rise in $Mroibvol$ from week $w-1$. Our analysis in sections 6.2 and 6.3 suggests that these patterns are due to price reversals that follow institutional price pressure in week $w-1$. Past negative $Mroibvol$ is a symptom of positive institutional flow faced by wholesalers with positive price pressure; as this price pressure reverses in the future weeks it tilts future returns downward. Conversely, past positive $Mroibvol$ 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), Akepanidtaworn, Di Mascio, Imas, and Schmidt (2023)). Table 10 shows that the positive link between $Mroib$ and future returns begins to weaken in week $w+1$, and it becomes $\cup$-shaped by week $w+6$. This $\cup$-shaped pattern persists into the distant future past week $w+36$.[30]

[29] 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 if we also use a \$1 price filter.

[30] Our findings are robust to using the exact specification used by BJZZ that include controls.

The strong association between $|Mroib|$ and illiquidity established earlier makes it clear that the ∪-shaped pattern in longer future returns is another manifestation of liquidity premia. Liquidity premia associated with expected trading costs as a stock characteristic imply *long-term* return differences according to the level of liquidity. The strong association between liquidity measures, institutional trading costs, and retail order flow internalization reinforces that stocks with more extreme $Mroibvol_{w-1}$ are less liquid. Such stocks should command higher *permanent* expected returns (higher cross-sectional returns) to compensate institutional investors for holding less liquid assets (where entering and exiting positions is costlier), as Amihud and Mendelson (1986) first argued.

7 Conclusion

We use observable imbalances in wholesaler-retail trades to develop stock-specific illiquidity measures for segmented U.S. equity markets. Our ILM measures exploit the abilities of wholesalers to interact with both retail and institutional segments of equity markets. Our evidence suggests wholesalers internalize unequal amounts of retail buy and sell orders to manage inventory when filling directional institutional liquidity demand, especially when liquidity is scarce. We show one can use the average absolute imbalance in observable wholesaler trades as a stock-specific liquidity measure.

We establish that ILMs have economically-meaningful stock- and investor-level relations with institutional holding horizons and are correlated with expected institutional price impacts. Unlike existing liquidity measures, ILMs robustly yield annualized liquidity premia of 2.7–3.2% post-2010. These findings are important for many reasons: (1) consistent with nontrivial institutional trading costs, they show that stock returns still reflect liquidity premia, indicating that recent failures of researchers to find significant liquidity premia reflected that friction-based measures no longer capture relative trading costs; (2) they uncover a new channel for the return predictability of retail order flow; and (3) they provide researchers with easy-to-construct stock liquidity measures that capture institutional investors' liquidity concerns without requiring proprietary institutional trade data.

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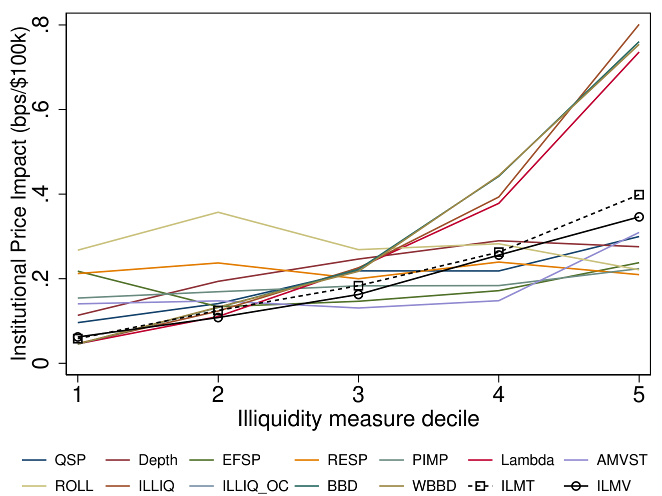
Figures and Tables

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

Panel A: Illiquidity deciles 1–5



Panel B: Illiquidity deciles 6–10

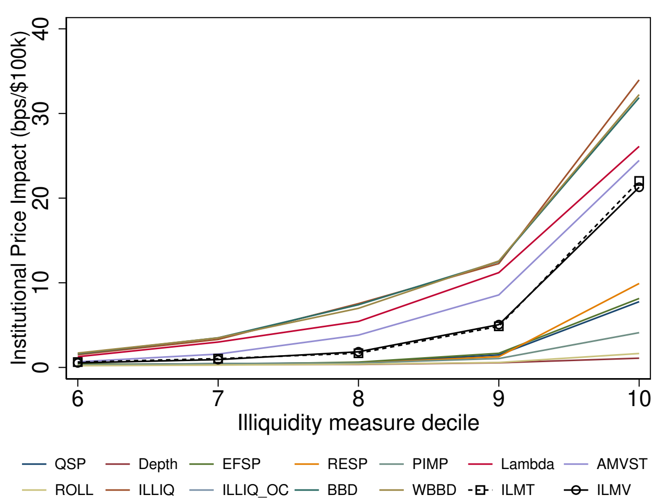


Figure 3. **EUM Liquidity and Holding Horizon.** This figure provides local polynomial estimates of equity under management (EUM) liquidity as a function of holding horizon. Holding weighted EUM liquidity, volatility, market capitalization, and institutional ownership are calculated for each manager. Every quarter, the residuals from regressing EUM liquidity on volatility, market capitalization, and institutional ownership are sorted into percentile statistics. Every quarter, manager-level holding horizons are calculated following Vovchak (2014) and sorted into percentile statistics. The figures present local polynomial estimates of residual EUM liquidity percentile statistics as functions of holding horizon percentile statistics. The sample includes all NMS common shares from January 2010 to December 2019. The sample for institutional price impacts (InPrIm) spans January 2010 through December 2019.

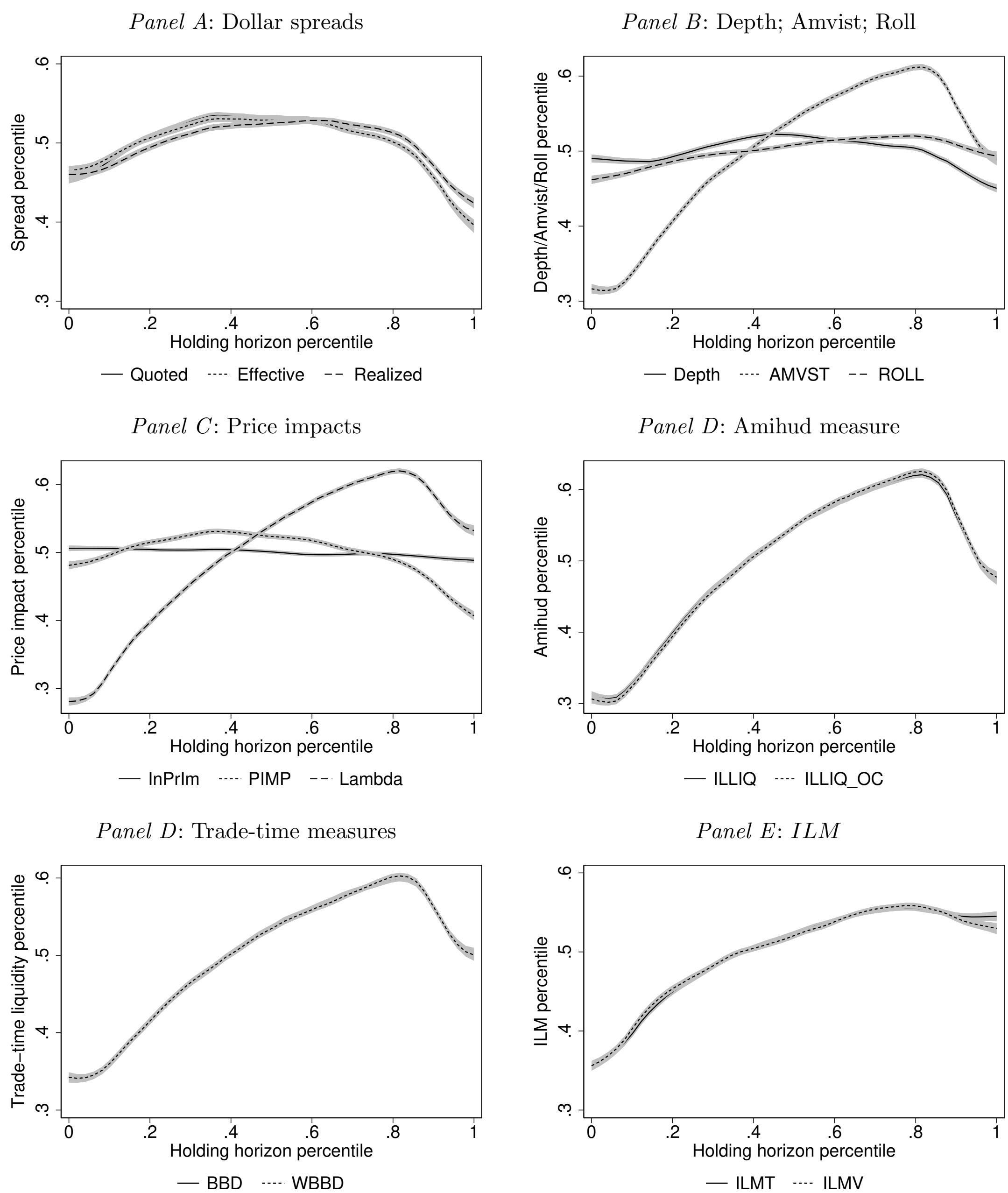
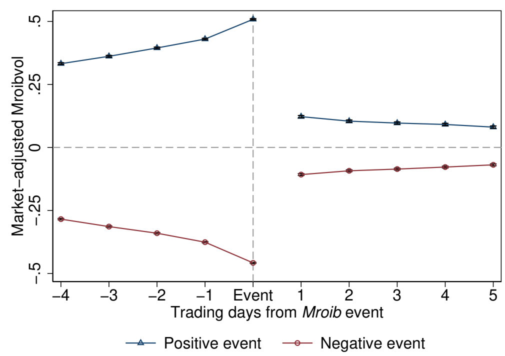
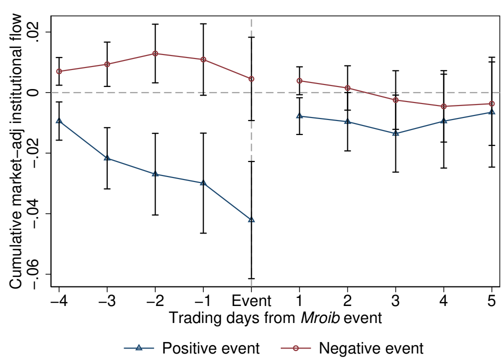


Figure 4. ***Mroib*, Institutional Price Pressure, and Subsequent Price Reversals.** This figure plots average daily $Mroib$s, cumulative returns, and cumulative institutional order imbalances around $Mroib$ events. An event window starts at the open of day -4 and ends at the close of day 5. To construct market-adjusted outcomes, daily observations of each outcome 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 reflecs 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.

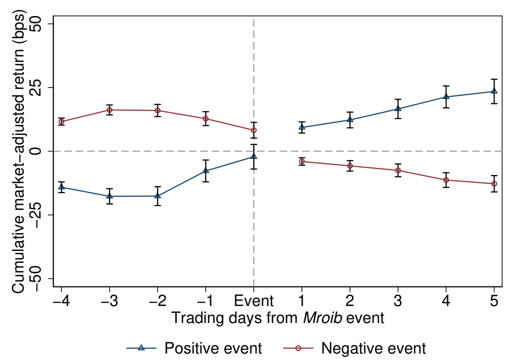
Panel A: Internalized retail flow imbalance ($Mroib$)



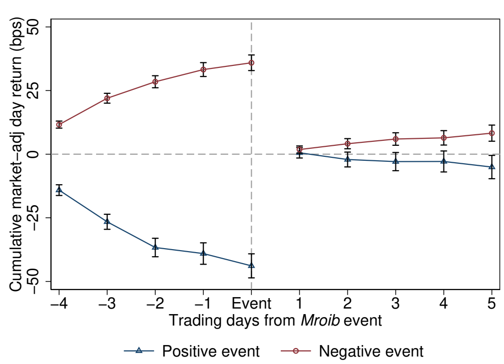
Panel B: Cumulative institutional trade imbalance



Panel C: Cumulative 24-hour returns



Panel D: Cumulative intraday returns



Panel E: Cumulative overnight returns

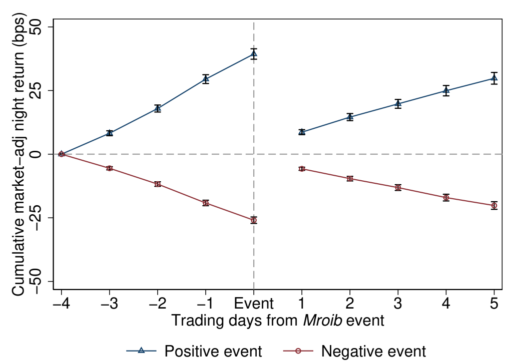
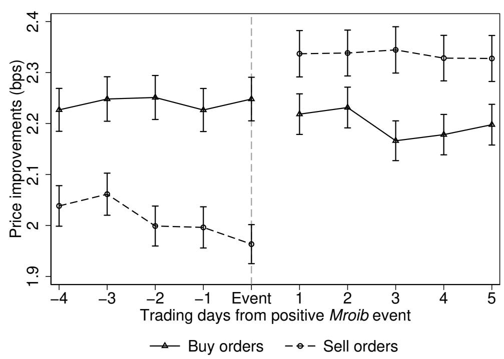
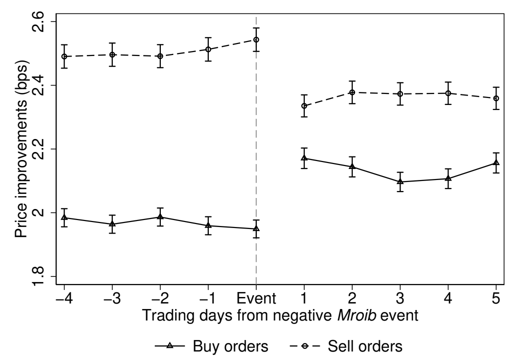


Figure 5. ***Mroib* Imbalance, the Size of Sub-penny Price Improvements, and the Volume of Internalized Retail Trades.** This figure plots average daily volume-weighted mean PI as well as the trading volume for BJZZ-identified buy and sell trades around $Mroib$ events. An event window starts at the open 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.

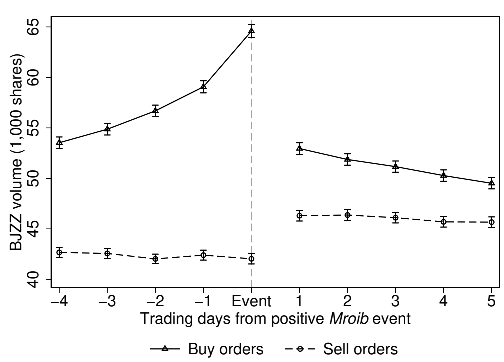
Panel A: PI around Positive $Mroib$ events



Panel B: PI around Negative $Mroib$ events



Panel C: Volume around Positive $Mroib$ events



Panel D: Volume around Negative $Mroib$ events

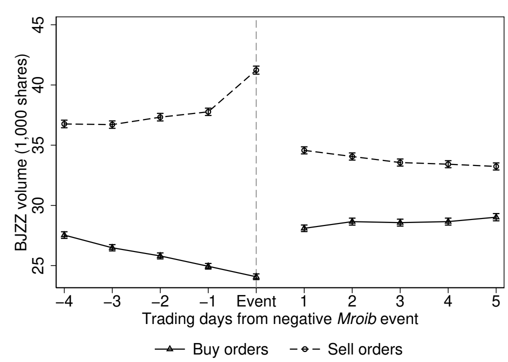


Table 1. Institutional Liquidity Measures and Stock Characteristics. The table reports on the cross-sectional relation between ILMs and (1) three-factor Fama-French betas, (2) book-to-market ratios (BM), (3) natural log of market capitalizations (ln(Mcap)), (4) dividend yields (DYD), (5) idiosyncratic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

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

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

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

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

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

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

Table 3. Stock Liquidity and Institutional Holding Horizon. This table reports on the relation between the holding horizons of institutional investors and stock liquidity using different liquidity measures. Institutional investor turnover measures are constructed by stock and quarter as the weighted averages of turnover across the institutional investors holding a stock. For each stock, the weight assigned to an investor's turnover is the fraction held by the investor relative to the total amount held by institutional investors. Each quarter, investor-level holding horizon percentile statistics, "HH pctile", are defined as 1 minus institutional turnover percentile statistics across all the stocks held by an investor. In Panel A, for each stock j in quarter q, liquidity measure $LIQ_{j,q}$ is regressed on the holding horizon percentile statistic, return volatility, natural log of market capitalization, and institutional ownership from quarter $q-1$. Panel B reports on the relation between institutional turnover and liquidity, after orthogonalizing $ILMT$ and $ILMV$ with respect to existing liquidity measures and vice versa. Z_{ILMT} and Z_{ILMV}, respectively, are the residuals from regressing quarterly cross-sections of $ILMT$ and $ILMV$ on existing liquidity measures. Y_{ILMT} and Y_{ILMV}, respectively, are the residuals from regressing quarterly cross-sections of individual existing liquidity measures on $ILMT$ and $ILMV$. Z_{ILMT}, Z_{ILMV}, Y_{ILMT}, and Y_{ILMV} from quarter q are then regressed on institutional turnover, return volatility, natural log of market capitalization, and institutional ownership from quarter $q-1$. Institutional turnover coefficients are reported. Estimates are from Fama-MacBeth regressions that have Newey-West corrected standard errors with 6 lags. The sample includes NMS common shares from January 2010 to December 2019, excluding stocks whose previous month-end's closing price is below $2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stock liquidity and institutional turnover

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

[†] 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 BBD and WBBD from 2010–2017.

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

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

Table 4. The Cross-Section of Expected Stock Returns and ILM. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (1) is estimated using liquidity measures ($LIQ_{j,m-2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m-1}$, $\beta^{hml}_{j,m-1}$, $\beta^{smb}_{j,m-1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m-1$, book-to-market ratio, ($\text{BM}_{j,m-1}$), natural log of market capitalization, ($\ln(\text{Mcap}_{j,m-1})$), dividend yield ($\text{DYD}_{j,m-1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m-1$, idiosyncratic volatility ($\text{IdVol}_{j,m-1}$), previous month's return ($RET_{(-1)}$), and preceding return from the prior 11 months ($RET_{(-12,-2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. The last column in Panel B use the residuals of $ILMT$ and $ILMV$ 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 \$2. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

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

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

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

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	All measures
ILMT residual	0.10	1.22***	1.19***	1.15***	1.18***	1.20***	1.30***	1.20***	1.38***	1.27***	1.13**	1.14**	1.12**	1.35**
	[0.19]	[3.51]	[2.92]	[3.27]	[2.85]	[2.90]	[2.85]	[2.77]	[3.35]	[2.90]	[2.48]	[2.18]	[2.17]	[2.59]
ILMV residual	0.055	1.31***	1.24***	1.25***	1.25***	1.28***	1.34***	1.25***	1.40***	1.31***	1.19***	1.17**	1.15**	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 5. The Cross-Section of Expected Stock Returns and ILM: Robustness Tests. This table reports on the robustness of the relation between between our institutional liquidity measures and the cross-section of expected stock returns. Equation (1) 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 ILM. Stocks whose previous month-end's closing price is below $p_{min} \in \{\$1, \$2, \$5\}$ are excluded. Panel B reports on the robustness of the estimates in equation (1) 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. Panel C reports on the robustness of the estimates in equation (1) to exclusion of institutional with sub-penny execution prices, identified from ANcerno in the 2010-2014 period, from $Mroib$ before constructing $ILMT$ and $ILMV$. 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. The numbers in brackets are t-statistics with ***, **, and * identifying statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Robustness to estimation method and sample selection

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

Panel B: Robustness to estimation by listing exchange

	$ILMT$		$ILMV$	
	NYSE/AMEX	NASDAQ	NYSE/AMEX	NASDAQ
Asparouhova et al. (2010)	0.83	1.11**	1.17**	1.25**
+ Price > $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]

Panel C: Robustness to excluding sub-penny institutional trades (2010-2014)

Liquidity measure	Underlying sub-penny trades		
	All sub-penny trades	Ancerno excluded	Ancerno only
$ILMT$	0.66	0.75	−0.46
	[1.42]	[1.58]	[−1.40]
$ILMV$	0.84*	0.89**	−0.24
	[1.83]	[2.59]	[−0.77]

Table 6. The Cross-Section of Expected Stock Returns and ILM: Robustness to Interactions with Institutional and Retail Participation. This table reports on the robustness of the relation between between our institutional liquidity measures and the cross-section of expected stock returns. Equation (1) 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 ILM 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

	ILMT			*ILMV*		
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×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 ($IOShr$ percentile = 0.5)	**1.35***	**1.41****	**0.82***	**1.41****	**1.38****	**1.04****
	[1.97]	**[2.27]**	**[1.70]**	**[2.17]**	**[2.33]**	**[2.14]**

Panel B: robustness to controlling for share of BJZZ volume

	ILMT			*ILMV*		
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×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 ($SPVS$ percentile = 0.5)	**1.17****	**1.37*****	**1.01****	**1.24****	**1.29*****	**1.12****
	[2.44]	**[2.90]**	**[2.04]**	**[2.61]**	**[2.83]**	**[2.31]**

Table 7. 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 ILM portfolios (deciles). Monthly portfolio returns are averages of monthly stock returns in the portfolio. The time-series feature 118 months. The time-series returns of each portfolio (after subtracting the 1-month Treasury-bill rate) including the long-short portfolio are then regressed on Fama-French three (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
$ILMT$	−0.32***	−0.34***	−0.19**	−0.17	−0.23***	−0.24*	−0.032	0.089	0.38**	0.64***	0.96***
	[−2.77]	[−3.82]	[−2.13]	[−1.58]	[−2.80]	[−1.83]	[−0.30]	[0.63]	[2.48]	[4.25]	[4.30]
$ILMV$	−0.63***	−0.44***	−0.25***	−0.25***	−0.11	0.00096	−0.027	0.32***	0.32**	0.64***	1.27***
	[−4.28]	[−4.40]	[−2.88]	[−3.56]	[−1.07]	[0.01]	[−0.28]	[2.85]	[2.10]	[4.76]	[5.49]

Panel B: CRSP breakpoints, $2 minimum share price

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

Panel C: CRSP breakpoints, $5 minimum share price

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

Continued on next page

Table 7 – *continued from previous page*

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

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

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

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

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

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

Continued on next page

Table 7 – *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
$ILMT$	−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]
$ILMV$	−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
$ILMT$	−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]
$ILMV$	−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
$ILMT$	−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]
$ILMV$	−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]

Table 8. 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	–

	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 9. Portfolios of *Mroibvol*: Contemporaneous Liquidity, Institutional Trading, Short Interest, and Return. The table presents the cross-sectional relationship between weekly $Mroibvol$ and the contemporaneous return, institutional trade, and liquidity outcomes. Outcome variables include (1) liquidity (abnormal off-exchange midpoint executions of larger trades, dollar and relative quoted spreads, and quoted depth, in shares, at then national best prices); (2) institutional trading (actual trade imbalance $Inoibvol$, market-adjusted trade imbalance, institutional price impact (in bps/$1m), and % changes in short interest imbalance); and (3) returns (close-to-close, intraday, and overnight returns). Each weekly cross-section is sorted into deciles of $Mroibvol$. The average of an outcome variable Y is calculated by $Mroibvol$ decile in each cross-section before the averages of mean-Y time-series are calculated. For short interest, bi-weekly relative % changes in short interest are constructed and $Mroibvol$ is aggregated over two-week periods, before forming $Mroibvol$ portfolios. Median short interest changes by $Mroibvol$ are calculated before averaging the time-series of medians.

	Deciles of internalized retail order flow imbalance ($Mroibvol$)									
	1	2	3	4	5	6	7	8	9	10
Mroibvol	−2.036	−1.126	−0.740	−0.463	−0.236	−0.032	0.173	0.415	0.758	1.597
Liquidity										
Large midpoint executions	0.81	0.90	0.95	0.98	1.00	1.04	1.07	1.06	1.03	0.99
Dollar quoted spread (¢)	9.3	7.0	6.0	5.5	5.5	5.8	5.6	5.6	6.5	9.6
Relative quoted spread (bps)	61.0	40.6	33.2	29.2	27.3	28.3	27.5	30.1	37.6	62.0
Ask-side depth	820	1058	1202	1370	1538	1658	1696	1554	1327	776
Bid-side depth	797	1033	1194	1369	1547	1683	1750	1619	1390	811
Institutional Trading										
Actual trade imbalance	0.345	0.304	0.286	0.268	0.255	0.248	0.232	0.231	0.237	0.221
Market-adj trade imbalance	0.082	0.042	0.023	0.005	−0.008	−0.014	−0.031	−0.032	−0.026	−0.042
Price impact	27.96	10.28	4.09	2.96	3.47	2.45	3.50	7.02	6.03	13.96
Short-seller Trading										
Change in Short Interest (%)	−1.34	−0.92	−0.60	−0.36	−0.23	−0.06	0.21	0.26	0.65	0.99
Returns (%)										
Close-to-close return	−0.150	−0.056	−0.031	−0.016	0.008	0.020	0.027	0.051	0.033	0.114
Intraday return	0.187	0.153	0.112	0.077	0.013	−0.054	−0.120	−0.154	−0.169	−0.045
Overnight return	−0.337	−0.209	−0.142	−0.093	−0.005	0.074	0.146	0.205	0.201	0.159

Table 10. Portfolios of *Mroibvol* and Future Weekly Returns. The table presents the cross-sectional relationships between $Mroibvol$ and future weekly (%) returns. Each cross-section is sorted into portfolios (deciles) of $Mroibvol_{w-1}$ to calculate portfolio-specific averages of future close-to-close 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 $Mroibvol$ decile.

		Deciles of $Mroibvol_{w-1}$									
		1	2	3	4	5	6	7	8	9	10
w	raw	0.06	0.12	0.12	0.13	0.14	0.13	0.13	0.15	0.24	0.37
	market-adjusted	−0.10	−0.04	−0.04	−0.03	−0.02	−0.03	−0.03	−0.01	0.08	0.21
$w+1$	raw	0.13	0.14	0.14	0.13	0.13	0.12	0.15	0.14	0.19	0.30
	market-adjusted	−0.03	−0.02	−0.02	−0.02	−0.03	−0.04	−0.01	−0.01	0.03	0.15
$w+2$	raw	0.14	0.16	0.15	0.15	0.15	0.14	0.14	0.15	0.18	0.30
	market-adjusted	−0.03	−0.01	−0.01	−0.02	−0.02	−0.02	−0.03	−0.01	0.01	0.13
$w+3$	raw	0.15	0.17	0.16	0.16	0.15	0.14	0.14	0.16	0.19	0.26
	market-adjusted	−0.02	0.00	0.00	−0.01	−0.02	−0.03	−0.02	−0.01	0.02	0.09
$w+6$	raw	0.16	0.14	0.16	0.16	0.13	0.13	0.14	0.14	0.17	0.24
	market-adjusted	0.01	−0.02	0.01	0.00	−0.03	−0.03	−0.02	−0.02	0.02	0.08
$w+9$	raw	0.14	0.15	0.15	0.13	0.12	0.12	0.11	0.10	0.15	0.17
	market-adjusted	0.01	0.01	0.02	0.00	−0.01	−0.02	−0.02	−0.03	0.01	0.03
$w+12$	raw	0.15	0.14	0.12	0.11	0.09	0.09	0.08	0.09	0.12	0.18
	market-adjusted	0.03	0.02	0.00	−0.01	−0.03	−0.03	−0.03	−0.02	0.00	0.06
$w+24$	raw	0.23	0.19	0.21	0.17	0.17	0.15	0.16	0.17	0.17	0.22
	market-adjusted	0.05	0.01	0.02	−0.02	−0.02	−0.03	−0.03	−0.01	−0.01	0.04
$w+36$	raw	0.17	0.16	0.12	0.09	0.07	0.07	0.06	0.07	0.09	0.12
	market-adjusted	0.07	0.05	0.02	−0.01	−0.03	−0.04	−0.04	−0.04	−0.01	0.02

Internet Appendix

A Variable Definitions

This section provides variables definitions.

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 soruces, 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 8
$Mrsvol$	Daily	Daily sahre volume of off-exchange trades with sub-penny price increments in $(0¢, 0.4¢)$	TAQ	Table 8, Figure 5
$Mrbtrd$	Daily	Daily number of off-exchange trades with sub-penny price increments in $(0.6¢, 1¢)$	TAQ	Table 8
$Mrbvol$	Daily	Daily sahre volume of off-exchange trades with sub-penny price increments in $(0.6¢, 1¢)$	TAQ	Table 8, Figure 5
$Mroibtrd$	Daily, Weekly	Daily: $Mroibtrd = (Mrbtrd - Mrstrd)/(Mrbtrd + Mrstrd)$; Weekly: Backward-looking rolling 5-day sum of $Mroibtrd$	TAQ	Table 8
$Mroibvol$	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 8, Table 9, Table 10
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 5
$Inoibvol$	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 5, Figure 4, Table 9

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Table A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
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 5, Figure 4, Table 9
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 2, Figure 3, Table 3, Table 4, Table 9
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 2, Figure 3, Table 3, Table 4, Table 9
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 2, Figure 3, Table 3, Table 4, Table 9
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 9
Changes in short interest	Bi-Weekly	Bi-weekly percentage change in the short interest, scaled by the number of shares outstanding.	FINRA, CRSP	Table 9
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 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 4, Table 9
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 midpoints) and opening prices from CRSP, respectively. Intraday returns are compunded over bachward-looking rolling 5-day windows.	CRSP	Figure 4, Table 9

Continued on next page

Table A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
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 4, Table 9
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 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4
Dollar price impacts (PIMP)	Monthly	For each stock, daily size-weighted dollar price impacts, define 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 2, Figure 3, Table 3, Table 4
Kyle's Lambda (Lambda)	Monthly	For each stock, individual trades are classified into buyer- vs. seller-initiated using the Lee-Ready algorithm to constructed 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 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4

Continued on next page

Table A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
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 are averaged across intervals. Rolling 3-month BBD and WBBD estimates, updated every month, are also constructed.	CRSP, TAQ	Figure 2, Figure 3, Table 3, Table 4
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 2, Figure 3, Table 3, Table 4
$ILMT$	Weekly, Monthly	Daily $\|Mroibtrd\|$ observations are averaged weekly and monthly. Rolling 3-month $ILMT$ estimates, updated every month, are also constructed.	TAQ	Figure 2, Figure 3, Table 1, Table 2, Table 3, Table 4, Table 5, Table 6, Table 7
$ILMV$	Weekly, Monthly	Daily $\|Mroibvol\|$ observations are averaged weekly and monthly. Rolling 3-month $ILMV$ estimates, updated every month, are also constructed.	TAQ	Figure 2, Figure 3, Table 1, Table 2, Table 3, Table 4, Table 5, Table 6, Table 7
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 6
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 6
Monthly excess return (RET_m)	Monthly	Holding period monthly return minus the corresponding 1-month T-Bill rate.	CRSP	able 3, Table 4, Table 5, Table 6, Table 7
Last month's return (RET_{m-1})	Monthly	Holding period return from the previous month	CRSP	Table 1, Table 4, Table 5, Table 6, Table 7
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 1, Table 4, Table 5, Table 6, Table 7
Market-capitalization (M_{m-12})	Monthly	The product of closing price and the number of shares outstanding 12 months earlier.	CRSP	Table 1, Table 3, Table 4, Table 5, Table 6, Table 7
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 1, Table 4, Table 5, Table 6, Table 7

Continued on next page

Table A.1 – *continued from previous page*

Notation	Frequency	Description	Source	Figure/Table
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 1, Table 4, Table 5, Table 6, Table 7
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 1, Table 4, Table 5, Table 6, Table 7
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 1, Table 4, Table 5, Table 6, Table 7
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 3
Stock churn ratio	Quarterly	For a stock j held by $I \in \{1, \ldots, I_j\}$ managers in quarter q, the weighted average $CR_q^j = \sum_{i=1}^{I+j} w_q^{ij} CR_q^{ij}$ is the stock-level churn ratio. 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 3

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

This section presents estimation results for equation (1) when low-priced stocks are excluded from the sample based on alternative cutoffs for prior month's share prices. Tables B.1 and B.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 B.1, in a more inclusive sample with a less strict (under $1) definition of penny stocks, ILMs continue to explain the cross-section of expected returns. However, reflecting the relevance of alternative liquidity measures for smaller firms, the open-to-close version of Amihud's liquidity measure, ILLIQ_OC, also explains expected stock returns in the 2010-2019 period, consistent with Barardehi et al. (2021). In addition, the trade-time liquidity measures, BBD and $WBBD$, explain expected stock returns in the 2010–2017 period, consistent with Barardehi et al. (2019). However, realized institutional price impacts (InPrIM) no longer explain expected returns, likely due to including stocks that institutional investors are reluctant or unable to hold.

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

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

Table B.1. Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILMs. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (1) is estimated using liquidity measures ($LIQ_{j,m-2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m-1}$, $\beta^{hml}_{j,m-1}$, $\beta^{smb}_{j,m-1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m-1$, book-to-market ratio, ($\mathrm{BM}_{j,m-1}$), natural log of market capitalization, ($\ln(\mathrm{Mcap}_{j,m-1})$), dividend yield ($\mathrm{DYD}_{j,m-1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m-1$, idiosyncratic volatility ($\mathrm{IdVol}_{j,m-1}$), previous month's return ($RET_{(-1)}$), and preceding return from the prior 11 months ($RET_{(-12,-2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. The last column in Panel B use the residuals of $ILMT$ and $ILMV$ 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	ILMT	ILMV
Constant	2.03	0.93	0.92	0.90	0.93	0.93	0.80	0.91	1.33	0.88	0.56	1.42	1.26	−0.87	−1.65
	[1.42]	[0.89]	[0.92]	[0.86]	[0.93]	[0.93]	[0.83]	[0.92]	[1.36]	[0.88]	[0.55]	[1.41]	[1.23]	[−0.58]	[−1.03]
Liquidity	**0.024**	**−0.023**	**−0.0000065**	**0.081**	**0.025**	**−0.068**	**0.034**	**0.10**	**−7.04*** **	**0.018**	**0.13****	**0.18***	**0.39****	**1.16****	**1.36*****
	[1.31]	**[−0.16]**	**[−1.51]**	**[0.41]**	**[0.32]**	**[−0.53]**	**[0.50]**	**[0.69]**	**[−3.27]**	**[0.68]**	**[2.20]**	**[1.75]**	**[2.07]**	**[2.57]**	**[3.04]**
β^{mkt}	−0.059	−0.25	−0.25	−0.25	−0.25	−0.25	−0.24	−0.25	−0.25	−0.25	−0.23	−0.26	−0.25	−0.17	−0.13
	[−0.15]	[−1.15]	[−1.13]	[−1.14]	[−1.13]	[−1.15]	[−1.11]	[−1.13]	[−1.14]	[−1.13]	[−1.06]	[−1.00]	[−0.97]	[−0.82]	[−0.66]
β^{hml}	−0.12	−0.080	−0.079	−0.080	−0.079	−0.079	−0.076	−0.079	−0.084	−0.081	−0.079	−0.045	−0.044	−0.091	−0.10
	[−0.83]	[−0.67]	[−0.66]	[−0.66]	[−0.66]	[−0.65]	[−0.63]	[−0.66]	[−0.70]	[−0.67]	[−0.66]	[−0.33]	[−0.32]	[−0.76]	[−0.84]
β^{smb}	0.046	0.033	0.034	0.034	0.033	0.032	0.036	0.035	0.028	0.033	0.052	0.061	0.067	0.066	0.079
	[0.44]	[0.44]	[0.45]	[0.46]	[0.44]	[0.43]	[0.49]	[0.47]	[0.38]	[0.45]	[0.74]	[0.77]	[0.85]	[0.91]	[1.09]
BM	0.19	0.046	0.046	0.046	0.046	0.045	0.036	0.045	0.049	0.049	0.034	0.065	0.062	0.043	0.043
	[1.27]	[1.08]	[1.10]	[1.09]	[1.08]	[1.06]	[0.84]	[1.06]	[1.18]	[1.13]	[0.82]	[1.29]	[1.21]	[1.02]	[1.03]
ln(Mcap)	−0.019	0.026	0.027	0.027	0.027	0.027	0.032	0.027	0.010	0.028	0.043	0.011	0.018	0.093	0.12*
	[−0.30]	[0.60]	[0.64]	[0.62]	[0.63]	[0.63]	[0.80]	[0.65]	[0.24]	[0.67]	[1.00]	[0.25]	[0.41]	[1.55]	[1.89]
DYD	0.16	−0.15	−0.17	−0.15	−0.17	−0.18	−0.18	−0.15	−0.17	−0.19	−0.18	−0.0020	0.0041	−0.23	−0.22
	[0.15]	[−0.28]	[−0.31]	[−0.29]	[−0.32]	[−0.34]	[−0.34]	[−0.28]	[−0.33]	[−0.35]	[−0.33]	[−0.00]	[0.01]	[−0.46]	[−0.44]
Id. Vol.	−0.19***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.21***	−0.19***	−0.20***	−0.21***	−0.25***	−0.25***	−0.19***	−0.18***
	[−2.82]	[−4.14]	[−4.14]	[−4.14]	[−4.14]	[−4.13]	[−4.23]	[−4.14]	[−3.93]	[−4.09]	[−4.21]	[−4.59]	[−4.59]	[−3.99]	[−3.84]
RET_{-1}	−0.69	−0.082	−0.084	−0.083	−0.068	−0.063	−0.070	−0.069	−0.11	−0.040	−0.080	−0.41	−0.44	−0.15	−0.21
	[−0.94]	[−0.16]	[−0.16]	[−0.16]	[−0.13]	[−0.12]	[−0.14]	[−0.13]	[−0.22]	[−0.08]	[−0.15]	[−0.72]	[−0.77]	[−0.29]	[−0.41]
$RET_{(-12,-2)}$	0.31*	0.17	0.16	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.19	0.19	0.21	0.21	0.23
	[1.87]	[1.04]	[1.01]	[1.03]	[1.04]	[1.04]	[1.06]	[1.03]	[1.01]	[1.02]	[1.26]	[1.08]	[1.18]	[1.29]	[1.40]
Observations	131,986†	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 ILMs in the cross-section of expected returns after orthogonalization relative to other liquidity measures

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	All measures
ILMT residual	0.18	1.22***	1.16**	1.17***	1.18**	1.18**	0.91*	1.16**	1.35***	1.06**	0.72	0.41	0.29	0.59
	[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)
ILMV residual	0.26	1.45***	1.33***	1.40***	1.36***	1.38***	1.10**	1.34***	1.49***	1.25***	0.95**	0.59	0.48	0.75
	[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.

the cross-section of expected returns.[31]

C Three-month and twelve-month ILMs and Expected Returns

This section establishes the robustness of our main asset pricing findings to constructing liquidity measures over rolling 3-month windows. We first uncover results similar to those in Table 4 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 $m-13$

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

Table B.2. Liquidity and the Cross-Section of Expected Stock Returns: 1-month ILMs. This table reports on the relation between alternative high-frequency liquidity measures and the cross-section of expected returns. In Panel A, equation (1) is estimated using liquidity measures ($LIQ_{j,m-2}$) constructed over 1-month horizons. Control variables include three-factor Fama-French betas ($\beta^{mkt}_{j,m-1}$, $\beta^{hml}_{j,m-1}$, $\beta^{smb}_{j,m-1}$), estimated using weekly observations from the two-year period ending in the final full week of month $m-1$, book-to-market ratio, ($\mathrm{BM}_{j,m-1}$), natural log of market capitalization, ($\ln(\mathrm{Mcap}_{j,m-1})$), dividend yield ($\mathrm{DYD}_{j,m-1}$), defined as total dividends over the past 12 months divided by the share price at the end of month $m-1$, idiosyncratic volatility ($\mathrm{IdVol}_{j,m-1}$), previous month's return ($RET_{(-1)}$), and preceding return from the prior 11 months ($RET_{(-12,-2)}$). Panel B replaces each high-frequency liquidity measure by the residuals of $ILMT$ and $ILMV$ with respect to each alternative liquidity measure, with residuals calculated separately for each monthly cross-section. The last column in Panel B use the residuals of $ILMT$ and $ILMV$ 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	ILMT	ILMV
Constant	1.34	1.42	1.31	1.39	1.35	1.39	1.90**	1.37	1.70*	1.52*	1.66*	2.71***	2.64***	0.26	−0.46
	[1.22]	[1.64]	[1.55]	[1.59]	[1.61]	[1.64]	[2.18]	[1.61]	[1.98]	[1.76]	[1.84]	[3.01]	[2.93]	[0.23]	[−0.38]
Liquidity	**0.027****	**−0.068**	**−0.000011****	**−0.032**	**0.055**	**−0.070**	**−0.17****	**−0.024**	**−8.31*****	**−0.050**	**−0.25***	**−0.86*****	**−1.23*****	**0.67***	**0.88****
	[2.11]	**[−0.72]**	**[−2.06]**	**[−0.22]**	**[0.69]**	**[−0.68]**	**[−2.37]**	**[−0.33]**	**[−3.80]**	**[−0.91]**	**[−1.88]**	**[−3.62]**	**[−3.21]**	**[1.94]**	**[2.49]**
β^{mkt}	−0.0056	−0.11	−0.10	−0.11	−0.10	−0.10	−0.12	−0.11	−0.099	−0.11	−0.12	−0.13	−0.13	−0.055	−0.026
	[−0.01]	[−0.51]	[−0.49]	[−0.50]	[−0.48]	[−0.49]	[−0.56]	[−0.50]	[−0.46]	[−0.54]	[−0.58]	[−0.52]	[−0.50]	[−0.27]	[−0.13]
β^{hml}	−0.11	−0.11	−0.10	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.11	−0.057	−0.056	−0.11	−0.12
	[−0.74]	[−0.81]	[−0.78]	[−0.81]	[−0.81]	[−0.81]	[−0.80]	[−0.81]	[−0.87]	[−0.81]	[−0.82]	[−0.38]	[−0.37]	[−0.85]	[−0.92]
β^{smb}	0.12	0.036	0.035	0.037	0.038	0.036	0.023	0.038	0.039	0.026	0.016	0.00	0.0052	0.065	0.076
	[1.21]	[0.46]	[0.45]	[0.47]	[0.48]	[0.45]	[0.29]	[0.48]	[0.49]	[0.34]	[0.21]	[0.00]	[0.06]	[0.85]	[1.01]
BM	0.12	−0.0050	−0.0045	−0.0048	−0.0047	−0.0060	−0.012	−0.0053	−0.00030	0.000071	0.0013	0.054	0.050	−0.0071	−0.0045
	[0.94]	[−0.16]	[−0.14]	[−0.15]	[−0.15]	[−0.19]	[−0.37]	[−0.17]	[−0.01]	[0.00]	[0.04]	[1.09]	[1.02]	[−0.23]	[−0.14]
ln(Mcap)	0.0049	−0.0015	0.0040	−0.00	0.0015	0.00	−0.022	0.00075	−0.012	−0.0056	−0.012	−0.058	−0.054	0.043	0.069
	[0.11]	[−0.04]	[0.11]	[−0.01]	[0.04]	[0.00]	[−0.61]	[0.02]	[−0.34]	[−0.16]	[−0.31]	[−1.54]	[−1.45]	[0.97]	[1.43]
DYD	0.68	0.24	0.23	0.24	0.22	0.22	0.25	0.22	0.21	0.20	0.20	0.53	0.53	0.19	0.20
	[0.61]	[0.42]	[0.40]	[0.42]	[0.39]	[0.40]	[0.44]	[0.39]	[0.38]	[0.35]	[0.35]	[0.82]	[0.83]	[0.34]	[0.37]
Id. Vol.	−0.11	−0.18***	−0.18***	−0.18***	−0.18***	−0.18***	−0.17***	−0.18***	−0.17***	−0.18***	−0.17***	−0.14**	−0.14**	−0.17***	−0.17***
	[−1.52]	[−3.47]	[−3.48]	[−3.47]	[−3.48]	[−3.47]	[−3.21]	[−3.44]	[−3.34]	[−3.30]	[−3.18]	[−2.22]	[−2.26]	[−3.47]	[−3.44]
RET_{-1}	−0.80	−0.88	−0.87	−0.88	−0.87	−0.87	−0.86	−0.89	−0.89	−0.87	−0.85	−0.84	−0.85	−0.90	−0.92
	[−1.12]	[−1.49]	[−1.47]	[−1.49]	[−1.46]	[−1.46]	[−1.46]	[−1.49]	[−1.52]	[−1.47]	[−1.44]	[−1.24]	[−1.26]	[−1.50]	[−1.54]
$RET_{(-12,-2)}$	0.38*	0.17	0.17	0.17	0.17	0.17	0.15	0.17	0.18	0.17	0.16	0.13	0.13	0.21	0.23
	[1.89]	[1.10]	[1.10]	[1.09]	[1.09]	[1.11]	[1.00]	[1.10]	[1.16]	[1.07]	[1.02]	[0.68]	[0.68]	[1.34]	[1.45]
Observations	115,759†	297337	297337	297337	297337	297337	296805	297335	297337	297,335††	297,335††	242442	242442	297,337†††	297,337†††

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

	InPrIm	QSP	ShrDepth	EFSP	RESP	PIMP	Lambda	AMVST	ROLL	ILLIQ	ILLIQ_OC	BBD	WBBD	All measures
ILMT residual	−0.27	0.73**	0.64*	0.69**	0.64*	0.69**	0.88***	0.68*	0.84**	0.81**	0.93***	1.19***	1.14***	0.95**
	[−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)
ILMV residual	−0.22	0.96***	0.84**	0.92***	0.85**	0.90**	1.03***	0.88**	1.00***	0.97***	1.06***	1.23***	1.18***	0.99***
	[−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.

through $m-2$. Tables C.1 and C.2 report that, with a \$2 minimum price requirement, $ILMT$ and $ILMV$ explain the cross-section of stock returns in month m, unlike other liquidity measures. Sample standard deviations for 3-month $ILMT$ and $ILMV$ are 0.176 and 0.195, respectively. Thus, a one standard deviation increase in $ILMT$ is associated with estimated monthly liquidity premium of $0.176 \times 1.45\% = 0.255\%$, or 3.06% per year. Similarly, the liquidity premium associated with a one standard deviation increase in $ILMV$ is $0.195 \times 1.60 = 0.312\%$ per month or 3.74% per year.

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

D 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

Table C.2. Liquidity and the Cross-Section of Expected Stock Returns: 12-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 (1) 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	ILMT	ILMV
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(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.

based on samples with minimum previous month's end share price filters of $1, $2, and $5.[32]

Table D.1 reports that ILMs are the only measures for which the traditional long-short strategy (4) consistently produces three-factor liquidity premia of nearly 1% or higher. In addition, $ILMV$ is the sole liquidity measure for which all four long-short strategies produce significant liquidity premia. This finding indicates that $ILMV$ identifies economically relevant differences in stock liquidity even for stocks with intermediate trading costs, highlighting the practical relevance of ILMs. Long-short strategies based on dollar quoted, effective, and realized spreads also produce relatively consistent liquidity premia. However, these measures are impacted by variations in share price: ceteris paribus, higher share price is associated with wider spreads measures. This observation is consistent with the finding that long-short strategies based on percentage (relative) quoted, effective, and realized spreads do *not* produce significant three-factor alphas. That is, when

[32]Note that the findings regarding $ILMT$ and $ILMV$ match those reported in Panels A–C in Table 7.

adjusted for share price, these spreads-based measures fail to capture liquidity. This interpretation is reinforced by the regression analyses reported in Tables 4, B.1, and B.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 D.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]
ILMT	−0.32***	−0.34***	−0.19**	−0.17	−0.032	0.089	0.38**	0.64***	0.14	0.28	0.72***	0.96***
	[−2.77]	[−3.82]	[−2.13]	[−1.58]	[−0.30]	[0.63]	[2.48]	[4.25]	[0.86]	[1.62]	[3.72]	[4.30]
ILMV	−0.63***	−0.44***	−0.25***	−0.25***	−0.027	0.32***	0.32**	0.64***	0.22**	0.57***	0.77***	1.27***
	[−4.28]	[−4.40]	[−2.88]	[−3.56]	[−0.28]	[2.85]	[2.10]	[4.76]	[2.15]	[4.17]	[4.28]	[5.49]

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Table D.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]
ILMT	−0.30***	−0.33***	−0.21**	−0.062	0.023	0.11	0.34**	0.62***	0.085	0.31*	0.67***	0.93***
	[−2.70]	[−4.05]	[−2.17]	[−0.82]	[0.27]	[0.92]	[2.54]	[4.48]	[0.72]	[1.81]	[4.32]	[4.33]
ILMV	−0.58***	−0.33***	−0.23***	−0.25***	0.041	0.28***	0.31**	0.63***	0.30***	0.50***	0.65***	1.20***
	[−3.97]	[−3.86]	[−2.76]	[−3.68]	[0.59]	[3.37]	[2.26]	[4.97]	[3.10]	[4.27]	[3.72]	[5.09]

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Table D.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]
ILMT	−0.29***	−0.24***	−0.14*	0.053	0.12	0.28***	0.38***	0.65***	0.067	0.42***	0.62***	0.95***
	[−2.66]	[−2.89]	[−1.98]	[0.78]	[1.25]	[2.84]	[3.49]	[4.73]	[0.56]	[3.25]	[4.39]	[4.30]
ILMV	−0.43***	−0.21***	−0.14**	−0.11	0.19***	0.37***	0.43***	0.68***	0.30***	0.51***	0.64***	1.10***
	[−3.35]	[−2.64]	[−2.16]	[−1.54]	[2.86]	[4.65]	[4.02]	[5.32]	[3.64]	[4.44]	[3.92]	[4.82]

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

E Portfolio Double Sorts

This section provides return differences between stocks falling in different levels of ILM and stock characteristics. Double sorts based on ILMs and other stock characteristics provide additional evidence that the 3-factor risk-adjusted portfolio return spreads associated with our liquidity measures are not concentrated in specific subsets of stocks. These double sorts control for market beta, market capitalization, book-to-market ratios, past returns, and the share of sub-penny volume. After excluding stocks priced below $5 at the end of the preceding month, we form an array of 5×5 portfolios that first condition on a stock characteristic, and then on an ILM.[33] 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 E.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 C establishes the robustness of these findings to constructing ILMs over 3-month rolling windows. Therefore, the liquidity premia associated with ILMs are largely orthogonal to stock characteristics known to influence expected returns.

Finally, we investigate whether trading costs can explain the returns of anomalies based on stock characteristics by changing the order of the double sorts—first conditioning on a ILM, and then on a stock characteristic. Table E.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)).[34]

[33] 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.

[34] Internet Appendix C confirms results are robust to constructing ILMs over 3-month rolling windows.

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

Panel A: Sequential double sorts on market beta and ILM

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

Panel B: Sequential double sorts on market capitalization and ILM

Portfolios of market capitalization	Portfolios of $ILMT$						Portfolios of $ILMV$					
	Low	2	3	4	High	High−Low	Low	2	3	4	High	High−Low
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 E.1 – *continued from previous page*

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

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

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

		Portfolios of $ILMT$						Portfolios of $ILMV$					
		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 E.1 − *continued from previous page*

Panel E: Sequential double sorts on institutional ownership and ILM

Portfolios of instl. ownership	Portfolios of $ILMT$: Low	2	3	4	High	High−Low	Portfolios of $ILMV$: 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 ILM

Portfolios of sub-penny volume	Portfolios of $ILMT$: Low	2	3	4	High	High−Low	Portfolios of $ILMV$: 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 E.2. **Portfolio Alphas:** ILM **and Stock Characteristic Double-Sorts.** This table presents three-factor alphas using CRSP breakpoints. Stocks are sorted into liquidity quintiles based on $LIQ \in \{ILMT, ILMV\}$. Within each liquidity quintile, stocks are further sorted into stock characteristic quintiles $X \in \{\beta^{mkt}, \text{Mcap}, RET_{(-12,-2)}, \text{BM}, \}$. 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 $ILMT$ and stock characteristics

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

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

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Table E.2 – *continued from previous page*

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

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

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

F Wholesalers' interactions with retail and institutional investors

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.

F.1 Institutional Details

F.1.1 Retail Trade Execution

Executions of retail orders in U.S. equity markets are subject to "best execution" principles.[35] 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 (2022)), ensuring best execution principles are met in addition to providing payment for order flow (PFOF) to certain brokers.[36]

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 order on exchanges/ATSs and fills the retail order once that proprietary order is executed.[37] The remaining 80% of marketable retail order executions are internalized, a process by which wholesalers execute retail order flow against their own inventory.[38] 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.

[35] 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.

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

[37] 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.

[38] 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)).

Panel A in Table 8 reports the distribution of order types across all non-directed orders[39] 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 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 (2022)).

Institutional details suggest two channels underlie these large PIs. Most importantly, the Manning rule requires wholesalers with access to proprietary data feeds on odd-lot liquidity to use any inside-quote liquidity to determine best execution terms. Due to the 1¢ tick size, inside-quote odd-lot liquidity is quoted at 1¢ price increments. Thus, when such liquidity exists, to price improve over the "best available price" some internalized marketable retail orders must receive greater-than-1¢ PI. Second, internalized orders executed at prices over 1¢ inside the NBBO may be inside-NBBO non-marketable limit orders, originally placed as marketable orders.[40] Internalizing such non-marketable limit orders is very costly, even when executed at minimal PI because non-marketable orders receive much higher PFOF.[41]

[39] 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.

[40] 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.

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

F.1.2 Implications for BJZZ's Algorithm

Wholesalers internalize about 80% of the marketable retail orders received (SEC (2022)),[42] 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. (2023)). 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.[43]

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.[44] 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 un-

option markets.

[42]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.

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

[44]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.

derlies the strength of our liquidity measures.

Battalio et al. (2023) 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. (2023), 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. (2023)'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 9, is a robust feature.

F.1.3 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.[45] 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.[46] 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

[45]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.

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

wholesaler to intermediate between retail and institutional investors by providing the institution with liquidity sourced from retail order flow.[47] In 2021, Citadel and Virtu combined to execute almost 17% of consolidated U.S. trading volume by internalizing retail orders, and their affiliated SDPs accounted for over 4% of this volume (Rosenblatt (2021)). Put differently, they internalized about 425 shares of retail orders per 100 shares of institutional orders filled on their SDPs.

When wholesalers use internalized retail buy (sell) order flow to fill unbalanced institutional sell (buy) liquidity demand, the internalized retail orders often receive sub-penny price improvements. Consequently, the corresponding $Mroib$ will be unbalanced and inversely related to institutional liquidity demand. As institutions with high liquidity demand are prepared to pay more to wholesalers, wholesalers can pay higher internalization costs in the form of high PI or high PFOF, internalizing orders that are executed by more that 1¢ inside the NBBO. This leads to a positive relation between $|Mroib|$ and the intensity with which these high-cost retail orders are internalized (see Figure 5).

F.2 Economics of Retail Order Internalization

F.2.1 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 $\$V$

[47]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.

- n_1^b limit buy orders at $\$(V+t)$

- n_2^b marketable buy orders at $\$(V+2t)$

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

The wholesaler chooses whether to internalize a retail order in return for giving the broker-dealer PFOF, or to reroute it directly to an exchange, in which case all rebates (or fees) go to the retail broker, where the rebate for liquidity-making limit orders exceeds that for liquidity-taking market orders.[48] 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).[49] 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

[48] 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.

[49] 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.

with marketable buy orders and limit buy orders at $\$(V+t)$, as the PFOF plus PI paid is less than the profit obtained by intermediating these orders. Thus, at least $min\{n^s_{-2}+n^s_{-1}, n^b_2+n^b_1\} = n^b_2+n^b_1$ is filled on each side by the wholesaler's internalization. The BJZZ algorithm identifies the subset of those internalized orders that receives price improvement, which comprise a total of $2(n^b_2+\alpha_{NM}n^b_1)$.

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

- 0 marketable sell orders at $\$(V-2t)$
- $n^s_{-2}+n^s_{-1}-(n^b_2+n^b_1)$ limit sell orders at $\$(V-t)$
- n^s_0 limit sell orders and n^b_0 limit buy orders at $\$V$
- 0 limit buy orders at $\$(V+t)$
- 0 marketable buy orders at $\$(V+2t)$

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[50] 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

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

[50] 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.

$|Mroibvol|$ 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 fraction α_{NM} receiving price improvement. Thus, if $\alpha_{NM} = 1$, then a peak of

$$|Mroibvol| = \frac{q^*}{2(n^b_2 + n^b_1) + q^*}$$

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

$$|Mroibvol| = \frac{q^* - \Delta_1}{2n^b_2 + q^* - \Delta_1}$$

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

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

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

In analyses that are available upon request, we document empirical evidence consistent with the predictions of our simple framework. We exploit the design of the Tick Size Pilot (TSP) to establish that variation in $Mroibtrd$ and $Mroibvol$ reflects the internalization decisions of wholesalers, rather than overall retail order flow. The TSP raised profitability of off-exchange internalization for a group of pilot stocks (Werner, Rindi, Buti, and Wen (2023)). Reflecting the importance of wholesaler incentives in determining $Mroib$, we find significant increases in the volume of BJZZ-identified trades for these stocks relative to the control group. The TSP also raised the cost of internalization for another group of pilot stocks. Again, consistent with the importance of wholesaler choices, find that $Mroib$ imbalances significantly rose due to this increase. This finding is consistent with impact of internalization costs on the choices of wholesalers whether to internalize the "marginal" retail order. These analyses let us link wholesaler cost-benefit considerations to their choices of which retail orders to internalize.