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Illiquidity and the Cost of Equity Capital: Evidence from Actual Estimates of Capital Cost for U.S. Data

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JEL Classification: G12

Keywords*:* Trading Costs; Cost of Capital; Determinants of Equity Returns; Liquidity Premia

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Abstract

Illiquidity measures appear to be related to monthly realized returns but do they impact long-run costs of capital (CoC) for firms? Using U.S. data, we find cross-sectional evidence that, controlling for market capitalization, illiquidity is negatively related to CoC estimates. Aggregate illiquidity innovations do not help forecast those in CoC. A difference-in-differences analysis around exogenous brokerage closures reveals that liquidity decreases without an impact on CoC. Liquidity risk and the probability of informed trade bear no relation to CoC. Our results raise questions about whether illiquidity or liquidity risk should be considerations in firms' discount rates for long-term projects.

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Do investors demand higher returns from less liquid securities? This is an intriguing question in financial economics and has attracted much attention. In their seminal work, Amihud and Mendelson (1986) show that asset returns are positively related to the quoted bid-ask spread. Using an alternative measure based on price moves per unit volume, Amihud (2002) confirms that liquidity measures are indeed positively related to average realized returns.[1] These findings suggest that the answer to the posed question is in the affirmative. Pointing to the centrality of this result in finance research, the papers of Amihud and Mendelson (1986) and Amihud (2002) have garnered more than 15,000 citations on Google Scholar® to date.

The method used for estimating the cross-sectional liquidity-return relation in the literature has generally been to regress monthly realized returns on an illiquidity measure lagged by one or two months. The argument is that illiquidity raises the required return, which manifests itself in monthly average returns. Extending this argument, Amihud and Mendelson (2008) propose that since required returns are proxies for costs of capital, corporations should be concerned about illiquidity having a potentially deleterious effect on such costs.[2]

The average monthly returns used to measure the illiquidity-return relation are not directly related to the cost of capital (or required return) for the typical firm's projects.[3] Most corporations are concerned more about capital costs for projects that take years to pay off. As such, the issue of whether illiquidity affects corporations' required returns should involve a measurement of the relation between illiquidity and a measure of the internal rate of return on firms' longer-term cash flows. Happily, such cost of capital measures are readily available in the

[1] See also Datar, Naik, and Radcliffe (1998). Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Kamara, Lou, and Sadka (2008), Korajczyk and Sadka (2008), and Lou and Sadka (2011) extend the liquidity pricing context to systematic liquidity and liquidity risk pricing. Ben-Rephael, Kadan, and Wohl (2015) analyze the trend in the liquidity premium and show that it has diminished over the years.
[2] Amihud and Levi (2019) use this idea to investigate the link between illiquidity and real investment.
[3] See Fama and French (1997) who find that the cost of capital estimates based on average realized returns are "unavoidably imprecise." Elton (1999) makes a similar point in his AFA presidential address.

existing literature. These measures combine analysts' forecasts and financial statements to back out a long-term discount rate on firm's equity, and this rate, in excess of a benchmark Treasury bond yield, is the implied equity cost of capital (*ICC*). The goal of our analysis is to explore the relation between equity illiquidity and *ICC* estimates for U.S. data.

First, when we perform a portfolio-based analysis and consider double sorts by size (using market capitalization as the proxy for size) and the standard Amihud (2002) measure of illiquidity, we find that the cost of capital is *lower* for portfolios with higher levels of illiquidity in all four size-based portfolios. For each size group, stocks in the lowest Amihud-based group have a cost of capital that is at least 1% higher than that for stocks in the group with the highest levels of the Amihud measure. Thus, we get a result opposite of what we expect a priori. We also conduct Fama and MacBeth (1973) (FM)-type regressions using *ICC* estimates as the dependent variable. In this analysis, we again find that illiquidity is negatively related to firms' cost of equity capital, controlling for previously known determinants of *ICC*. Regressions where variables are reduced to a rank ordering yield qualitatively similar results: that illiquidity is negatively related to *ICC*.

We are cognizant that *ICC* estimation is reliant on analysts' forecasts, but given that the literature extensively uses these as inputs to cost of capital estimates (Easton, 2009), we feel justified in simply extending this literature to liquidity pricing. But we do perform robustness checks with alternative *ICC* measures. Specifically, while for the most part we use *ICC* adapted from Pástor, Sinha, and Swaminathan (2008), we report similar conclusions for alternative analysts-based *ICC* computations developed by Easton (2004) and Ohlson and Juettener-Nauroth (2005). We also find that our central conclusion is unchanged when we use a regression-based approach (Li and Mohanram, 2014), instead of analysts' estimates, to compute earnings forecasts.

The Amihud (2002) measure, which is a monthly average of the ratio of daily absolute returns to daily dollar volume, is not without controversy. Most prominently, Lou and Shu (2017) show that the explanatory power of the Amihud measure is primarily due to the denominator, dollar volume, and argue therefore that the measure captures mispricing, as opposed to illiquidity. Amihud and Noh (2021) respond by arguing that the expected Amihud measure also includes a term for the covariance between absolute return and (the inverse of) dollar volume, and after accounting for the expected sign of this covariance, illiquidity remains positively priced. We do include the different components proposed by Amihud and Noh (2021) and continue to find evidence that supports a negative relation between Amihud's illiquidity measure and cost of capital estimates. More specifically, while the covariance term is positively priced in standard FM regressions using monthly returns, it is negatively priced in regressions that use the cost of capital as the dependent variable.

Market capitalization (size) plays a crucial role in our cross-sectional regressions. This control is desirable because Lee, Ng, and Swaminathan (2009) have already shown that market capitalization is negatively related to *ICC*. Further, since both market capitalization and the Amihud illiquidity measure are highly skewed, it is desirable to use functional forms that reduce the influence of extreme size and illiquidity observations. We therefore follow Lou and Shu (2019) as well as Amihud and Noh (2021) and use the logarithms of size and Amihud in our regressions. While these variables are highly negatively correlated in the cross-section, we show that it is only illiquidity that flips sign from positive to negative when it is included along with market capitalization, suggesting that it noisily proxies for (inverse) size when size is excluded.

We examine the robustness of our findings in a "holdout" sample of NASDAQ stocks from 1983 to 2018. The findings are qualitatively unchanged relative to those for stocks listed on NYSE/AMEX. Splitting our sample into two equal halves by time also results in unchanged conclusions within each sub-period.

We consider alternative illiquidity measures; specifically, the Lesmond, Ogden, and Trzcinka (1999) measure, the Pástor and Stambaugh (2003) measure, and the original measure, namely, the quoted spread, considered by Amihud and Mendelson (1986). We further extend our analysis to account for liquidity risk. Specifically, we consider whether the standard measures of liquidity risk developed by Acharya and Pedersen (2005) as well as Pástor and Stambaugh (2003) are related to *ICC*. Finally, we consider whether higher values of the information risk measure *PIN* (Easley, Hvidkjaer, and O'Hara, 2002, as modified by Duarte, Hu, and Young, 2020) lead to higher values of *ICC*. We find no evidence that alternative illiquidity proxies, liquidity risk, or *PIN* are reliably related to cost of capital estimates.

To see if *ICC* and illiquidity are related at the aggregate (market-wide) level, we model the joint dynamics between the value-weighted levels of the Amihud measure and *ICC*. Specifically, we perform a vector autoregression (VAR) between these measures. The resulting impulse response functions do not yield evidence that innovations in illiquidity help forecast those in aggregate *ICC* or vice versa.

For effectively addressing the joint determination of *ICC* and liquidity, we next perform a difference-in-differences (DiD) estimation around the exogenous brokerage closures described in Kelly and Ljungqvist (2012).[4] These authors show that the closures led to a loss of sell-side analyst coverage and made the affected stocks less liquid (with the proposed pathway of

[4] We eschew decimalization, owing to the controversy surrounding the impact of this event on trading costs (Chakravarty, Panchapagesan, and Wood, 2005; Eaton, Irvine, and Liu, 2021).

increased information asymmetry). In our sample, we first verify the basic Kelly and Ljungqvist (2012) finding of decreased liquidity following the closures. We then examine how *ICC* behaves in the same event windows for treated and control stocks. We find no evidence of an increase in *ICC* for the treated stocks relative to the controls; in fact, the point estimates show a decrease instead, which is not statistically significant. Thus, the DiD confirms our basic finding that liquidity decreases are not accompanied by increases in corporations' cost of capital.

We are aware of the paper by Saad and Samet (2017), who show that cost of capital estimates are positively related to illiquidity, using panel data across several countries. We instead use U.S. data to benchmark our work against the extensive work done on domestic illiquidity premia. Nonetheless, we point out another key difference: Saad and Samet (2017) use the book value of assets as a measure of firm size, whereas we use market capitalization, to be consistent with Amihud and Noh (2021). Since we confirm Lee, Ng, and Swaminathan's (2009) finding that market capitalization is inversely related to *ICC*,[5] there is a possibility that this variable may be picking up the effect of a hitherto undiscovered liquidity measure that commands an *ICC* premium. However, we do include an arsenal of direct illiquidity proxies, and find no evidence that these are positively related to firms' costs of capital. We note that any as-yet undiscovered measure, in addition to being cross-sectionally priced, would need to be reconciled with the following additional findings that do not depend on size controls: First, the dynamics of the standard Amihud illiquidity measure are not related to those of *ICC* at the market-wide level. Second, our DiD event (Kelly and Ljungqvist, 2012) increases Amihud illiquidity but is not associated with an *ICC* increase.

[5] Berk (1993) proposes that market capitalization can be priced because it measures omitted risk-based variables. He notes that high values of such risk proxies would depress the price, implying lower market capitalization (with higher *ICC* and higher required returns).

Our findings support Constantinides (1986), who argues that transactions costs have no effect on long-run equity premia, since investors respond to illiquidity by scaling back the frequency and volume of their trades. But we do confirm that the Amihud measure is positively related to short-horizon (monthly) returns, especially for small firms. Thus, we emphasize that our results do not imply that illiquidity does not lead to higher short-term required returns. As Amihud and Mendelson (1986) and Constantinides (1986) point out, investor horizons matter in illiquidity pricing. Short-horizon investors may well price liquidity at their trading horizon. This possibility notwithstanding, we find no robust evidence from all of our tests that the discount rates of long-term projects should be adversely affected by illiquidity or liquidity risk.

The negative sign on illiquidity in *ICC* regressions, and its strong significance, are intriguing. First, that we do find this relation reduces the likelihood that our cross-sectional regressions suffer from a lack of power to detect an *ICC*-illiquidity connection. But why is this connection in a counter-intuitive direction? On this issue we find that risk-based determinants of the cost of capital are generally of a consistent sign. For example, both market beta and book-to-market are significantly positively related to *ICC*. The former is consistent with the simple Capital Asset Pricing Model (CAPM) and the latter is consistent with book-to-market being a proxy for distress risk, as in Fama and French (1992). The signs of these coefficients lend confidence that the cost of capital regression is well-specified, which in turn lends confidence to the reliability of the Amihud coefficient estimates. We further consider why illiquid firms have lower costs of capital. We find that such firms tend to have lower book-market ratios as well as low share turnover. These findings indicate illiquid firms have low differences of opinion amongst investors and are thus perceived to be low risk in the sense of Berk, Green, and Naik (1999), which implies lower *ICC*.

This paper is organized as follows. Section 1 discusses the method for computing *ICC*. Section 2 discusses data and summary statistics. Section 3 presents cross-sectional results linking illiquidity with firms' costs of capital. Section 4 analyzes the aggregate time-series links between illiquidity and cost of capital. Section 5 presents the analysis involving NASDAQ stocks. Section 6 presents results involving alternate liquidity measures, liquidity risk, and the probability of informed trading. Section 7 performs a DiD estimation around brokerage closures. Section 8 analyzes why illiquid firms command lower costs of capital. Section 9 concludes.

1. Implied Cost of Capital

In this section, we describe the methodology used to estimate the firm-level implied cost of capital (*ICC*). Our estimation of firm-level *ICC* follows the approach of Li, Ng, and Swaminathan (2013).[6] The firm-level *ICC* is constructed as the internal rate of return that equates the present value of future dividends/free cash flows to the current stock price:[7]

$$P_t = \sum_{k=1}^{\infty} \frac{E_t(FCFE_{t+k})}{(1+r_e)^k}, \tag{1}$$

where P_t is the current stock price, $E_t(FCFE_{t+k})$ is the expected future free cash flows to equity for period $t+k$ conditional on information available at time t, and r_e is the long-term cost of equity capital at time t.

There are two key assumptions in our empirical implementation of the free cash flow model: (a) short-run earnings growth rates converge in the long-run to the growth rate of the overall economy and (b) competition drives economic profits on new investments to zero in the long-run (the marginal rate of return on investment—the ROI on the next dollar of investment—

[6] Also see Pástor, Sinha, and Swaminathan (2008) and Lee, Ng, and Swaminathan (2009).

[7] We use the term "dividends" interchangeably with free cash flows to equity ($FCFE$) to describe all cash flows available to equity.

will converge to the cost of capital). We use these assumptions to forecast earnings growth rates and free cash flows during the transition period from the short-run to the long-run steady-state.

We implement Equation (1) in two parts: i) the present value of free cash flows up to a terminal period $t+T$, and ii) a terminal value that captures the present value of free cash flows beyond the terminal period. We estimate free cash flows up to year $t+T$, as the product of annual earnings forecasts and one minus the plowback rate:

$$E_t(FCFE_{t+k}) = FE_{t+k} \times (1 - b_{t+k}), \tag{2}$$

where FE_{t+k} and b_{t+k} are earnings forecasts and plowback rate forecasts for year $t+k$, respectively. Beyond $t+T$, we assume that future investments produce zero economic profits and thus apply a steady state perpetuity formula to determine terminal value. The value of T, following Li, Ng, and Swaminathan (2013), is set to be 15 years. *ICC* is then determined as the discount rate that satisfies Equation (1). We present full details of our *ICC* computations in the Appendix. Our basic premise is that if illiquidity is a consideration in setting long-term discount rates for corporations, then higher illiquidity should imply higher *ICC* in the cross-section. We use our panel of monthly *ICC* estimates to formally test this hypothesis.

2. Data and Summary Statistics

For empirical tests involving *ICC*, our sample begins in January 1977 due to the availability of I/B/E/S analyst consensus earnings forecasts. Our sample period ends in December 2018. For tests involving monthly returns, we extend our sample back to 1955 in order to replicate the analysis in Amihud and Noh (2021). To be consistent with these authors, we also limit our primary sample to NYSE/AMEX stocks. However, we examine the robustness of our key findings with a "holdout" sample of NASDAQ stocks in Section 5. The previous section described the methodology for computing *ICC*, and now we turn to describing the other key variables used in our empirical analysis.

ILLIQ is the Amihud (2002) measure of illiquidity calculated at the end of every month using daily return and dollar trading volume over the prior 12 months (with minimum 200 trading days while excluding days with negative prices or trading volume below 100 shares). It is defined as the average of the ratio of absolute return to dollar trading volume for a given stock i at the end of month t:

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{id}|}{VOLD_{id}}, \tag{3}$$

where D_{it} is the number of eligible trading days over the prior 12 months, R_{id} is the daily stock return and $VOLD_{id}$ is the daily dollar trading volume. The ratio is a measure of the daily price impact of order flow.

SIZE is the market capitalization in billions of dollars computed at the end of every month.

B/M is the ratio of book value equity to market value of equity computed at the end of every month where the book value of equity is computed as in Fama and French (1992).

Return11 is the 11-month cumulative stock return skipping the most recent month and is a measure of past price momentum. For instance, this measure as of the end of December 2018 would be the cumulative return from January 2018 to November 2018.

Return1 is the most recent month's stock return and captures monthly return reversals as in Jegadeesh (1990).

Beta is the market beta calculated using monthly data over the last 60 months with a minimum requirement of 36 months.

GP*/*AT is the ratio of gross profits to total assets as in Novy-Marx (2013).

AG is the percentage growth in total assets as in Cooper, Gulen, and Schill (2008).

The sample consists of all NYSE/AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% each month (as in Amihud and Noh, 2021). In addition, we also exclude all ADRs, REITs, closed-end funds, and unit trusts (excluding CRSP share codes above 11). The accounting variables in the list above are assumed to be known only six months after the fiscal year-end.

Panel A of Table 1 reports summary statistics on *ILLIQ* and other firm characteristics described above. The key thing to note in Panel A is that both *ILLIQ* and *SIZE* have very high positive (standardized) skewness with values of 4.858 and 5.092 respectively (skewness of the normal distribution is zero). This potentially induces an undue influence of extreme observations in regression analysis. However, taking natural logs reduces the skewness of both *ILLIQ* and *SIZE* and brings it close to zero: *Ln*(*ILLIQ*) has a skewness of 0.221 and *Ln*(*SIZE*) has a skewness of 0.109. This can also be seen intuitively by comparing the difference between the means and medians of both variables before and after taking natural logs. The importance of taking logs will become clearer when we examine the cross-sectional correlation between *ILLIQ* and *SIZE* (Table 2). We also take the natural log of (1+*AG*) to take into account the high skewness in asset growth (skewness of 9.488 in *AG* vs. skewness of 1.643 in *Ln*(1+*AG*)).

Panel B of Table 1 reports annual (as of June 30) summary statistics for the implied risk premium (*ICC* − 10-year Treasury yield). For convenience, in the remainder of the paper, we continue to use the same notation (i.e., *ICC*) for this adjusted cost of capital. The number of NYSE/AMEX firms with available *ICC* estimates increases from 655 in 1977 to around 1,000 towards the end of the sample period. The drop in sample size towards the end of the period is due to the exclusion of NASDAQ firms. The equal-weighted mean *ICC* exhibits considerable time variation over time.

Table 2 reports (time-series averages of) cross-sectional correlations among *ICC* and the various firm characteristics. We report Pearson correlations below the diagonal and Spearman rank correlations in *italics* above the diagonal. The Pearson correlation between *SIZE* and *ILLIQ* is only −0.175 which does not seem that high, but this is distorted by the high positive skewness in both variables. The rank correlation between *ILLIQ* and *SIZE* which eliminates the effects of outliers and accounts for skewness, on the other hand, is a very high (in absolute value) –0.943. The Pearson correlation increases to −0.538 if we take the logarithm of *SIZE* but leave *ILLIQ* untouched. The correlation increases further to −0.586 if we take the logarithm of *ILLIQ* but leave *SIZE* untouched. But the correlation increases to −0.937 (similar to the rank correlation) when we take logarithms of both *ILLIQ* and *SIZE* revealing that a stock's *Amihud illiquidity is strongly associated with its market capitalization*: large firms are highly liquid and small firms are highly illiquid. Overall, the results in Table 2 show that Pearson correlations after taking the logarithm of *ILLIQ* are similar to rank correlations involving *ILLIQ* suggesting that it is desirable to use logarithms of *ILLIQ* (or ranks of *ILLIQ*) for robust empirical findings. We take this into account in our cross-sectional asset pricing tests that examine the relationship between illiquidity and cost of capital.

ICC is positively correlated with *ILLIQ* and *Ln*(*ILLIQ*) suggesting that highly illiquid firms have high cost of capital, and negatively correlated with *SIZE* and *Ln*(*SIZE*) suggesting large firms have low cost of capital. Given the high negative correlation between *Ln*(*SIZE*) and *Ln*(*ILLIQ*), however, it is unclear based on these univariate results whether *SIZE* or *ILLIQ* might be a proxy of the other. We examine this more carefully using conditional portfolio sorts and cross-sectional regression tests.

In other correlations, *ICC* is positively correlated with *Beta* and *Ln*(*B*/*M*) and negatively correlated with *Return11*. The positive correlation between *ICC* and *Beta* is consistent with the predictions of the simple CAPM (unlike in the case of realized returns). The positive correlation between *ICC* and *Ln*(*B*/*M*) can be consistent with both risk and mispricing interpretations. The negative correlation between *ICC* and past price momentum, however, is inconsistent with a risk interpretation because it suggests high momentum stocks, in fact, have lower expected returns not higher expected returns. As discussed earlier, in all of the above, rank correlations are similar to those based on logs.

3. Empirical Results

In this section, we discuss our central results connecting illiquidity to monthly realized returns and *ICC*, using portfolio and regression approaches.

3.1. Results from Size-Illiquidity Portfolios

Ever since Banz (1981) and Fama and French (1992), it has been known that market capitalization influences realized returns. Fama and French (1993) provide a risk-based interpretation for size, arguing that small firms are more likely to get distressed, and therefore command higher expected returns. As we show in the previous section, size and illiquidity exhibit extremely high cross-sectional correlation. So, the question is the following: Controlling for *SIZE*, is illiquidity positively priced in short-term returns and long-term cost of capital? We examine this issue first through portfolio tests. This analysis has the virtue of not depending on any specific functional form of illiquidity or market capitalization.

One possible approach is to form four *SIZE*-based portfolios and then divide each *SIZE* portfolio into four *ILLIQ* portfolios to construct a total of 16 *SIZE-ILLIQ* portfolios. Then, in each *SIZE* quartile, we can compute average returns and average *ICC* across the 4 *ILLIQ* portfolios to address our illiquidity pricing question. Given the high correlation between *SIZE* and *ILLIQ* ranks, however, a simple conditional bivariate sort does not suffice to control for the *SIZE* effect in *ILLIQ*.[8] Sorting first on *SIZE* and then sorting again on *ILLIQ* potentially could sort and simply re-sort on *SIZE*. In a 4×4 bivariate conditional sort, indeed the median *SIZE* of *ILLIQ* portfolios (not reported in a table) declines sharply from low to high *ILLIQ* portfolios in every *SIZE* quartile. For instance, in the largest size quartile, the median size declines from \$31 billion to \$5 billion as we move from the lowest to the highest *ILLIQ* portfolio and in the smallest size quartile from \$0.35 billion and \$0.12 billion.

We pursue a different approach to keep the median *SIZE* more stable across the four *ILLIQ* portfolios. First, we construct four *SIZE* portfolios, then we divide each *SIZE* portfolio into four more *SIZE* portfolios, and finally we divide each of the second-stage *SIZE* portfolios into four *ILLIQ* portfolios. This generates a total of 64 *SIZE-SIZE-ILLIQ* portfolios. Let us denote each portfolio with the index (i, j, k) where $i = 1$ to 4 denotes the first-stage *SIZE* sort, $j = 1$ to 4 denotes the second-stage *SIZE* sort and $k = 1$ to 4 denotes the third stage *ILLIQ* sort. Then for each i, we combine the same rank *ILLIQ* portfolios across the four second-stage *SIZE* portfolios. Thus, we combine $(i, 1{,}1)$, $(i, 2{,}1)$, $(i, 3{,}1)$, and $(i, 4{,}1)$ to construct the Low *ILLIQ* portfolio, $(i, 1{,}2)$, $(i, 2{,}2)$, $(i, 3{,}2)$, and $(i, 4{,}2)$ to construct *ILLIQ* portfolio 2, and so on. We thus reduce the 64 *SIZE-SIZE-ILLIQ* portfolios into 16 *SIZE-ILLIQ* portfolios (we go from (i, j, k) to

[8] Results from portfolio sorts are less influenced by outliers since they are analogous to discrete ranks. Using continuous ranks (from 0 to 1) of independent variables in cross-sectional regressions is the equivalent of portfolio sorts since the slope coefficients can be interpreted as returns on zero-investment long-short portfolios constructed on that variable in a multivariate setting. Multivariate portfolio sorts, on the other hand, can better capture any non-linearity in the relationship between the variable of interest and expected returns.

(i, k)). This sequential sorting approach does a better job of controlling for the high correlation between *SIZE* and *ILLIQ* ranks and ensures that the median *SIZE* remains more stable across the four *ILLIQ* portfolios. In the largest size quartile, now the median size declines from \$20 billion to \$10 billion moving from the lowest to the highest *ILLIQ* portfolio, and in the smallest size quintile from \$0.26 billion to \$0.23 billion (we discuss these portfolio characteristics further in Section 8).

Now we turn to discussing the results. Panel A of Table 3 reports average annualized excess returns (in excess of monthly T-bill return) <u>two months after the portfolio formation date</u> for the 16 *SIZE*-*ILLIQ* portfolios. We employ this two-month gap to minimize any microstructure concerns such as bid-ask bounce. The results show that *ILLIQ* is priced only in small stocks even in the short run. The average spread between low and high *ILLIQ* portfolio is 6.56% annualized and highly significant in the Small portfolio and an insignificant 0.20% in the Big portfolio. The spread is positive and insignificant in portfolio Q3 and only marginally significant in portfolio Q2.

Panel B reports results for long-term implied cost of capital. The results uniformly show that in every *SIZE* quartile, the high *ILLIQ* portfolio has a lower cost of capital than the low *ILLIQ* portfolio in spite of the fact that the high *ILLIQ* portfolios are still a bit smaller in size (smaller firms have higher *ICC* as we can see in Panel B). Specifically, in each *SIZE* quartile, the high *ILLIQ* portfolio has an implied cost of capital that is at least 1% lower than that of the low *ILLIQ* portfolio. The *t*-statistics (computed with 36 Newey-West lags to control for the high serial dependence in *ICC*) are all statistically significant. The portfolio with the lowest average *ICC* in Panel B is the *Big* portfolio with *High* illiquidity.

In Figure 1, we provide a three-dimensional chart for average realized returns and *ICC,* which depicts how these quantities vary across size and illiquidity groups. As can be seen, while there is some evidence that realized returns do increase with illiquidity, there is no corresponding pattern for *ICC* across illiquidity sorts. Overall, the portfolio results show that there is no illiquidity premium in firms' cost of capital controlling for firm size, and that the illiquidity premium in monthly returns may be a short-lived phenomenon concentrated among small stocks.

3.2 Fama-MacBeth Regressions

In this section, we discuss results from FM regressions involving returns and *ICC* regressed on *ILLIQ* and other firm characteristics. For our base case, we modify the regression specification from Amihud and Noh (2021) and Lou and Shu (2017) with the addition of market beta:[9]

$$\begin{aligned} R_{it} - R_{ft} = a + b_1 Ln(ILLIQ_{it-2}) + b_2 Ln(SIZE_{it-2}) + b_3 Ln\big(B/M_{iy-1}\big) \\ +b_4 Return11_{it-2} + b_5 Return_{it-1} + b_6 Beta_{it-2} + e_{it}, \end{aligned} \tag{4}$$

where $(R_{it} - R_{ft})$ is the monthly excess returns in excess of monthly T-bill returns. Just as in Amihud and Noh (2021) the independent variables (except the last-month return) are lagged by two months to minimize microstructure effects. *Ln*(*B*/*M*) is calculated at the end of previous year of the current month. The monthly *ICC* regression specification is as follows:

$$\begin{aligned} ICC_{it} = a + b_1 Ln(ILLIQ_{it-1}) + b_2 Ln(SIZE_{it-1}) + b_3 Ln\big(B/M_{iy-1}\big) \\ +b_4 Return11_{it-2} + b_5 Return_{it-1} + b_6 Beta_{it-1} + e_{it}, \end{aligned} \tag{5}$$

where ICC_{it} is the implied cost of capital (in excess of the 10-year treasury yield). All independent variables are lagged by only one month (except 11-month return) since microstructure concerns are not an issue with *ICC*. We note that in principle, it is not necessary

[9] Estimating the regressions without the market beta does not significantly change any of our findings. We add market beta because it is an important risk control for *ICC* and is positively correlated with *ICC* (see Table 2).

to lag illiquidity at all in *ICC* regressions, as the theoretical arguments suggest a contemporaneous positive relation between these variables. Nonetheless, to ensure that the inputs to *ICC* are available to the investor in real time when the relation is estimated, we lag illiquidity by one month. Not doing so gives substantially similar results.

The main results are presented in Table 4. Panel A presents results for two time periods and quantities: i) realized returns for the 1955 to 2016 time-period to be consistent with Amihud and Noh (2021) and ii) realized returns as well as *ICC* for the 1977 to 2018 time period, which corresponds to the availability of the *ICC* data. Given the high negative correlation between *Ln*(*ILLIQ*) and *Ln*(*SIZE*) we first estimate the cross-sectional regressions by only including one or the other variable. In specification (1), where we estimate the regressions without *Ln*(*SIZE*), the coefficient on *Ln*(*ILLIQ*) has a uniformly positive sign in both return and *ICC* regressions. In the return regressions, the coefficient on *Ln*(*ILLIQ*) is statistically significant for the 1955 to 2016 time period but insignificant for the 1977-2018 time period. In the *ICC* regressions, the coefficient on *Ln*(*ILLIQ*) is positive and highly significant. In specification (2), where we estimate the regressions without *Ln*(*ILLIQ*), *Ln*(*SIZE*) has a uniformly negative sign although the coefficients in the return regressions are statistically insignificant. In specification (3) where we include both *Ln*(*ILLIQ*) and *Ln*(*SIZE*), in the return regressions, the coefficient on *Ln*(*ILLIQ*) is positive and statistically significant for the 1955-2016 time period, and its magnitude is roughly similar to that in Amihud and Noh (2021); see their Table 1. The coefficient, however, is insignificant for the 1977-2018 time period.

In the *ICC* regressions, the *Ln*(*ILLIQ*) coefficient flips sign and becomes significantly negative while the coefficient on *Ln*(*SIZE*) remains significantly negative. This strongly suggests that *Ln*(*ILLIQ*) is a proxy of *Ln*(*SIZE*) and its positive relationship with *ICC* in the absence of *Ln*(*SIZE*) is due to its high negative correlation with *Ln*(*SIZE*). The negative relationship between *Ln*(*ILLIQ*) and *ICC* in the presence of *Ln*(*SIZE*) is also consistent with the portfolio results in Table 3. The coefficient of −0.285 for *Ln*(*ILLIQ*) implies that a one standard deviation increase in *Ln*(*ILLIQ*) leads to a decline of 0.62% in *ICC*.[10]

Ln(*B*/*M*) is significantly positively related to both returns and *ICC* which is consistent with the risk interpretations in Fama and French (1992) and Berk, Green, and Naik (1999). While *Beta* is not related to realized returns, it is significantly positively related to *ICC* suggesting that investors do require a higher cost of capital for higher beta stocks. Past price momentum, *Return11*, not surprisingly has a positive sign in the return regressions although it is negatively related to *ICC* which suggests that past winners have low long-term cost of capital. This is inconsistent with risk-based interpretations of price momentum.

In Figure A1 in the online appendix, we plot the time-series of FM coefficients on *Ln*(*ILLIQ*) where the dependent variable is *ICC* for specification 3 in Panel A of Table 4. The figure demonstrates that outliers do not drive our result of a negative relation between illiquidity and *ICC*. The coefficient remains below zero for sustained periods of time, though there also are episodes of positivity. Overall, the time-series pattern is inconsistent with the notion that illiquidity implies higher costs of capital.

Recent research shows theoretically and empirically that profitability and asset growth are strongly related to the cross-section of stock returns (see Novy-Marx, 2013; Kogan and Papanikolaou, 2013; Cooper, Gulen, and Schill, 2008; and Cohen, Gompers, and Vuolteenaho, 2002). Therefore, in Panel B of Table 4 we add two additional control variables: *GP*/*AT* and *Ln*(1+*AG*). *Ln*(*ILLIQ*) continues to be strongly negatively associated with *ICC* in the presence of

[10] We use the maximum number of stocks available for each estimation. However, using the same sample across the *ICC* and realized returns regressions does not materially alter the conclusions. Results are available on request.

GP/*AT* and *Ln*(1+*AG*). The slope coefficient on *Ln*(*ILLIQ*) is, in fact, slightly higher in magnitude at −0.346 and more significant (*t*-statistic = −3.00) in Panel B than in Panel A (a coefficient of −0.285 and *t*-statistic of −2.28), implying that a one standard deviation increase in *Ln*(*ILLIQ*) leads to a decline of 0.75% in *ICC*. While profitability (*GP*/*AT*), as expected, is positively related to monthly returns, it is significantly negatively related to *ICC* which suggests profitable firms tend to have low long-term cost of capital. Asset growth is negatively related to both returns and *ICC*.

We also estimate the regression specifications in Equations (4) and (5) in ranks, i.e., where all the independent variables are converted to rank order with values between 0 and 1. We find (see Table A1 of the online appendix) that the negative relationship between Amihud illiquidity and *ICC* is noticeably stronger (*t*-statistic of −6.61) in the rank regressions. The coefficients in rank regressions are annualized premiums for each independent variable. The negative premium of −4.294% corresponding to *Ln*(*ILLIQ*) is economically significant and comparable in magnitude to the premiums for *Ln*(*SIZE*) (−7.823%) and *Ln*(*B*/*M*) (3.777%).

In Table A2 of the online appendix, we include additional factor betas beyond the market beta as controls. Specifically, we estimate betas using the five factor Fama and French model, with the same method as that used for the market beta, and include them as controls. The results do not change appreciably. We find that *ICC* continues to be negatively related to *ILLIQ*, while monthly returns continue to be positively related to *ILLIQ*. In Table A3, we consider the robustness of our findings by splitting the time-series into two equal halves and estimating the *ICC* regressions separately for each subsample. The coefficient on *ILLIQ* continues to be negative and is significant at the 10% level or less in all cases save one.

Both Brennan, Huh, and Subrahmanyam (2013) and Lou and Shu (2017) emphasize the need to have a dimensionless measure in the denominator of Amihud (2002) illiquidity, as opposed to using dollar volume, which depends on the scale of the firm. In other words, dollar volume might be higher simply because the firm is bigger. They suggest replacing dollar volume with share turnover which is dimensionless. Accordingly, in Table 5 we replace the dollar volume measure of Amihud with its turnover-based counterpart. The only change relative to Table 4 is that the denominator of the measure is replaced with share turnover.

Again, we find that the turnover based Amihud measure is positively related to realized returns (although marginally significantly for the 1977-2018 time period) but negatively related to *ICC*.[11] The significance of illiquidity for *ICC* drops, however, relative to Panel B of Table 4 (t-statistic of −2.14 vs. −3.00). Regardless, there is no evidence that higher values of the turnover-based version of the Amihud illiquidity measure are associated with higher *ICC*.

The results in Table 3 suggest that illiquidity is priced (in monthly realized returns) only within small stocks. We explore this further in a multivariate regression setting. Table 6 reports regression results for large stocks and small stocks separately. Stocks with market capitalization above the NYSE median market capitalization are classified as 'Large' and those with market capitalization below the median are classified as 'Small.' Panel A of Table 6 reports results for the base specification and Panel B reports results with the two additional control variables. The results from the return regressions confirm that *Ln*(*ILLIQ*) is related to monthly realized returns only in small stocks. The slope coefficients corresponding to *Ln*(*ILLIQ*) are much bigger and highly significant in small stocks compared to large stocks. For instance, in Panel A for the 1955-2016 time period, the slope coefficient on *Ln*(*ILLIQ*) is 0.206 (t-statistic = 5.11) among small stocks while it is 0.003 (t-statistic = 0.09) among large stocks. In contrast, the negative

[11] For realized returns, we consider the illiquidity-induced bias described by Asparouhova, Bessembinder, and Kalcheva (2010). Specifically, as suggested by these authors, we implement a weighted least squares regression, using previous months' gross returns as weights. The results are substantively unchanged.

relationship between *Ln*(*ILLIQ*) and *ICC* is significant among both large and small stocks (*t*-statistics of −8.03 and −2.76, respectively) although it is stronger among large stocks. This is consistent with the finding in Panel B of Table 3 which shows that the Big portfolio with High illiquidity has the lowest *ICC*. The negative relationship between *Ln*(*ILLIQ*) and *ICC* are stronger in Panel B, where we include the two additional controls *GP*/*AT* and *Ln*(1+*AG*).

Finally, we examine the robustness of our findings using two variations on our *ICCs*. Our first variation on the *ICC* calculation is to use alternative approaches to incorporate analysts' projections. These computations are based on Easton (2004) and Ohlson and Juettener-Nauroth (2005). Our second variation uses regression forecasts of earnings, instead of analysts' estimates, to compute *ICC*. We thus apply our base case *ICC* methodology described in Section 1 while using the Li and Mohanram (2014) regression-based approach. The computations of earnings forecasts in this case are based on equation (7) of Li and Mohanram (2014). The results are presented in Table A4 of the online appendix.

We find that the negative relation between *Ln*(*ILLIQ*) and *ICC* is even stronger with the alternative *ICCs* based on analyst forecasts (see Columns 1 and 2). For the Easton (2004) *ICC* measure, the *t*-statistic corresponding to *Ln*(*ILLIQ*) is −12.93 and for the Ohlson and Juettner-Nauroth (2005) *ICC* measure, the *t*-statistic is −15.12. The results based on regression forecasts of earnings (see Column 3) show that the relation between *Ln(ILLIQ)* and *ICC* is still negative but insignificant. Overall, the results show that our findings are not dependent on any one approach to estimating the *ICC*.

3.3 Components of Illiquidity

Lou and Shu (2017) critique Amihud (2002)'s finding that illiquidity is priced, specifically with respect to the *ILLIQ* measure introduced in that paper. They argue that the pricing of the Amihud illiquidity measure is driven mainly by the denominator of *ILLIQ*, the dollar trading volume. They test an alternative measure, which is the average of 1 divided by daily dollar trading volume and report that this measure has a correlation of 0.90 with the original measure and that it is priced similarly to the original Amihud measure. Furthermore, they find that the piece of the original measure that is orthogonal to the new measure is not priced. In turn, Amihud and Noh (2021) point out that Lou and Shu's analysis misses an important term present in the decomposition of *ILLIQ*. Using our notation, the Amihud and Noh (2021) decomposition of *ILLIQ* (using the average as an estimator of expected value) is:

$$ILLIQ_{it} = \overline{|R_{it}|} \times \overline{1/DVOL_{it}} + \text{cov}(|R_{it}|, 1/DVOL_{it}), \tag{6}$$

where $\overline{|R_{it}|} = \left(\sum_{d=1}^{D_{it}} |R_{id}|\right)/D_{it}$ and $\overline{1/DVOL_{it}} = \left(\sum_{d=1}^{D_{it}} 1/VOLD_{id}\right)/D_{it}$ are calculated in the same way as $ILLIQ_{it}$ in Equation (3). The Lou and Shu (2017) decomposition of *ILLIQ* is the first term on the right-hand side of Equation (6) which applies if the covariance is zero. Amihud and Noh (2021) propose the difference between *Ln*(*ILLIQ*) and the natural log of the Lou and Shu (2017) decomposition (which is just the sum of $Ln(\overline{|R_t|})$ and $Ln(\overline{1/DVOL_t})$) as an approximate measure of the missing covariance term:

$$DIF_{it} = Ln(ILLIQ_{it}) - (Ln(\overline{|R_{it}|}) + Ln(\overline{1/DVOL_{it}}\,)). \tag{7}$$

In Table 7, we replace *Ln*(*ILLIQ*) with *Ln*(|*R*|), *Ln*(1/*DVOL*), and *DIF* to understand how the different components of illiquidity are priced. For the 1955-2016 time period, we find that both *Ln*(1/*DVOL*) and *DIF* are priced positively in monthly returns but mostly for small stocks. The absolute return component, *Ln*(|*R*|), is negatively related to returns, but again significantly only for small stocks. Although the signs on the components are similar, the results are quite a bit weaker for the 1977-2018 time period.

In the *ICC* regressions we find that the absolute return component is strongly positively related to *ICC* (similar to the positive relationship reported between volatility and *ICC* among international stocks in Lee, Ng, and Swaminathan, 2009) while inverse dollar volume and *DIF* are negatively related. The negative relationship between inverse dollar volume and *ICC* is particularly strong among large stocks, suggesting that those large stocks with lower dollar trading volume (low liquidity) have low costs of capital. Overall, our results involving monthly returns confirm the findings in Amihud and Noh (2021) but with the added proviso that the short-term illiquidity pricing is really a small stock phenomenon. Illiquidity does not earn a positive premium in the long-term cost of capital net of previously known *ICC* determinants.

4. Aggregate Liquidity and *ICC*

In this section, we examine the dynamic relation between illiquidity and *ICC* at the aggregate level. The notion, as in Amihud (2002), is that market-level illiquidity should positively influence aggregate (market-wide) required returns. We address the issue using simple time-series regressions and a vector autoregression (VAR) analysis.

4.1 Regression Analysis Using *ICC* and Illiquidity Innovations

Amihud and Noh (2021) and Amihud (2002) examine the relationship between shocks to aggregate illiquidity and stock returns. They hypothesize that an increase in aggregate market illiquidity should increase the expected return on the market and result in a decline in current stock prices, all else equal. They also suggest that shocks to market illiquidity should affect small stocks more than large stocks because the former are less liquid.

Following the Amihud and Noh (2021) approach, each month, we value-weight *ILLIQ* and its components across individual stocks to construct market-wide illiquidity measures. We transform the market wide measures to logs and denote them as *mILLIQ*, $m|R|$, $m1/DVOL$, and the difference between *mILLIQ* and the sum of $m|R|$ and $m1/DVOL$ as *mDIF* corresponding to the individual stock measures defined in Equation (7). We then compute the innovations in these aggregate time series as follows. We first estimate an AR(2) model for each time-series over a rolling window of 60 months ending in month t (the models for *mILLIQ* and $m1/DVOL$ also include a time trend). We then compute the innovation at time $t+1$ as the difference between the actual value and the predicted value from the AR(2) model.

We contemporaneously regress monthly excess market returns (in excess of monthly T-bill return) and, in turn, an aggregate *ICC* measure, on innovations to illiquidity and its components. The aggregate *ICC* is computed by value-weighting the individual stock *ICC* values. The results are presented in Table 8. The sample period is 1955-2016 for the return regressions and 1977-2018 for the *ICC* regressions. While *mILLIQ* and its components are all negatively related to excess market returns as in Amihud and Noh (2021), we do not observe the same level of statistical significance and our R^2s are also only about one-fifth of the R^2s reported in their paper.

The regressions involving aggregate *ICC* show that there is no reliable relationship between this variable and aggregate Amihud-based illiquidity. Since *ICC* is a slowly mean reverting variable we have also regressed changes in *ICC* (which is a proxy for discount rate news) on innovations to aggregate illiquidity and its components and can report that there is no reliable relationship there either. Overall, the evidence does not support the conjecture that shocks to aggregate illiquidity might be associated with increases in aggregate *ICC*.

4.2 Vector Autoregressions

To allow for the possibility that *ICC* and illiquidity are jointly determined, we also conduct a vector autoregression (VAR) between these variables. The VAR detects the joint dynamics between the two variables while allowing for their cross-dependence. The idea is that a simple contemporaneous regression with illiquidity on the right-hand side and implied risk premium on the left-hand side might fail to capture the nature of leads and lags across the series.

It is appropriate to perform VARs on stationary series. However, there is reason to believe that liquidity has increased over time (Chordia, Roll, and Subrahmanyam, 2001), suggesting non-stationarity. We, therefore, detrend *mILLIQ* (using a linear time trend). We plot the *mICC* series, and the detrended *mILLIQ* series in Figure 2. Visual inspection does not reveal evidence of non-stationarity. Indeed, in untabulated tests, following the de-trending, we can reject the hypothesis that the resulting *mILLIQ* series has a unit root, based on an augmented Dickey-Fuller statistic. The unadjusted *mICC* series also does not indicate evidence of a unit root.

The lag length in the VAR is chosen using the Akaike information criterion. The suggested lag length is one and this is what we use in our analysis.[12] Table 9 reports the VAR coefficients and *t*-statistics in parentheses below the coefficients. While there is persistence in both series (in the sense that own lags are strongly significant), we find no evidence that one series forecasts the other in the simple VAR; the cross-lag coefficients are both insignificant.

In Figure 3 we report the impulse response functions for each variable relative to the other. We find that the standard error bounds include zero in each case, again suggesting that neither variable is useful in forecasting the other. Finally, the last row in Table 9 indicates that the contemporaneous correlation in the innovations to the two series is an insignificant 3.1%.

[12] Alternative lag lengths of up to twelve make no material difference to our results.

The VAR results therefore confirm that there is no dynamic relation between aggregate cost of capital estimates and aggregate illiquidity. Aggregate illiquidity does not help forecast changes in costs of capital, and there is no significant contemporaneous relation between the two variables.

5. Cross-Sectional Regressions Involving NASDAQ Stocks

In this section, we examine the robustness of our cross-sectional findings in Section 3 involving NYSE/AMEX stocks using NASDAQ stocks. The filters employed for NASDAQ stocks are the same as those for NYSE/AMEX stocks, as described in Section 2. Further, it is known that trading volume is often overstated for NASDAQ stocks, and therefore we use the procedure recommended by Anderson and Dyl (2005) to adjust for this overstatement.[13] The sample period is 1983-2018, since NASDAQ trading volume is not available prior to 1983. We report results for two samples: a NASDAQ sample and a combined NYSE/AMEX/NASDAQ sample. The results are presented in Table 10. Specification (1) presents results using *Ln*(*ILLIQ*), while specification (2) replaces *Ln*(*ILLIQ*) with its components and drops *GP*/*AT* and *Ln*(1+*AG*). *Return* refers to excess returns and *ICC* is the cost of capital estimate (less the ten-year Treasury bond yield).

The results show that *Ln*(*ILLIQ*) is positively priced in monthly realized returns in both the NASDAQ sample and the combined sample. In the *ICC* regressions, just as in Table 4 involving NYSE/AMEX stocks, *Ln*(*ILLIQ*) is significantly negatively related to *ICC*. The coefficients on *Ln*(*ILLIQ*) (in absolute terms) are in fact higher and more significant than the corresponding one in Panel B of Table 4. The results involving components of *Ln*(*ILLIQ*) mirror

[13] We correct for double counting of volume in NASDAQ by following Anderson and Dyl (2005). Specifically, for the periods prior to February 2001, February to December 2001, and calendar years 2002 to 2004, we divide NASDAQ volume by 2.0, 1.8, and 1.6, respectively.

the results in Table 7. The absolute return component, *Ln*(|*R*|), is negatively related to returns and the inverse dollar volume and *DIF* are positively related to realized returns. In the *ICC* regressions, the absolute return component is strongly positively related to *ICC* while the inverse dollar volume and *DIF* are negatively related. In summary, the results involving NASDAQ stocks confirm our key findings and provide an important robustness check for our primary results.

6. Alternative Measures of Liquidity, Liquidity Risk, and Information Risk

In this section, we examine the relationship between *ICC* and measures of liquidity other than that of Amihud (2002), and also investigate the role of liquidity risk and information risk in determining a firm's long-term cost of capital.

Table 11 reports results from cross-sectional regressions examining the relationship among returns, *ICC*, and three alternative measures of liquidity. Specifically, we consider the Lesmond, Ogden, and Trzcinka (1999) measure (*LOT*), which is the proportion of zero return days within a month, the Pástor and Stambaugh (2003) measure (*PS*), and the original Amihud and Mendelson (1986) measure, which is the closing quoted spread from CRSP. We take natural logs of the quoted spread and (1+*LOT*) (since *LOT* can be zero) and leave the *PS* measure as is (since *PS* can be negative). The sample consists of NYSE, AMEX, and NASDAQ stocks. The time period is 1977 to 2018 for *LOT* and the quoted spread and 1983 to 2018 for *PS*. The results show that *Ln*(*Spread*) is negatively related to both returns and *ICC*. *PS* and *Ln*(1+*LOT*) are not significantly related to either returns or *ICC*.[14]

A major branch of the literature on liquidity is the introduction of the role of liquidity

[14] Results based on just using *LOT* are no different. We have also tried the *LM12* liquidity measure of Liu (2006) and can report that *Ln*(*LM12*) is significantly positively related to monthly returns and negatively related to *ICC* just as in the case of *Ln*(*ILLIQ*).

risk. The idea is that fluctuations in illiquidity should be priced in addition to illiquidity itself. The two seminal contributions to this area are Acharya and Pedersen (2005) and Pástor and Stambaugh (2003). A second and parallel development on linking market microstructure to asset pricing is to measure the probability of informed trading (or information risk) directly using a structural model. This model uses signed buys and sells on a daily basis to compute *PIN,* a measure of informed trading. The original *PIN* measure of Easley, Hvidkjaer, and O'Hara (2002) is modified by Duarte, Hu, and Young (2020) and is termed *GPIN*.[15] The key contribution in Easley, Hvidkjaer, and O'Hara (2002) is to show that the probability of information-based trading commands a positive premium in the cross-section of monthly stock returns. The logic is that such trading distorts the portfolios of uninformed traders, thus inducing them to demand a return premium. This return premium could extend to a premium in firms' cost of capital or *ICC* (Easley and O'Hara, 2004).

Based on the above reasoning, we compute three quantities: *AP beta* is the liquidity beta calculated as in Acharya and Pedersen (2005), *PS beta* is the liquidity beta calculated as in Pástor and Stambaugh (2003), and *GPIN* is the generalized *PIN* calculated as in Duarte, Hu, and Young (2020). The exact procedure is as follows:

AP beta: We form 25 illiquidity portfolios based on Acharya and Pedersen (2005) for the sample period from July 1962 to December 2018. Specifically, we sort NYSE and AMEX stocks with prices between \$5 and \$1,000 based on their Amihud illiquidity over the prior year (with a minimum of 100 days of observations) into 25 portfolios. We form value-weighted portfolios at the end of December of each year with annual rebalancing, and compute portfolio-level normalized illiquidity each month using prior month's market capitalization as weights.

[15] Duarte, Hu, and Young (2020) modify the original *PIN* measure to account for uninformed noise trading that is captured by high levels of turnover; see their paper for details.

We also calculate illiquidity for a market portfolio of NYSE and AMEX stocks with prices between \$5 and \$1,000 and at least 15 days of return and volume data each month and rebalance this portfolio monthly. Innovations in portfolio illiquidity, market illiquidity, and market returns are calculated using an AR(2) regression following Acharya and Pedersen (2005). From Equation (24) of their paper, we then calculate four illiquidity betas and a net illiquidity beta based on the four illiquidity betas. The net illiquidity beta (*AP beta*) is the measure of liquidity risk. The full-sample portfolio net illiquidity betas are then reassigned to individual stocks based on the portfolio to which the stock belongs at the end of each year.

PS beta: We form Pástor and Stambaugh (2003) 10 illiquidity portfolios for the sample period from December 1977 to December 2018. We first calculate liquidity betas for all stocks in a regression with three Fama and French (1993) factors and a liquidity innovation factor. The regression uses monthly data over the past five years (with 60 observations) on a rolling basis. We then form decile portfolios separately for NYSE/AMEX and NASDAQ stocks (ten portfolios for each sample) with prices between \$5 and \$1,000 based on their liquidity betas. Portfolios are formed at the end of December of each year and rebalanced annually. The full-sample portfolio illiquidity betas are then reassigned to individual stocks based on the portfolio to which the stock belongs at the end of each year.

GPIN: We follow Duarte, Hu, and Young (2020) and calculate the conditional probability of informed trading using the generalized *PIN* model daily for NYSE stocks from 1993 to 2018.[16] *GPIN* is then the monthly average of these probabilities. We take the logistic transformation of *GPIN*, *Ln*[*GPIN*/(1−*GPIN*)], as our information risk variable.

In Table A5 in the internet appendix, we present an expanded version of the correlation matrix in Table 2, which includes the three measures above. The *PIN* measure and *PS beta* show

[16] We thank the authors for providing code and data on https://edwinhu.github.io/pin/.

low correlations with other variables (they are mostly less than 0.06 in absolute terms). *AP beta* is modestly positively correlated with *ICC* (0.050) but is also negatively correlated with the natural log of firm size (−0.269). This underscores the importance of disentangling the effect of liquidity risk after controlling for firm size.

Table 12 presents the regression results. We continue to include the level of Amihud illiquidity as a control. Consistent with Easley, Hvidkjaer, and O'Hara (2002), *GPIN* is positively priced in realized returns (*t*-statistic = 2.50), but there is no evidence that higher values of liquidity betas and *GPIN* lead to higher cost of capital. Indeed, both *AP beta* and *GPIN* are negatively related to *ICC*, and *AP beta* significantly so. Further, *Ln*(*ILLIQ*) continues to be significantly negatively related to *ICC* in the presence of these liquidity risk measures. Overall, our results do not support the notion that firms should care about liquidity or information risk in setting their costs of capital for long-term projects.[17]

We want to emphasize that we are not implying that liquidity and information risk are irrelevant to a typical investor. Instead, we argue that given the arsenal of available measures, we are not able to uncover evidence that these measures should be of concern to firms in setting their long-term discount rates.[18]

[17] In unreported tests, we also include the Roll (1984) measure as well as Kyle's (1985) lambda (Glosten and Harris, 1988; Brennan and Subrahmanyam, 1996). We use a WRDS off-the-shelf variable (*TSignSqrtDVol2*) to measure lambda and the usual two times the square root of the sign-flipped daily serial covariance as the Roll measure. We do not include these in Table 11 as the Roll (1984) measure is similar to the bid-ask spread, and Kyle's (1985) lambda measures price impact, which is similar to the Amihud (2002) concept. Further, the requirement in Roll (1984) that the serial covariance needs to be negative causes a large drop in sample size. Consistent with the findings in Table 11, we find that neither the Roll (1984) measure nor the lambda are consistently positive determinants of *ICC*.

[18] Keloharju, Linnainmaa, and Nyberg (2021) show that long-term realized returns do not incorporate premia associated with a large number of "return anomalies" that emerge in short-term (monthly) realized returns. We instead focus on the relation between illiquidity and *ICC*, where the latter is a proxy for the actual cost of capital for long-term corporate projects. Our design sheds light on whether publicly traded corporations should account for illiquidity in setting their discount rates.

7. Difference-in-Differences (DiD) Around Brokerage Closures

So far, our analysis focused on the cross-sectional relationship between Amihud illiquidity and the cost of capital. In this section, we focus on the effects of changes in liquidity of individual stocks due to exogenous reasons. For this experiment, we follow Kelly and Ljungqvist (2012) and construct a sample of stocks whose sell-side analyst coverage declined following brokerage closures or brokerage mergers that occurred between the first quarter of 2000 and the first quarter of 2008.[19] For each brokerage closure, we identify stocks that were covered by the broker before the closure ended the coverage. For mergers, we identify stocks that had a sell-side-earnings estimate by both brokers in the quarter before the event but by only one of the two brokers in the quarter after the event. This sample constitutes the sample of treated (not necessarily unique) stocks numbering 2,563. For every treated stock, we choose *five* control stocks at random in the same size and book-to-market quintile as the treated stock in the quarter preceding the event; subject to the condition that the control firms were themselves not subject to coverage termination in the one year around the event.

We calculate *Ln*(*ILLIQ*) and *ICC* for each treated stock in the month immediately before and the month immediately after the event. We choose this window to avoid the confounding effects of any other exogenous firm-specific events that might affect a stock's liquidity. The window also allows us to compute changes in *ICC* based on the *ICCs* computed immediately before and immediately after the brokerage closure thus reflecting any changes in consensus earnings estimates resulting from the brokerage closures. Thus, the window is likely to provide the cleanest test of the effect of brokerage closures on cost of capital. We also average *Ln*(*ILLIQ*) and *ICC* across the five control stocks corresponding to each treated stock to obtain

[19] We thank Feng Jiang for help in constructing these data.

one number for that control group (for the same one-month window).

Table 13 reports the cross-sectional averages of the above statistics before and after the event for both treated and control firms as well as the double difference. Since brokerage closures are clustered in time, multiple brokerages can stop covering a stock at the same time, so that the same stock can show up as a treated stock multiple times within a short time period. To control for this clustering effect, we follow Kelly and Ljungqvist (2012) in calculating the standard error of the DiD difference with a block bootstrap simulation procedure with a block length 100 and 10,000 repetitions. We report these statistics for the entire sample as well as for sub-samples grouped based on the number of sell-side analysts covering the treated firm in the month preceding the event.

The results in Panel A of Table 13 show that *Ln*(*ILLIQ*) increases significantly (meaning that liquidity declines) following brokerage closures in the overall sample and in every sub-sample by number of analysts. Specifically, in the overall sample, *Ln*(*ILLIQ*) increases by six standard deviations while in the sub-samples it increases by three to seven standard deviations. These results confirm Kelly and Ljungqvist (2012).

The point estimates of *ICC*, on the other hand, decline by ten basis points in the overall sample and in every sub-sample except the one with analyst coverage of 5 or less. To put this finding in context, Kelly and Ljungqvist (2012) report that in the days after a stock loses coverage, its price drops on average by about 1.0% (adjusting for market movements). Similarly, we find that in our sample of 2,563 firms, prices decline by about 0.8% (net of control firm price changes) during the event month. If consensus earnings estimates do not change appreciably from the month before to the month after the event, a decline in price should mechanically lead to an increase in *ICC*. We do not see such increases but decreases instead.

These decreases, however, are not statistically significant. Thus, the cost of capital does not increase with an increase in Amihud illiquidity following the exogenous decrease in analyst coverage. Overall, the DiD results involving brokerage closures mirror our earlier findings that high illiquidity does not lead to higher costs of capital for firms.

In Table A6 within the internet appendix, we provide the DiD results for market capitalization. This is because market capitalization is negatively related to *ICC* in cross-sectional regressions (Lee, Ng, and Swaminathan, 2009, and our Table 4), and might possibly be an (inverse) illiquidity proxy. We find that while the point estimates of market capitalization shifts are negatively affected by the brokerage closures, the changes are economically modest (less than 2%), and statistically insignificant in all cases but one. From Panel A of Table 13, however, the changes in illiquidity itself are consistently significant in every case. These findings indicate that even if market capitalization is a proxy for illiquidity, it is, at best, a very noisy one. Coupled with the observation that *ICC* is unaffected by the brokerage closures, it seems unlikely that the pricing of market capitalization in *ICC* reflects a premium for illiquidity.

8. Why is there a Negative Illiquidity-*ICC* Relation in the Cross-Section?

The result that illiquidity varies inversely with cost of capital estimates in the cross-section (controlling for size) is quite puzzling. Why is this the case? We investigate this question by documenting various characteristics of the size/illiquidity-sorted portfolios in Table 3. We document values of these portfolios' *B*/*M*, dollar volume, gross profitability, share turnover, asset growth, volatility, the past month's return, past momentum return, and the past return computed over the interval $(t - 35, t - 12)$ as well as $(t - 35, t)$. The latter two returns capture the long-term reversals of De Bondt and Thaler (1985). The characteristics appear in

Table 14.

The robust pattern is that across all size groups, more illiquid stocks have lower *B*/*M* ratios and lower trading volume. For example, the *B*/*M* for the smallest, highly illiquid firms is in fact 17% lower than that for the smallest, most liquid firms. The dollar volume is one-ninth lower for the smallest, most illiquid firms relative to the most liquid counterparts. At the same time, the illiquid firms have very high momentum. The momentum return over the last year (skipping the most recent month) for the smallest, most illiquid firms is 26.26%, whereas it is −7.34% for the smallest, least illiquid firms. However, the cumulative returns over the prior two years ($t - 35$ to $t - 12$) exhibit the opposite pattern to momentum returns: highly illiquid stocks underperform the more liquid stocks. The other size groups show similar characteristic rankings as that for the smallest size group. Finally, the point estimate differentials for asset growth and profitability are not materially different across the various illiquidity-sorted groups, and illiquid firms are slightly *less* volatile than their liquid counterparts.

While the patterns are somewhat complex and do not lend themselves to an easy interpretation, the results in Table 14 seem consistent with the theoretical work of Berk, Green, and Naik (1999). These authors argue that low *B*/*M* firms (Panel B shows high *ILLIQ* firms have low *B*/*M*) are low risk going forward due to the fact that they have taken on low-risk projects in their recent past, as reflected in their increasingly high market value relative to book value. This interpretation is consistent with the fact that such firms have extremely high momentum returns. Furthermore, low risk should mean lower disagreement, and thus, lower trading activity (Hong and Stein, 2007; Carlin, Longstaff, and Matoba, 2014), as we find in Panels D and F of Table

14.[20] Going forward such low-risk firms should command a lower cost of capital, which is consistent with our findings. Thus, illiquidity might imply an influence of *B*/*M* beyond just a linear control in regressions. Whether this explanation is indeed correct may require further investigation.

9. Summary and Concluding Remarks

A large body of literature finds evidence that high illiquidity implies high monthly realized returns. This finding is interpreted as supporting the notion that investors demand higher returns for more illiquid firms. Using standard U.S. data, we test if illiquidity is related to estimates of firms' costs of capital (*ICC*), which correspond to long-term internal rates of return (in excess of a benchmark 10-year Treasury yield) on expected cash flows. We are unable to uncover cross-sectional evidence that illiquidity (as measured by Amihud, 2002) is positively related to costs of capital, after controlling for other known determinants of *ICC*. This conclusion is robust to using different measures of *ICC* using both analyst- and regression-based earnings forecasts. Further, at the aggregate level, illiquidity innovations do not help forecast *ICC* innovations (or vice versa). A difference-in-differences analysis around exogenous brokerage closures shows a decrease in liquidity (as in Kelly and Ljungqvist, 2012) but no accompanying increase in *ICC*.

Our evidence accords with Constantinides (1986), who indicates that agents with long horizons respond to illiquidity by scaling back their volume and frequency of trade, and therefore do not demand illiquidity premia. On the other hand, our analysis does not rule out the possibility that illiquidity might be of concern to short-horizon investors and thus might

[20] While low *B*/*M* could also mean excessive overconfident optimism (Daniel, Hirshleifer, and Subrahmanyam, 2001), which also implies low returns going forward, it is not clear why this should imply lower trading activity relative to high *B*/*M*.

influence monthly returns; indeed, we do confirm that illiquidity positively forecasts monthly returns. We also note that since market capitalization is inversely related to *ICC*, it is a candidate for a priced liquidity proxy. But, we consider an arsenal of alternative, and more economically intuitive, proxies for liquidity, liquidity risk, and information risk, neither of which yield evidence of being priced in *ICC*.

As a byproduct of our analysis, we provide evidence that, net of standard controls, cost of capital estimates are lower for more illiquid firms. Our analyses suggest that illiquid firms tend to have lower trading activity and lower book-market ratios. These findings support the view that such firms have low disagreement and are thus low risk in the sense of Berk, Green, and Naik (1999). Their high market to book might reflect that they have taken on low-risk opportunities, and going forward, such low risk implies lower costs of capital. These findings, however, likely need further attention in future work.

Appendix

Details of the *ICC* Estimation

We use a three-stage approach to forecasting earnings up to year $t+T$. In the first stage, earnings forecast for year $t+1$ is based on median security analyst earnings forecasts, FY_1 and FY_2, for the next two fiscal years where $FY_1 > 0$ and $FY_2 > 0$. We use a weighted average of the FY_1 and FY_2 to construct a 12-month ahead earnings forecast $FE_1 = w \times FY_1 + (1-w) \times FY_2$, where w is the number of months to the next fiscal year-end divided by 12. In the second stage, we compute the implied growth rate, $g_2 = FY_2/FY_1 - 1$, and use it to forecast the two-year-ahead earnings forecast, $FE_2 = FE_1 \times (1 + g_2)$. This ensures that the forecasts for the next two years are always 12 months and 24 months ahead from the current month. The implied growth rate g_2 is winsorized to be between 1% and 75%. In the third stage, earnings from year $t+3$ to year $t+T+1$ are estimated by assuming that the year $t+2$ earnings growth rate g_2 mean-reverts exponentially to its steady-state value by year $t+T+2$. The steady-state growth rate in year $t+T+2$ is assumed to be the long-run nominal GDP growth rate, g, which is computed as an expanding average of annual nominal GDP growth rates starting in the calendar year 1930 and ending in the prior calendar year.[21] Thus, earnings growth rates and earnings forecasts for years $t+3$ to $t+T+1$ ($k = 3, \ldots, T+1$) are computed as follows:

$$
\begin{aligned}
g_{t+k} &= g_{t+k-1} \times \exp[\log(g/g_2)/T] \\
FE_{t+k} &= FE_{t+k-1} \times (1 + g_{t+k}). \qquad \text{(A1)}
\end{aligned}
$$

The exponential rate of mean-reversion is the same as linear interpolation in logs and provides a more rapid rate of mean reversion for very high growth rates. This is consistent with the

[21] For instance, the average used for the *ICC* calculations in calendar year 1977 is the arithmetic average of annual nominal GDP growth rates from 1930 to 1976, the average used for 1978 is the arithmetic average of annual nominal GDP growth rates from 1930 to 1977 and so on.

evidence in Nissim and Penman (2001) and Chan, Karceski, and Lakonishok (2003).

We forecast plowback rates also using a two-stage approach. In the first stage, plowback rate for year $t+1$ is estimated as one minus the most recent year's dividend payout ratio. The dividend payout ratio is calculated as the ratio of the most recent fiscal year dividends to the most recent fiscal year (positive) earnings.[22] We exclude share repurchases and new equity issues due to the difficulty in forecasting their recurrence in future periods.[23] We winsorize payout ratios to be between zero and one. In the second stage, we assume that the plowback rate in year $t+1$, b_1, reverts linearly to a steady-state value by year $t+T+1$ computed from the sustainable growth rate formula which assumes that the product of the return on new investments and the plowback rate $ROE \times b$ is equal to the steady-state growth in earnings g. Because competition will drive return on these investments down to the cost of equity, we further assume that in the steady state, ROE (return on new investments) equals r_e. Substituting ROE with cost of equity r_e in the sustainable growth rate formula gives us the steady-state value for the plowback rate, g/r_e. We compute the intermediate plowback rates from $t+2$ to $t+T$ ($k = 2, \dots, T$) using linear interpolation:

$$b_{t+k} = b_{t+k-1} - (b_1 - b)/T\,. \tag{A2}$$

The terminal value TV is the present value of a perpetuity equal to the year $t+T+1$ earnings forecast divided by the cost of equity:[24]

$$TV_{t+T} = FE_{t+T+1}/r_e, \tag{A3}$$

It is easy to show that the constant growth model for TV simplifies to Equation (A3) when ROE

[22] If the fiscal year earnings are negative, then we scale dividends by median FY_1 earnings forecasts.

[23] To gauge the impact of share repurchases and new equity issuances, we re-estimate the payout ratio by incorporating share repurchases net of new equity issuances. Our results are robust to *ICC* estimated using this alternate payout ratio.

[24] Note that the use of the no-growth perpetuity formula does not imply that earnings or cash flows do not grow after period $t+T$. Rather, it simply means that any new investments after year $t+T$ will earn zero economic profits. In other words, any growth in earnings or cash flows after year T is value irrelevant.

equals r_e. Combining Equations (1), (2), and (A1) to (A3) provides the following empirically implementable finite horizon model:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k} \times (1 - b_{t+k})}{(1 + r_e)^k} + \frac{FE_{t+T+1}}{r_e (1 + r_e)^T}. \tag{A4}$$

Following Li, Ng, and Swaminathan (2013), we use a 15-year horizon ($T = 15$) to implement the model in Equation (A4) and compute r_e as the rate of return that equates the present value of free cash flows to the current stock price.[25] The resulting r_e is the firm-level *ICC* measure used in our empirical analysis. We compute *ICC* for each month from January 1977 to December 2018 for all firms with available positive fiscal year 1 and fiscal year 2 consensus earnings forecasts ($FY_1 > 0$, $FY_2 > 0$) and the other data requirements described earlier.[26]

[25] Lee, Ng, and Swaminathan (2009) and Li, Ng, and Swaminathan (2013) test the robustness of *ICC* estimates by using different values of T ($T = 10$ or $T = 20$) and report that their cross-sectional and time-series results are robust to these alternative time horizons.

[26] See also Balakrishnan, Shivakumar, and Taori (2021) who construct cost of equity (CoE) estimates directly from analysts' CoE estimates which necessarily limits their cross-sectional sample to a few hundred firms per month on average. We have also estimated alternate *ICC*s based on Easton (2004) and Ohlson and Juettner-Nauroth (2005). We discuss the results using these alternate *ICC*s in Section 3.2.

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Figure 1: Average returns and *ICC* for portfolios sorted by size and illiquidity

We triple sort portfolios in sequential order into quartiles as in Table 3. The first and second sorts are on *SIZE* and the third sort is on *ILLIQ*. Variables are defined in Table 1. The breakpoints for all quintiles are from NYSE stocks. For each *ILLIQ* quartile, we average the four size quartiles of the second sort. The figure then plots post-formation statistics on the resulting 4×4 *SIZE* and *ILLIQ* portfolios. We show post-formation returns (in excess of risk-free rate) two months after the formation period and post-formation *ICC* (in excess of the long-term government bond yield) one month after the formation period. Excess returns are annualized. The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ* at the time of portfolio formation. The sample period is October 1977 to November 2018.

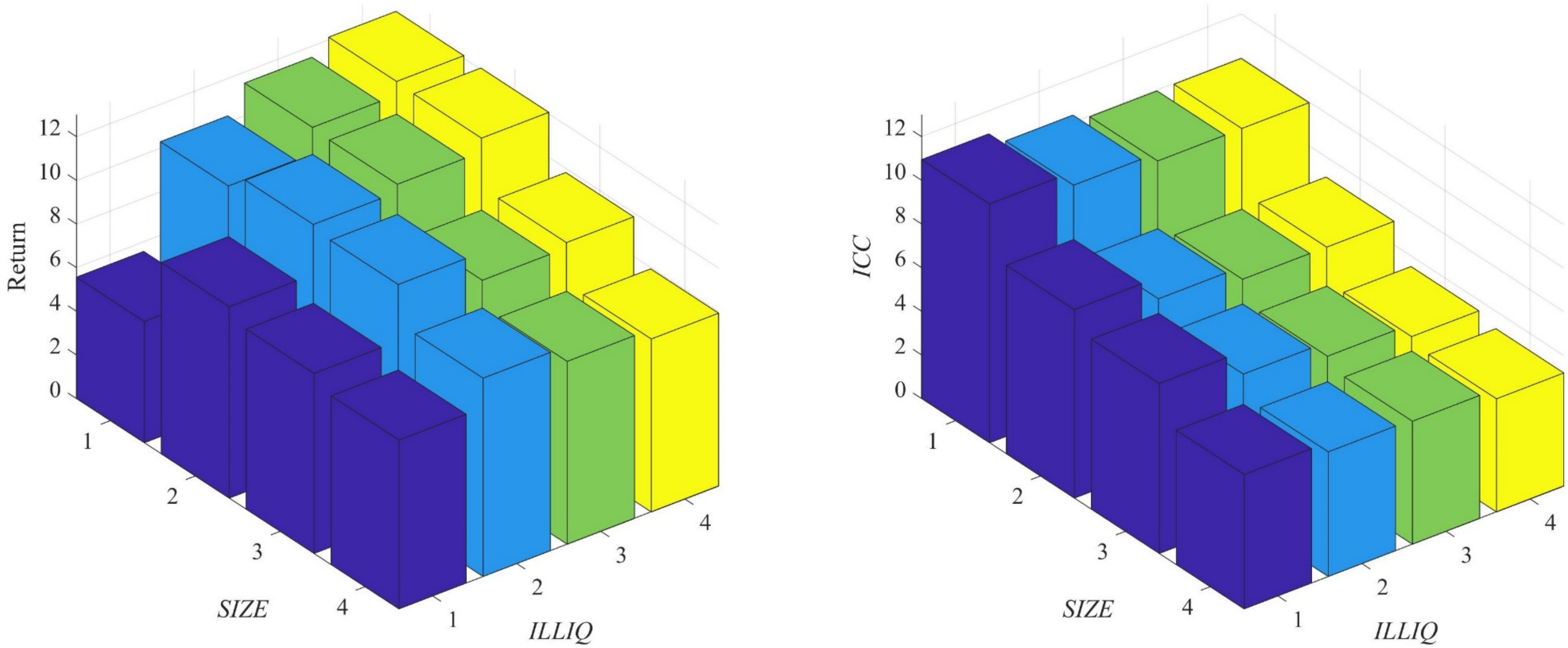

Figure 2: Market-wide *ICC* and illiquisity

We calculate market level *ICC* and illiquidity. *mICC* is the market implied risk premium (*ICC* – 10-year treasury yield) calculated as the value-weighted average of individual stock level *ICC*. *mILLIQ* is the linearly detrended logarithm of monthly market averages of individual stock level *ILLIQ*. The stock sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The figure plots the time-series variation in *mICC* and *mILLIQ*. The sample period is 1977 to 2018.

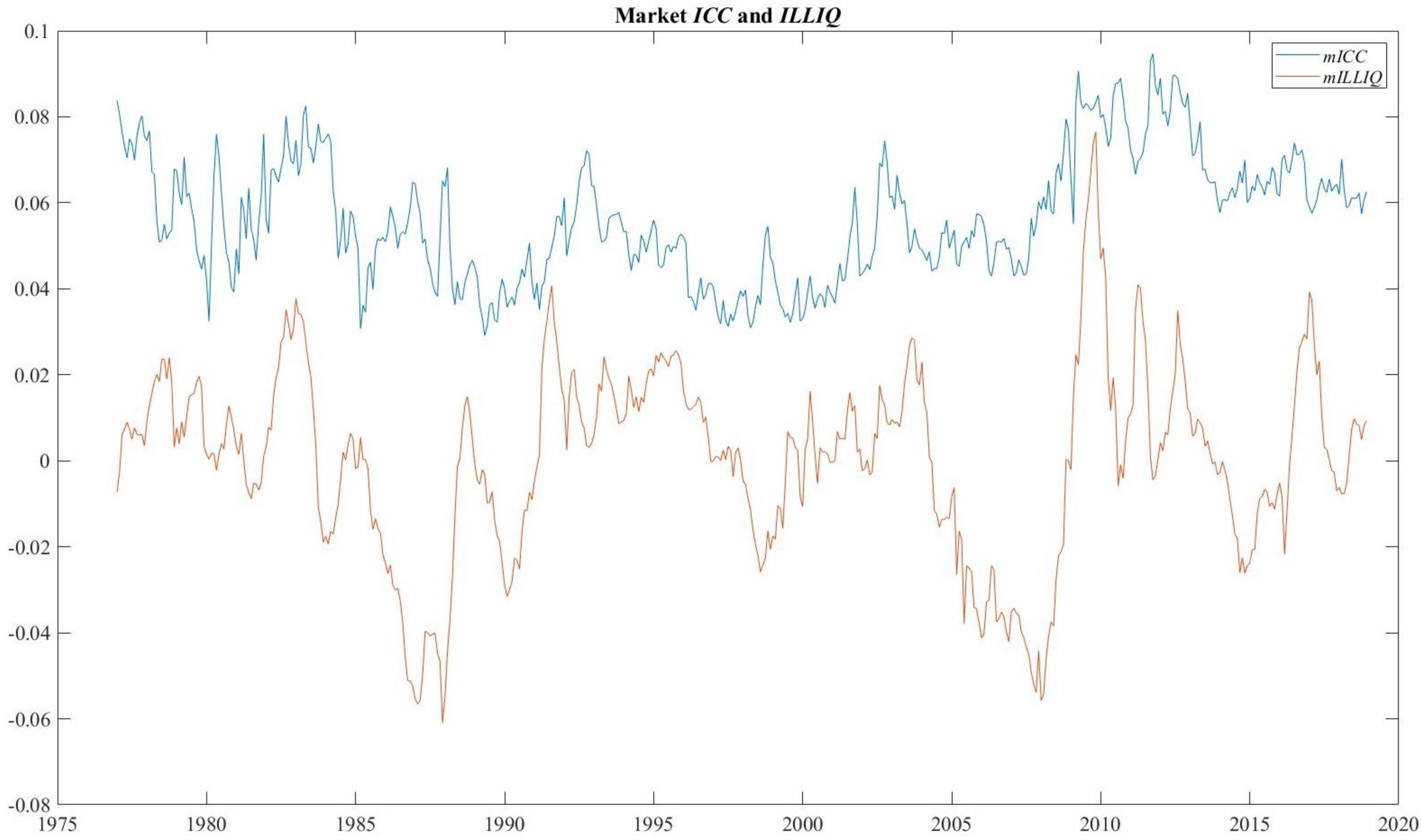

Figure 3: Impulse response functions for VAR using aggregate ICC and illiquidity

This figure plots the impulse response function (IRF) for the VAR estimated in Table 9. The top panel shows the IRF of *mICC* to shocks in *mICC* (in black) and shocks to *mILLIQ* (in red). The bottom panel shows the IRF of *mILLIQ* to shocks in *mICC* (in black) and shocks to *mILLIQ* (in red). The dotted lines plot the 95% confidence interval to IRFs. We plot these IRFs for sixty months after the shock.

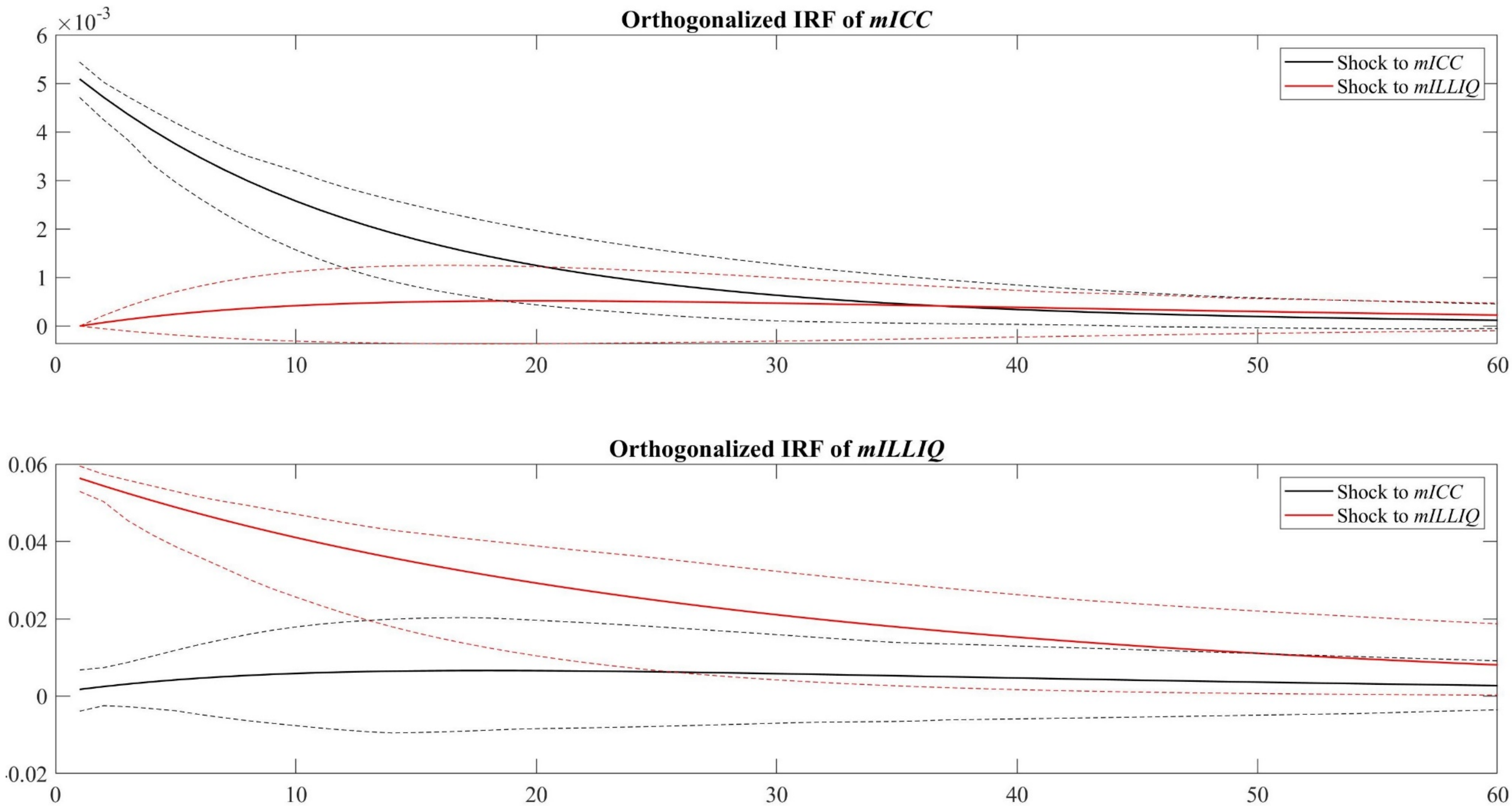

Table 1: Summary statistics

ICC is computed based on the 15-year discounted cash-flow method (please see the text and the Appendix for more details). We subtract the yield on 10-year treasuries to compute the implied premium. The *ICC* in Panels A and B refer to this implied premium. In Panel A, *ILLIQ* is the Amihud (2002) illiquidity calculated using one year of data (using a minimum of 200 days with available data) as the average of the ratio of absolute return to dollar volume (stock-days with negative prices or volume below 100 shares are deleted). *SIZE* is the market capitalization in billions of dollars. *B/M* is the ratio of book equity to market capitalization where book equity is calculated as in Fama and French (1993).). *Return11* is the 11-month cumulative return skipping one month. *Beta* is the market beta calculated using monthly data over the past 60 months (36 months minimum). *GP/AT* is the ratio of gross profit to total assets as in Novy-Marx (2013). *AG* is the percentage growth in total assets as in Cooper, Gulen, and Schill (2008). We use *Ln*(1+*AG*) to reduce the skewness in *AG*. All accounting variables are assumed to be known six months after the fiscal-year end. We compute cross-sectional statistics (mean, standard deviation, skewness and percentiles) of each variable each month. Panel A reports the time-series averages of these cross-sectional statistics. Panel B reports year by year cross-sectional distribution of *ICC* as of June of each year (column N shows the number of stocks). The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is 1977 to 2018.

Panel A: Summary statistics for various firm characteristics

	ILLIQ	*SIZE*	*Ln*(*ILLIQ*)	*Ln*(*SIZE*)	*Ln*(*B*/*M*)	*Return11*	*Beta*	*GP*/*AT*	*Ln*(1+*AG*)	*Return*	*ICC*
5^{th} percentile	0.001	82	−7.940	4.019	−1.966	−0.318	0.295	0.036	−0.128	−0.132	0.002
Median	0.041	1,093	−4.697	6.545	−0.551	0.119	1.038	0.281	0.072	0.006	0.053
Mean	0.195	3,940	−4.580	6.584	−0.630	0.179	1.088	0.323	0.102	0.012	0.073
95^{th} percentile	0.993	17,471	−0.774	9.281	0.469	0.847	2.077	0.785	0.450	0.172	0.218
StdDev	0.397	8,775	2.172	1.598	0.777	0.426	0.550	0.253	0.224	0.102	0.069
Skewness	4.858	5.092	0.221	0.109	−0.844	3.044	0.698	0.725	1.643	1.432	2.133

Panel B: Cross-sectional distribution of *ICC* by year							
	5%	Median	Mean	95%	StdDev	Skewness	N
1977	0.020	0.071	0.082	0.181	0.056	2.138	655
1978	−0.007	0.049	0.060	0.169	0.057	2.034	774
1979	0.006	0.062	0.071	0.158	0.064	3.748	922
1980	−0.005	0.059	0.073	0.224	0.070	1.869	964
1981	−0.023	0.043	0.066	0.243	0.097	5.362	1,093
1982	−0.020	0.054	0.087	0.300	0.106	2.223	1,020
1983	−0.018	0.054	0.082	0.277	0.095	1.906	1,092
1984	−0.026	0.038	0.065	0.250	0.090	1.773	1,239
1985	−0.018	0.037	0.062	0.242	0.078	1.482	1,159
1986	−0.006	0.045	0.072	0.242	0.077	1.377	1,144
1987	−0.011	0.044	0.064	0.203	0.068	1.392	1,139
1988	−0.016	0.036	0.053	0.184	0.063	1.679	1,139
1989	−0.010	0.036	0.053	0.181	0.063	2.110	1,165
1990	−0.004	0.041	0.064	0.218	0.071	1.830	1,132
1991	−0.005	0.045	0.072	0.240	0.078	1.526	1,109
1992	0.004	0.056	0.081	0.246	0.075	1.314	1,144
1993	0.009	0.054	0.074	0.218	0.065	1.621	1,272
1994	0.001	0.043	0.063	0.206	0.062	1.630	1,374
1995	0.012	0.052	0.069	0.191	0.058	1.922	1,427
1996	0.001	0.042	0.057	0.180	0.055	1.729	1,506
1997	−0.006	0.036	0.050	0.174	0.054	2.127	1,582
1998	0.007	0.046	0.062	0.184	0.056	1.943	1,589
1999	0.001	0.047	0.063	0.188	0.057	1.721	1,521
2000	−0.004	0.056	0.070	0.198	0.064	2.113	1,325
2001	0.000	0.047	0.065	0.212	0.062	1.674	1,192
2002	0.009	0.050	0.074	0.231	0.066	1.595	1,153
2003	0.013	0.057	0.073	0.203	0.058	1.696	1,183
2004	0.003	0.043	0.060	0.184	0.056	1.950	1,238
2005	0.015	0.050	0.066	0.180	0.053	2.264	1,253
2006	0.004	0.045	0.061	0.179	0.056	2.477	1,261
2007	0.002	0.041	0.056	0.170	0.051	1.907	1,234
2008	0.011	0.056	0.074	0.214	0.063	2.200	1,133
2009	0.006	0.066	0.088	0.252	0.075	1.603	986
2010	0.023	0.075	0.095	0.238	0.066	1.566	1,071
2011	0.024	0.074	0.092	0.227	0.063	1.695	1,112
2012	0.041	0.090	0.106	0.236	0.061	1.633	1,114
2013	0.025	0.067	0.082	0.190	0.055	2.040	1,110
2014	0.022	0.064	0.079	0.201	0.053	1.700	1,131
2015	0.019	0.061	0.074	0.180	0.051	1.801	1,087
2016	0.033	0.074	0.088	0.200	0.054	2.132	1,006
2017	0.024	0.060	0.078	0.204	0.058	2.160	1,006
2018	0.020	0.060	0.076	0.195	0.055	1.969	1,031

Table 2: Cross-sectional correlations among returns, *ICC*, illiquidity, and firm characteristics

This table provides time-series averages of cross-sectional correlations among return, *ICC*, illiquidity, and various other firm characteristics. Variables are defined in Table 1. The upper part of the matrix (in italics) contains rank correlations. The lower part of the matrix contains correlations in levels. The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is 1977 to 2018.

	ILLIQ	*SIZE*	*Ln*(*ILLIQ*)	*Ln*(*SIZE*)	*Ln*(*B*/*M*)	*Return11*	*Beta*	*GP*/*AT*	*Ln*(1+*AG*)	*Return*	*ICC*
ILLIQ		*−0.943*	*1.000*	*−0.943*	*0.270*	*−0.013*	*0.036*	*0.065*	*−0.074*	*0.007*	*0.195*
SIZE	−0.175		*−0.943*	*1.000*	*−0.283*	*0.097*	*−0.084*	*−0.088*	*0.068*	*0.043*	*−0.242*
Ln(*ILLIQ*)	0.632	−0.586		*−0.943*	*0.270*	*−0.013*	*0.036*	*0.065*	*−0.074*	*0.007*	*0.195*
Ln(*SIZE*)	−0.538	0.674	−0.937		*−0.283*	*0.097*	*−0.084*	*−0.088*	*0.068*	*0.043*	*−0.242*
Ln(*B*/*M*)	0.176	−0.155	0.250	−0.258		*−0.121*	*−0.089*	*−0.340*	*−0.218*	*0.015*	*0.202*
Return11	0.047	0.011	0.047	0.034	−0.117		*−0.021*	*0.008*	*−0.058*	*0.004*	*−0.162*
Beta	−0.056	−0.092	0.025	−0.084	−0.089	0.015		*0.101*	*0.051*	*−0.004*	*0.193*
GP/*AT*	0.023	−0.022	0.047	−0.069	−0.284	0.017	0.061		*0.015*	*0.007*	*−0.054*
Ln(1+*AG*)	−0.058	0.009	−0.054	0.038	−0.149	−0.063	0.064	−0.005		*−0.012*	*−0.061*
Return	0.039	0.005	0.041	0.014	0.027	0.002	0.010	0.005	−0.016		*−0.046*
ICC	0.138	−0.128	0.207	−0.245	0.197	−0.119	0.165	−0.075	−0.033	−0.035	

Table 3: Average returns and *ICC* for portfolios sorted by size and illiquidity

We triple sort portfolios in sequential order into quartiles. The first and second sorts are on *SIZE* and the third sort is on *ILLIQ*. Variables are defined in Table 1. The breakpoints for all quintiles are from only NYSE stocks. For each *ILLIQ* quartile, we average the four size quartiles of the second sort. The table then reports post-formation statistics on the resulting 4×4 *SIZE* and *ILLIQ* portfolios. We calculate post-formation returns (in excess of the risk-free rate) two months after the formation period and post-formation *ICC* (in excess of the long-term government bond yield) one month after the formation period. Excess returns are annualized in Panel A. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for realized returns and calculated using the Newey and West (1987) correction with 36 lags for *ICC*. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ* at the time of portfolio formation. The sample period is October 1977 to November 2018.

	ILLIQ				
SIZE	Low	Q2	Q3	High	High − Low
Panel A: Post-formation Returns					
Small	5.56	10.29	11.49	12.12	6.56
	(1.49)	(3.19)	(3.87)	(4.33)	(3.83)
Q2	8.77	11.06	11.42	12.06	3.29
	(2.48)	(3.73)	(4.01)	(4.43)	(1.99)
Q3	8.25	10.84	9.56	9.81	1.56
	(2.68)	(4.14)	(3.78)	(3.96)	(1.09)
Big	7.73	9.09	8.38	7.93	0.20
	(3.05)	(3.98)	(3.61)	(3.24)	(0.19)
Big − Small	2.17	−1.20	−3.12	−4.19	—
	(1.01)	(−0.64)	(−1.78)	(−2.59)	
Panel B: Post-formation *ICC*					
Small	10.94	10.32	9.95	9.96	−0.98
	(39.62)	(39.40)	(38.24)	(37.93)	(−3.39)
Q2	8.64	7.65	7.07	7.06	−1.57
	(40.22)	(32.17)	(29.42)	(26.60)	(−6.91)
Q3	7.79	6.74	6.08	5.50	−2.29
	(27.36)	(25.13)	(22.71)	(23.79)	(−9.13)
Big	6.15	5.71	5.64	5.19	−0.97
	(24.96)	(20.65)	(18.81)	(13.99)	(−3.77)
Big − Small	−4.79	−4.61	−4.32	−4.78	—
	(−19.19)	(−24.15)	(−20.96)	(−15.99)	

Table 4: Fama-MacBeth regressions for realized returns and *ICC*

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on illiquidity and various firm characteristics. Variables are defined in Table 1. Panel A includes the variables in Amihud and Noh (2021) plus market beta, while Panel B adds two more control variables. Each panel has three specifications. *Ln*(*ILLIQ*), *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is indicated in each column.

	Specification (1)			Specification (2)			Specification (3)		
	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018
	Panel A: Without additional controls								
Constant	0.851	0.816	8.513	1.018	0.957	11.252	0.609	0.694	12.503
	(6.19)	(4.62)	(21.48)	(4.83)	(3.69)	(30.24)	(2.31)	(2.16)	(17.97)
Ln(*ILLIQ*)	0.054	0.035	0.495	—	—	—	0.113	0.062	−0.285
	(2.61)	(1.60)	(15.29)				(3.36)	(1.66)	(−2.28)
Ln(*SIZE*)	—	—	—	−0.051	−0.041	−0.750	0.070	0.039	−1.101
				(−1.87)	(−1.32)	(−14.72)	(1.44)	(0.67)	(−6.11)
Ln(*B*/*M*)	0.169	0.113	1.893	0.170	0.114	1.802	0.169	0.112	1.767
	(3.91)	(2.45)	(5.39)	(3.92)	(2.44)	(5.26)	(3.91)	(2.40)	(5.23)
Return11	0.892	0.585	−2.324	0.890	0.590	−2.111	0.855	0.565	−2.042
	(6.73)	(3.82)	(−7.29)	(6.77)	(3.83)	(−6.60)	(6.57)	(3.76)	(−6.54)
Return1	−3.722	−2.598	−5.820	−3.821	−2.621	−5.168	−3.846	−2.634	−4.850
	(−11.33)	(−6.65)	(−13.90)	(−11.71)	(−6.75)	(−12.54)	(−11.87)	(−6.82)	(−12.20)
Beta	−0.034	0.012	2.293	−0.047	0.002	2.114	−0.007	0.016	1.990
	(−0.32)	(0.09)	(9.44)	(−0.46)	(0.01)	(8.83)	(−0.07)	(0.13)	(7.84)
#stocks	1,257	1,345	1,038	1,260	1,348	1,038	1,257	1,345	1,038
adj-R^2	6.4%	5.6%	13.3%	6.6%	5.7%	13.8%	6.9%	6.0%	14.2%

Table 4, contd.

	Specification (1)			Specification (2)			Specification (3)		
	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018
	Panel B: With additional controls								
Constant	0.703	0.722	8.804	0.888	0.832	11.763	0.559	0.565	13.189
	(4.98)	(4.06)	(19.63)	(4.17)	(3.23)	(27.09)	(2.09)	(1.78)	(20.02)
Ln(*ILLIQ*)	0.052	0.030	0.504	—	—	—	0.090	0.064	−0.346
	(2.54)	(1.40)	(13.69)				(2.61)	(1.75)	(−3.00)
Ln(*SIZE*)	—	—	—	−0.054	−0.033	−0.779	0.046	0.049	−1.203
				(−1.99)	(−1.09)	(−14.33)	(0.93)	(0.86)	(−7.29)
Ln(*B*/*M*)	0.206	0.139	1.731	0.195	0.139	1.594	0.193	0.137	1.559
	(4.66)	(3.02)	(4.92)	(4.38)	(3.02)	(4.64)	(4.31)	(2.98)	(4.61)
Return11	0.966	0.570	−2.420	0.963	0.570	−2.218	0.934	0.546	−2.119
	(7.07)	(3.75)	(−7.17)	(7.09)	(3.73)	(−6.57)	(6.93)	(3.65)	(−6.36)
Return1	−3.863	−2.734	−5.811	−3.975	−2.758	−5.143	−4.014	−2.768	−4.754
	(−11.41)	(−7.05)	(−13.96)	(−11.77)	(−7.16)	(−12.38)	(−11.97)	(−7.22)	(−11.74)
Beta	0.044	0.027	2.322	0.031	0.019	2.144	0.061	0.034	2.011
	(0.42)	(0.21)	(9.17)	(0.30)	(0.15)	(8.54)	(0.63)	(0.28)	(7.55)
GP/*AT*	0.350	0.356	−0.924	0.352	0.361	−1.168	0.341	0.365	−1.165
	(3.35)	(2.74)	(−3.26)	(3.37)	(2.81)	(−4.18)	(3.31)	(2.85)	(−4.14)
Ln(1+*AG*)	−0.499	−0.367	−0.772	−0.552	−0.379	−0.892	−0.530	−0.374	−0.924
	(−5.21)	(−3.74)	(−1.90)	(−5.82)	(−3.89)	(−2.25)	(−5.67)	(−3.87)	(−2.43)
#stocks	1,158	1,337	1,035	1,160	1,339	1,035	1,158	1,337	1,035
adj-R^2	7.1%	6.1%	13.7%	7.3%	6.2%	14.4%	7.6%	6.5%	14.7%

Table 5: Fama-MacBeth regressions for realized returns and *ICC* using the turnover-based version of the Amihud illiquidity measure

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on illiquidity and various firm characteristics. We replace dollar volume-based *ILLIQ* with turnover-based $ILLIQ^{Turn}$. Other variables are defined in Table 1. $Ln(ILLIQ^{Turn})$, *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose $ILLIQ^{Turn}$ is not in the top 1% or bottom 1% of $ILLIQ^{Turn}$. The sample period is indicated in each column.

	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018
Constant	−0.216	0.053	14.011
	(−0.46)	(0.10)	(10.85)
$Ln(ILLIQ^{Turn})$	0.106	0.073	−0.243
	(2.91)	(1.86)	(−2.14)
Ln(*SIZE*)	−0.043	−0.016	−0.749
	(−1.62)	(−0.52)	(−10.45)
Ln(*B*/*M*)	0.185	0.129	1.623
	(4.09)	(2.76)	(4.61)
Return11	0.977	0.544	−2.284
	(7.21)	(3.63)	(−6.82)
Return1	−4.180	−2.923	−5.089
	(−12.53)	(−7.69)	(−12.21)
Beta	0.075	0.042	2.001
	(0.78)	(0.34)	(7.50)
GP/*AT*	0.326	0.348	−1.051
	(3.16)	(2.72)	(−3.56)
Ln(1+*AG*)	−0.535	−0.373	−0.941
	(−5.82)	(−3.98)	(−2.47)
#stocks	1,161	1,340	1,036
adj-R^2	7.6%	6.4%	14.6%

Table 6: Fama-MacBeth regressions for realized returns and *ICC* by size

This table shows the same regressions as in specification (3) of Table 4 but separately for Large and Small stocks. Stocks above the NYSE median market capitalization are defined as Large and the rest of the stocks are defined as Small. *Ln*(*ILLIQ*), *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is indicated in each column.

	Return (1955-2016)		Return (1977-2018)		*ICC* (1977-2018)	
	Large	Small	Large	Small	Large	Small
	Panel A: Without controls					
Constant	1.213	−0.076	1.415	−0.251	7.851	18.533
	(4.38)	(−0.26)	(4.12)	(−0.70)	(9.53)	(15.59)
Ln(*ILLIQ*)	0.003	0.206	−0.040	0.153	−0.834	−0.411
	(0.09)	(5.11)	(−0.93)	(3.60)	(−8.03)	(−2.76)
Ln(*SIZE*)	−0.079	0.237	−0.119	0.252	−1.074	−2.159
	(−1.55)	(3.90)	(−1.89)	(3.46)	(−8.85)	(−8.35)
Ln(*B*/*M*)	0.136	0.176	0.090	0.113	1.865	1.606
	(2.83)	(3.63)	(1.71)	(2.07)	(4.99)	(5.40)
Return11	0.848	0.865	0.458	0.626	−1.338	−2.411
	(5.22)	(6.79)	(2.30)	(4.53)	(−4.14)	(−6.67)
Return1	−3.949	−3.758	−2.591	−2.478	−3.956	−4.863
	(−9.88)	(−11.16)	(−5.11)	(−6.47)	(−9.23)	(−9.67)
Beta	−0.065	0.035	−0.045	0.064	2.284	1.740
	(−0.55)	(0.40)	(−0.30)	(0.59)	(7.29)	(7.73)
#stocks	610	648	654	691	607	433
adj-R^2	9.4%	5.0%	9.0%	4.1%	12.8%	10.9%

Table 6, contd.

	Return (1955-2016)		Return (1977-2018)		*ICC* (1977-2018)	
	Large	Small	Large	Small	Large	Small
	Panel B: With controls					
Constant	1.134	−0.187	1.324	−0.452	8.408	19.573
	(4.03)	(−0.58)	(3.86)	(−1.29)	(10.91)	(16.00)
Ln(*ILLIQ*)	−0.019	0.190	−0.028	0.158	−0.938	−0.491
	(−0.50)	(4.34)	(−0.65)	(3.74)	(−8.93)	(−3.32)
Ln(*SIZE*)	−0.099	0.234	−0.107	0.276	−1.203	−2.322
	(−1.91)	(3.55)	(−1.73)	(3.85)	(−11.31)	(−8.80)
Ln(*B*/*M*)	0.187	0.184	0.138	0.132	1.619	1.399
	(3.68)	(3.54)	(2.62)	(2.38)	(4.11)	(4.75)
Return11	0.930	0.835	0.469	0.594	−1.395	−2.480
	(5.59)	(6.12)	(2.36)	(4.33)	(−4.13)	(−6.52)
Return1	−4.162	−3.822	−2.688	−2.649	−3.808	−4.731
	(−10.39)	(−10.56)	(−5.37)	(−6.97)	(−8.60)	(−9.17)
Beta	0.006	0.094	−0.013	0.074	2.316	1.743
	(0.05)	(0.99)	(−0.09)	(0.69)	(7.07)	(7.28)
GP/*AT*	0.424	0.244	0.374	0.406	−1.367	−1.385
	(3.27)	(2.10)	(2.33)	(2.99)	(−3.57)	(−3.81)
Ln(1+*AG*)	−0.463	−0.599	−0.357	−0.369	−0.964	−0.887
	(−3.73)	(−4.99)	(−2.86)	(−3.04)	(−2.24)	(−2.33)
#stocks	566	648	652	685	606	431
adj-R^2	10.3%	5.3%	9.9%	4.5%	13.7%	11.6%

Table 7: Fama-MacBeth regressions for realized returns and *ICC*, using components of illiquidity

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on components of illiquidity and various firm characteristics similar to those in Table 4. Variables are defined in Table 1. *Ln*(|*R*|), *Ln*(1/*DVOL*), *DIF*, *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*) is calculated at the end of previous year of the current month. Stocks above the NYSE median market capitalization are defined as Large and the rest of the stocks are defined as Small. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is indicated in each column.

	Return (1955-2016)			Return (1977-2018)			*ICC* (1977-2018)		
	All	Large	Small	All	Large	Small	All	Large	Small
Constant	10.043	7.486	10.327	5.974	7.732	2.515	9.606	13.392	39.718
	(3.14)	(1.60)	(2.87)	(1.28)	(1.16)	(0.50)	(1.35)	(0.94)	(4.72)
Ln(|*R*|)	−0.388	−0.227	−0.507	−0.547	−0.352	−0.663	5.200	4.300	5.200
	(−2.91)	(−1.55)	(−3.34)	(−3.16)	(−1.77)	(−3.51)	(14.31)	(10.43)	(11.89)
Ln(1/*DVOL*)	0.117	0.001	0.194	0.064	−0.042	0.130	−0.197	−0.704	−0.219
	(3.75)	(0.04)	(5.10)	(1.82)	(−1.05)	(3.26)	(−1.68)	(−7.12)	(−1.48)
DIF	0.815	0.521	0.925	0.547	0.548	0.403	−1.774	−1.192	0.031
	(3.63)	(1.56)	(3.73)	(1.70)	(1.18)	(1.15)	(−3.45)	(−1.16)	(0.05)
Ln(*SIZE*)	0.006	−0.092	0.096	−0.026	−0.132	0.105	−0.560	−0.724	−1.379
	(0.15)	(−2.00)	(1.92)	(−0.53)	(−2.28)	(1.66)	(−3.32)	(−6.03)	(−5.01)
Ln(*B*/*M*)	0.142	0.128	0.137	0.088	0.086	0.074	2.035	2.106	1.856
	(3.45)	(2.75)	(2.95)	(1.97)	(1.68)	(1.40)	(5.59)	(5.11)	(5.90)
Retun11	0.936	0.888	0.985	0.646	0.510	0.736	−2.410	−1.633	−2.782
	(7.55)	(5.74)	(7.91)	(4.52)	(2.69)	(5.45)	(−9.06)	(−6.29)	(−8.28)
Return1	−3.971	−4.097	−3.927	−2.665	−2.687	−2.537	−5.529	−4.561	−5.648
	(−12.62)	(−10.64)	(−11.89)	(−7.23)	(−5.60)	(−6.86)	(−14.43)	(−11.70)	(−10.85)
Beta	0.137	0.003	0.209	0.185	0.044	0.259	0.232	0.464	0.180
	(1.85)	(0.03)	(3.00)	(2.02)	(0.38)	(3.08)	(1.68)	(2.68)	(1.07)
#stocks	1,257	610	648	1,345	654	691	1,038	607	433
adj-R^2	8.0%	10.9%	6.0%	7.2%	10.7%	5.2%	18.2%	17.1%	14.3%

Table 8: Market excess return, market *ICC*, and market illiquidity

This table reports results of time-series regressions for excess market returns and aggregate *ICC* on innovations to market illiquidity and its components. *dmILLIQ* , *dm*|*R*|, and *dm*1/*DVOL* are shocks to the time-series *mILLIQ*, *m*|*R*|, and *m*1/*DVOL*, the (logarithm of) monthly market averages of, respectively, *ILLIQ*, |*R*|, and 1/*DVOL* for individual stocks. The stock sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The average across stocks is value-weighted using market capitalization at the end of the preceding month. The shocks in each of these series indicated by the prefix "*d*" are calculated by estimating an AR(2) model over a rolling window of 60 months ending in month t (the models for *mILLIQ* and *m*1/*DVOL* also include a time trend) and setting the shock in month $t + 1$ as the difference between the actual value of the series and its predicted value, using the estimated slope coefficients from the preceding 60-month window. We define *dmDIF* = *dmILLIQ* − (*dm*|*R*|+*dm*1/*DVOL*). *T*-statistics in return regressions are based on the White correction for heteroskedasticity while those in *ICC* regressions are based on the Newey and West (1987) correction with 36 lags. The sample period is 1955 to 2016 for return regressions and 1977 to 2018 for *ICC* regressions.

	Market excess return		Market *ICC* – 10-year yield	
dmILLIQ	−0.120	—	−0.012	—
	(−4.01)		(−0.89)	
*dm*1/*DVOL*	—	−0.076	—	0.001
		(−2.14)		(0.24)
dm|*R*|	—	−0.450	—	−0.035
		(−4.01)		(−1.11)
dmDIF	—	−0.084	—	−0.045
		(−1.24)		(−1.68)
adj-R^2	2.5%	5.6%	0.0%	0.5%

Table 9: VAR for market *ICC* and market illiquidity

This table reports results of a VAR on market *ICC* and market illiquidity. *mICC* is the market implied risk premium ($ICC -$ 10-year treasury yield) calculated as the value-weighted average of individual stock level *ICC*. *mILLIQ* is the linearly detrended logarithm of monthly market averages of the individual stock level *ILLIQ*. The stock sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The lag length in VAR is chosen using the Akaike information criterion. The table reports the coefficients and *t*-statistics in parentheses below the coefficients. The last row of the table reports the contemporaneous correlation between the residuals and its p-value. The sample period is 1977 to 2018.

	Dependent variable	
	$mICC(t)$	$mILLIQ(t)$
Constant	0.004	−0.009
	(4.74)	(−0.80)
$mICC(t-1)$	0.926	0.157
	(60.07)	(0.81)
$mILLIQ(t-1)$	0.001	0.965
	(1.33)	(74.23)
adj-R^2	87.3%	93.6%
Correlation in residuals	3.1% (p-value = 0.49)	

Table 10: Fama-MacBeth regressions of realized returns and *ICC* using NASDAQ stocks

This table shows the same regressions as in specification (3) of Table 4 and Table 7 but for NASDAQ stocks, and the combined sample of NYSE, AMEX, and NASDAQ stocks. *Ln*(*ILLIQ*), *Ln*(|*R*|), *Ln*(1/*DVOL*), *DIF*, *Ln*(*SIZE*), and *Beta* are lagged by two months in the return regressions and by one month in the *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is 1983 to 2018 for the sample of NASDAQ stocks and 1977 to 2018 for the sample of all stocks.

	NASDAQ stocks				NYSE, AMEX, and NASDAQ stocks			
	Specification 1		Specification 2		Specification 1		Specification 2	
	Return	*ICC*	Return	*ICC*	Return	*ICC*	Return	*ICC*
Constant	−0.319	16.897	10.577	9.860	0.250	14.208	8.854	−0.645
	(−0.76)	(20.82)	(2.63)	(1.41)	(0.76)	(20.32)	(2.70)	(−0.12)
Ln(*ILLIQ*)	0.119	−0.403	—	—	0.117	−0.452	—	—
	(2.53)	(−3.82)			(3.50)	(−3.94)		
Ln(|*R*|)	—	—	−0.485	4.481	—	—	−0.413	4.524
			(−2.28)	(17.23)			(−2.45)	(13.43)
Ln(1/*DVOL*)	—	—	0.082	−0.243	—	—	0.091	−0.315
			(1.88)	(−2.01)			(2.81)	(−2.44)
DIF	—	—	0.900	−1.670	—	—	0.732	−2.375
			(3.15)	(−3.47)			(3.13)	(−5.89)
Ln(*SIZE*)	0.273	−1.914	0.124	−1.085	0.137	−1.432	0.030	−0.759
	(3.59)	(−9.03)	(2.06)	(−6.21)	(2.41)	(−7.90)	(0.67)	(−4.07)
Ln(*B*/*M*)	0.254	0.833	0.181	1.258	0.192	1.535	0.133	2.007
	(4.24)	(6.50)	(3.53)	(7.18)	(3.88)	(4.76)	(2.90)	(5.85)
Return11	0.626	−1.372	0.684	−1.696	0.621	−1.826	0.714	−2.116
	(5.42)	(−5.25)	(6.20)	(−8.25)	(5.56)	(−5.35)	(6.65)	(−7.58)
Return1	−3.024	−3.207	−2.977	−4.135	−3.205	−4.223	−3.100	−5.029
	(−8.50)	(−11.91)	(−8.58)	(−14.61)	(−9.69)	(−10.01)	(−9.65)	(−12.72)
Beta	0.048	1.319	0.151	0.350	0.081	1.710	0.179	0.268
	(0.41)	(7.87)	(1.75)	(2.18)	(0.70)	(7.32)	(2.15)	(1.92)
GP/*AT*	0.605	−0.559	—	—	0.527	−0.695	—	—
	(4.43)	(−1.45)			(4.71)	(−2.66)		
Ln(1+*AG*)	−0.560	0.348	—	—	−0.465	−0.491	—	—
	(−5.45)	(1.77)			(−5.38)	(−1.52)		
#stocks	1,164	824	1,177	830	2,305	1,714	2,324	1,723
adj-R^2	5.2%	15.5%	5.7%	18.4%	5.9%	14.1%	6.4%	17.1%

Table 11: Fama-MacBeth regressions for realized returns and *ICC*, using alternative proxies of illiquidity

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on alternative proxies of illiquidity (*XILLIQ*) and various firm characteristics. *LOT* is the Lesmond, Ogden, and Trzcinka (1999) proportion of zero return days in a month. *PS* is the Pástor and Stambaugh (2003) measure of illiquidity. *Ln*(*Spread*) is the logarithm of the quoted bid-ask spread. All other variables are defined in Table 1. *XILLIQ*, *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample consists of NYSE, AMEX, and NASDAQ stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is October 1977 to November 2018 (*PS* is available for NASDAQ stocks only from 1983 onwards).

	XILLIQ =*Ln*(1+ *LOT*)		*XILLIQ* = *PS*		*XILLIQ* = *Ln*(*Spread*)	
	Return	*ICC*	Return	*ICC*	Return	*ICC*
Constant	0.746	12.114	0.818	11.912	0.617	11.562
	(2.70)	(37.22)	(3.30)	(33.59)	(2.34)	(30.73)
XILLIQ	0.411	1.131	−0.001	0.003	−0.084	−0.417
	(1.04)	(1.29)	(−0.38)	(1.25)	(−1.76)	(−2.16)
Ln(*SIZE*)	−0.016	−0.846	−0.023	−0.832	−0.003	−0.919
	(−0.48)	(−16.88)	(−0.72)	(−17.43)	(−0.10)	(−25.92)
Ln(*B*/*M*)	0.193	1.587	0.196	1.579	0.189	1.565
	(3.96)	(4.78)	(3.93)	(4.81)	(3.91)	(4.56)
Return11	0.676	−1.986	0.677	−1.972	0.687	−1.928
	(6.05)	(−5.77)	(6.01)	(−5.78)	(6.23)	(−5.40)
Return1	−3.195	−4.790	−3.190	−4.753	−3.224	−4.596
	(−9.66)	(−11.34)	(−9.59)	(−11.26)	(−9.77)	(−8.93)
Beta	0.056	1.891	0.054	1.913	0.053	1.759
	(0.47)	(8.52)	(0.44)	(8.35)	(0.46)	(7.41)
GP/*AT*	0.498	−0.643	0.496	−0.634	0.492	−0.726
	(4.38)	(−2.38)	(4.37)	(−2.33)	(4.36)	(−2.79)
Ln(1+*AG*)	−0.483	−0.410	−0.484	−0.405	−0.478	−0.444
	(−5.55)	(−1.21)	(−5.53)	(−1.18)	(−5.47)	(−1.36)
#stocks	2,313	1,714	2,313	1,714	2,310	1,711
adj-R^2	5.7%	13.6%	5.6%	13.6%	5.8%	14.2%

Table 12: Fama-MacBeth regressions of realized returns and *ICC*, using liquidity risk and information risk Proxies

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on illiquidity, various firm characteristics, and proxies of liquidity risk. *AP Beta* is the liquidity beta calculated as in Acharaya and Pedersen (2005), *PS Beta* is the liquidity beta is estimated as in Pástor and Stambaugh (2003), and *GPIN* is the generalized *PIN* calculated as in Duarte, Hu, and Young (2020). Please see the text for further details. All other variables are defined in Table 1. *Ln*(*ILLIQ*), *Ln*(*SIZE*), *Beta*, and liquidity betas are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The *PS Beta* sample includes NYSE, AMEX, and NASDAQ stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample for *AP Beta* includes only NYSE and AMEX stocks, and the sample for *GPIN* includes only NYSE stocks. The sample period is October 1977 to November 2018 for regressions using *AP Beta* and *PS Beta* and January 1993 to November 2018 for regressions using *GPIN*.

	LiqRisk = *AP Beta*		*LiqRisk* = *PS Beta*		*InfRisk* = *Ln*[*GPIN*/(1−*GPIN*)]	
	Return	*ICC*	Return	*ICC*	Return	*ICC*
Constant	−0.011	23.984	0.384	13.812	1.000	12.038
	(−0.02)	(18.35)	(1.21)	(20.42)	(2.32)	(24.34)
Ln(*ILLIQ*)	0.089	−0.530	0.103	−0.456	0.049	−0.332
	(2.31)	(−5.07)	(3.04)	(−4.13)	(0.81)	(−3.06)
Ln(*SIZE*)	0.084	−1.700	0.106	−1.392	−0.006	−1.007
	(1.40)	(−11.14)	(1.88)	(−8.17)	(−0.07)	(−7.71)
Ln(*B*/*M*)	0.140	1.514	0.168	1.656	0.060	1.105
	(3.06)	(4.41)	(3.45)	(5.03)	(0.96)	(4.86)
Return11	0.507	−2.134	0.597	−2.064	0.134	−1.702
	(3.24)	(−6.35)	(4.89)	(−6.07)	(0.53)	(−8.32)
Return1	−2.868	−4.573	−3.477	−4.547	−1.937	−3.993
	(−7.39)	(−10.32)	(−9.87)	(−11.29)	(−3.57)	(−13.69)
Beta	0.039	2.063	0.075	1.856	0.093	1.908
	(0.32)	(7.57)	(0.62)	(6.78)	(0.60)	(12.23)
GP/*AT*	0.379	−1.349	0.475	−0.616	0.098	−0.941
	(2.94)	(−4.52)	(4.12)	(−2.43)	(0.49)	(−2.85)
Ln(1+*AG*)	−0.341	−0.895	−0.297	−0.631	−0.120	−1.091
	(−3.48)	(−2.32)	(−3.19)	(−1.67)	(−0.88)	(−3.95)
LiqRisk	0.415	−7.473	0.177	1.504	0.035	−0.020
	(1.56)	(−10.54)	(0.25)	(0.86)	(2.50)	(−1.77)
#stocks	1,304	1,021	1,943	1,490	906	817
adj-R^2	6.8%	15.6%	6.3%	14.7%	8.1%	15.4%

Table 13: Brokerage coverage terminations, illiquidity, and *ICC*

This table reports results of a difference-in-differences (DiD) test around coverage terminations by brokerage firms. The sample construction is described in the text. Control stocks are chosen by selecting five stocks at random in the same size and book-to-market quintiles as the treated stock in the quarter preceding the event subject to the condition that the control firms were themselves not subject to coverage termination in the one year around the event. For each treated stock we calculate the statistic of interest in the first month before and after the event. We repeat this calculation for each control stock and take the average across control stocks. The table reports the cross-sectional averages of these statistics before and after the event for both treated and control firms as well as the double difference (reported under the column 'Coeff'). We calculate the standard error (SE) of the DiD difference with a block bootstrap of block length 100 and 10,000 repetitions. The number of observations is reported in the column 'N.' We report these statistics for the entire sample as well as the sample broken up based on the number of analysts for the treated firm in the month preceding the event.

	Treated		Control		DiD		
# Analysts	Before	After	Before	After	Coeff	SE	N
			Panel A: *Ln*(*ILLIQ*)				
All	−6.06	−6.03	−5.41	−5.44	0.06	0.01	2,563
≤ 5	−2.72	−2.65	−2.15	−2.15	0.07	0.02	413
(5 10]	−5.04	−5.02	−4.48	−4.50	0.04	0.01	578
(10 15]	−6.36	−6.31	−5.77	−5.80	0.07	0.02	479
(15 20]	−7.14	−7.13	−6.66	−6.70	0.05	0.01	434
> 20	−8.31	−8.28	−7.34	−7.39	0.07	0.01	644
			Panel B: *ICC*				
All	11.82	12.04	11.26	11.58	−0.10	0.15	1,996
≤ 5	13.65	14.07	13.71	13.71	0.41	0.25	210
(5 10]	12.58	12.84	12.24	12.71	−0.21	0.25	443
(10 15]	12.89	13.33	11.51	11.98	−0.03	0.37	405
(15 20]	10.87	10.88	10.78	11.02	−0.23	0.18	369
> 20	10.39	10.51	9.71	9.99	−0.17	0.15	569

Table 14: Characteristics of portfolios sorted by size and illiquidity

We form portfolios as in Table 3. This table then reports formation-period statistics on the resulting 4×4 *SIZE* and *ILLIQ* portfolios. *SIZE* is the market capitalization in billions of dollars, *Ln*(*ILLIQ*) is Amihud illiquidity, *B/M* is the book-to-market ratio, *DVOL* is the average dollar trading volume over the last 12-months in billions of dollars, *GP/AT* is the ratio of gross profit to total assets, *Turn* is the average turnover over last 12 months, *AG* is the asset growth, *TotVol* is the total volatility calculated using daily returns over the last 12 months. We also calculate the formation-month return ($Return(t)$), the 11-month return skipping the most recent month ($Return(t-11{:}\,t-1)$), the 24-month skipping the recent 12 months ($Return(t-35{:}\,t-12)$), and the 36-month including the formation period month ($Return(t-35{:}\,t)$). All returns are in percent. For the differences in portfolio characteristics, ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The standard errors for these differences are corrected using the Newey and West (1987) approach with 36 lags. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ* at the time of portfolio formation. The sample period is October 1977 to November 2018.

	ILLIQ					*ILLIQ*				
SIZE	Low	Q2	Q3	High	High − Low	Low	Q2	Q3	High	High − Low
	Panel A: $SIZE(t)$					Panel B: $Ln(ILLIQ(t))$				
Small	0.26	0.25	0.24	0.23	-0.02^{***}	−3.67	−2.95	−2.44	−1.51	2.16^{***}
Q2	0.83	0.82	0.82	0.81	-0.02^{***}	−5.25	−4.65	−4.21	−3.37	1.88^{***}
Q3	2.23	2.20	2.17	2.14	-0.09^{***}	−6.39	−5.90	−5.54	−4.79	1.61^{***}
Big	19.67	13.89	11.52	10.13	-9.54^{***}	−7.92	−7.51	−7.22	−6.68	1.24^{***}
	Panel C: $B/M(t)$					Panel D: $DVOL(t-11{:}\,t)$				
Small	0.97	0.85	0.81	0.80	-0.17^{***}	0.09	0.04	0.02	0.01	-0.07^{***}
Q2	0.75	0.67	0.63	0.64	-0.12^{***}	0.31	0.15	0.10	0.06	-0.24^{***}
Q3	0.69	0.64	0.58	0.52	-0.17^{***}	0.68	0.39	0.28	0.19	-0.49^{***}
Big	0.59	0.57	0.55	0.50	-0.09^{***}	2.60	1.71	1.34	0.99	-1.61^{***}
	Panel E: $GP/AT(t)$					Panel F: $Turn(t-11{:}\,t)$				
Small	0.37	0.34	0.34	0.32	-0.05^{***}	0.18	0.10	0.07	0.05	-0.13^{***}
Q2	0.35	0.33	0.33	0.32	-0.03^{***}	0.22	0.13	0.09	0.06	-0.16^{***}
Q3	0.32	0.29	0.30	0.31	−0.02	0.21	0.13	0.10	0.07	-0.14^{***}
Big	0.32	0.30	0.29	0.29	-0.03^{***}	0.15	0.11	0.10	0.08	-0.07^{***}
	Panel G: $AG(t)$					Panel H: $TotVol(t-11{:}\,t)$				
Small	0.20	0.14	0.14	0.13	-0.06^{***}	0.48	0.43	0.42	0.43	-0.05^{***}
Q2	0.19	0.15	0.14	0.16	-0.03^{*}	0.42	0.37	0.35	0.37	-0.05^{***}
Q3	0.15	0.13	0.13	0.14	−0.01	0.36	0.32	0.32	0.32	-0.04^{***}
Big	0.14	0.13	0.13	0.14	0.00	0.30	0.28	0.29	0.30	0.00
	Panel I: $Return(t)$					Panel J: $Return(t-11{:}\,t-1)$				
Small	−2.26	0.36	1.63	3.06	5.31^{***}	−7.34	7.22	15.31	26.26	33.60^{***}
Q2	−1.37	0.97	1.92	3.01	4.38^{***}	−1.28	11.94	18.18	27.17	28.45^{***}
Q3	−0.65	0.95	1.90	2.62	3.28^{***}	2.97	12.15	17.41	23.45	20.48^{***}
Big	−0.07	0.87	1.43	2.39	2.45^{***}	6.61	11.17	14.80	21.03	14.42^{***}
	Panel K: $Return(t-35{:}\,t-12)$					Panel L: $Return(t-35{:}\,t)$				
Small	52.56	30.45	25.43	21.49	-31.07^{***}	35.88	40.06	45.91	53.20	17.32^{***}
Q2	48.73	36.38	31.21	27.89	-20.84^{***}	42.40	55.59	59.04	66.39	23.98^{***}
Q3	47.10	33.45	31.67	33.52	-13.58^{***}	50.16	53.27	59.25	70.62	20.47^{***}
Big	38.32	31.08	30.38	32.88	−5.44	47.48	48.90	54.12	66.66	19.18^{***}

Online Appendix

"Illiquidity and the Cost of Equity Capital: Evidence from Actual Estimates of Capital Cost for U.S. Data"

Figure A1: Fama-MacBeth coefficients for *ILLIQ*

This figure plots the time-series of FM coefficients on *Ln*(*ILLIQ*) where the dependent variable is *ICC,* for specification (3) in Panel A of Table 4.

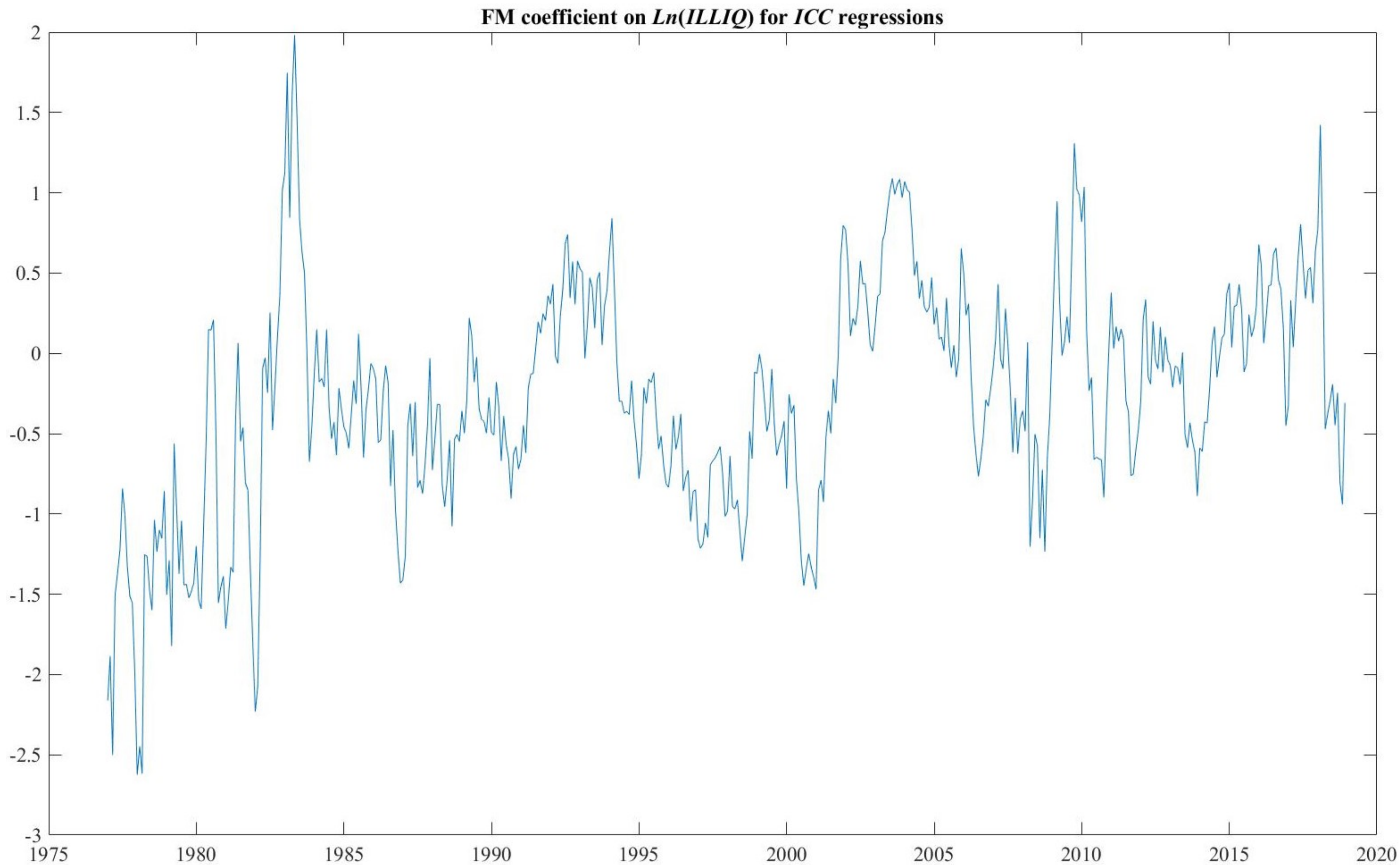

Table A1: Fama-MacBeth Regressions for realized returns and *ICC* using ranks

This table reports results of Fama-MacBeth cross-sectional regressions for realized returns (in excess of the risk-free rate) and *ICC* (in excess of the yield on long-term government bonds) on illiquidity and various firm characteristics similar to those in specification (3) of Panel B of Table 4, except that we use ranks of all independent variables (cross-sectionally assigned each month, and scaled to lie between 0 and 1). Variables are defined in Table 1. *Ln*(*ILLIQ*), *Ln*(*SIZE*), and *Beta* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between $5 and $1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is indicated in each column.

	Return 1955-2016	Return 1977-2018	*ICC* 1977-2018
Constant	0.248	0.177	13.007
	(0.68)	(0.40)	(14.67)
Ln(*ILLIQ*)	0.604	0.636	−4.294
	(2.77)	(2.32)	(−6.61)
Ln(*SIZE*)	0.286	0.416	−7.823
	(1.05)	(1.25)	(−11.20)
Ln(*B*/*M*)	0.463	0.374	3.777
	(4.16)	(3.04)	(5.09)
Return11	1.059	0.833	−3.023
	(6.99)	(4.37)	(−7.45)
Return1	−1.424	−1.101	−1.416
	(−13.04)	(−7.93)	(−9.76)
Beta	0.039	0.014	3.561
	(0.25)	(0.07)	(9.11)
GP/*AT*	0.342	0.410	−1.113
	(3.83)	(3.60)	(−3.79)
Ln(1+*AG*)	−0.318	−0.252	−1.257
	(−5.48)	(−3.41)	(−4.69)
#stocks	1,158	1,337	1,035
adj-R^2	7.5%	6.5%	16.3%

Table A2: Fama-MacBeth regressions for realized returns and *ICC*, with additional beta controls

This table reports results of Fama-MacBeth cross-sectional regressions for realized excess returns (in excess of the riskfree rate) and future excess *ICC* (in excess of the yield on long-term government bonds) on illiquidity and various firm characteristics similar to those in Table 4 except that we include five Fama and French (2015) betas instead of a single market beta on the right hand side. Variables are defined in Table 1. *Ln*(*ILLIQ*), *Ln*(1/*DVOL*), *DIF*, *Ln*(*SIZE*), and *Betas* are lagged by two months in return regressions and by one month in *ICC* regressions. *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*) is calculated at the end of previous year of the current month. Stocks above the NYSE median market capitalization are defined as Large and the rest of the stocks are defined as Small. All coefficients are multiplied by 100. *T*-statistics in parentheses are the standard ones for return regressions and calculated using the Newey and West (1987) correction with 36 lags for *ICC* regressions. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is indicated in each column.

	Return (1966-2016)			Return (1977-2018)			*ICC* (1977-2018)		
	All	Large	Small	All	Large	Small	All	Large	Small
Constant	0.341	1.126	−0.482	0.463	1.277	−0.505	11.751	6.981	18.348
	(1.24)	(3.72)	(−1.52)	(1.65)	(4.08)	(−1.50)	(17.91)	(10.54)	(14.28)
Ln(*ILLIQ*)	0.116	−0.019	0.199	0.074	−0.038	0.162	−0.309	−0.901	−0.456
	(3.26)	(−0.49)	(4.80)	(2.11)	(−0.94)	(3.92)	(−2.69)	(−8.84)	(−3.06)
Ln(*SIZE*)	0.096	−0.095	0.287	0.060	−0.116	0.280	−1.003	−0.997	−2.177
	(1.99)	(−1.85)	(4.48)	(1.18)	(−2.10)	(4.02)	(−6.15)	(−9.11)	(−7.88)
Ln(*B*/*M*)	0.167	0.154	0.160	0.118	0.121	0.119	1.546	1.540	1.451
	(3.80)	(3.08)	(3.16)	(2.83)	(2.48)	(2.29)	(4.42)	(3.85)	(4.75)
Return11	0.615	0.555	0.620	0.541	0.495	0.571	−2.343	−1.741	−2.636
	(4.51)	(3.25)	(4.57)	(3.91)	(2.74)	(4.22)	(−6.91)	(−4.87)	(−6.72)
Return1	−3.885	−3.812	−3.958	−2.982	−3.023	−2.843	−5.048	−4.173	−4.954
	(−10.87)	(−8.51)	(−10.81)	(−8.01)	(−6.30)	(−7.62)	(−12.90)	(−9.64)	(−9.66)
Beta1	0.058	−0.017	0.095	0.068	0.014	0.089	1.915	2.196	1.717
	(0.56)	(−0.14)	(1.01)	(0.61)	(0.11)	(0.90)	(8.25)	(7.35)	(8.04)
Beta2	−0.039	−0.038	−0.041	0.000	−0.009	0.010	0.950	1.074	0.892
	(−0.68)	(−0.53)	(−0.71)	(−0.01)	(−0.13)	(0.19)	(7.55)	(6.92)	(5.47)
Beta3	0.159	0.175	0.142	0.133	0.118	0.129	−0.049	0.062	−0.126
	(2.73)	(2.44)	(2.63)	(2.03)	(1.47)	(2.16)	(−0.27)	(0.31)	(−0.79)
Beta4	0.019	0.045	−0.019	0.012	0.055	−0.037	−0.394	−0.396	−0.372
	(0.46)	(0.86)	(−0.49)	(0.26)	(0.98)	(−0.86)	(−4.77)	(−4.73)	(−3.70)
Beta5	0.057	0.065	0.049	0.029	0.016	0.032	0.011	0.065	−0.050
	(1.36)	(1.27)	(1.24)	(0.66)	(0.30)	(0.78)	(0.13)	(0.69)	(−0.67)
GP/*AT*	0.304	0.364	0.315	0.371	0.356	0.425	−1.171	−1.353	−1.419
	(2.69)	(2.62)	(2.60)	(3.06)	(2.39)	(3.21)	(−4.93)	(−4.04)	(−4.51)
Ln(1+*AG*)	−0.526	−0.471	−0.591	−0.356	−0.312	−0.366	−0.827	−0.800	−0.846
	(−5.70)	(−4.00)	(−5.19)	(−3.96)	(−2.74)	(−3.15)	(−2.44)	(−1.97)	(−2.46)
#stocks	1,340	643	705	1,337	652	685	1,035	606	431
adj-R^2	8.3%	12.3%	6.0%	7.7%	12.2%	5.5%	16.2%	15.9%	12.9%

Table A3: Fama-MacBeth regressions for *ICC*: Subsample results with additional beta controls

This table reports results of Fama-MacBeth cross-sectional regressions for *ICC* on illiquidity and various firm characteristics as in Table A1, except that we report results for two subsamples of 1977 to 1997 and 1998 to 2018.

	ICC (1977-1997)			*ICC* (1998-2018)		
	All	Large	Small	All	Large	Small
Constant	12.061	7.265	16.388	11.438	6.694	20.300
	(10.52)	(6.85)	(9.13)	(18.99)	(8.70)	(13.72)
Ln(*ILLIQ*)	−0.502	−0.732	−0.386	−0.114	−1.072	−0.527
	(−2.98)	(−7.02)	(−1.65)	(−0.97)	(−7.28)	(−2.92)
Ln(*SIZE*)	−1.290	−0.905	−1.925	−0.714	−1.090	−2.428
	(−5.17)	(−5.45)	(−4.61)	(−5.01)	(−8.46)	(−7.32)
Ln(*B*/*M*)	2.354	2.472	2.159	0.731	0.601	0.746
	(4.64)	(4.30)	(4.89)	(3.88)	(2.82)	(4.18)
Return11	−2.993	−2.403	−3.597	−1.688	−1.075	−1.679
	(−5.69)	(−4.56)	(−6.71)	(−8.17)	(−3.46)	(−8.33)
Return1	−5.881	−5.132	−6.375	−4.208	−3.207	−3.539
	(−10.28)	(−9.29)	(−11.14)	(−17.54)	(−8.22)	(−10.17)
Beta1	2.261	2.674	1.876	1.565	1.715	1.558
	(5.73)	(5.49)	(4.93)	(13.05)	(9.62)	(9.84)
Beta2	1.055	1.410	0.814	0.845	0.736	0.970
	(5.00)	(7.55)	(2.82)	(6.91)	(4.41)	(6.57)
Beta3	−0.468	−0.343	−0.567	0.374	0.471	0.313
	(−2.51)	(−1.43)	(−4.61)	(1.97)	(2.12)	(1.85)
Beta4	−0.281	−0.439	−0.166	−0.507	−0.352	−0.577
	(−2.21)	(−2.92)	(−1.28)	(−6.00)	(−5.06)	(−5.30)
Beta5	0.018	0.094	−0.078	0.004	0.036	−0.021
	(0.17)	(0.76)	(−0.89)	(0.03)	(0.27)	(−0.19)
GP/*AT*	−0.761	−0.468	−1.254	−1.585	−2.246	−1.583
	(−2.14)	(−1.33)	(−2.52)	(−6.87)	(−7.20)	(−4.07)
Ln(1+*AG*)	−0.963	−1.153	−0.708	−0.690	−0.443	−0.984
	(−1.51)	(−1.54)	(−1.18)	(−3.20)	(−1.94)	(−2.99)
#stocks	1,032	603	433	1,038	609	428
adj-R^2	16.7%	15.7%	12.9%	15.7%	16.1%	12.9%

Table A4: Fama-MacBeth regressions with alternative measures of *ICC*

This table reports results of Fama-MacBeth cross-sectional regressions for *ICC* (in excess of the yield on long-term government bonds) on illiquidity and various firm characteristics as in specification (3) of Panel B of Table 4, except that we use different measures of *ICC*. The first column uses an *ICC* based on Easton (2004), the second column uses an *ICC* based on Ohlson and Juettener-Nauroth (2005), and the third column uses an *ICC* based on the Li and Mohanram (2014) approach of computing earnings forecasts from regressions, instead of analysts' projections. Independent variables are defined in Table 1. *Ln*(*ILLIQ*), *Ln*(*SIZE*), and *Beta* are lagged by one month, *Return11* is lagged by two months and *Return1* is lagged by one month in all regressions. *Ln*(*B*/*M*), *GP*/*AT*, and *Ln*(1+*AG*) are calculated at the end of previous year of the current month. All coefficients are multiplied by 100. *T*-statistics in parentheses are calculated using the Newey and West (1987) correction with 36 lags. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is 1977 to 2018.

	Easton (2004)	Ohlson and Juettener-Nauroth (2005)	Li and Mohanram (2014)
Constant	3.731	7.713	7.582
	(1.67)	(4.67)	(12.17)
Ln(*ILLIQ*)	−1.588	−1.043	−0.107
	(−12.93)	(−15.12)	(−0.92)
Ln(*SIZE*)	−1.223	−1.448	−0.436
	(−3.40)	(−7.15)	(−2.55)
Ln(*B*/*M*)	0.868	1.021	3.744
	(3.68)	(4.75)	(9.93)
Return11	−1.666	−1.685	−2.280
	(−4.73)	(−5.65)	(−9.12)
Return1	−1.277	−0.983	−4.517
	(−2.47)	(−2.49)	(−14.54)
Beta	3.021	2.942	−0.259
	(9.64)	(10.85)	(−2.32)
GP/*AT*	−0.232	−0.902	−0.466
	(−0.75)	(−2.92)	(−3.01)
Ln(1+*AG*)	0.691	0.408	−1.244
	(2.20)	(1.49)	(−8.57)
#stocks	1,341	1,341	1,148
adj-R^2	14.3%	15.7%	53.6%

Table A5: Cross-sectional correlations among returns, *ICC*, illiquidity, and firm characteristics

This table provides time-series average of cross-sectional correlations among return, *ICC*, illiquidity, and various other firm characteristics. Variables are defined in Table 1. The upper part of the matrix (in italics) contains rank correlations. The lower part of the matrix contains correlations in levels. The sample includes NYSE and AMEX stocks with prices between \$5 and \$1,000 and whose *ILLIQ* is not in the top 1% or bottom 1% of *ILLIQ*. The sample period is 1993 to 2018.

	ILLIQ	*SIZE*	*Ln*(*ILLIQ*)	*Ln*(*SIZE*)	*Ln*(*B*/*M*)	*Return11*	*Beta*	*GP*/*AT*	*Ln*(1+*AG*)	*Return*	*ICC*	*APBeta*	*PSBeta*	*GPIN*
ILLIQ		*−0.947*	*1.000*	*−0.947*	*0.331*	*−0.012*	*0.006*	*0.024*	*−0.066*	*0.008*	*0.210*	*0.262*	*−0.005*	*−0.122*
SIZE	−0.133		*−0.947*	*1.000*	*−0.343*	*0.107*	*−0.042*	*−0.059*	*0.060*	*0.042*	*−0.254*	*−0.266*	*0.009*	*0.115*
Ln(*ILLIQ*)	0.593	−0.551		*−0.947*	*0.331*	*−0.012*	*0.006*	*0.024*	*−0.066*	*0.008*	*0.210*	*0.262*	*−0.005*	*−0.122*
Ln(*SIZE*)	−0.483	0.659	−0.936		*−0.343*	*0.107*	*−0.042*	*−0.059*	*0.060*	*0.042*	*−0.254*	*−0.266*	*0.009*	*0.115*
Ln(*B*/*M*)	0.173	−0.182	0.299	−0.305		*−0.127*	*−0.016*	*−0.329*	*−0.155*	*0.014*	*0.188*	*0.054*	*0.016*	*−0.042*
Return11	0.057	0.013	0.056	0.036	−0.116		*−0.017*	*−0.001*	*−0.052*	*−0.001*	*−0.146*	*−0.018*	*0.020*	*0.022*
Beta	−0.105	−0.065	−0.016	−0.038	−0.015	0.020		*0.057*	*0.000*	*0.002*	*0.221*	*0.109*	*−0.010*	*0.030*
GP/*AT*	−0.004	−0.014	0.008	−0.044	−0.271	0.006	0.019		*−0.009*	*0.005*	*−0.047*	*0.030*	*−0.016*	*−0.014*
Ln(1+*AG*)	−0.049	0.010	−0.056	0.039	−0.083	−0.059	0.015	−0.014		*−0.008*	*−0.054*	*0.046*	*−0.010*	*0.003*
Return	0.036	0.005	0.042	0.014	0.027	0.000	0.013	0.001	−0.013		*−0.044*	*0.002*	*0.005*	*0.038*
ICC	0.137	−0.127	0.229	−0.260	0.180	−0.097	0.187	−0.078	−0.026	−0.033		*0.052*	*0.021*	*−0.004*
APBeta	−0.394	−0.538	0.138	−0.269	0.056	−0.040	0.110	0.024	0.039	−0.004	0.050		*−0.006*	*−0.038*
PSBeta	0.004	0.005	−0.022	0.028	0.018	0.008	−0.059	−0.040	−0.007	0.003	0.016	−0.012		*0.003*
GPIN	−0.005	−0.007	−0.032	0.025	−0.010	0.010	0.008	−0.001	0.002	0.017	−0.006	0.013	−0.003	

Table A6: Brokerage coverage terminations and market capitalization

This table reports results of a difference-in-differences (DiD) test around coverage terminations by brokerage firms, for market capitalization (*Ln*(*SIZE*)). Sample construction is described in the text. Control stocks are chosen by selecting five stocks at random in the same size and book-to-market quintile as the treated stock in the quarter preceding the event subject to the condition that the control firms were themselves not subject to coverage termination in the one year around the event. For each treated stock we calculate the statistic of interest in the first month before and after the event. We repeat this calculation for each control stock and take the average across control stocks. The table reports the cross-sectional averages of these statistics before and after the event for both treated and control firms as well as the double difference (reported under the column 'Coeff'). We calculate the standard error (SE) of the DiD difference with a block bootstrap of block length 100 and 10,000 repetitions. The number of observations is reported in the column 'N.' We report these statistics for the entire sample as well as the sample broken up based on the number of analysts for the treated firm in the month preceding the event.

	Treated		Control		DiD		
# Analysts	Before	After	Before	After	Coeff	SE	N
				Ln(*SIZE*)			
All	7.64	7.58	7.37	7.33	−0.020	0.014	2,557
≤ 5	5.33	5.26	5.03	5.00	−0.047	0.011	417
(5 10]	6.72	6.65	6.57	6.52	−0.019	0.016	574
(10 15]	7.69	7.62	7.61	7.56	−0.017	0.026	473
(15 20]	8.44	8.39	8.31	8.28	−0.018	0.023	434
> 20	9.51	9.45	8.91	8.85	−0.007	0.021	640