Price Impact or Trading Volume: Why is the Amihud (2002) Illiquidity Measure Priced?

XIAOXIA LOU

TAO SHU*

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* Lou is at the Alfred Lerner College of Business, University of Delaware. Email: lous@udel.edu. Shu is at the Terry College of Business, University of Georgia. Email: taoshu@terry.uga.edu.

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The return premium associated with the Amihud (2002) measure is generally considered a liquidity premium that compensates for price impact. We find that the pricing of the Amihud measure is not attributable to the construction of the return-to-volume ratio that is intended to capture price impact, but driven by the trading volume component. Additionally, the high-frequency price impact and spread benchmarks are priced only in January and do not explain the pricing of the trading volume component of the Amihud measure. Further analyses suggest that the trading volume effect on stock return is due to mispricing, not compensation for illiquidity.

The Amihud (2002) measure is one of the most widely used liquidity proxies in the finance literature.[1] During 2009-2015, over one hundred and twenty papers published in the Journal of Finance, the Journal of Financial Economics, and the Review of Financial Studies use the Amihud measure for their empirical analyses.[2] The Amihud measure has two advantages over many other liquidity measures. First, the Amihud measure has a simple construction that uses the absolute value of the *daily* return-to-volume ratio to capture price impact. Second, the measure has a strong positive relation with expected stock return (Amihud 2002; Chordia, Huh, and Subrahmanyam 2009, among many studies). The positive return premium of the Amihud measure is generally considered a liquidity premium that compensates for price impact.

Theoretically, however, it is unclear that the Amihud measure would be priced because of the compensation for price impact. As discussed in Chordia, Huh, and Subrahmanyam (2009), "*Although many microstructure theories have been developed, extant economic models are unable to map precisely onto the Amihud (2002) construct of the ratio of absolute return to volume.*" (p. 3630). Since the Amihud measure is widely used to examine liquidity premium or control for liquidity, it is important to know whether the pricing of the Amihud measure is indeed due to price impact or other reasons. Furthermore, examining the pricing of the Amihud measure also helps us understand liquidity measurement and liquidity premium. For example, the return premium of the Amihud measure is generally considered as direct evidence that investors, as predicted by theory, demand compensation for price impact or transaction cost.

This paper studies the pricing of the Amihud (2002) measure from a new perspective, the close connection between the Amihud measure and trading volume, as illustrated by the construction

[1] Besides the Amihud (2002) measure as a price impact (cost-per-dollar-volume) proxy, the finance literature has also proposed many measures for the three aspects of liquidity: spread, price impact, and resilience (see Holden, Jacobsen, and Subrahmanyam 2014 for a survey).

[2] Note that we count only published papers and exclude any forthcoming papers.

of the measure:

$$A_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{|r_{id}|}{Dvol_{id}}, \tag{1}$$

where A_{it} is the Amihud measure of firm *i* estimated in month *t*; r_{id} and $Dvol_{id}$ are daily return and daily dollar trading volume for stock *i* on day *d*; D_{it} is the number of days with available ratio in month *t*.[3] With everything else equal, higher trading volume leads to a lower Amihud measure.[4] This linkage is particularly strong because the trading volume component has a much greater cross-sectional variation than the stock return component. For example, the 75th percentile cutoff of the trading volume component is over 100 times its 25th percentile cutoff, but the 75th percentile cutoff of the return component is just twice its 25th percentile cutoff.[5]

To focus on the trading volume component of the Amihud measure, we construct a "constant" version of the Amihud measure, *A_C*, by replacing absolute return in the Amihud measure with one:

$$A\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{1}{Dvol_{id}}, \tag{2}$$

where all the components are as defined in equation (1). The *A_C* measure has a correlation of 0.90 with the original Amihud measure, suggesting that the variation in the Amihud measure is driven in large part by the variation in the trading volume component. Additionally, we find that the "constant" measure is priced similarly as the original measure: stocks in the top quintile of *A_C* outperform those

[3] Amihud (2002) constructs the measure annually, and existing studies use both monthly and annual measures. We use monthly measure for the main analysis because it reflects more recent information, and conduct robustness tests using annual measure.

[4] Some studies further adjust the Amihud measure for inflation or trend in trading volume. The approaches of our analyses are such that we need not to do so. For sorting analysis, we sort stocks into portfolios every month. For the Fama-MacBeth regression analysis that uses the Amihud measures as independent variables, we follow the literature (e.g., Brennan, Huh, and Subrahmanyam 2013) and transform the measures into natural logs, which makes the scaling irrelevant.

[5] The corresponding statistics are presented in Table 1 and discussed in Section 1.2.

in the bottom quintile by 0.61 percent (t-stat 2.95) per month in raw return and 0.44 percent (t-stat 3.20) in four-factor alpha that controls for the three Fama-French factors and the momentum factor. This is very close to the spread based on the original Amihud measure: 0.56 percent (t-stat 2.36) per month in raw return and 0.35 percent (t-stat 2.31) in four-factor alpha.

We further find that a residual Amihud measure, the residual from cross-sectional regressions of A on A_C and therefore orthogonal to the constant measure A_C, is not associated with a positive return premium. In fact, the top quintile of the residual measure *underperforms* the bottom quintile by 0.17 percent (t-stat 1.05) per month in raw return and 0.16 percent (t-stat 0.96) in four-factor alpha. These results indicate that the pricing of the Amihud measure is driven by its trading volume component, not by its construct of return-to-volume ratio. We reach the same conclusion using the firm-level Fama-MacBeth (1973) regressions of monthly stock returns on the Amihud measures controlling for size, book-to-market ratio, momentum, and short-term return reversal. The coefficient on the "constant" measure is significantly positive but on the residual Amihud measure it is either insignificant or significantly negative.

Our results are similar when we use the turnover-based Amihud measure proposed by Brennan, Huh, and Subrahmanyam (2013) that is constructed using the absolute return-to-turnover ratio instead of the absolute return-to-volume ratio. The results also hold for a battery of robustness tests including using annual Amihud measures, the NASDAQ stocks, the sub-periods, the ranks instead of raw values of the independent variables, or controlling for idiosyncratic return volatility.

Since the pricing of the Amihud measure is generally considered compensation for price impact, we directly examine the role of price impact in explaining the pricing of the Amihud measure using a high-frequency price impact benchmark widely used in the literature (Hasbrouck 2009; Goyenko, Holden, and Trzcinka 2009). The price impact benchmark, λ, is constructed for NYSE/AMEX stocks from 1983 to 2012 as the slope coefficient of five-minute stock return regressed on signed square-rooted five-minute trading volume for a firm-month. We also consider an alternative non-volume-based price impact measure, the percent 5-minute price impact (*PI*), which evaluates the permanent price change of a given trade (Goyenko, Holden, and Trzcinka 2009). We further expand the analysis to bid-ask spread and construct three widely used high-frequency spread benchmarks including percent quoted spread (*QS*), percent effective spread (*ES*), and percent realized spread (*RS*) (Goyenko, Holden and Trzcinka 2009; Fong, Holden and Trzcinka 2016).

We first examine the pricing of these liquidity benchmarks. Consistent with Eleswarapu and Reinganum (1993) and Hasbrouck (2009) who show that liquidity premium is concentrated in January, we find that these liquidity benchmarks are indeed priced in January but not in non-January months. As a result, these liquidity benchmarks are not associated with a return premium in the full sample period. The finding that the liquidity benchmarks are priced only in January is puzzling and unexplained by the existing theory of liquidity premium (Hasbrouck 2009). More importantly, the return regression analyses show that the price impact benchmark, either the λ measure or the *PI* measure, does not explain the pricing of the Amihud measure. The spread benchmarks do not explain the pricing of the Amihud measure, either.

The existing literature (Hasbrouck 2009; Goyenko, Holden, and Trzcinka 2009) documents that the Amihud measure is highly correlated with the high-frequency price impact benchmark. Consistent with their studies, we find a correlation of 0.74 between the Amihud (2002) measure and the λ measure, which indicates that, indeed, the Amihud (2002) measure does a good job capturing price impact. However, the λ measure has a much lower correlation of 0.35 with the turnover component, which drives the pricing of the Amihud measure. We decompose the Amihud measure into a transaction-cost component and a non-transaction-cost component and examine their pricing separately. Specifically, we estimate cross-sectional regressions of the Amihud measure on the price impact and spread benchmarks, and calculate the transaction-cost component as the fitted value of the regressions, and the non-cost component as the residual of the regressions. The non-cost component, therefore, is orthogonal to the price impact and spread benchmarks. The results of return regressions show that the non-cost component is priced but the transaction-cost component is not, indicating that the pricing of the Amihud measure is not due to its association with common liquidity benchmarks.

Our results show that the pricing of the Amihud measure is due to its association with trading volume, and such pricing cannot be explained by existing liquidity benchmarks. Then what drives the pricing of trading volume? In particular, is the return premium of trading volume a liquidity premium from some dimension of liquidity that is not captured by the existing liquidity benchmarks, or is it caused by non-liquidity factors as suggested by some studies? For example, previous studies have related trading volume or its return premium to various factors such as investor disagreement (e.g., Harris and Raviv 1993; Blume, Easley, and O'Hara 1994; Kandel and Pearson 1995), value investing (Lee and Swaminathan 2000), stock visibility (Gervais, Kaniel, and Mingelgrin 2001), information uncertainty (Jiang, Lee, and Zhang 2004; Barinov 2014), or investor sentiment (Baker and Wurgler 2006).[6]

We conduct four tests to distinguish the liquidity and non-liquidity explanations of the volume premium and the results suggest that the volume premium is likely to be attributed to mispricing rather than liquidity premium. We first examine the seasonality of the volume premium, and find that the volume premium completely disappears in January while it remains strong the rest of the year. This is a stark contrast with liquidity benchmarks which are priced in January but not in non-January, suggesting that the underlying source of the volume premium may differ vastly from liquidity premium. Our second test is based on the notion that liquidity premium should be larger when

[6] Some studies also document a weak or even negative relation between volume and stock liquidity (Foster and Viswanathan 1993; Lee, Mucklow, and Ready 1993; and Johnson 2008). As another example, trading volume can be high when the markets are *illiquid* as seen in the flash crash of 2010.

liquidity is scarce and investors care more about stock illiquidity, such as the time periods when the aggregate liquidity is low (Pástor and Stambaugh, 2003). However, contrary to this liquidity premium predication, we find that the volume premium is *not* larger after episodes of higher market illiquidity.

We also conduct two tests to explore the mispricing explanation of the volume premium. Our first test is based on Stambaugh, Yu, and Yuan (2012) who suggest that mispricing, especially overpricing will be greater following periods of high market sentiment. We find that, consistent with the mispricing hypothesis, the volume premium is significantly larger following the high-sentiment period, and the difference is driven by the short leg. Our second test is based on La Porta, Lakonishok, Shleifer, Vishny (1997) who suggest that if an anomaly is associated with mispricing, then it will be stronger in the earnings announcement window, as the release of earnings helps correct mispricing.[7] We find that, consistent with this prediction, the volume premium is large and significant in the three-day earnings announcement window but disappears in the non-announcement window. Our examination of analyst forecast errors also suggests that earnings release helps correct market over-optimism about high volume stocks relative to low volume stocks.

Finally, we extend our analysis to the use of the Amihud measure to examine the pricing of liquidity risk (e.g., Acharya and Pedersen 2005; Wu 2015). We construct systematic liquidity factors using the Amihud measure and its trading volume component, and conclude that the trading volume component is also primarily responsible for the pricing of the Amihud measure as a systematic factor.

1. Measure Construction and Sample Selection

1.1 Measure Construction

The measures used in this paper are constructed as below:

- A: the Amihud (2002) measure, defined by equation (1).

[7] A contemporaneous study by Engelberg, McLean, and Pontiff (2016) uses this approach to study a strategy that combines 94 anomalies documented by the existing literature.

- *A_C*: the "constant" Amihud measure corresponding to *A*, defined by equation (2).
- *AT*: the turnover-based Amihud illiquidity measure from Brennan, Huh, and Subrahmanyam (2013)

$$AT_{it} = \frac{1}{D_{id}} \sum_{d=1}^{Dit} \frac{|r_{id}|}{TO_{id}}, \tag{3}$$

where AT_{it} is the turnover-based Amihud measure for stock *i* in estimation month *t*, and TO_{id} is the turnover of stock *i* on day *d*, calculated as daily share volume divided by total shares outstanding. The other variables are as defined in equation (1).

- *AT_C*: the "constant" turnover-based Amihud measure corresponding to *AT*

$$AT\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{1}{TO_{id}}, \tag{4}$$

which differs from equation (3) only in replacing the numerator of the ratio $|r_{id}|$ with a constant 1.

- $|Ret|$: return component of the Amihud measure, calculated as the monthly average of daily absolute returns over the estimation month.

We follow the literature and winsorize these measures at the 1 and 99 percentage points in each cross-section to minimize the influence of outliers. Definitions of all the variables used in the paper are summarized in Appendix A. In addition to the turnover-based Amihud measure, we also examine the square-root version of the Amihud measure that is constructed as the Amihud (2002) measure but taking the square root of the daily absolute return-to-volume ratio. Hasbrouck (2009) proposes the square-root measure to control for skewness. We construct the "constant" measure corresponding to the square-root Amihud measure by replacing the numerator with a constant one, and repeat the tests in this paper. The results are not reported for the sake of brevity, but all our findings in this paper hold for the square-root version of the Amihud measure as well.

1.2 Sample Construction

Our sample stocks include ordinary common shares (share codes 10 and 11) listed on the NYSE and the AMEX.[8] We exclude NASDAQ stocks because their trading volume is inflated relative to that of NYSE/AMEX stocks due to different trading mechanisms.[9] We require a stock to have at least 10 days of valid return and volume data to compute the ratios in the estimation month. We obtain the data on stock price, return, trading volume, and shares outstanding from the Center for Research in Security Prices (CRSP) daily file and construct monthly Amihud measures. We follow the literature (e.g., Brennan, Huh, and Subrahmanyam 2013) and match the Amihud measures of month *t*-2 to stock returns in month *t*, and the period of our return analysis is from January 1964 to December 2012. Our main analyses use the monthly measure because it reflects more recent information, and we report the robustness tests using the annual measure.

Panel A of Table 1 presents summary statistics of the Amihud measure and its various components for the 1,197,252 firm-months in our sample, as well as firm size and book-to-market ratio. Firm size is the market capitalization at the end of the previous year. Book-to-market ratio is the ratio of the book value of equity to the market value of equity, where the book value of equity is defined as stockholders' equity plus balance-sheet deferred taxes and investment tax credit, minus the book value of preferred stock.[10] Panel A shows that the trading volume component of the Amihud measure is much more volatile than the return component. The standard deviation of A_C is almost

[8] A firm-month is dropped from the sample if the firm's stock is traded in a non-NYSE/AMEX exchange on any day of the calendar year of the month.

[9] We nevertheless conduct robustness tests using the NASDAQ sample and report the results in Section 2.4.

[10] Balance-sheet deferred taxes is the Compustat item TXDB, and investment tax credit is item ITCB. We use redemption value (PSTKRV), liquidation value (PSTKL), or par value (PSTK), in that order, for the book value of preferred stock. Stockholders' equity is what is reported by Moody's (see Davis, Fama, and French 2000), or Compustat (SEQ). If neither is available, we then use the book value of common equity (CEQ) plus the book value of preferred stock. If common equity is not available, stockholders' equity is then defined as the book value of assets (AT) minus total liabilities (LT). We use the book value of the fiscal year ending in calendar year y and market value at the end of year y to calculate book-to-market ratio and match it to stock returns in the one-year period from July of y+1 to June of year y+2. We winsorize the book-to-market ratio in each month at the 0.5% and 99.5% level to reduce the influences of data error and extreme observations.

three times its mean, but the standard deviation of $|ret|$ is only 70 percent of the mean. Additionally, the 75th percentile cutoff of *A_C* is over 100 times its 25th percentile cutoff, but the 75th percentile cutoff of $|ret|$ is only twice its 25th percentile cutoff. This contrast is also true for the turnover-based Amihud measure. These results suggest that the variation of the trading volume component can account for the majority of the variation in the Amihud measure.

Panel B of Table 1 presents correlations among the various versions of the Amihud measure. We first calculate cross-sectional correlation coefficients among the variables in each month and then report the time-series averages. The Amihud measures are highly correlated with their "constant" measures constructed with only the trading volume components. The correlations are 0.90 between *A* and *A_C*, and 0.75 between *AT* and *AT_C*. These results confirm that the trading volume component alone accounts for a vast majority of the variations in the Amihud measures.

2. Does the Trading Volume Component Explain the Pricing of the Amihud Measure?

We motivate our analyses by examining the pricing of the components of the Amihud measure separately, and then formally test whether the pricing of the Amihud measure is attributable to its association with trading volume.

2.1 Decomposition of the Amihud (2002) Measure

Brennan, Huh, and Subrahmanyam (2013) decompose the Amihud (2002) measure into the turnover-based Amihud measure and firm size (market capitalization) as in equation (5) below. They examine these two metrics with regressions of stock returns, and suggest that removing the impact of firm size clarifies the effect of the Amihud measure on stock return. Since our focus is trading volume, we decompose the Amihud (2002) measure into the trading volume component (the *A_C* measure) and the absolute return component as in equation (6), and further into the turnover component (the *AT_C* measure), the absolute return component, and the firm size component as in equation (7):

$$\ln(A) = \ln(\frac{|ret|}{Dvol}) = \ln(\frac{|ret|}{TO} \times \frac{1}{S}) = \ln(AT) - \ln(S) \tag{5}$$

$$\ln(A) = \ln(\frac{|ret|}{Dvol}) = \ln(|ret|) + \ln(\frac{1}{Dvol}) = \ln(|ret|) + \ln(A\_C) \tag{6}$$

$$\ln(A) = \ln(\frac{|ret|}{Dvol}) = \ln(|ret| \times \frac{1}{TO} \times \frac{1}{S}) = \ln(|ret|) + \ln(AT\_C) - \ln(S) \tag{7}$$

where *S* is daily market capitalization, and the remaining variables are as previously defined. We compute the natural logs of the monthly averages of various daily components: |ret|, *A_C*, *AT*, *AT_C*, and *S*, and estimate regressions of stock returns on these components. We follow Brennan, Chordia, and Subrahmanyam (1998) and use the Fama-French three-factor adjusted return (henceforth FF3-adjusted return) as dependent variable of the return regressions. FF3-adjusted return of firm *i* in month *t* is defined as:

$$r_{it}^{ff3} = (r_{it} - r_{ft}) - (\hat{\beta}_{it}^{MKT} \times MKT_t + \hat{\beta}_{it}^{SMB} \times SMB_t + \hat{\beta}_{it}^{HML} \times HML_t) \tag{8}$$

where $\hat{\beta}_{it}^{MKT}$, $\hat{\beta}_{it}^{SMB}$, and $\hat{\beta}_{it}^{HML}$ are estimated for each firm using the monthly excess returns and the three Fama-French factors in the previous sixty-month window from *t*-60 to *t*-1.[11] We perform cross-sectional regressions and report the time-series averages of coefficients and the associated t-statistics using the Newey-West (1987) standard errors with six lags. We also include the usual control variables such as size, book-to-market ratio, and past stock returns that control for momentum and short-term price reversal. When a regression includes the size component of the Amihud measure (*S*), we drop the control variable of firm size (market capitalization at the end of previous year).

Model (1) of Table 2 revisits the pricing of the Amihud measure by regressing return on ln(*A*), where the coefficient on ln(*A*) is significantly positive, confirming a positive return premium of the Amihud measure. Model (2) regresses return on ln(*AT*) and ln(*S*) as the decomposition in equation

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[11] We require at least 24 observations in the estimation of factor loadings. We thank Professor Kenneth French for making the data of factor returns available.

(5). The results are consistent with Brennan, Huh, and Subrahmanyam (2013) in that the turnover-based Amihud measure is priced. Model (3) decomposes ln(*A*) into the volume component (ln(*A_C*)) and the absolute return component (ln(|*ret*|)) as in equation (6). The coefficient on ln(*A_C*) is positive and significant at the 0.01 level but the coefficient on ln(|*ret*|) is significantly negative. Model (4) presents the full decomposition of the Amihud measure as in equation (7). While the coefficient on ln(*AT_C*) is significantly positive at the 0.01 level, ln(*S*) has a significantly negative coefficient, and the coefficient on ln(|*ret*|) is negative and marginally significant. Overall, Table 2 shows that the trading volume component of the Amihud measure is positively related to expected return but the absolute return component is not. In the following sub-sections, we will formally test whether the pricing of the Amihud measure is due to its association with trading volume.

2.2 Sorting Analysis

We sort stocks at the beginning of month *t* from 1964 to 2012 into quintiles based on their monthly Amihud measures of month *t*-2. We then calculate the equal-weighted portfolio returns each month, and report their time-series averages. The return spreads between the top and bottom quintiles are also reported with the associated t-statistics calculated using Newey-West (1987) standard errors with six lags. We report both raw returns and four-factor alphas calculated using the three Fama-French factors (*MKT*, *SMB*, *HML*) and the momentum factor (*UMD*).

Panel A of Table 3 presents the sorting analysis for the Amihud (2002) measure (*A*). The raw return is increasing in the *A* measure, with the spread between the extreme quintiles being 0.56 percent per month. This spread is not only economically significant but also statistically significant (t-stat 2.36). The spread in four-factor alpha is 0.35 percent (t-stat 2.31) per month, which translates to an annual profit of 4.28 percent. These results are consistent with the regression analyses that the Amihud (2002) measure is strongly related to expected return. When we sort stocks on the “constant” measure, *A_C*, the return spread is very similar to that of the Amihud measure. The spread is 0.61 percent per month in raw return and 0.44 percent in four-factor alpha, both statistically significant. Therefore, excluding the absolute-return component has no impact on the pricing of the Amihud measure.

Next, we use a residual approach to examine whether the *A* measure is still priced after controlling for the *A_C* measure. We estimate monthly cross-sectional regressions of the *A* measure on *A_C*, and obtain the residuals as the residual *A* measure. The residual measure therefore represents the variation in the Amihud (2002) measure that is not due to *A_C*. We sort stocks based on the residual measure, and the results show that a higher residual Amihud measure does not lead to higher expected return. The return spread between the top and the bottom quintiles of the residual measure is insignificantly negative in both raw return (-0.17 percent, t-stat -1.05) and four-factor alpha (-0.16 percent, t-stat -0.96).

We further examine *AT*, the turnover-based Amihud measure, in a similar fashion. Panel B of Table 3 shows that *AT* has a significantly positive relation with expected stock return, and the constant measure *AT_C* is priced similarly as the *AT* measure. We then construct a residual *AT* measure as residuals from monthly cross-sectional regressions of *AT* on *AT_C*. When we sort stocks on the residual *AT* measure, the return spread becomes insignificantly negative (-0.03 percent, t-stat -0.21).

We also make use of factor returns to examine whether the pricing of the Amihud measure is explained by its trading volume component. This approach is in the same spirit as using the *SMB* factor, for example, to examine if the abnormal return of a portfolio can be attributed to the size factor. For each month from 1964 to 2012, we sort stocks into terciles according to the "constant" measure *A_C* of month *t*-2, and then calculate the monthly factor return IML^{A_C} as the equal-weighted return of the top *A_C* tercile minus that of the bottom *A_C* tercile.[12] We then repeat the sorting

[12] The results are similar when we construct factor returns by sorting stocks into two or four portfolios instead of three portfolios.

analysis of the Amihud (2002) measure in Table 3 but examine the one-factor alpha calculated using the IML^{A_C} factor, and the five-factor alpha calculated using the IML^{A_C} factor, the three Fama-French factors, and the momentum factor. The results, reported in Table A.1 of the Internet Appendix, show that the positive return premium of the Amihud (2002) measure disappears after controlling for the IML^{A_C} factor. Specifically, the return spread is -0.04 percent (t-stat -0.77) in one-factor alpha and -0.08 percent (t-stat -1.66) in five-factor alpha. The results are similar when we examine the turnover-based Amihud measure (*AT*).

2.3 Regression Analysis

We further estimate multiple Fama-MacBeth (1973) regressions to examine the pricing of the Amihud (2002) measure. We perform cross-sectional regressions of returns on the Amihud measures, and report the time-series averages of coefficients and the associated t-statistics using the Newey-West (1987) standard errors with six lags. To alleviate the impact of extreme values, we follow the literature (e.g., Brennan, Huh, and Subrahmanyam 2013) and take natural logs of the Amihud measure and its components. We also include the usual control variables such as size, book-to-market ratio, and past stock returns that control for momentum and short-term price reversal. We follow Brennan, Chordia, and Subrahmanyam (1998) and use the FF3-adjusted return as discussed in Section 2.1.

Panel A of Table 4 presents the results of the regressions. In Model (1), the coefficient on ln(*A*) is significantly positive, confirming the return premium associated with the Amihud (2002) measure. In Model (2), the coefficient on the "constant" Amihud measure (ln(*A_C*)) is also significantly positive, indicating that this measure also leads to a return premium. The estimated coefficient of 0.119 for *ln(A)* implies that one standard deviation increase in *ln(A)* (2.69 in our sample period) is associated with a monthly return of 0.32%, in line with the 0.35% alpha spread in the sorting analysis (Table 3). With an estimated coefficient of 0.183 for *ln(A_C)* in Model 2, one standard deviation change (2.53) in *ln(A_C)* leads to an increase in monthly return by 0.46%. In Model (3), we regress return on the residual *ln(A)* measure, which is the residual from the monthly cross-sectional regressions of *ln(A)* on *ln(A_C)*. The coefficient on residual *ln(A)* is significantly negative. Model (4) includes both components of the Amihud measure, *ln(A_C)* and residual *ln(A)*. The coefficient on *ln(A_C)* continues to be significantly positive, and that on residual *ln(A)* remains significantly negative.

In Model (5), we further control for idiosyncratic return volatility, defined as standard deviation of residuals from regressions of a firm's daily returns on the daily Fama-French three factors in the previous year. We control for return volatility as the absolute return component of the Amihud measure is positively correlated with return volatility, and the idiosyncratic volatility is known to affect future returns (e.g., Ang, Hodrick, Xing, and Zhang 2006). Model (5) shows that the coefficients on both *ln*(*A_C*) and residual *ln*(*A*) are unaffected by the control of idiosyncratic return volatility.

We observe a significantly positive coefficient on firm size, as found by Brennan, Huh, and Subrahmanyam (2013). This result does not mean that larger firms have higher expected returns, because firm size is also a part of the Amihud measure. To illustrate this point, the coefficient on firm size is no longer significantly positive in Panel B which examines the turnover-based Amihud measure that excludes the firm-size component.

In Panel B, the coefficients on *ln(AT)* and *ln(AT_C)* are significantly positive when these measures enter the return regressions separately. The estimated coefficient of 0.163 for *ln(AT)* implies that one standard deviation increase in *ln(AT)* (1.10) is associated with a monthly return premium of 0.18%. One standard deviation change (1.09) in *ln(AT_C)* leads to an increase in monthly return by 0.24%. Not surprisingly, these return premiums are lower than those in Panel A since the size effect is removed in the turnover versions of the Amihud measures. When *ln(AT_C)* and the residual *ln(AT)* are included in the regression, the coefficient on ln(*AT_C*) is positive and significant at the 0.01 level, but on the residual *ln(AT)* it is significantly negative.

2.4 Robustness Tests

2.4.1 Annual Measures

Our first robustness test uses annual Amihud measures instead of monthly measures. We follow Amihud (2002) and construct annual Amihud measures, requiring a stock to have at least 100 days of valid return and volume data to compute the ratios in the estimation year. We match the Amihud measures of year *y*-1 to monthly stock returns in year *y*, and the period of our return analysis is from January 1964 to December 2012, the same as our main analyses using monthly measures. The constant annual measures and residual annual measures are constructed similar to the monthly measure analysis.

Panel A of Table 5 reports the correlations among the annual Amihud measures, where *A* is highly correlated with *A_C*, with a correlation of 0.94. The *AT* measure is also highly correlated with the *AT_C* measure. Panel B reports the monthly four-factor alphas of portfolios sorted on the annual Amihud measures. Panel C repeats the firm-level Fama-MacBeth return regressions on the annual measures, where the coefficients on the Amihud measures and the constant measures are significantly positive, but those on the residual measures are not. The economic significance of the coefficients is also in line with the sorting analyses. For example, the coefficient of 0.200 for *ln(A)* implies that one standard deviation increase in *ln(A)* (2.68 in our sample period) is associated with a monthly return of 0.52%. With an estimated coefficient of 0.209 for *ln(A_C)* in Model 2, one standard deviation change (2.51) in ln(A_C) leads to an increase in monthly return by 0.53%, almost the same as that for *ln(A)*. These results are consistent with the analyses using monthly measures in that the pricing of the Amihud measure is explained by its trading volume component.

2.4.2 NASDAQ Sample

Since our main analyses use NYSE- and AMEX-listed stocks, for robustness we examine the pricing of the Amihud measure for NASDAQ stocks. Table 5 reports the return regressions for the

NASDAQ stocks using annual measures (Panel D) or monthly measures (Panel E). The results using the NASDAQ sample are similar to our results using the NYSE/AMEX sample. While the Amihud and constant measures are positively associated with expected returns, the residual measure is not. For example, the estimated coefficient of 0.164 for *ln(AT)* in Panel D implies that one standard deviation increase in *ln(AT)* (1.52) is associated with a monthly return premium of 0.25%, similar to the monthly return increase of 0.27% associated with one standard deviation change (1.48) in *ln(AT_C)*. Our conclusions regarding the pricing of the Amihud measures are therefore further supported by the analysis of NASDAQ stocks.

2.4.3 Other Robustness Tests

To align the scales of the measures in the regression analysis and further control for outliers, we repeat the regressions using standardized ranks of the independent variables. In each cross-section, we convert the independent variables into uniform distributions between 0 and 1, where 0 corresponds to the lowest value and 1 the highest value. We then use the transformed variables in the regressions and report the results in Table A.2 of the Internet Appendix. The results are similar to those using the raw values of the variables.

We conduct two additional robustness tests and report the results in Table A.3 of the Internet Appendix, where Panel A repeats the regression analysis but using raw return as the dependent variable instead of FF3-adjusted return, and Panel B and C repeat the regression analysis for the two equal sub-periods 1964-1988 and 1989-2012 separately. The results of these robustness tests are also consistent with our main analysis.

We also consider two alternative Amihud measures. *A_C2* is the intermediate version of the monthly Amihud measure, where we first calculate daily ratio of absolute return to average daily dollar trading volume over the month, and then average the daily ratios across all days in a month. *AT_C2* is constructed as *A_C2* but the denominator is monthly average of daily turnover. We examine the monthly stock returns of portfolios sorted on these two measures and report the results in Table A.4 of the Internet Appendix. The results also show that the intermediate measures are priced but the residual measures are not.

2.4.4 Using Trading Volume or Turnover Directly

Our main analyses use the "constant" measures to retain the volume component of the Amihud measures. Since the "constant" measures are the monthly averages of daily reciprocal of dollar trading volume or turnover, they could have distributions and properties different from the dollar trading volume and turnover themselves. We therefore repeat the regression analyses using the monthly average of daily dollar trading volume or turnover directly.

In Table 6, we estimate return regressions using the natural logarithm of monthly average of daily dollar volume (*ln(VOLUME)*) and residual *ln*(*A*) measure that is the residual of cross-sectional regression of *ln*(*A*) on *ln*(*VOLUME*). Models (1) and (2) present the results for monthly measures and annual measures, respectively. The coefficient on *ln*(*VOLUME*) is significantly negative in both models, indicating that high volume stocks earn lower returns subsequently, a finding consistent with the existing literature (e.g., Brennan, Chordia, and Subrahmanyam 1998). More importantly, the coefficient on residual *ln*(*A*) is negative in both models, suggesting that the Amihud measure is not priced after controlling for the dollar trading volume. Models (3) and (4) further present return regressions on the logarithm of average of daily turnover (*ln*(*TO*)) and residual *ln*(*AT*) that is the residual of cross-sectional regression of *ln*(*AT*) on *ln*(*TO*). The coefficient on *ln*(*TO*) is significantly negative and that on residual *ln*(*AT*) is negative. Overall, the results in Table 6 show that our findings hold when we directly examine dollar trading volume or turnover.

2.5 "Half" and "Directional" Amihud Measures

Brennan, Huh, and Subrahmanyam (2013) propose two "half" Amihud measures constructed using the return-to-turnover ratio on the positive and negative return days separately. They find that, while both "half" measures are associated with a return premium when examined separately, in the multiple return regression framework only the down-day half measure commands a return premium. We therefore examine if the pricing of the "half" Amihud measures is also due to their trading volume component.

The down-day and up-day "half" Amihud measures, *AN* and *AP*, are constructed using the return-to-turnover ratios on the negative and positive return days, respectively:

$$AN_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id}, 0]}{Dvol_{id}} \tag{9}$$

$$AP_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id}, 0]}{Dvol_{id}} \tag{10}$$

where the r_{id} and $Dvol_{id}$ are daily return and daily dollar volume for stock i on day d; D_{it} is the number of days with available ratio in month t.[13] We construct the "constant" measures *AN_C* and *AP_C* corresponding to *AN* and *AP* by replacing the numerator of the daily ratio with a constant one when the ratio is non-zero. We also construct "half" measures corresponding to the turnover-based Amihud measure, *ATN* and *ATP,* where the denominator is daily turnover instead of dollar trading volume.

Panel A of Table 7 presents regression analyses for the *AN* and *AP* measures. Consistent with Brennan, Huh, and Subrahmanyam (2013), both *AN* and *AP* are associated with a return premium when examined separately. More importantly, their constant measures, *AN_C* and *AP_C*, are priced similarly as the half Amihud measures but the residual half measures are not priced. Panel B of Table 7 examines the *ATN* and *ATP* measures, and the results are similar. These results suggest that the pricing of the "half" Amihud measures is also due to their trading volume component.

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[13] We require a stock to have at least 10 days with valid return and volume data in the estimation month to compute the ratios, and at least two positive return days and two negative return days in the estimation month.

Brennan, Huh, and Subrahmanyam (2013) also suggest two "directional" turnover-based Amihud measures based on buy- and sell-volumes. We follow their approach and separate the trading volume into buy and sell volumes using the Lee and Ready algorithm, and construct *ATNS* and *ATPB*, where *ATNS* (*ATPB*) is constructed similarly as *ATN (ATP)* but the denominator of the daily ratio is daily sell (buy) turnover. We also construct the constant versions of these two directional measures and denote them as *ATPB_C* and *ATNS_C*. Panel C of Table 7 repeats the regression analysis for these four measures, and the results indicate that the pricing of the two directional turnover-based Amihud measures (*ATPB* and *ATNS*) is also explained by their trading volume component (*ATPB_C* and *ATNS_C*).

We further include the pairs of half or directional Amihud measures simultaneously in the return regressions. In Panel D of Table 7, Models (1) to (3) show that the coefficients on the down-day "half" measures or sell-volume "directional" measures remain significantly positive and those on the up-day or buy-volume measures are insignificant and close to zero. This result verifies the finding in Brennan, Huh, and Subrahmanyam (2013) that the down-day half measure is priced but not the up-day half measure when both are included in the same regression. Models (4) to (6) re-estimate the regressions but use the constant "half" or "directional" measures, and the results show that the constant down-day measures are priced but the constant up-day measures are not. These results suggest that the observed asymmetric relations between the half or directional Amihud measures and expected return also result from their trading volume component.

3. Does Price Impact or Bid-Ask Spread Explain the Pricing of the Amihud Measure?

3.1 High-Frequency Liquidity Benchmarks

Our findings so far show that the pricing of the Amihud measure is explained by its association with trading volume. A natural question, therefore, is whether the pricing of the trading volume component of the Amihud measure is due to the compensation for price impact. We therefore examine this question using λ, a high-frequency benchmark of cost-per-dollar-volume price impact (Hasbrouck 2009; Goyenko, Holden, and Trzcinka 2009). Previous studies construct this high-frequency price impact benchmark using the intra-day high-frequency trading data and examine how well the low-frequency liquidity proxies capture price impact.

We obtain the transaction data for NYSE/AMEX stocks from 1983 to 2012, including the ISSM data from 1983 to 1992 and the TAQ data from 1993 to 2012. We follow the literature to clean the quotes and trades data, and apply a list of filters on quotes data before calculating NBBO as detailed in Appendix B. We also adopt the methodology in Holden and Jacobsen (2014) to match the trade and quote data for the post-2006 period.

We then follow the literature (Hasbrouck 2009; Goyenko, Holden, and Trzcinka 2009) and construct the high-frequency price impact benchmark. Specifically, for each firm-month, we estimate the price impact benchmark as the slope coefficient λ of the following regression:

$$r_n = \lambda \times SVol_n + u_n, \tag{11}$$

where for the n^{th} five-minute period, r_n is the five-minute stock return calculated as the natural log of the price change over the n^{th} period (We use quote midpoint instead of trade price to calculate the returns).[14] $SVol_n$ is the signed square-root dollar volume of the n^{th} period, and u_n is the error term. We calculate signed square-root dollar volume as $SVol_n = \sum_{k=1}^{K_n} sign_k \times \sqrt{dvol_k}$, where $dvol_n$ is the dollar volume of the k^{th} trade in the n^{th} five-minute period, K_n is the number of trades in the n^{th} period, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification

[14] For the return calculation, the opening trade of each day is deleted to remove the overnight return impact.

method or the tick test.[15 16]

To corroborate the analysis using the cost-per-dollar-volume λ measure, we also examine a non-volume-based percent price impact measure (*PI*), proposed by Goyenko, Holden, and Trzcinka (2009). Unlike the λ measure which evaluates the price response to trading volume, the *PI* measure evaluates the permanent price change of a given trade. Specifically, the percent 5-minute price impact for a trade is defined as the dollar effective spread minus the dollar realized spread, scaled by the prevailing midpoint five minutes after the trade. We then calculate the monthly *PI* measure as the average *PI* for all trades in the estimation month.

In addition to the price impact benchmarks, the high-frequency spread measures are also widely used by the existing literature as liquidity benchmarks. We therefore extend the analysis to the three widely used high-frequency spread benchmarks (Goyenko, Holden and Trzcinka 2009; Fong, Holden, and Trzcinka 2016): 1) Percent quoted spread (*QS*): defined as the difference between the bid and ask quote, divided by the midpoint; 2) Percent effective spread (*ES*): defined as $2 \times |P_k - M_k|$, where P_k is the price of the k^{th} trade, and M_k is the prevailing midpoint for the k^{th} trade. We divide the dollar effective spread by the midpoint and obtain the percent effective spread (*ES*); and 3) Percent realized spread (*RS*): We first calculate the dollar realized spared as $2 \times Sign_k \times |P_k - M_{k+5}|$ where M_{k+5} is the prevailing midpoint 5 minutes after the k^{th} trade, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification method or the tick test. Dividing the dollar realized spread by M_{k+5} yields the percent realized spread (*RS*). We calculate the monthly averages of these spread measures. We winsorize all the high-frequency liquidity benchmarks at the 1st and 99th percentage points in each cross-section to control for outliers.

[15] Joel Hasbrouck estimated the high-frequency price impact measure for a sample of approximately 300 firms each year from 1993 to 2005. For this comparative sample, the correlation between our estimated annual measure and his estimate is 0.97. We thank Joel Hasbrouck for providing his estimates on his website.

[16] We requires at least 10 observations in the regressions of monthly λ estimation. Some of the monthly λ estimates (1.12%) are negative and dropped from the regressions after taking the logarithm.

Before examining the relation between the liquidity benchmarks and the pricing of the Amihud measure, we first examine if the liquidity benchmarks themselves are priced. We examine January and non-January months separately, as the existing literature suggests a seasonality of liquidity premium. Specifically, Eleswarapu and Reinganum (1993) show that the return premium of bid-ask spread is significant only in January, a result confirmed by Hasbrouck (2009) using the Gibbs estimate of effective costs. Table 8 presents return regressions on the liquidity benchmarks for January (Panel A) and non-January (Panel B) separately. We control for firm size because it is well-known that small stocks earn higher returns in January ("January anomaly"). We also include other usual controls such as the book-to-market ratio, momentum, and short-term return reversal.

Panel A of Table 8 shows that the coefficients on the liquidity benchmarks are significantly positive in January except for the *PI* measure which is insignificantly positive. In a stark contrast, Panel B of Table 8 shows that the coefficients on the liquidity benchmarks are insignificant or significantly negative in non-January months. Although consistent with the seasonality of liquidity premium documented by Eleswarapu and Reinganum (1993) and Hasbrouck (2009), the finding that the liquidity benchmarks are priced only in January is puzzling and unexplained by the existing theory of liquidity premium.

3.2 Do High-Frequency Liquidity Benchmarks Explain the Pricing of the Amihud Measure?

Hasbrouck (2009) and Goyenko, Holden, and Trzcinka (2009) find that the Amihud measure has a high correlation with λ. We first revisit this result in Panel A of Table 9, where we calculate cross-sectional correlation coefficients between the liquidity benchmarks and the Amihud measures each month, and then report the time-series averages. Consistent with Hasbrouck (2009) and Goyenko, Holden, and Trzcinka (2009), we find that the Amihud measure (A) has a correlation of 0.737 with price impact (λ), suggesting that the Amihud (2002) measure performs well capturing price impact.

When we remove the size component of the Amihud measure, the resulting *AT* measure has a lower correlation of 0.598 with the price impact measure. When we further focus on the turnover component of the Amihud measure, its correlation with the price impact measure is a mild 0.352. Therefore, although the price impact benchmark is highly correlated with the Amihud (2002) measure, it has a much lower correlation with *AT_C*, the component that drives the pricing of the Amihud measure (Table 2).[17]

Panel B of Table 9 presents the Fama-MacBeth regressions of returns on the price impact benchmark and Amihud measures. In Model (1), the main independent variable *ln(λ)* is the natural log of the price impact measure λ of the month *t*-2. We also include the usual control variables such as size, book-to-market ratio, and past returns that control for momentum and short-term return reversal. The coefficient on *ln(λ)* is insignificantly negative (t-stat -0.67), indicating that the price impact benchmark itself is not positively related to expected return. In Model (2), the coefficient on the "constant" Amihud measure *ln(A_C)* is significantly positive (t-stat 3.80) after controlling for the price impact benchmark. Model (3) further examines the turnover-based Amihud measure, and the results show that the pricing of the constant measure, *ln(AT_C)* also persists after controlling for price impact.

We conduct a number of robustness tests of the λ measure. First, to avoid the estimation of λ being driven by certain days of the estimation month, we estimate daily λ and then average across the days of the estimation month. Second, Easley, Lopez de Prado, and O'Hara (2012) point out that the Lee and Ready algorithm may be more error-prone in the recent high-frequency trading era. As a result, Brennan, Huh, and Subrahmanyam (2013) exclude the post-2006 period from some of their analyses. We therefore conduct the robustness test by excluding the 2006-2012 period. Third, we repeat the analyses without skipping a month between the λ measure and stock return, i.e., matching

[17] For robustness, we also examine the correlations between the price impact benchmark and the half and directional constant Amihud measures (*ATN_C*, *ATP_C*, *ATNS_C*, and *ATPB_C*), and the correlations overall are just around 0.2.

λ of month *t*-1 with return in month *t*. Fourth, we construct annual λ measure instead of monthly measure, and match monthly stock returns with λ of the previous year. For brevity we report these tests in Tables A.5 to A.7 of the Internet Appendix, which confirm our finding that the price impact benchmark is neither priced nor explaining the pricing of the Amihud measure.

In addition to the λ measure, we repeat the regression analysis using the *PI* measure and report the results in Models (4) to (6) in Table 9 Panel B, where the coefficient on *PI* is insignificantly negative like the λ measure, suggesting that this alternative high-frequency price impact measure is not priced either. Moreover, the coefficient on *A_C* or *AT_C* remains significantly positive after controlling for the *PI* measure.

Panel C of Table 9 further presents the Fama-MacBeth return regressions on the natural logs of the high-frequency spread benchmarks. Models (1) and (3) in Panel A of Table 9 show that when the three spread benchmarks are examined separately, none of them has a significantly positive coefficient. Model (4) includes all three spread benchmarks, the price impact benchmark ($ln(\lambda)$), and the constant Amihud measure (*ln*(*A_C*)). The coefficient is significantly positive for *ln*(*A_C*) (t-stat 3.71) but insignificantly negative for the liquidity benchmarks. Model (5) is similar to Model (4) but examine the constant turnover-based Amihud measure (*ln*(*AT_C*)), where the coefficient on *ln*(*AT_C*) is significantly positive but those on the liquidity benchmarks are not. These results show that the pricing of the trading volume component of the Amihud measure is not due to its association with the spread benchmarks either. For the robustness test, we repeat this analysis using the annual Amihud measures and liquidity benchmarks instead of monthly measures in Table A.8 of the Internet Appendix, and find similar results.

3.3 Transaction Cost Component and Non-Cost Component of the Amihud Measure

Consistent with the existing literature, our results show that the Amihud measure is strongly positively correlated with the price impact benchmark. However, the Amihud measure is priced but the price impact benchmark is not. To further understand this contrast, we decompose the Amihud measure into the component associated with transaction costs and the residual component ("non-cost" component), and examine the pricing of the two components separately. We first estimate monthly cross-sectional regressions of *ln(A)*, the natural log of the original Amihud measure, on the natural logs of the high-frequency liquidity benchmarks including *ln(λ)*, *ln(QS)*, *ln(ES)*, and *ln(RS)*. We then calculate the transaction-cost component of the Amihud measure as the fitted value of the regression, and non-cost component as the residual of the regression. The non-cost component, therefore is the part of the Amihud measure that is orthogonal to the transaction cost benchmarks.

The left panel of Table 10 presents the return regressions on the two components of the Amihud measure. In Model (1), the coefficient on the transaction-cost component is insignificantly negative.[18] In contrast, Model (2) shows that the coefficient on the non-cost component is significantly positive. These results remain when both components are included in Model (3), consistent with our previous findings that the pricing of the Amihud measure is not explained by its association with transaction costs. The analyses using the turnover-based Amihud measure (*AT*) also show that the non-cost component of *AT* is priced but the transaction-cost component is not. These results reveal that, although the Amihud measure is highly correlated with transaction costs, it is the non-transaction-cost component that drives the pricing of the Amihud measure.

4. Is the Pricing of Trading Volume Due to Liquidity Premium or Mispricing?

Our results so far show that the pricing of the Amihud measure is explained by its association with trading volume, and that the pricing of the trading volume component is unlikely explained by

[18] We also examine the January seasonality of the pricing of the transaction cost component, and find that, like the transaction cost benchmarks, the transaction cost component is priced in January but not in non-January months.

the compensation for price impact or association with other liquidity benchmarks. Then why is trading volume priced? Is the return premium of trading volume, a.k.a. volume premium, a liquidity premium or not?

It is worth noting that the source of volume premium is the subject of debate in a quite large finance literature. On one hand, trading volume is generally considered a (noisy) liquidity proxy, and it is possible that the volume premium is a liquidity premium associated with some aspect of liquidity that is not reflected in the high-frequency liquidity benchmarks that we examined. On the other hand, a large number of studies have attributed the pricing of trading volume to various non-liquidity factors, most of which are associated with mispricing (investor disagreement, sentiment, investor attention, etc.).

We attempt to distinguish the liquidity and the non-liquidity explanations of the volume premium with a balanced analysis, including two tests on each side of the argument based on the existing literature. This is a challenge as illustrated by the existence of many studies on this topic, and this topic by itself can constitute a stand-alone paper. We acknowledge that none of our tests are perfect but we believe that together they can shed light on the nature of the volume premium.

4.1 Tests of the Liquidity Explanation

4.1.1 Seasonality of Liquidity Premium

Our first test of the liquidity explanation is motivated by the literature on the seasonality of liquidity premium discussed in Section 3.1. If the volume premium is a liquidity premium, then we expect it to demonstrate a similar January seasonality. We focus on two clean measures of trading volume from which the size effect is removed: 1) *AT_C*, the constant version of the turnover-based Amihud measure; and 2) *Turnover*, the monthly average of daily turnover. Both are constructed using only the turnover of a stock.

We estimate firm-level Fama-MacBeth return regressions on the turnover measures for January and non-January separately in Panels A and B of Table 11. We control for firm size as it is well-known that small stocks earn higher returns in January ("January anomaly"). We also include other usual controls including book-to-market ratio, momentum, and reversal. Models (1) and (3) examine the seasonality of volume premium by regressing return on *AT_C* and turnover, respectively. The coefficient on *AT*_C is significantly negative and on turnover is significantly positive, indicating that the volume premium reverses in January. In contrast, the coefficient on *AT_C* is significantly positive and that on turnover is significantly negative in non-January, suggesting that the volume premium remains strong in non-January. When we add the high-frequency liquidity benchmarks, the patterns remain consistent. Therefore, we find that the volume premium exhibits an opposite seasonality to that of the liquidity premium.[19] A caveat of this analysis is that the existing literature offers no theory about the seasonality of liquidity premium. Thus, a conservative interpretation of our findings is that the opposite seasonality suggests that the return premium of trading volume and that of the known liquidity benchmarks may be shaped by distinct mechanisms.

4.1.2 Sub-Periods of Stock Market Illiquidity

Investors demand a liquidity premium because it is costly to liquidate illiquid assets, and such liquidation costs will be higher when market illiquidity is higher (Pástor and Stambaugh 2003). Pástor and Stambaugh also suggest that illiquidity is a state variable and investors whose wealth drops during episodes of high market illiquidity will find greater liquidation costs especially unfavorable. As a result, liquidity premium is expected to be larger in the episodes of high market illiquidity.

Therefore, our second test of the liquidity explanation is to examine the relation between the volume premium and market illiquidity. We use Pástor and Stambaugh's (2003) market illiquidity

[19] For robustness, we also repeat the regression analysis using annual measures and find similar results. These results are reported in Tables A.9 of the Internet Appendix.

measure for this analysis because it is a widely used proxy for aggregate illiquidity and it coincides well with the cycle of market illiquidity. We obtain the monthly measure of market illiquidity for our sample period 1964-2012 from Professor Pástor's data library, and our test design follows Stambaugh, Yu, and Yuan (2012) who examine the relation between anomalies and market sentiment except that our variable of interest is market illiquidity instead of market sentiment. [20]

Panel A of Table 12 examines the volume premium across high and low market illiquidity periods. To ease reading, we denote the "long" portfolio as the top quintile of *AT_C* or the bottom quintile of turnover, and the "short" portfolio as the bottom quintile of *AT_C* or the top quintile of turnover. "Long-Short" is therefore the volume premium. The period of high (low) market illiquidity contains the months where market illiquidity of month t-1 is above (below) the median. The results show that the volume premium is very similar across the period of high market illiquidity and that of low market illiquidity. For example, the return spread of *AT_C* is 0.33% for the low market illiquidity period and 0.32% for the high illiquidity period, with a difference of just 0.02% (t-stat 0.08).

Next, we estimate time-series regressions of portfolio returns to further examine the effect of market illiquidity on the volume premium and control for return factors:

$$R_{it} = a + bIlliq_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t, \tag{12}$$

where R_{it} is the return of turnover-based portfolio i of month t, in excess of risk-free rate. $Illiq_{t-1}$ is market illiquidity measure of month t-1. MKT_t , SMB_t, HML_t and MOM_t are the three Fama-French factors and momentum factor of month t. Stambaugh, Yu, and Yuan (2012) use a similar approach to examine the relation between an anomaly and market sentiment, and our model differs in that our main independent variable is market illiquidity rather than investor sentiment.

Panel B of Table 12 presents the coefficient on the market illiquidity (b) in equation (12). The

[20] We thank Professor Pástor for making this dataset available.

independent variables are returns of quintile portfolios of *AT_C* or turnover, as well as the return spread ("Long-Short"). In the regression of return spread, the coefficient on market illiquidity is significantly negative for both *AT_C* and turnover (t-stats -2.38 and -2.05), indicating that the volume premium is *smaller* in episodes of high market illiquidity after controlling for the return factors. This result does not support the liquidity explanation of the volume premium.

4.2. Tests of Mispricing Explanation

Next, we turn to the mispricing explanation of the volume premium and conduct two tests based on the existing literature.

4.2.1 Sub-Periods of Market Sentiment.

Our first test is motivated by Stambaugh, Yu, and Yuan (2012) who suggest that market wide investor sentiment can be used to identify mispricing and especially overpricing. Specifically, Miller's (1977) theory suggests that in the presence of short-sale constraints, overpricing can be caused by a group of over-optimistic investors. Therefore, overpricing will be greater in the period of high market sentiment which is accompanied by a larger number of over-optimistic investors. Stambaugh, Yu, and Yuan (2012) hypothesize that an anomaly associated with overpricing will be much stronger following high market sentiment, driven by the more negative return of the short leg of the anomaly.

Following Stambaugh, Yu, and Yuan (2012), we obtain the monthly market-wide investor sentiment index (Baker and Wurgler 2006) from July 1965 to December 2010, and define the period of high (low) sentiment as the months with lagged sentiment index above (below) the median.[21] Panel A of Table 13 reports the sorting analyses across high- and low-sentiment periods. To ease reading, we define the "long" portfolio as the top quintile of *AT_C* or the bottom quintile of turnover, and the "short" portfolio as the bottom quintile of *AT_C* or the top quintile of turnover. "Long-Short" is

[21] We thank Professor Jeff Wurgler for making the sentiment index available on his website.

the return spread (volume premium).

Panel A shows that stock returns are lower following high sentiment than following low sentiment. This general pattern is consistent with Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012), indicating that stocks are likely to be overvalued after a high sentiment period. More importantly, consistent with Stambaugh, Yu, and Yuan's prediction, the return spread of *AT_C* or turnover is much larger following high market sentiment than following low market sentiment, and this difference is driven by the more negative return of the short leg. For example, for the *AT_C* portfolios, the short leg is 1.02% lower following high market sentiment than following low market sentiment, which is much larger than the corresponding 0.66% difference for the long leg.

We further estimate time-series regressions to controls for the return factors:

$$R_{it} = a + bSent_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t, \tag{13}$$

where R_{it} is return of *AT_C* or turnover portfolio *i* of month *t*, in excess of risk-free rate. $Sent_{t-1}$ is sentiment index of month *t*-1. MKT_t, SMB_t, HML_t and MOM_t are the Fama-French factors and momentum factor of month *t*. Panel B of Table 13 presents the coefficient on the sentiment index (*b*). For both *AT_C* and turnover, the coefficient for the short leg is significantly negative, indicating a negative relation between short leg return and market sentiment. The coefficient on long leg, on the contrary, is insignificant, suggesting that market sentiment does not have a significant impact on the long leg return. The coefficient on the return spread ("Long-Short") is significantly positive, indicating that the volume premium is stronger following episodes of high market sentiment. These results support the mispricing explanation of the volume premium.

4.2.2 Earnings-Announcement and Non-Earnings-Announcement Periods

Our second test of the mispricing explanation examines the volume premium in the earnings announcement period and non-announcement period separately. This approach is proposed by La

Porta, Lakonishok, Shleifer, Vishny (1997) who suggest that an anomaly associated with mispricing will be more pronounced in an earnings announcement period as earnings news helps correct mispricing. A contemporaneous study by Engelberg, McLean, and Pontiff (2016) also uses this approach to examine a strategy that combines 94 anomalies.[22] If the volume premium is due to high volume stocks being overpriced and therefore earning low future returns, then we expect the volume premium to be more pronounced in the earnings announcement period than in the non-earnings-announcement period.

We collect earnings announcement dates from COMPUSTAT from 1972 to 2012 since the announcement dates are available from 1972. At the beginning of month *t*, we examine the subset of sample firms with earnings announcement in month *t*, and classify these stocks into quintile portfolios according to *AT_C* or turnover of month *t*-2. We use the full sample ranks of *AT_C* or turnover to form portfolios in case the full sample distribution differs from that of the announcement sample. Then for each stock in month *t*, we calculate buy-and-hold abnormal return in the three-day window [-1,1] surrounding the announcement date (BHAR [-1,1]) as the buy-and-hold raw return minus the buy-and-hold value-weighted CRSP return.[23] We also calculate buy-and-hold abnormal returns for the non-announcement days in month *t*. We then calculate portfolio BHARs every month and report time-series averages.

Panel A of Table 14 shows that BHAR [-1,1] is increasing in *AT_C*, and the spread between the top and the bottom quintiles is a large 0.63 percent (t-stat 7.53). We observe very similar results when sorting stocks on the turnover measure. In stark contrast, BHAR for the non-announcement

[22] Engelberg, McLean, and Pontiff (2016) combine 94 anomalies to a single strategy instead of examining these anomalies separately. They find that the abnormal return of this strategy is much stronger in earnings announcement and news days than other days.

[23] If only part of the three-day earnings announcement window [-1,1] falls in month *t*, we do not drop the announcement but use the partial earnings announcement return in month *t*. We conduct robustness tests by dropping these partial announcements, and the results are similar.

period does not vary much across *AT_C* or turnover despite the fact that the non-announcement period is much longer than the announcement window. For example, the spread in non-announcement BHAR is an insignificantly negative -0.10% (t-stat -0.73) for *AT_C*. Panel B further presents Fama-MacBeth regressions of BHARs on *AT_C* or turnover, with the usual controls of firm size, book-to-market ratio, momentum, and short-term return reversal. In the regression of announcement BHAR, the coefficient is significantly positive for *AT_C* and significantly negative for turnover. In the regressions of non-announcement BHAR, however, the coefficient on *AT_C* or turnover becomes insignificant and the sign flips. These results support the sorting analyses that the volume premium is concentrated in the earnings announcement window. [24]

We further investigate analyst forecast errors to directly examine if earnings news indeed helps correct investor misperception. Analyst forecast error for an announcement is the consensus forecast minus actual earnings, scaled by stock price at the end of the previous quarter.[25] A positive forecast error suggests that earnings news corrects investor over-optimism, and a negative error suggests correction of investor over-pessimism. If earnings news corrects overpricing of high volume stocks relative to low volume stocks, then we would expect the forecast error to decrease in *AT_C* and increase in turnover. Models (5) and (6) in Table 14 Panel B regresses forecast error on *AT_C* and turnover, respectively. The coefficient on *AT_C* is significantly negative, and that on turnover is significantly positive, consistent with correction of mispricing. This result is consistent with Lee and Swaminathan (2000) who find that high volume firms experience lower earnings surprises in the subsequent period. To summarize, the four tests in this section do not support the liquidity premium explanation but are consistent with the mispricing explanation of the volume premium.

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[24] To address the concern that the relation between trading volume and liquidity varies across earnings announcement and non-announcement periods, we show in Table A.10 of the Internet Appendix similar correlations between the price impact benchmarks and Amihud measures for earnings announcement period and non-earnings announcement period.

[25] Consensus analyst forecast is the monthly median analyst forecast proceeding the earnings announcement. We obtain both consensus forecast and actual earnings from the IBES unadjusted summary file.

5. Pricing of the Amihud Measure as a Systematic Factor

The Amihud measure has also been used to examine the liquidity commonality (Kamara, Lou and Sadka, 2008; Karolyi, Lee, and van Dijk, 2012) and the pricing of liquidity as a systematic risk factor (Acharya and Pedersen, 2005; Wu, 2015). Consistent with the findings in our paper, Karolyi, Lee, and van Dijk (2012) find that the commonality in turnover is the most reliable liquidity-demand-side variable to explain the time-variation in liquidity commonality where liquidity is measured by the Amihud measure. In this section, we extend our analysis to examine whether the trading volume component is also primarily responsible for the pricing of the Amihud measure as a systematic factor.

We create a systematic factor for each Amihud measure: the original Amihud (2002) measure *A*, the turnover-based Amihud measure *AT*, and their constant versions (*A_C* and *AT_C*), respectively. Following the literature (e.g., Pástor and Stambaugh 2003; Sadka 2006), for each Amihud measure, we obtain the monthly aggregate measure by calculating the equal-weighted average across all stocks, and then estimate time-series regressions using an AR(2) model. We construct the monthly factor as the residual of the AR(2) model multiplied by -1 so that negative values of the factor signify deteriorating market conditions.

We examine the pricing of the systematic factors using the monthly Fama-MacBeth regressions of stock returns on the factor loadings, the level of the Amihud measure (as a characteristic), as well as our standard control variables. The factor loadings are the coefficients on the respective Amihud factor in a firm-level time-series regression using data from month t-60 to t-1, where the model includes the Fama-French three factors, momentum factor, and the respective factor based on the Amihud measure. The monthly regressions are estimated from 1967 to 2012, a total of 552 months, and the results are presented in Table 15. We first include our usual controls and then further control for idiosyncratic volatility for robustness test as in our main analysis (Table 5).

Consistent with Acharya and Pedersen (2005), we find that the original Amihud measure is priced as a systematic factor. The coefficient for the *A* factor beta is 0.004 in Model (4) of Panel A, which is translated into a monthly premium of 0.17% for one standard deviation change in beta (41.86 in our sample). The *A_C* beta is also priced but the Residual *A* factor beta, the residual of a cross-sectional regression of A factor beta on *A_C* factor beta, is not priced. The estimated coefficient for the *A_C* factor beta (0.083) in Model (5) corresponds to a monthly premium of 0.12% for one standard deviation change in beta (1.485 in our sample). This magnitude is slightly higher than the premium (0.09%) documented in Acharya and Pedersen (2005).

The results in Panel B further provide evidence that the *AT_C* beta has similar information as the *AT* beta. When idiosyncratic volatility is not included as a control variable, neither beta has a significant premium, but when idiosyncratic volatility is included, both yield significant premia and the economic magnitude is similar too. The estimated coefficients in Model (4) and (5) imply that the return premium for one standard deviation increase in *AT* beta (4.18) and *AT_C* beta (0.064) are 0.09% and 0.08%, respectively, which are comparable to the premium (0.09%) reported in Archaya and Pedersen (2005). Additionally, when *AT_C* beta and Residual *AT* factor beta—the residual of a cross-sectional regression of *AT* factor beta on *AT_C* factor beta—are included, the coefficient on Residual *AT* factor beta is not significant while the coefficient for AT_C factor beta remains significant. Overall, the results in Table 15 suggest that the pricing of the Amihud measure as a systematic factor is also primarily driven by the volume component, not its return-to-volume construct.

Differing from the existing literature on liquidity risk, Wu (2015) finds that an extreme liquidity risk factor created using the Amihud measure is priced. We follow her empirical framework but construct an alternative measure of extreme risk factor by replacing the Amihud measure with its constant version. We find similar return premia for the factor loadings on the two measures of extreme risk. The result, not tabulated for the sake of brevity, indicates that our conclusion that the pricing of the Amihud measure as a systematic factor is due to its volume component can be extended to the use of the Amihud measure in evaluating extreme liquidity risk.

6. Conclusion

We examine the pricing of the Amihud (2002) measure, one of the most widely used liquidity proxies in the current finance literature. We find that the return premium associated with the Amihud (2002) measure is driven by its association with trading volume but not its construct of return-to-volume ratio to capture price impact. A "constant" measure using only the trading volume component exhibits a return predictability matching that of the Amihud (2002) measure, and the return premium associated with the Amihud (2002) measure disappears once the variation of the trading volume component is removed. These findings survive a broad set of robustness tests. Further analyses show that the high-frequency price impact and spread benchmarks do not explain the pricing of the trading volume component of the Amihud measure. In fact, the pricing of these liquidity benchmarks exhibits strong January seasonality and disappears outside of January. Additionally, we find evidence that the return premium associated with trading volume is associated with mispricing but not liquidity premium. Finally, we extend the analysis to systematic liquidity factor and the results show that the pricing of the Amihud measure as a systematic factor is also due to its volume component.

Our findings deepen the understanding of the Amihud (2002) measure, a very widely used liquidity measure in the finance literature. On one hand, we confirm that the Amihud (2002) measure does a good job capturing stock liquidity and price impact, as the Amihud measure is highly correlated with the high-frequency price impact benchmark. Therefore, the Amihud measure is useful in measuring the level of stock illiquidity. On the other hand, our findings contradict the general view that the pricing of the Amihud measure captures the compensation for price impact or liquidity premium. One may find it puzzling that the Amihud measure is highly correlated with the price impact measure, but the former is priced and the latter is not. It is worth noting that all the three components of the Amihud measure (absolute return, size, and turnover) could contribute to the correlation between the Amihud measure and price impact. The turnover component (*AT_C*), which drives the pricing of the Amihud measure, has a much lower correlation with price impact (0.352, Table 8). Our findings therefore call for caution in the use of the Amihud measure to examine liquidity premium, control for liquidity in the tests of asset pricing, or construct liquidity factor.

Our findings also have important general implications for how to measure liquidity and how liquidity affects security prices. Motivated by the rapidly growing literature of stock liquidity, a number of studies have proposed low-frequency liquidity proxies using daily stock market data, and the validity of these measures is usually assessed by whether they are correlated with expected returns. Goyenko, Holden and Trzinka (2009) realize this issue and shed light on how well these low-frequency measures measure liquidity by examining their correlations with the corresponding high-frequency liquidity benchmarks.[26] Our findings illustrate the importance of conducting in-depth analysis of the return premium of low-frequency liquidity measure. Additionally, our results show that the price impact and spread benchmarks, the major components of transaction cost, are priced only in January but not in the full sample period. This puzzling result seems to contradict the theory and calls for further analysis.

[26] Corwin and Schultz (2012) is another example of validating low-frequency measures using corresponding high-frequency liquidity benchmarks.

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Appendix A: Variable Definitions

Variable	Definition
A	The original Amihud (2002) measure, constructed as $A_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\vert r_{id} \vert}{Dvol_{id}}$ where r_{id} and $Dvol_{id}$ are daily return and daily dollar trading volume for stock *i* on day *d*; D_{it} is the number of days with available ratio in the estimation period *t*.
A_C	The "constant" version of the Amihud measure, constructed as $A\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{1}{Dvol_{id}}$
AT	The turnover-based Amihud measure from Brennan, Huh, and Subrahmanyam (2013), constructed as $AT_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\vert r_{id} \vert}{TO_{id}}$ where TO_{id} is the daily turnover.
AT_C	The "constant" version of the turnover-based Amihud measure, $AT\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{1}{TO_{id}}$
Res. A Measure	The residual *A* measure, residuals from the monthly cross-sectional regressions of the *A* measures on the *A_C* measures.
Res. AT Measure	The residual AT measure, residuals from the monthly cross-sectional regressions of the *AT* measures on the *AT_C* measures.
|Ret|	The return component of the Amihud measure, calculated as the average of daily absolute returns over the estimation period of the Amihud measure.
S	The size component of the Amihud measure, calculated as the average of market capitalization over the estimation period of the Amihud measure.
AN and AP	The two "half" Amihud measures: $AN_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]}{Dvol_{id}}$, $AP_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]}{Dvol_{id}}$
AN_C and AP_C	The "constant" version of the half Amihud measures: $AN\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]/r_{id}}{Dvol_{id}}$, $AP\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]/r_{id}}{Dvol_{id}}$
ATN and ATP	The two "half" turnover-based Amihud measures from Brennan, Huh, and Subrahmanyam (2013): $ATN_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]}{TO_{id}}$, $ATP_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]}{TO_{id}}$
ATN_C and ATP_C	The "constant" version of the half turnover-based Amihud measures: $ATN\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]/r_{id}}{TO_{id}}$, $ATP\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]/r_{id}}{TO_{id}}$
ATNS and ATPB	The two "half and directional" turnover-based Amihud measures constructed using buy volume and sell volume: $ATNS_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]}{STO_{id}}$, $ATPB_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]}{BTO_{id}}$, where BTO and STO are daily buy- and sell-turnover.
ATNS_C and ATPB_C	The "constant" versions of ATNS and ATPB. $ATNS\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{-\min[r_{id},0]/r_{id}}{STO_{id}}$, $ATPB\_C_{it} = \frac{1}{D_{it}} \sum_{d=1}^{Dit} \frac{\max[r_{id},0]/r_{id}}{BTO_{id}}$

Variable	Definition
ME	Market capitalization at the end of the previous year
B/M	The book-to-market ratio
Ret[-12,-2]	The cumulative stock return from month t-12 to month t-2
Ret[-1]	Stock return of month t-1.
λ	High-frequency price impact measure from Hasbrouck (2009), estimated using the regression model $r_n = \lambda \times SVol_n + u_n$, where for the n^{th} five-minute period, r_n is the five-minute stock return calculated as the natural log of the price change over the n^{th} period (We use quote midpoint instead of trade price to calculate price change). $SVol_n$ is the signed square-root dollar volume of the n^{th} period, and u_n is the error term. We calculate signed square-root dollar volume as $SVol_n = \sum_{k=1}^{K_n} sign_k \times \sqrt{dvol_k}$, where $dvol_n$ is the dollar volume of the k^{th} trade in the n^{th} five-minute period, K_n is the number of trades in the n^{th} period, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification method or the tick test.
QS	Percent quoted spread, defined as the difference between the bid and ask quote, divided by the midpoint. The spread is averaged across the estimation period.
ES	Percent effective spread, defined as the dollar effective spread, $2 \times \lvert P_k - M_k \rvert$, divided by the quotes midpoint, where P_k is the price of the k^{th} trade, and M_k is the prevailing midpoint for the k^{th} trade. The spread is calculated for each trade and then averaged across the estimation period.
RS	Percent realized spread, defined as the dollar realized spread, $2 \times Sign_k \times \lvert P_k - M_{k+5} \rvert$, divided by the post-trade quotes midpoint M_{k+5}. M_{k+5} is the prevailing midpoint 5 minutes after the k^{th} trade, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification method or the tick test. The spread is calculated for each trade and then averaged across the estimation period.
PI	The percent 5-minute price impact (*PI*), defined is the dollar effective spread minus the dollar realized spread, scaled by $M_{k+5.}$ The *PI* measure is calculated for each trade and then averaged across the estimation period.

Appendix B: Procedures to Clean the Quotes and Trades Data

Following Holden and Jacobsen (2014), we use only NBBO eligible quotes from 9:00am to 4:00pm. For TAQ data, we do not consider quotes with mode among {4,7,9,11,13,14,19,20,27,28}. For ISSM data, NBBO eligible quotes are those with mode in (' ', 'A', 'B', 'H', 'O', 'R'). Quotes meeting one of the filters below are not considered in the NBBO calculation: 1. Bid > offer >0; 2. Bid >0 and offer =0; 3. Offer >0 and bid = 0; 4. Spread >5 and bid >0 and offer > 0; 5. Offer if offer <=0 or missing; Offer if size <= 0 or missing; 6. Bid if bid <=0 or missing; Bid if size <=0 or missing. Note that these invalid quotes are not deleted although they are not considered for the purpose of calculating NBBOs.

We only keep trades in the trading hours from 9:30am to 4:00pm. For ISSM data, trades with special sale condition ('C', 'L', 'N', 'R', 'O', 'Z') are excluded. For TAQ data, trades with sale condition ('A' 'C' 'D' 'G' 'L' 'N' 'O' 'R' 'X' 'Z' '8' '9') are excluded. A trade also needs to have a positive price and size. After cleaning up the quotes and trades data, we then match each trade with the prevailing NBBO. Before 1999, we assume a quote delay of 2 seconds, and zero second between 1999 and 2005. For the year 2006 and afterwards, we adopt the methodology in Holden and Jacobsen (2014). Each trade is then assigned according to the Lee and Ready (1991) trading classification method or the tick test. A trade is classified as buyer (seller) initiated if the trade price is above (below) the prevailing quote midpoint. If the trade price is equal to the midpoint, then we use the tick test.

Table 1
Summary Statistics and Correlations

Panel A presents summary statistics of the main variables that are constructed monthly from November 1963 to October 2012 for the 1,197,252 firm-months in our sample. Our sample contains ordinary common shares (share codes 10 or 11) listed in NYSE or AMEX. *A* is the original Amihud (2002) measure, defined as the daily ratio of absolute return to dollar trading volume, averaged across all days in a month. *AT* is the turnover-based Amihud (2002) measure, defined as the monthly average of the daily ratio of absolute return to turnover, where turnover is daily share volume divided by the shares outstanding. *A_C* and *AT_C* are constructed as *A* and *AT*, respectively, but the numerators of the ratios are 1 instead of the absolute return. |Ret| is the monthly average of daily absolute return. The Amihud measures, as well as |Ret|, are winsorized at the 1 and 99 percentage points in each cross-section. *ME* for a firm is the firm's market capitalization at the end of the previous year (in millions of dollars). *B/M* is the book-to-market ratio calculated as a firm's book value divided by the firm's market capitalization. The B/M ratio is winsorized at the 0.5% and 99.5% level in each cross-section. To ease reading, we multiply *A* and *A_C* by 10^6. Panel B presents the time-series averages of the cross-sectional correlation coefficients among the various versions of the Amihud measure and |Ret|. We first calculate cross-sectional correlation coefficients among the variables for each month, and then report the time-series averages of the cross-sectional correlation coefficients.

Panel A: Summary Statistics

	Mean	STD	Q10	Q25	Q50	Q75	Q90
A	3.133	14.978	0.001	0.008	0.101	0.861	4.908
AT	35.87	70.75	2.46	5.68	14.46	35.87	80.97
A_C	116.35	329.34	0.07	0.62	8.29	72.29	302.82
AT_C	2427.22	3451.93	180.74	423.06	1169.49	2989.59	5993.75
|Ret|	0.020	0.014	0.008	0.011	0.016	0.024	0.035
ME ($M)	2,303.2	11,717.0	10.8	35.1	179.9	964.3	3,712.9
B/M	0.987	0.976	0.249	0.438	0.747	1.218	1.889

Panel B: Correlations Among Amihud Measures

	A	AT	A_C	AT_C	|Ret|
A	1.000				
AT	0.691	1.000			
A_C	0.899	0.685	1.000		
AT_C	0.312	0.746	0.443	1.000	
|Ret|	0.489	0.347	0.394	-0.040	1.000

Table 2

Monthly Fama-MacBeth Regressions of Stock Returns: Decomposition of Amihud Measure

This table presents monthly Fama-MacBeth regressions of stock returns on the components of the Amihud (2002) measure from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return of month *t*, calculated based on the Fama-French three-factor model, where the factor loadings are estimated in the preceding sixty months. The independent variables include the natural logs of the Amihud measure and its components in month *t*-2. *A* is the original monthly Amihud measure, and *A_C* is defined as *A* but the numerator of the ratio is 1 instead of absolute return. *AT* is the turnover-based Amihud (2002) measure, and *AT_C* is constructed as *AT* but the numerator of the ratio is 1 instead of absolute return. |*Ret*| is the average of daily absolute return over the estimation month. *S* is the monthly average of daily market capitalization over the estimation month. We also control for a number of firm characteristics. *ME* is a firm's market capitalization at the end of the previous year (in millions of dollars). *B/M* is the book-to-market ratio calculated as a firm's book value divided by the firm's market capitalization. For the regression of month *t*, *Ret*[-12,-2] is the cumulative stock return from month *t*-12 to month *t*-2, and *Ret*[-1] is the stock return of month *t*-1. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). We also report the time-series averages of the number of observations and adjusted R^2 of the cross-sectional regressions. All the regressions include a constant which is not reported for brevity. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: FF3-Adjusted Return			
	(1)	(2)	(3)	(4)
ln(A)	0.119***			
	(3.01)			
ln(AT)		0.254***		
		(4.99)		
ln(A_C)			0.165***	
			(3.92)	
ln(AT_C)				0.202***
				(4.57)
ln|Ret|			-0.319**	-0.265*
			(-2.13)	(-1.67)
ln(S)		0.012		-0.052**
		(0.53)		(-2.11)
ln(ME)	0.080**		0.091**	
	(2.04)		(2.01)	
B/M	0.044	0.030	0.011	0.004
	(1.04)	(0.72)	(0.26)	(0.10)
Ret[-12,-2]	0.430**	0.355*	0.320*	0.330*
	(2.05)	(1.67)	(1.74)	(1.68)
Ret[-1]	-6.755***	-6.942***	-7.242***	-7.232***
	(-12.88)	(-13.24)	(-13.80)	(-13.78)
Adj. R^2	0.031	0.031	0.037	0.037
Ave. # obs	1,775	1,775	1,775	1,775
# Months	588	588	588	588

Table 3: Monthly Stock Returns of Portfolios Sorted on Amihud Measures

Panel A presents monthly returns (%) of portfolios sorted on the Amihud measures. *A* is the monthly Amihud (2002) measure, defined as the daily ratio of absolute return to dollar trading volume, averaged across all days in a month. At the beginning of each month *t* from 1964 to 2012, stocks are sorted into quintile portfolios according to the *A* measures of month *t*-2. We then calculate monthly equal-weighted portfolio returns for the quintile portfolios and report time-series average portfolio returns or four-factor alphas, where the four-factor alpha is constructed using the three Fama-French factors and the momentum factor (UMD). The differences between the top and bottom quintiles are also reported with associated t-statistics. We then repeat the sorting for the *A_C* measure and the residual *A* measure, where *A_C* is constructed as *A* but the numerator of the ratio is 1 instead of absolute return, and the residual *A* measure is the residual from the monthly cross-sectional regression of the *A* measure on the *A_C* measure. Panel B is similar to Panel A except that we sort stocks based on *AT*, *AT_C*, and residual *AT*, where *AT* is the turnover-based Amihud (2002) measure, defined as the monthly average of the daily ratio of absolute return to turnover. *AT_C* is constructed as *AT* but the numerator of the ratio is 1 instead of absolute return, and the residual *AT* measure is the residual from the monthly cross-sectional regression of the *AT* measure on the *AT_C* measure. The t-statistics (in parentheses) are calculated using Newey-West robust standard errors with 6 lags.

	Portfolios Sorted on Amihud Measures						
	Low	**2**	**3**	**4**	**High**	**H – L**	**t-stat**
Panel A: Sorted on Original Amihud Measures							
Sorted on A							
Raw Return	0.96	1.16	1.23	1.29	1.53	0.56	(2.36)
Four-Factor Alpha	-0.03	0.04	0.03	0.10	0.32	0.35	(2.31)
Sorted on A_C							
Raw Return	0.96	1.13	1.23	1.28	1.57	0.61	(2.95)
Four-Factor Alpha	-0.05	-0.01	0.03	0.11	0.39	0.44	(3.20)
Sorted on Res. A Measure							
Raw Return	1.39	1.29	1.19	1.10	1.21	-0.17	(-1.05)
Four-Factor Alpha	0.25	0.14	0.04	-0.05	0.09	-0.16	(-0.96)
Panel B: Sorted on Turnover-Based Amihud Measures							
Sorted on AT							
Raw Return	1.02	1.18	1.25	1.31	1.41	0.39	(2.64)
Four-Factor Alpha	-0.19	0.04	0.13	0.19	0.30	0.49	(3.65)
Sorted on AT_C							
Raw Return	1.00	1.26	1.23	1.36	1.33	0.33	(2.39)
Four-Factor Alpha	-0.26	0.07	0.10	0.26	0.30	0.55	(4.47)
Sorted on Res. AT Measure							
Raw Return	1.17	1.18	1.23	1.25	1.35	0.18	(0.74)
Four-Factor Alpha	0.19	0.06	0.03	0.03	0.16	-0.03	(-0.21)

Table 4
Monthly Fama-MacBeth Regressions of Stock Returns on Amihud Measures

Panel A presents the results of monthly Fama-MacBeth regressions of stock returns on the Amihud (2002) measures from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return in month *t,* which is calculated based on the Fama-French three-factor model where the factor loadings are estimated over the preceding sixty months [*t*-60,*t*-1] with at least 24 observations for each firm-level time-series regression. The independent variables are measured at month *t*-2. *Ln*(*A*) is the natural log of the monthly Amihud (2002) measure (*A*). *Ln*(*A_C*) is the natural log of *A_C*. *Res. ln*(*A*) is the residual from the monthly cross-sectional regression of *ln*(*A*) on *ln*(*A_C*). We also control for firm characteristics including size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), reversal (Ret[-1]), and idiosyncratic return volatility (Idio. Vol.). We estimate a cross-sectional regression in each month and then report the time-series means of the coefficients and t-statistics (in parentheses, using Newey-West robust standard errors with 6 lags). We also report the time-series averages of the number of observations and adjusted R^2 of the cross-sectional regressions. Panel B is similar to Panel A except that the independent variables are turnover-based Amihud measures. *Res. ln*(*AT*) is the residual from the monthly cross-sectional regression of *ln*(*AT*) on *ln*(*AT_C*). All the regressions include an intercept. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Original Amihud Measures						**Panel B: Turnover-Based Amihud Measures**				
	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
ln(A)	0.119***					**ln(AT)**	0.163***				
	(3.01)						(3.95)				
ln(A_C)		0.183***		0.130***	0.120***	**ln(AT_C)**		0.223***		0.198***	0.192***
		(4.79)		(3.31)	(3.11)			(5.77)		(5.10)	(5.12)
Res. ln(A)			-0.383***	-0.248***	-0.303***	**Res. ln(AT)**			-0.246***	-0.207**	-0.267***
			(-5.07)	(-3.14)	(-4.65)				(-3.02)	(-2.53)	(-3.79)
Idio. Vol.					-2.903	**Idio. Vol.**					-2.768
					(-0.57)						(-0.54)
ln(ME)	0.080**	0.144***	-0.067***	0.069*	0.062*	**ln(ME)**	-0.025	-0.027	-0.069***	-0.053**	-0.058**
	(2.04)	(3.14)	(-2.48)	(1.82)	(1.74)		(-0.99)	(-0.91)	(2.96)	(-2.15)	(-2.51)
B/M	0.044	0.034	0.028	0.026	0.007	**B/M**	0.041	0.027	0.044	0.025	0.006
	(1.04)	(0.81)	(0.66)	(0.61)	(0.16)		(0.97)	(0.65)	(1.04)	(0.58)	(0.13)
Ret[-12,-2]	0.430**	0.542***	0.372*	0.423**	0.408**	**Ret[-12,-2]**	0.453**	0.505**	0.334*	0.429**	0.415**
	(2.05)	(2.63)	(1.88)	(2.09)	(2.02)		(2.18)	(2.49)	(1.67)	(2.13)	(2.06)
Ret[-1]	-6.755***	-6.716***	-6.910***	-6.915***	-7.066***	**Ret[-1]**	-6.725***	-6.734***	-6.919***	-6.897***	-7.051***
	(-12.88)	(-12.83)	(-13.27)	(-13.23)	(-13.42)		(-12.86)	(-12.91)	(-13.28)	(-13.23)	(-13.42)
Adj. R^2	0.031	0.032	0.033	0.035	0.040	**Adj. R^2**	0.031	0.032	0.032	0.035	0.040
Ave. # obs	1,775	1,775	1,775	1,775	1,775	**Ave. # obs**	1,775	1,775	1,775	1,775	1,775
# Months	588	588	588	588	588	**# Months**	588	588	588	588	588

Table 5: Robustness Tests: Annual Measures and NASDAQ Sample

The table presents the robustness results using the annual measures and NASDAQ sample. Panel A presents the correlations among the annual Amihud measures for the 98,244 firm-years from 1963 to 2011. Panel B presents monthly four-factor alphas of portfolios sorted on the annual Amihud measures. Panel C presents the monthly Fama-MacBeth regressions of FF3-adjusted returns from 1964 to 2012. Panels D and E report the monthly Fama-MacBeth regressions of FF3-adjusted returns for the NASDAQ sample. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels.

Panel A: Correlations Among Amihud Measures: Annual Measures

	A	AT	A_C	AT_C
A	1.000			
AT	0.682	1.000		
A_C	0.941	0.705	1.000	
AT_C	0.303	0.782	0.406	1.000

Panel B: Four-Factor Alphas (%) Sorted on Amihud Measures: Annual Measures

	Low	2	3	4	High	H – L	t-stat
Original Amihud Measures							
Sorted on A	0.04	-0.01	-0.02	0.04	0.47	0.43	(2.83)
Sorted on A_C	0.01	-0.04	-0.02	0.07	0.51	0.50	(3.50)
Sorted on Residual A	0.33	0.12	-0.02	-0.04	0.14	-0.20	(-1.40)
Turnover-Based Amihud Measures							
Sorted on AT	-0.16	0.02	0.09	0.08	0.49	0.65	(4.23)
Sorted on AT_C	-0.23	0.03	0.08	0.23	0.41	0.63	(4.98)
Sorted on Residual A	0.18	0.06	-0.02	-0.02	0.32	0.14	(0.74)

Panel C: Fama-MacBeth Regressions of Stock Returns: Annual Measures

	(1)	(2)	(3)		(4)	(5)	(6)
ln(A)	0.200***			**ln(AT)**	0.246***		
	(4.12)				(4.86)		
ln(A_C)		0.209***	0.183***	**ln(AT_C)**		0.244***	0.238***
		(4.74)	(3.78)			(5.60)	(5.14)
Res. ln(A)			-0.158	**Res. ln(AT)**			-0.099
			(-1.15)				(-0.70)
Controls	Yes	Yes	Yes		Yes	Yes	Yes

Panel D: Regressions on the *Annual* Amihud Measures: NASDAQ Sample (1983-2012)

	(1)	(2)	(3)		(4)	(5)	(6)
ln(A)	0.090*			**ln(AT)**	0.164***		
	(1.85)				(3.41)		
ln(A_C)		0.113**	0.113**	**ln(AT_C)**		0.183***	0.185***
		(2.00)	(2.29)			(3.21)	(3.62)
Res. ln(A)			-0.076	**Res. ln(AT)**			-0.016
			(-0.51)				(-0.12)
Controls	Yes	Yes	Yes		Yes	Yes	Yes

Panel E: Regressions on the *Monthly* Amihud Measures: NASDAQ Sample (1983-2012)

	(1)	(2)	(3)		(4)	(5)	(6)
ln(A)	0.055			**ln(AT)**	0.094*		
	(1.01)				(1.73)		
ln(A_C)		0.158**	0.119*	**ln(AT_C)**		0.190***	0.168***
		(2.55)	(1.95)			(3.06)	(2.73)
Res. ln(A)			-0.313***	**Res. ln(AT)**			-0.261**
			(-3.05)				(-2.52)
Controls	Yes	Yes	Yes		Yes	Yes	Yes

Table 6
Monthly Fama-MacBeth Regressions of Stock Returns: Measures Using Average Dollar Trading Volume or Turnover

This table presents the estimation results of monthly Fama-MacBeth regressions of stock returns on the Amihud (2002) measures from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return. FF3-adjusted return of month *t* is calculated based on the Fama-French three-factor model where the factor loadings are estimated over the preceding sixty months [*t*-60,*t*-1] with at least 24 observations for each firm-level time-series regression. For the independent variables, *ln*(*VOLUME*) is the natural log of the dollar trading volume measure, defined as the average daily dollar trading volume in the month *t*-2 for monthly measure or year *y*-1 for annual measure. *Res. ln*(*A*) is the residual from the monthly cross-sectional regression of *ln*(*A*) on *ln*(*VOLUME*), where *ln(A)* is the natural log of the Amihud (2002) measure in the month *t*-2 for monthly measure or year *y*-1 for annual measure. The right panel is similar to the left panel except that *ln*(*TO*) is the natural log of the turnover measure, defined as the average daily turnover in the month t-2 or year t-1. *Res. ln*(*AT*) is the residual from the monthly cross-sectional regression of *ln*(*AT*) on *ln*(*TO*), where *ln*(*AT*) is the natural log of the turnover-based Amihud measure in t-2 or year t-1. We also control for a number of firm characteristics. *ln(ME)* is the natural log of market capitalization; *B/M* is the ratio of book value of equity to market value of equity; *Ret*[-12,-2] is the cumulative return from month *t*-12 to month *t*-2, and *Ret*[-1] is the stock return of month *t*-1. We estimate a cross-sectional regression in each month and then report the time-series means of the coefficients and t-statistics (in parentheses). We also report the time-series averages of the number of observations and adjusted R^2 of the cross-sectional regressions. All the regressions include a constant which is not reported for brevity. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return					
	Monthly Measures	**Annual Measures**		**Monthly Measures**	**Annual Measures**
	(1)	(2)		(3)	(4)
ln(VOLUME)	-0.158***	-0.248***	**ln(TO)**	-0.216***	-0.297***
	(-3.65)	(-4.82)		(-5.09)	(-5.86)
Res. ln(A)	-0.167***	-0.129	**Res. ln(AT)**	-0.106*	-0.102
	(-2.74)	(-1.45)		(-1.69)	(-1.08)
ln(ME)	0.091**	0.186***	**ln(ME)**	-0.067***	-0.057**
	(2.28)	(4.09)		(-2.71)	(-2.25)
B/M	0.026	0.007	**B/M**	0.023	-0.000
	(0.62)	(0.16)		(0.55)	(-0.01)
Ret[-12,-2]	0.477**	0.363**	**Ret[-12,-2]**	0.468**	0.394**
	(2.32)	(2.00)		(2.30)	(2.00)
Ret[-1]	-6.902***	-7.182***	**Ret[-1]**	-6.894***	-7.129***
	(-13.15)	(-13.78)		(-13.18)	(-13.69)
Adj. R^2	0.034	0.036	**Adj. R^2**	0.034	0.036
Ave. # obs	1,771	1,765	**Ave. # obs**	1,769	1,765
# Months	588	588	**# Months**	588	588

Table 7
Monthly Fama-MacBeth Regressions of Stock Returns:
"Half" and "Directional" Amihud Measures

This table presents the estimation results of monthly Fama-MacBeth regressions of stock returns on the half and directional Amihud measures from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return. FF3-adjusted return of month *t* is calculated based on the Fama-French three-factor model where the factor loadings are estimated over the preceding sixty months [*t*-60,*t*-1] with at least 24 observations for each firm-level time-series regression. The independent variables are monthly Amihud measures of month *t*-2. In Panel A, the independent variables are half Amihud measures. *Ln*(*AN*) is the natural log of the monthly half Amihud measure for negative return days (*AN*), which is constructed as *A* but the absolute return-to-volume ratio is non-zero for only the negative return days. *Ln*(*AN_C*) is the natural log of *AN_C* which is constructed as *AN* but the numerator of the ratio is 1 instead of absolute return. *Res. ln*(*AN*) is the residual from the monthly cross-sectional regression of *ln*(*AN*) on *ln*(*AN_C*). *AP* is the monthly half Amihud measure for positive return days, and *AP_C* is the constant version of the *AP* measure. *Res. ln*(*AP*) is the residual from the monthly cross-sectional regression of *ln*(*AP*) on *ln*(*AP_C*). Panel B is similar to Panel A except that independent variables are the half turnover-based Amihud measures. *ATN* and *ATN_C* (*ATP* and *ATP_C*) are constructed as *AN* and *AN_C* (*AP* ad *AP_C*) except that the denominator of the daily ratio is turnover instead of dollar trading volume. Panel C is similar to Panel A except that independent variables are the directional turnover-based Amihud measures. *ATNS* and *ATNS_C* are constructed as *ATN* and *ATN_C* except that the denominator of the daily ratio is sell turnover (sell volume divided by total shares outstanding). *ATPB* and *ATPB_C* are constructed as *ATP* and *ATP_C* except that the denominator of the daily ratio is buy turnover (buy volume divided by total shares outstanding). Panel D includes the pairs of half measures or directional measures in the same regressions. The regressions also control for size, book-to-market ratio, momentum, reversal, and an intercept, but for brevity their coefficients are not reported. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return							
Panel A: Regressions on the Negative/Positive Amihud Measures: Monthly Measures							
	(1)	(2)	(3)		(4)	(5)	(6)
ln(AN)	0.121***			**ln(AP)**	0.087**		
	(3.55)				(2.35)		
ln(AN_C)		0.172***	0.123***	**ln(AP_C)**		0.152***	0.087**
		(5.17)	(3.42)			(4.25)	(2.29)
Res. ln(AN)			-0.220**	**Res. ln(AP)**			-0.276***
			(-2.33)				(-3.28)
Controls	Yes	Yes	Yes	**Controls**	Yes	Yes	Yes
Panel B: Regressions on the Negative/Positive Turnover-Based Amihud Measures							
	(1)	(2)	(3)		(4)	(5)	(6)
ln(ATN)	0.219***			**ln(ATP)**	0.264***		
	(4.36)				(5.33)		
ln(ATN_C)		0.239***	0.219***	**ln(ATP_C)**		0.258***	0.253***
		(5.45)	(4.70)			(6.05)	(5.75)
Res. ln(ATN)			-0.137	**Res. ln(ATP)**			-0.034
			(-0.99)				(-0.25)
Controls	Yes	Yes	Yes	**Controls**	Yes	Yes	Yes
Panel C: Regressions on the Directional Turnover-Based Amihud Measures							
	(1)	(2)	(3)		(4)	(5)	(6)
ln(ATNS)	0.088***			**ln(ATPB)**	0.053		
	(2.55)				(1.52)		
ln(ATNS_C)		0.157***	0.136***	**ln(ATPB_C)**		0.117***	0.100***
		(4.41)	(4.14)			(3.18)	(2.97)
Res. ln(ATNS)			-0.226*	**Res. ln(ATPB)**			-0.248**
			(-1.79)				(-2.20)
Controls	Yes	Yes	Yes	**Controls**	Yes	Yes	Yes
Panel D: Regressions on the Negative and Positive Amihud Measures: Horse Race							
	(1)	(2)	(3)		(4)	(5)	(6)
ln(AN)	0.143***			**ln(AN_C)**	0.134***		
	(3.54)				(4.49)		
ln(AP)	-0.021			**ln(AP_C)**	0.052		
	(-0.46)				(1.33)		
ln(ATN)		0.166***		**ln(ATN_C)**		0.164***	
		(4.18)				(5.60)	
ln(ATP)		0.000		**ln(ATP_C)**		0.060	
		(0.01)				(1.55)	
ln(ATNS)			0.107**	**ln(ATNS_C)**			0.136***
			(2.21)				(4.14)
ln(ATPB)			-0.016	**ln(ATPB_C)**			0.036
			(-0.33)				(0.91)
Controls	Yes	Yes	Yes	**Controls**	Yes	Yes	Yes

Table 8
Monthly Fama-MacBeth Regressions of Stock Returns: High-Frequency Liquidity Benchmarks: January vs. Non-January

This table reports the monthly Fama-Macbeth regressions of stock returns on the high-frequency liquidity benchmarks. The dependent variable is the monthly FF3-adjusted return of month *t*. The independent variables include the natural logs of the monthly high-frequency liquidity measures of month *t*-2. The price impact measure λ is estimated as the slope coefficient of the monthly regression of five-minute stock returns on signed square-root dollar volume in the same time period. We require at least 10 valid observations for the regressions. The percent 5-minute price impact (*PI*) is the dollar effective spread minus the dollar realized spread, scaled by M_{k+5}, the prevailing midpoint five minutes after the trade. The dollar effective spread is $2 \cdot |P_k - M_k|$, where P_k is the price of the k^{th} trade, and M_k is the prevailing midpoint for the k^{th} trade. The dollar realized spread, $2 \cdot Sign_k \cdot |P_k - M_{k+5}|$, divided by the post-trade quotes midpoint M_{k+5}. M_{k+5} is the prevailing midpoint 5 minutes after the k^{th} trade, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification method or the tick test. *QS* is the percent quoted spread. *ES* is the percent effective spread. *RS* is the percent realized spread. We calculate the means of these spread measures for each stock-month. To control for outliers, we winsorize the high-frequency liquidity measures at the 1 and 99 percentage points in each cross-section. We also control for firm characteristics including size (*ln(ME)*), book-to-market ratio (*B/M*), momentum (Ret[-12,-2]), reversal (Ret[-1]) and an intercept but do not report them for brevity. We estimate a cross-sectional regression in each month from March 1983 to December 2012 and then report the time-series means and t-statistics (in parentheses), separately for January (Panel A) and non-January (Panel B). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return

Panel A: Regressions of Stock Returns on Liquidity Benchmarks: January

	ln(λ)	ln(PI)	ln(QS)	ln(ES)	ln(RS)
Liq. Benchmark	0.485**	0.565	3.013***	3.053***	1.489***
	(2.15)	(1.11)	(3.77)	(4.20)	(4.56)
ln(ME)	-0.648***	-0.743***	-0.743***	0.340	-0.352***
	(-4.51)	(-3.47)	(-3.47)	(1.46)	(-4.75)
B/M	0.219	0.200	0.200	0.105	0.073
	(0.81)	(0.77)	(0.77)	(0.41)	(0.30)
Ret[-12,-2]	-2.936***	-2.944***	-2.944***	-2.484***	-2.528***
	(-4.25)	(-4.35)	(-4.35)	(-3.58)	(-3.62)
Ret[-1]	-16.197***	-16.100***	-16.100***	-16.375***	-15.978***
	(-9.50)	(-9.80)	(-9.80)	(-10.05)	(-9.97)

Panel B: Regressions of Stock Returns on Liquidity Benchmarks: Non-January

	ln(λ)	ln(PI)	ln(QS)	ln(ES)	ln(RS)
Liq. Benchmark	-0.078	-0.178**	-0.540***	-0.537***	-0.265***
	(-1.45)	(-2.18)	(-4.07)	(-4.21)	(-4.24)
ln(ME)	-0.018	-0.043	-0.180***	-0.177***	-0.062***
	(-0.53)	(-1.30)	(-4.62)	(-4.98)	(-2.70)
B/M	-0.050	-0.045	-0.033	-0.029	-0.021
	(-0.93)	(-0.83)	(-0.63)	(-0.56)	(-0.40)
Ret[-12,-2]	0.516*	0.504*	0.284	0.292	0.379
	(1.70)	(1.66)	(0.97)	(1.00)	(1.27)
Ret[-1]	-3.964***	-3.988***	-4.087***	-4.122***	-4.035***
	(-7.08)	(-7.15)	(-7.25)	(-7.28)	(-7.15)

Table 9

Do High-Frequency Liquidity Benchmarks Explain the Pricing of Amihud Measures?

Panel A presents the time-series averages of the cross-sectional correlation coefficients between the monthly high-frequency measures and the Amihud measures for NYSE/AMEX stocks from 1983 to 2012. The price impact measure λ is estimated as the slope coefficient of the monthly regression of five-minute stock returns on signed square-root dollar volume in the same time period. We require at least 10 valid observations for the firm-month regressions. The percent 5-minute price impact (*PI*) is the dollar effective spread minus the dollar realized spread, scaled by M_{k+5}, the prevailing midpoint five minutes after the trade. The dollar effective spread is $2 \cdot |P_k - M_k|$, where P_k is the price of the k^{th} trade, and M_k is the prevailing midpoint for the k^{th} trade. The dollar realized spread, $2 \cdot Sign_k \cdot |P_k - M_{k+5}|$, divided by the post-trade quotes midpoint M_{k+5}. M_{k+5} is the prevailing midpoint 5 minutes after the k^{th} trade, and $sign_k$ is the sign of the k^{th} trade assigned according to the Lee and Ready (1991) trading classification method or the tick test. *QS* is the percent quoted spread. *ES* is the percent effective spread. *RS* is the percent realized spread. We calculate the means of these spread measures for each stock-month. To control for outliers, we winsorize the high-frequency liquidity measures at the 1 and 99 percentage points in each cross-section. In Panel A, we first calculate cross-sectional correlation coefficients each month, and then report the time-series averages of the cross-sectional correlation coefficients. Panel B presents monthly Fama-MacBeth regressions of stock returns for NYSE/AMEX stocks from 1983 to 2012. The dependent variable is the monthly FF3-adjusted return. FF3-adjusted return of month *t* is calculated based on the Fama-French three-factor model in which the factor loadings are estimated in the preceding sixty months [*t*-60,*t*-1] with at least 24 observations for each firm-level time-series regression. The independent variables include the natural logs of the price impact measures (λ or *PI*) and the constant Amihud measures estimated in month *t*-2. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). Panel C is similar to Panel B except that we consider spread measures as well. We also report the time-series averages of the number of observations and adjusted R^2 of the cross-sectional regressions. All regressions controls for size (*ln(ME)*), book-to-market ratio (*B/M*), momentum (R*et[-12,-2]*), reversal (R*et[-1]*) and an intercept but we do not report them for brevity. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Correlations between Price Impact and Amihud Measures										
	λ	**PI**	**QS**	**ES**	**RS**	**A**	**A_C**	**Res. A**	**AT**	**AT_C**
PI	0.844									
QS	0.793	0.812								
ES	0.755	0.786	0.960							
RS	0.610	0.580	0.902	0.936						
A	0.737	0.651	0.764	0.731	0.669					
A_C	0.747	0.683	0.755	0.705	0.633	0.902				
Res. A	0.149	0.084	0.190	0.215	0.222	0.426	0.000			
AT	0.598	0.593	0.670	0.634	0.574	0.748	0.745	0.172		
AT_C	0.352	0.386	0.391	0.352	0.307	0.400	0.548	-0.224	0.761	
Res. AT	0.504	0.457	0.562	0.551	0.510	0.674	0.491	0.545	0.637	0.000

Panel B: Regressions of FF3-adjusted Returns on Price Impact Dependent Variable: FF3-Adjusted Return							
	(1)	(2)	(3)		(4)	(5)	(6)
ln(λ)	-0.034	-0.155**	-0.164***	**ln(PI)**	-0.114	-0.219***	-0.222***
	(-0.67)	(-2.51)	(-2.66)		(-1.57)	(-2.60)	(-2.63)
ln(A_C)		0.180***		**ln(A_C)**		0.165***	
		(3.80)				(3.71)	
ln(AT_C)			0.227***	**ln(AT_C)**			0.207***
			(4.82)				(4.68)
Controls	Yes	Yes	Yes	**Controls**	Yes	Yes	Yes
Adj. R^2	0.027	0.030	0.030	**Adj. R^2**	0.027	0.030	0.030
Ave. # obs	1725	1725	1725	**Ave. # obs**	1745	1745	1745
# Months	358	358	358	**# Months**	358	358	358

Panel C: Regressions of Stock Returns on Liquidity Benchmarks and Amihud Measures					
	(1)	(2)	(3)	(4)	(5)
ln(QS)	-0.254*			-0.182	-0.194
	(-1.93)			(-0.91)	(-1.00)
ln(ES)		-0.248*		0.254	-0.213
		(-1.94)		(-1.23)	(-1.05)
ln(RS)			-0.124*	0.056	0.055
			(-1.95)	(1.06)	(1.03)
ln(λ)				-0.065	-0.074*
				(-1.54)	(-1.73)
ln(A_C)				0.210***	
				(3.71)	
ln(AT_C)					0.244***
					(4.33)
Controls	Yes	Yes	Yes	Yes	Yes

Table 10

Monthly Fama-MacBeth Regressions of Stock Returns on the Transaction-Cost Component and the Non-Cost Component of Amihud Measures

This table presents the results of monthly Fama-MacBeth regressions of stock returns on the transaction-cost component and the non-transaction-cost component of the Amihud measures from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return. FF3-adjusted return of month *t* is calculated based on the Fama-French three-factor model where the factor loadings are estimated over the preceding sixty months [*t*-60,*t*-1] with at least 24 observations for each firm-level time-series regression. The independent variables include the transaction-cost and non-cost components of the monthly Amihud measures of month *t*-2. In the left panel, we first estimate monthly cross-sectional regression of *ln*(*A*), natural log of the original Amihud measure, on the natural logs of the high-frequency liquidity benchmarks including *ln*(*λ*), *ln*(*QS*), *ln*(*ES*), and *ln*(*RS*), where *λ* is the monthly price impact measure, *QS* is the monthly measure of quoted spread, *ES* is the monthly measure of effective spread, and *RS* is the monthly measure of realized spread. We then measure the transaction-cost component of the Amihud measure as the fitted value of the regression, and non-cost component as the residual of the regression. We also control for firm characteristics including size (*ln(ME)*), book-to-market ratio (*B/M*), momentum (*Ret*[-*12,-2*]), and reversal (*Ret*[-*1*]). We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). We also report the time-series average of the number of observations and adjusted R^2 of the cross-sectional regressions. The right panel is similar as the left panel except that the independent variables are the transaction-cost and non-cost component of the turnover-based Amihud measure (*AT*). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return						
	Original Amihud Measure			Turnover-Based Amihud Measure		
	(1)	(2)	(3)	(4)	(5)	(6)
Cost Component	-0.047		0.015	-0.121		-0.312**
	(-1.11)		(0.35)	(-0.97)		(-2.28)
Non-Cost Component		0.186***	0.191***		0.208***	0.248***
		(3.04)	(3.10)		(3.99)	(3.84)
ln(ME)	-0.109***	-0.037	-0.020	-0.101***	-0.063*	-0.191***
	(-2.80)	(-1.01)	(-0.42)	(-2.70)	(-1.80)	(-4.14)
B/M	-0.029	-0.035	-0.039	-0.029	-0.035	-0.049
	(-0.52)	(-0.63)	(-0.70)	(-0.52)	(-0.64)	(-0.88)
Ret[-12,-2]	0.145	0.278	0.214	0.151	0.313	0.166
	(0.48)	(0.93)	(0.71)	(0.50)	(1.03)	(0.57)
Ret[-1]	-5.028***	-4.961***	-5.017***	-5.009***	-4.909***	-5.034***
	(-8.89)	(-8.88)	(-8.91)	(-8.87)	(-8.71)	(-8.90)
Adj. R^2	0.028	0.028	0.030	0.028	0.028	0.030
Ave. # obs	1693	1693	1693	1693	1693	1693
# Months	358	358	358	358	358	358

Table 11

Monthly Fama-MacBeth Regressions of Stock Returns on High-Frequency Liquidity Benchmarks and Turnover Measures: January vs. Non-January

This table presents the results of monthly Fama-MacBeth regressions of stock returns on the monthly high-frequency liquidity benchmarks and turnover measures in January (Panel A) and non-January months (Panel B) from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return of month *t*. The independent variables include the natural logs of the monthly high-frequency liquidity measures and turnover measures of month *t*-2. The price impact measure λ is estimated as the slope coefficient of the monthly regression of five-minute stock returns on signed square-root dollar volume in the same time period. *QS* is the percent quoted spread. *ES* is the percent effective spread. *RS* is the percent realized spread. We calculate the means of these spread measures for each stock-month. *Ln*(*AT_C*) is the constant version of the turnover-based Amihud measure. *Ln(TO)* is the monthly average of the daily turnover. We also control for size (*ln(ME)*), book-to-market ratio (*B/M*), momentum (*Ret*[*-12,-2*]), reversal (*Ret*[*-1*]), and an intercept but they are not reported for brevity. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fama-MacBeth Regressions of Stock Returns: January

	(1)	(2)	(3)	(4)
ln(AT_C)	-0.367**	-0.623***		
	(-2.27)	(-2.03)		
ln(TO)			0.340*	0.574*
			(1.81)	(1.70)
ln(λ)		-0.077		-0.082
		(-0.41)		(-0.42)
ln(QS)		-0.338		-0.626
		(-0.35)		(-0.77)
ln(ES)		3.052***		3.200***
		(10.25)		(10.14)
ln(RS)		0.485**		0.516**
		(2.24)		(2.45)
Controls	Yes	Yes	Yes	Yes

Panel B: Fama-MacBeth Regressions of Stock Returns: Non-January

	(1)	(2)	(3)	(4)
ln(AT_C)	0.230***	0.304***		
	(6.28)	(5.71)		
ln(TO)			-0.246***	-0.347***
			(5.94)	(-5.55)
ln(λ)		-0.075*		-0.113**
		(-1.76)		(-2.38)
ln(QS)		-0.201		-0.070
		(-0.95)		(-0.35)
ln(ES)		-0.519***		-0.518**
		(-2.47)		(-2.57)
ln(RS)		0.018		-0.017
		(0.32)		(-0.29)
Controls	Yes	Yes	Yes	Yes

Table 12
Volume Premium across Sub-periods of Market Illiquidity

This table reports the results on the relation between the volume premium and market illiquidity. We obtain the monthly measure of market illiquidity for our sample period 1964-2012 from Professor Luboš Pástor's data library and define a month *t* as period of high (low) market illiquidity if the market illiquidity of month *t*-1 is above (below) the median. The turnover measures used include *AT_C,* the constant version of the turnover-based Amihud measure, and *TO,* the monthly average of the daily turnover. We match returns of month *t* to turnover measures of *t*-2. Panel A reports the monthly returns of portfolios sorted on the turnover measures across high and low market illiquidity periods. The "long" portfolios are the top (bottom) quintile of *AT_C* (turnover), and the "short" portfolios are the bottom (top) quintile of *AT_C* (turnover). "Long-Short" is the monthly volume premium. In Panel B, we estimate the following time-series regressions to further control for return factors: $R_{it} = a + bIlliq_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t$, where R_{it} is the return of turnover-based portfolio *i* of month *t*, in excess of risk-free rate. $Illiq_{t-1}$ is market illiquidity measure of month *t*-1. MKT_t , SMB_t , HML_t and MOM_t are the Fama-French factors and momentum factor of month *t*. Panel B presents the coefficient on the market illiquidity (*b*) and its t-statistics.

Panel A: Returns of Portfolios Sorted on Turnover Measures: Periods of High and Low Market Illiquidity

	Short	2	3	4	Long	L – S	t-stat
Sorted on AT_C							
High Market Illiquidity	1.11	1.36	1.31	1.45	1.44	0.33	(1.67)
Low Market Illiquidity	0.89	1.16	1.15	1.27	1.21	0.32	(1.30)
High – Low						-0.02	
t-stat						(-0.08)	
Sorted on TO							
High Market Illiquidity	1.13	1.38	1.37	1.45	1.33	0.20	(1.00)
Low Market Illiquidity	0.95	1.14	1.17	1.21	0.21	0.26	(1.06)
High – Low						-0.06	
t-stat						(-0.30)	

Panel B: Coefficients on Market Illiquidity (b) in the FF4-Model

$$R_{it} = a + bIlliq_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t,$$

	Short	2	3	4	Long	Long – Short
Sorted on AT_C						
Coefficient (b)	0.031	0.017	0.008	-0.005	-0.016	-0.048
t-stat	(2.18)	(1.51)	(0.80)	(-0.46)	(-1.11)	(-2.38)
Sorted on TO						
Coefficient (b)	0.008	0.009	-0.011	-0.010	-0.030	-0.038
t-stat	(0.58)	(0.87)	(-1.16)	(-0.87)	(-2.14)	(-2.05)

Table 13

Volume Premium across Sub-periods of Market Investor Sentiment

This table reports the results on the relation between the volume premium and market sentiment. The monthly market-wide investor sentiment index (Baker and Wurgler 2006) is obtained from Professor Jeffrey Wurgler's website for the period from July 1965 to December 2010. Periods of high (low) sentiment are the months with lagged sentiment index above (below) the median. The turnover measures used include *AT_C,* the constant version of the turnover-based Amihud measure, and *TO,* the monthly average of the daily turnover. We match returns of month *t* to turnover measures of *t*-2. Panel A reports monthly returns of portfolios sorted on the turnover measures across high- and low-sentiment periods. We define the "long" portfolio as the top (bottom) quintile of *AT_C* (turnover), and the "short" portfolio as the bottom (top) quintile of *AT_C* (turnover). "Long-Short" is the monthly volume premium. In Panel B we estimate the following time-series regression: $R_{it} = a + bSent_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t$, where R_{it} is return of *AT_C* (or turnover) portfolio *i* of month *t*, in excess of risk-free rate. $Sent_{t-1}$ is sentiment index of month *t*-1. MKT_t, SMB_t, HML_t and MOM_t are the Fama-French factors and momentum factor of month *t*. Panel B presents the coefficient on the sentiment index (*b*) and its t-statistics.

Panel A: Returns of Portfolios Sorted on Turnover Measures: Periods of High and Low Market Sentiment

	Short	2	3	4	Long	Long – Short	t-stat
Sorted on AT_C							
Low Sentiment	1.54	1.63	1.51	1.75	1.70	0.16	(0.65)
High Sentiment	0.52	0.92	0.98	1.00	1.04	0.52	(2.34)
High - Low	-1.02	-0.71	-0.53	-0.75	-0.66	0.36	
t-stat	(-1.64)	(-1.35)	(-1.10)	(-1.51)	(-1.41)	(1.08)	
Sorted on TO							
Low Sentiment	1.61	1.65	1.62	1.63	1.63	0.02	(0.06)
High Sentiment	0.54	0.89	0.97	1.07	0.99	0.45	(2.03)
High - Low	-1.07	-0.75	-0.65	-0.56	-0.64	0.43	
t-stat	(-1.70)	(-1.39)	(-1.31)	(-1.18)	(-1.43)	(1.30)	

Panel B: Coefficients on Sentiment (b) in the FF4-Model

$$R_{it} = a + bSent_{t-1} + cMKT_t + dSMB_t + eHML_t + fMOM_t + u_t,$$

	Short	2	3	4	Long	Long – Short
Sorted on AT_C						
Coefficient (b)	-0.25	-0.17	-0.12	-0.04	-0.01	0.24
t-stat	(-2.67)	(-2.18)	(-1.81)	(-0.57)	(-0.10)	(1.81)
Sorted on TO						
Coefficient (b)	-0.25	-0.19	-0.10	-0.03	-0.02	0.23
t-stat	(-2.67)	(-2.42)	(-1.47)	(-0.53)	(-0.23)	(1.85)

Table 14

Volume Premium and Earnings Announcements: 1972-2012

Panel A of the table reports the buy-and-hold returns in the earnings-announcement period and non-earnings announcement-period of portfolios sorted on the turnover measures (*AT_C* and *TO*). At the beginning of each month *t* from 1972 to 2012, stocks with earnings announcement in the month are sorted into quintile portfolios according to the *AT_C* and *TO* measures of month *t*-2. We define the "long" portfolio as the top (bottom) quintile of *AT_C* (turnover), and the "short" portfolio as the bottom (top) quintile of *AT_C* (turnover). Then for each firm-month, we calculate the buy-and-hold abnormal return in the three-day window [-1,1] surrounding the earnings announcement, where the buy and hold return is calculated as the buy-and-hold raw return minus the buy-and-hold value-weighted CRSP return. We denote this return as BHAR [-1,1]. We also calculate the monthly buy-and-hold return for the days other than the [-1,1] earnings announcement window. In Panel A, we first calculate monthly average of BHAR [-1,1] for the quintile portfolios and report time-series average portfolio returns. The differences between the top and bottom quintiles are also reported with associated t-statistics. We also report buy-and-hold abnormal returns in the non-earnings-announcement period instead of BHAR. The t-statistics (in parentheses) are calculated using Newey-West robust standard errors with 6 lags. In Panel B, the left Panel presents Fama-Macbeth regressions of BHAR for earnings announcement or non-announcement period on the turnover measures. The right panel presents Fama-Macbeth regressions of analyst forecast errors on the turnover measures, where analyst forecast error for an announcement is the consensus forecast minus actual earnings, scaled by stock price at the end of the previous quarter. We control for size (*ln(ME)*), book-to-market ratio (*B/M*), momentum (*Ret*[*-12,-2*]), reversal (*Ret*[*-1*]), and an intercept and they are not reported for brevity. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Earnings Announcement Return and Non-Announcement Return Sorted on Turnover Measures

	Short	2	3	4	Long	L – S	t-stat
Earnings Announcement Return (BHAR [-1, 1])							
Sorted on AT_C	0.02	0.11	0.17	0.27	0.65	0.63	(7.53)
Sorted on TO	0.01	0.15	0.18	0.31	0.59	0.58	(6.80)
BHAR for Non-Earnings-Announcement Days							
Sorted on AT_C	0.36	0.49	0.38	0.39	0.26	-0.10	(-0.73)
Sorted on TO	0.41	0.51	0.39	0.33	0.22	-0.20	(-1.31)

Panel B: Fama-Macbeth Regressions of Earnings-Announcement Return or Non-Announcement Returns on Turnover Measures

	Dep. Var.: Buy-and-Hold Stock Return				Dep. Var.: Analyst Forecast Errors	
	Earnings Ann. Ret.		Non-Ann. Ret.			
	(1)	(2)	(3)	(4)	(5)	(6)
ln(AT_C)	0.213***		-0.044		-0.089***	
	(7.30)		(-0.74)		(-5.18)	
ln(TO)		-0.240***		0.083		0.106***
		(-7.73)		(1.22)		(6.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.014	0.013	0.051	0.050	0.051	0.050
Ave. # obs	579	579	579	579	579	579
# Months	492	492	492	492	492	492

Table 15

The Pricing of Amihud Measures as Systematic Factors

This table presents the estimation results of monthly Fama-MacBeth regressions of stock returns on the loadings of factors created using various versions of the Amihud (2002) measure from 1967 to 2012 (552 months). For each Amihud measure, we obtain an aggregate measure by calculating the equal-weighted average of the Amihud measure. We create a factor from the residuals of an AR(2) model on the aggregate measure. We multiply the residual series by -1. The factor beta is the coefficient for the Amihud factor in a firm-level time-series regression using data from month *t*-60 and *t*-1 where the model includes the Fama-French four-factors and the respective Amihud measure factor. Residual *A* factor beta is the residual of a cross-sectional regression of *A* factor beta on *A_C* factor beta. Residual *AT* factor beta is the residual of a cross-sectional regression of *AT* factor beta on *AT_C* factor beta. In addition to ln(*A*), we also control for *ln(ME)*, B/M, R*et*[-12,-2], and *Ret*[-1]. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). T-statistics are calculated using Newey-West robust standard errors with 6 lags. We also report the time-series average of the number of observations and adjusted R^2 of the cross-sectional regressions. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Factors Using the Original Amihud Measures

	(1)	(2)	(3)	(4)	(5)	(6)
A factor beta	0.003**			0.004**		
	(1.99)			(2.33)		
A_C factor beta		0.066*	0.068*		0.083**	0.086**
		(1.89)	(1.95)		(2.42)	(2.52)
Residual A factor beta			0.003			0.003
			(0.95)			(0.88)
Ln(A)	0.113***	0.114***	0.112***	0.104***	0.105***	0.103***
	(2.78)	(2.78)	(2.76)	(2.69)	(2.70)	(2.66)
Idio. Vol.				-13.207**	-13.174**	-13.034**
				(-2.57)	(-2.56)	(-2.55)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.033	0.033	0.035	0.041	0.041	0.043
Ave. # obs	1735	1735	1735	1735	1735	1735

Panel B: Factors Using on the Turnover-Based Amihud Measures

	(1)	(2)	(3)	(4)	(5)	(6)
AT factor beta	0.019			0.022**		
	(1.62)			(1.95)		
AT_C factor beta		0.971	0.846		1.213*	1.111*
		(1.41)	(1.20)		(1.83)	(1.65)
Residual AT factor beta			0.018			0.020
			(0.82)			(0.98)
Ln(A)	0.115***	0.117***	0.115***	0.106***	0.108***	0.106***
	(2.83)	(2.88)	(2.85)	(2.75)	(2.79)	(2.76)
Idio. Vol.				-12.901**	-12.901**	-12.464**
				(-2.53)	(-2.52)	(-2.45)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.033	0.033	0.036	0.041	0.041	0.043
Ave. # obs	1735	1735	1735	1735	1735	1735

Internet Appendix

Price Impact or Trading Volume: Why is the Amihud (2002) Illiquidity Measure Priced?

August 2016

Table A.1
Monthly Stock Returns of Portfolios Sorted on Amihud Measures: Alphas using the Return Factors Based on Trading Volume Components

Panel A presents monthly one-factor and five-factor alphas (%) of portfolios sorted on the Amihud measures. *A* is the original Amihud (2002) measure, defined as the daily ratio of absolute return to dollar trading volume, averaged across all days in a month. At the beginning of month *t* from 1964 to 2012, stocks are sorted into quintile portfolios according to the *A* measures of month *t-2*. We then calculate monthly equal-weighted portfolio returns for the quintile portfolios and report time-series one-factor alpha and five-factor alpha. One-factor alpha is constructed using the IML^{A_C} factor, where the monthly factor return of IML^{A_C} ("High minus Low") is the monthly equal-weighted returns of the top *A_C* tercile minus that of the bottom *A_C* tercile. *A_C* is constructed as *A* but the numerator of the ratio is 1 instead of absolute return. Five-factor alpha is constructed using the IML^{A_C} factor together with the three Fama-French factors and the momentum factor (UMD). We also report the differences between the top and bottom quintiles and associated t-statistics. *AT* is the turnover-based Amihud (2002) measure, defined as the average of the daily ratio of absolute return to turnover, and *AT_C* is constructed as *AT* but the numerator of the ratio is 1 instead of absolute return. Panel B is similar to Panel A but uses annual measures. The corresponding Amihud measures are constructed each year, and stocks in a month are sorted by the Amihud measures constructed in the previous year. The t-statistics (in parentheses) are calculated using Newey-West robust standard errors with 6 lags.

	Portfolios Sorted on Amihud Measures						
	Low	**2**	**3**	**4**	**High**	**High-Low**	**t-stat**
Panel A: Monthly Measures							
Sorted on A							
One-Factor Alpha: IML^{A_C}	0.57	0.68	0.64	0.56	0.53	-0.04	(-0.77)
Five-Factor Alpha: IML^{A_C} & 4 Factors	0.03	0.10	0.06	0.00	-0.05	-0.08	(-1.66)
Sorted on AT							
One-Factor Alpha: IML^{AT_C}	0.89	1.00	1.03	1.05	1.05	0.16	(1.44)
Five-Factor Alpha: IML^{AT_C} & 4 Factors	0.02	0.17	0.17	0.13	0.01	-0.02	(-0.20)
Panel B: Annual Measures							
Sorted on A							
One-Factor Alpha: IML^{A_C}	0.59	0.58	0.53	0.44	0.57	-0.02	(-0.46)
Five-Factor Alpha: IML^{A_C} & 4 Factors	0.10	0.04	0.00	-0.07	0.06	-0.03	(-0.74)
Sorted on AT							
One-Factor Alpha: IML^{AT_C}	1.03	1.12	1.15	1.13	1.34	0.31	(1.05)
Five-Factor Alpha: IML^{AT_C} & 4 Factors	0.07	0.16	0.14	0.02	0.15	0.08	(0.87)

Table A.2

Monthly Fama-MacBeth Regressions of Stock Returns on Amihud Measures: Standardized Ranks

This table is similar to Table 4 but uses the standardized ranks of independent variables. In each cross-section, we convert the independent variables into uniform distributions between 0 and 1, where 0 corresponds to the lowest value and 1 the highest value. Panel A presents the results of monthly Fama-MacBeth regressions of stock returns on the Amihud (2002) measures from 1964 to 2012. The dependent variable is the monthly FF3-adjusted return in month *t,* which is calculated based on the three-factor model where the factor loadings are estimated over the preceding sixty months [t-60,t-1] with at least 24 observations for each firm-level time-series regression. The independent variables are measured at month t-2. *Ln*(*A*) is the natural log of the monthly Amihud (2002) measure (*A*). *Ln*(*A_C*) is the natural log of *A_C*. *Res. ln*(*A*) is the residual from the monthly cross-sectional regression of *ln*(*A*) on *ln*(*A_C*). We also control for firm characteristics including idiosyncratic return volatility (Idio. Vol.), size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), reversal (Ret[-1]). We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses, using Newey-West robust standard errors with 6 lags). We also report the time-series average of the number of observations and adjusted R^2 of the cross-sectional regressions. Panel B is similar to Panel A except that the independent variables are turnover-based Amihud measures. *Res. ln*(*AT*) is the residual from the monthly cross-sectional regression of *ln*(*AT*) on *ln*(*AT_C*). All the regressions include an intercept. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return											
	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
ln(A)	1.005***					**ln(AT)**	0.526***				
	(3.57)						(4.45)				
ln(A_C)		1.705***		1.149***	0.969***	**ln(AT_C)**		0.830***		0.690***	0.565***
		(6.03)		(4.18)	(3.61)			(6.41)		(5.42)	(4.69)
Res. ln(A)			-0.770***	-0.501***	-0.298***	**Res. ln(AT)**			-0.583***	-0.474**	-0.332***
			(-5.71)	(-3.67)	(-2.41)				(-4.62)	(-3.79)	(-3.02)
Idio. Vol.					-0.593***	**Idio. Vol.**					-0.513***
					(-3.61)						(-2.89)
ln(ME)	0.793***	1.383***	-0.029	0.804***	-0.309	**ln(ME)**	0.031	0.054	-0.035**	-0.181	-0.496***
	(2.80)	(4.48)	(-1.61)	(3.33)	(-1.42)		(0.18)	(0.28)	(-2.14)	(-1.10)	(-3.30)
B/M	0.238**	0.192**	0.156	0.154	0.083	**B/M**	0.239**	0.192**	0.195*	0.153	0.090
	(2.42)	(2.06)	(1.58)	(1.58)	(0.84)		(2.41)	(1.99)	(1.93)	(1.56)	(0.89)
Ret[-12,-2]	0.766***	0.860***	0.604**	0.696**	0.665**	**Ret[-12,-2]**	0.746***	0.789**	0.568**	0.680***	0.655**
	(2.80)	(3.19)	(2.17)	(2.51)	(2.43)		(2.71)	(2.92)	(2.05)	(2.45)	(2.38)
Ret[-1]	-2.535***	-2.542***	-2.624***	-2.611***	-2.667**	**Ret[-1]**	-2.528***	-2.547***	-2.614***	-2.608***	-2.657***
	(-11.04)	(-11.05)	(-11.34)	(-11.31)	(-1149)		(-10.97)	(-11.02)	(-11.31)	(-11.21)	(-11.41)
Adj. R^2	0.028	0.029	0.030	0.032	0.034	**Adj. R^2**	0.028	0.030	0.029	0.031	0.034
Ave. # obs	1,775	1,775	1,775	1,775	1,775	**Ave. # obs**	1,775	1,775	1,775	1,775	1,775
# Months	588	588	588	588	588	**# Months**	588	588	588	588	588

Table A.3

Monthly Fama-MacBeth Regressions of Stock Returns on Amihud Measures: *Raw Returns and Sub-Period Analysis*

Panel A presents monthly Fama-MacBeth regressions of stock returns on the Amihud measures. The regressions are similar to those in Table 4 except that the dependent variable in this table is monthly raw return instead of FF3-adjusted return. Panels B and C are similar to Table 4 except that they cover the sub-period of 1964-1988 and 1989-2012, respectively. The regressions include the same control variables as in Table 4 but are not reported for brevity. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regressions of Raw Returns

	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
ln(A)	0.081**					**ln(AT)**	0.121***				
	(2.08)						(3.02)				
ln(A_C)		0.095*		0.089**	0.075**	**ln(AT_C)**		0.131**		0.129***	0.134***
		(1.93)		(2.34)	(1.99)			(2.54)		(2.79)	(3.25)
Res. ln(A)			-0.143	-0.053	-0.185**	**Res. ln(AT)**			-0.030	-0.015	-0.153*
			(-1.13)	(-0.45)	(-2.23)				(-0.24)	(-0.12)	(-1.82)
Idio. Vol.					3.386	**Idio. Vol.**					-3.539
					(0.56)						(0.58)

Panel B: Sub-period of 1964-1988

	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
ln(A)	0.203***					**ln(AT)**	0.236***				
	(3.27)						(3.50)				
ln(A_C)		0.272***		0.217***	0.203***	**ln(AT_C)**		0.305***		0.283***	0.263***
		(4.71)		(3.52)	(3.37)			(5.02)		(4.57)	(4.35)
Res. ln(A)			-0.448***	-0.222**	-0.174***	**Res. ln(AT)**			-0.210***	-0.199*	-0.157**
			(-4.59)	(-2.24)	(-2.55)				(-2.03)	(-1.96)	(-2.29)
Idio. Vol.					-9.641	**Idio. Vol.**					-8.676
					(-1.35)						(-1.23)

Panel C: Sub-period of 1989-2012

	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
ln(A)	0.032					**ln(AT)**	0.087**				
	(0.71)						(1.99)				
ln(A_C)		0.902**		0.040	0.033	**ln(AT_C)**		0.138***		0.109***	0.117***
		(1.98)		(0.90)	(0.76)			(3.16)		(2.61)	(2.92)
Res. ln(A)			-0.315***	-0.275**	-0.438***	**Res. ln(AT)**			-0.283**	-0.215*	-0.381***
			(-2.73)	(-2.21)	(-4.01)				(-2.24)	(1.65)	(-3.11)
Idio. Vol.					4.115	**Idio. Vol.**					3.386
					(0.57)						(0.47)

Table A.4

Monthly Stock Returns of Portfolios Sorted on Amihud Measures: *A_C2* and *AT_C2*

Panel A presents the monthly returns (%) of portfolios sorted on two alternative Amihud measures. *A_C2* is the intermediate version of the monthly Amihud measure. We first calculate daily ratio of absolute daily return to average daily dollar trading volume over the month, and then average the daily ratios across all days in a month. At the beginning of each month *t* from 1964 to 2012, stocks are sorted into quintile portfolios according to the *A_C2* measures of month *t*-2. We then calculate monthly equal-weighted portfolio returns for the quintile portfolios and report time-series average portfolio returns or four-factor alphas, where the four-factor alpha is constructed using the three Fama-French factors and the momentum factor (UMD). The differences between the top and bottom quintiles are also reported with associated t-statistics. The residual *A* measure is the residual from the monthly cross-sectional regression of the *A* measure on the *A_C2* measure. Panel B is similar to Panel A except that we sort stocks based on *AT_C2*, and residual *AT*. *AT_C2* is constructed as *A_C2* but the denominator is monthly average of daily turnover, and the residual *AT* measure is the residual from the monthly cross-sectional regression of the *AT* measure on the *AT_C2* measure. The t-statistics (in parentheses) are calculated using Newey-West robust standard errors with 6 lags.

	Portfolios Sorted on Amihud Measures						
	Low	**2**	**3**	**4**	**High**	**High-Low**	**t-stat**
Panel A: Sorted on Original Amihud Measures: Monthly Measures							
Sorted on A_C2							
Raw Return	0.96	1.16	1.24	1.33	1.49	0.52	(2.14)
Four-Factor Alpha	-0.02	0.05	0.03	0.11	0.30	0.32	(2.08)
Sorted on Res. A Measure							
Raw Return	1.27	1.24	1.15	1.10	1.42	0.15	(1.17)
Four-Factor Alpha	0.14	0.03	0.03	0.04	0.24	0.10	(0.76)
Panel B: Sorted on Turnover-Based Amihud Measures: Monthly Measures							
Sorted on AT_C2							
Raw Return	1.05	1.23	1.22	1.35	1.33	0.28	(1.81)
Four-Factor Alpha	-0.17	0.08	0.11	0.22	0.23	0.40	(2.86)
Sorted on Res. AT Measure							
Raw Return	1.22	1.17	1.15	1.25	1.38	0.16	(1.79)
Four-Factor Alpha	0.17	0.05	-0.01	0.06	0.19	0.02	(0.25)

Table A.5
Monthly Fama-MacBeth Regressions of Stock Returns on the High-Frequency Liquidity Benchmarks in January vs. Non-January: *Annual Measures*

This table presents the robustness analysis of Table 8 using annual high-frequency liquidity measures instead of monthly measures. The dependent variable is the monthly FF3-adjusted return. The independent variables include the natural logs of the annual high-frequency liquidity measures of the previous year. The price impact measure λ is the slope coefficient of the annual regression of five-minute stock returns on signed square-root dollar volume in the same time period. We require at least 100 observations for each firm-year regression. PI is the 5-minute price impact measure; QS is the percent quoted spread; ES is the percent effective spread; and RS is the percent realized spread. We calculate these measures for each stock-year instead of stock-month. We also include the same control variables as in Table 8 including size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), and reversal (Ret[-1]) but they are not reported for brevity. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). Panel A presents the results for January and Panel B presents the results for non-January. T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return					
Panel A: Regressions of Returns on High-Frequency Measures: Annual Measure: January					
	(1)	(2)	(2)	(3)	(4)
ln(λ)	-0.168				
	(-0.41)				
ln(PI)		0.809			
		(1.42)			
ln(QS)			3.170***		
			(3.95)		
ln(ES)				3.570***	
				(4.45)	
ln(RS)					2.043***
					(4.33)
Controls	Yes	Yes	Yes	Yes	Yes
Panel B: Regressions of Returns on High-Frequency Measures: Annual Measure: Non-January					
	(1)	(2)	(3)	(4)	(5)
ln(λ)	0.077				
	(1.01)				
ln(PI)		-0.097			
		(-0.94)			
ln(QS)			-0.405***		
			(-2.79)		
ln(ES)				-0.418***	
				(-3.03)	
ln(RS)					-0.263***
					(-3.60)
Controls	Yes	Yes	Yes	Yes	Yes

Table A.6

Monthly Fama-MacBeth Regressions of Stock Returns on the λ Measure and the Amihud Measures: *Alternative Construction of λ and Alternative Sample Period*

This table reports the robustness analysis on the λ measure of Panel B of Table 9. The price impact measure λ is the slope coefficient of five-minute stock returns on signed square-root dollar volume in the same time period. In Panel A, to avoid the estimation of λ being driven by certain days of the estimation month, we estimate λ daily and then average across the days of estimation month. Panel B is similar to Panel B of Table 9 except that we exclude the 2006-2012 period here. Easley, Lopez de Prado, and O'Hara (2012) point out that the Lee and Ready algorithm may be more error-prone in the recent high-frequency trading era. As a result, Brennan, Huh, and Subrahmanyam (2013) exclude the years since 2006 from some of their analyses. We therefore conduct this robustness test. In addition to the monthly measure, we construct annual λ measure and match monthly stock returns with λ of the previous year.

Dependent Variable: FF3-Adjusted Return						
Panel A: Regressions of Returns on Price Impact Measure: Average of Daily Lambdas						
	Monthly Measures			**Annual Measures**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(λ)	-0.063	-0.186***	-0.185***	-0.042	-0.228***	-0.257***
	(-1.32)	(-3.26)	(-3.25)	(-0.56)	(-2.63)	(-2.92)
ln(A_C)		0.209***			0.226***	
		(4.54)			(3.96)	
ln(AT_C)			0.246***			0.292***
			(5.43)			(5.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Regressions of Returns on Price Impact Measure: 1984-2005						
	Monthly Measures			**Annual Measures**		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(λ)	-0.008	-0.138*	-0.151**	0.123	-0.040	-0.102
	(-0.13)	(-1.84)	(-2.00)	(1.20)	(-0.31)	(-0.79)
ln(A_C)		0.192***			0.202***	
		(3.46)			(2.97)	
ln(AT_C)			0.245***			0.279***
			(4.47)			(4.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7
Monthly Fama-MacBeth Regressions of Stock Returns on the High-Frequency Liquidity Measures and Amihud Measures: Not Skip a Month

This table reports the robustness analysis on the pricing of λ and other high-frequency liquidity benchmarks of Table 9 without skipping a month between the liquidity measures and stock returns, i.e., matching liquidity measures of month *t-1* with return in month *t*. The independent variables include the natural logs of the high-frequency liquidity measures and Amihud measures of month *t*-2. The λ measure is the slope coefficient of the monthly regression of five-minute stock returns on signed square-root dollar volume in the same time period. QS is the percent quoted spread. ES is the percent effective spread. RS is the percent realized spread. We calculate the means of these spread measures for each stock-month. A_C is the constant version of the original Amihud measure. AT_C is the constant version of the turnover-based Amihud measure. We also control for firm characteristics including size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), reversal (Ret[-1]) but do not report them for brevity. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return						
	(1)	(2)	(3)	(4)	(6)	(7)
ln(λ)	-0.234***				-0.293***	-0.295***
	(-4.19)				(-5.40)	(-5.32)
ln(QS)		-0.382***			-0.630**	-0.631**
		(-2.87)			(-2.40)	(-2.42)
ln(ES)			-0.316**		0.084	0.117
			(-2.36)		(0.32)	(0.44)
ln(RS)				-0.122*	0.092	0.092
				(-1.87)	(1.49)	(1.46)
ln(A_C)					0.312***	
					(6.13)	
ln(AT_C)						0.339***
						(6.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.028	0.030	0.031	0.030	0.037	0.037
Ave. # obs	1682	1682	1682	1682	1682	1682
# Months	358	358	358	358	358	358

Table A.8

Monthly Fama-MacBeth Regressions of Stock Returns on the High-Frequency Liquidity Measures and Amihud Measures: Annual Measures

This table reports the robustness analysis on the pricing of λ and other high-frequency liquidity benchmarks of Table 9 using annual measures. The dependent variable is the monthly FF3-adjusted return. The independent variables include the natural logs of the annual high-frequency liquidity measures and Amihud measures of the previous year. The price impact measure λ is the slope coefficient of the annual regression of five-minute stock returns on signed square-root dollar volume in the same time period. We require at least 100 observations in the annual regressions. QS is the percent quoted spread. ES is the percent effective spread. RS is the percent realized spread. We calculate the means of these spread measures for each stock-year. A_C is the constant version of the original Amihud measure. AT_C is the constant version of the turnover-based Amihud measure. We also control for firm characteristics including size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), reversal (Ret[-1]) but do not report them for brevity. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(7)	(8)
ln(λ)	0.057				0.019	-0.043
	(0.62)				(0.25)	(-0.49)
ln(QS)		-0.107			-0.221	-0.308
		(-0.72)			(-0.88)	(-1.20)
ln(ES)			-0.086		-0.182	-0.059
			(-0.59)		(-0.82)	(-0.26)
ln(RS)				-0.071	0.028	-0.009
				(-0.87)	(0.38)	(-0.12)
ln(A_C)					0.228***	
					(3.60)	
ln(AT_C)						0.306***
						(5.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table A.9

Monthly Fama-MacBeth Regressions of Stock Returns on the Turnover Measures: January vs. Non-January: *Annual Measures*

This table presents the robustness analysis of Table 11 using annual high-frequency turnover measures and high-frequency liquidity benchmarks. The dependent variable is the monthly FF3-adjusted return. The independent variables include the natural logs of the annual turnover measures and annual high-frequency liquidity measures of previous year. *AT_C* is the constant version of the annual turnover-based Amihud measure. *TO* is the annual average of the daily turnover. The price impact measure λ is the slope coefficient of the annual regression of five-minute stock returns on signed square-root dollar volume in the same time period. We require at least 100 observations in the annual regressions. QS is the percent quoted spread. ES is the percent effective spread, and RS is the percent realized spread. We calculate the means of these spread measures for each stock-year. We also control for firm characteristics including size (ln(ME)), book-to-market ratio (B/M), momentum (Ret[-12,-2]), reversal (Ret[-1]) but do not report them for brevity. We estimate a cross-sectional regression in each month and then report the time-series means and t-statistics (in parentheses). T-statistics are calculated using Newey-West robust standard errors with 6 lags. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: FF3-Adjusted Return				
Panel A: Regressions of Returns on High-Frequency Measures: Annual Measure: January				
	(1)	(2)	(3)	(4)
ln(AT_C)	-0.293*	-0.082		
	(-1.95)	(-0.37)		
ln(TO)			0.368*	-0.065
			(1.77)	(-0.20)
ln(λ)		-1.113*		-1.303**
		(-1.96)		(-2.41)
ln(QS)		-2.946*		-2.838*
		(-1.87)		(-1.92)
ln(ES)		5.577***		5.409***
		(7.75)		(7.25)
ln(RS)		0.529		0.613
		(1.01)		(1.28)
Controls	Yes	Yes	Yes	Yes
Panel B: Regressions of Returns on High-Frequency Measures: Annual Measure: Non-January				
	(1)	(2)	(3)	(4)
ln(AT_C)	0.259***	0.342***		
	(6.35)	(5.41)		
ln(TO)			-0.376***	0.513***
			(7.76)	(6.80)
ln(λ)		-0.055		-0.125
		(-0.82)		(-1.63)
ln(QS)		-0.068		0.025
		(-0.26)		(0.10)
ln(ES)		-0.572**		-0.493**
		(-2.56)		(-2.24)
ln(RS)		-0.058		-0.111
		(-0.72)		(-1.41)
Controls	Yes	Yes	Yes	Yes

Table A.10

Relations between the High-Frequency Price Impact Measure and Amihud Measures: Earnings Announcement Period and Non-Announcement Period

This table presents the time-series averages of the cross-sectional correlation coefficients between the high-frequency price impact measure (**λ**) and Amihud measures in the earnings announcement period and non-announcement period separately. The sample includes NYSE/AMEX stocks from 1983 to 2012. We first calculate for each stock-year the lambda measure and the Amihud measures in the earnings announcement and non-announcement period separately, where earnings announcement period includes the [-1,1] window of surrounding quarterly earnings announcement in the year, and the rest of the days are the non-announcement period. A is the original Amihud measure. A_C is the constant version of the original Amihud measure. AT is the turnover-based Amihud measure. AT_C is the constant version of the turnover-based Amihud measure. The price impact measure λ is the slope coefficient of the regression of five-minute stock returns on signed square-root dollar volume in the same time period. We then calculate cross-sectional correlation coefficients each year, and report the time-series averages of the cross-sectional correlation coefficients.

	Earnings Announcement					**Non-Earnings Announcement**			
	λ	**A**	**AT**	**A_C**	**AT_C**	**λ**	**A**	**AT**	**A_C**
Earnings Announcement									
A	0.693								
AT	0.530	0.734							
A_C	0.696	0.876	0.717						
AT_C	0.316	0.394	0.755	0.563					
Non-Earnings Announcement									
λ	0.838	0.785	0.585	0.782	0.351				
A	0.732	0.865	0.589	0.803	0.319	0.838			
AT	0.630	0.692	0.829	0.707	0.662	0.706	0.755		
A_C	0.775	0.848	0.630	0.866	0.415	0.876	0.937	0.782	
AT_C	0.385	0.386	0.705	0.488	0.834	0.427	0.396	0.785	0.517