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Real Asset Illiquidity and the Cost of Capital

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Abstract

We show that firms with more illiquid real assets have a higher cost of capital. This effect is stronger when real illiquidity arises from lower within-industry acquisition activity. Real asset illiquidity increases the cost of capital more for firms that face more competition, have less access to external capital, or are closer to default, and for those facing negative demand shocks. The effect of real asset illiquidity is distinct from that of firms' stock illiquidity or systematic liquidity risk. These results suggest that real asset illiquidity reduces firms' operating flexibility and through this channel their cost of capital.

I. Introduction

Understanding what are the sources of risk that drive firms' cost of capital is of fundamental interest in financial economics. However, little is known about how the cost of capital may be affected by the illiquidity of a firm's real (or physical) assets. Yet, illiquidity affects a firm's ability to redeploy its real assets to alternative uses and thus its flexibility in responding to a changing business environment. For example, during June 2009 Qwest Communications solicited bids for its long-distance business, with the objectives of exiting an unprofitable business and raising cash to pay down debt. The bids came at a 50% discount from the asking price, so Qwest faced the choice of calling off the auction or accepting a large price discount.[1]

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[1]See A. Sharma, "Qwest's Long-Distance Arm Draws Bids Below Targets," *The Wall Street Journal* (June 5, 2009).

In this paper, we argue that real asset illiquidity reduces firms' operating flexibility and is thus an economically important source of equity risk. Our study is motivated by the observation that sales of real assets in illiquid markets fetch large price discounts relative to their fundamental values (e.g., Pulvino (1998), Ramey and Shapiro (2001), and Gavazza (2011)), which increases firms' cost of unwinding their capital stock and reduces their ability to raise cash with asset sales. Since asset sales are central to firms' restructuring processes (Maksimovic and Phillips (1998)) and are affected by the illiquidity of real asset markets (Schlingemann, Stulz, and Walkling (2002)), real asset illiquidity might increase equity risk.

Real asset illiquidity is especially harmful in bad times, when firms are under pressure to restructure their operations and maneuver to avoid default. In particular, real asset illiquidity can induce firms facing economic adversity to remain burdened with unproductive assets, which often generate large fixed costs. The resulting operating leverage increases the covariance of a firm's performance with macroeconomic conditions, especially during downturns, leading to a higher cost of capital. Hence, we examine whether, by reducing firms' operating flexibility, real asset illiquidity increases their cost of capital, in particular during downturns.

Our key dependent variable is the implied cost of capital (*ICC*), which does not rely on noisy realized returns or specific asset pricing models, and which Pástor, Sinha, and Swaminathan (2008) show is a good proxy for a stock's conditional expected return. Elton (1999) argues against using realized returns in asset pricing tests and highlights that the relation between realized returns and risk can be negative for long periods. Lundblad (2007) shows that a very long sample is needed to detect a positive risk-return relation using realized returns. In contrast, the *ICC* detects a positive intertemporal risk-return tradeoff (Pástor et al. (2008)) and a positive relation between distress risk and expected returns (Chava and Purnanandam (2010)).[2] For robustness, we also measure expected returns using Fama and French's (1993) 3-factor model cost of capital (*FFCC*), but this measure is imprecise (Fama and French (1997), Pástor and Stambaugh (1999)).

We use asset illiquidity measures that capture the illiquidity of *real* (fixed) assets at the industry level and of balance-sheet measures that capture the illiquidity of *total* assets at the firm level. The industry-level measures of real asset illiquidity are motivated by Almeida, Campello, and Hackbarth (2011) and Schlingemann et al. (2002). They reflect the "industry equilibrium" aspect of real asset illiquidity stressed by Shleifer and Vishny (1992), that is, a firm can more easily sell its industry-specific assets to other firms in the industry with financial slack. The firm-level measures of total asset illiquidity assign illiquidity scores to each asset class in a firm's balance sheet and capture the differential illiquidity of the different types (or composition) of assets a firm holds as in Berger and Bouwman (2009) and Gopalan, Kadan, and Pevzner (2012).

We show that real asset illiquidity is a major source of operating inflexibility, and that it has an economically significant impact on a firm's cost of capital. In univariate tests using both the *ICC* and the *FFCC* and the measures of real asset illiquidity, we find a *real asset illiquidity premium* (i.e., the cost of capital

[2]In an international setting, Lee, Ng, and Swaminathan (2009) further show that the *ICC* provides clear evidence of economic relations that would otherwise be obscured by the noise in realized returns.

is higher for firms in the highest vs. the lowest real asset illiquidity quintiles). Supporting the view that operating inflexibility causes time-varying equity risk, the illiquidity premium is countercyclical, which suggests it is driven by costly reversibility of investment. Our multivariate cross-sectional and time-series tests further support our hypothesis: Firms with more illiquid real assets have higher cost of capital than firms with less illiquid real assets, and firms' cost of capital is higher during periods of high real asset illiquidity. These tests imply that a 1-standard-deviation increase in real asset illiquidity across firms increases the *ICC* by 0.9 to 1.4 percentage points and that a similar increase over time increases it by 0.5 to 1.4 percentage points. We further show that the balance-sheet measures of total asset illiquidity at the firm level also have a positive impact on the *ICC*, and that this impact is largely driven by firms' cash holdings. This evidence suggests that the illiquidity of both real and total assets are important determinants of firms' flexibility and thus of their cost of capital.

Our results are robust to the worry that the *ICC* might measure expected returns with systematic error due to either biases or sluggish revisions in the analyst earnings forecasts used to calculate it. Our results are similar if we use an *ICC* corrected for the sluggishness of analyst earnings forecast revisions as suggested by Guay, Kothari, and Shu (2011) and if we restrict attention to firms with small analyst earnings forecast errors. They are also similar if we discard the possibly more noisy estimates of the cost of capital, which are below the risk-free rate.

We also distinguish between "inside" real asset illiquidity (provided by acquirers of assets that operate in the industry) and "outside" real asset illiquidity (provided by acquirers of assets that operate outside the industry). Buyers from inside the industry can better redeploy the asset to a productive use and are willing to pay higher prices (Shleifer and Vishny (1992)). Hence, less mergers and acquisitions (M&A) activity by industry insiders should make real asset markets more illiquid than less M&A activity by industry outsiders. Supporting this view, we find that inside illiquidity increases firms' *ICC* by more than outside illiquidity. This result is in line with that in Almeida et al. (2011), who find that distressed firms with industry-specific assets can often sell them to financially flexible industry insiders rather than to industry outsiders.

The effect of real asset illiquidity on the cost of capital varies across firms in ways that are broadly consistent with the operating inflexibility channel. Specifically, the effect is larger when the cost of inflexible operations due to illiquid asset markets is arguably higher. First, it is larger for firms that face more competitive risk in product markets, that is, for firms in low-concentration (more competitive) industries and for the smaller firms within the industry. Second, it is larger for firms that have less access to external capital or are closer to default. Last, it is larger for firms facing negative demand shocks (i.e., for firms with low valuations or in industry downturns).

Our main results hold after controlling for firm value, growth options, and asset specificities. We further show that the effect of real asset illiquidity on the cost of capital is robust to controlling for the illiquidity and systematic liquidity risk of firms' stocks. In addition, we show that real asset illiquidity increases the *ICC* after controlling for the industry's valuation. This shows that our results are not biased by a correlation between our measures of real asset illiquidity and changes in industry valuation or the supply of capital. Moreover, our results hold if we measure expected returns using the *unlevered* implied cost of capital, and if we do the tests using industry averages of the variables. In addition, real asset illiquidity reduces firm value after controlling for cash flow effects, further suggesting that it affects firms' discount rates. Lastly, our results also hold if we use business segment-weighted measures of real asset illiquidity.

Our paper is related to early work that suggests that operating inflexibility increases the systematic risk of a firm's equity, such as Rubinstein (1973), Lev (1974), Mandelker and Rhee (1984), and Booth (1991), who show that operating leverage increases expected returns in the capital asset pricing model. We contribute to these studies by identifying real asset illiquidity as a key source of operating leverage and showing that it impacts the cost of capital.

Our evidence complements that of Benmelech and Bergman (2009), who highlight the role of real asset illiquidity in debt markets. They find that debt tranches of airlines secured with more redeployable collateral have higher ratings and lower yield spreads. Hence, the evidence from our study and theirs suggests that real asset illiquidity increases a firm's overall cost of capital.

Also related is the recent investment-based asset pricing literature that argues that differences in operating flexibility across value and growth firms can explain the value premium (e.g., Kogan (2004), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006)). We add to this work by showing that real asset illiquidity, which directly reduces operating flexibility, significantly increases a firm's cost of equity.

Last, our work adds to the literature on what determines the implied cost of capital, such as earnings attributes (Francis, LaFond, Olsson, and Schipper (2004)), institutions and securities regulation (Hail and Leuz (2006)), leverage and taxes (Dhaliwal, Heitzman, and Li (2006)), cross-listing (Hail and Leuz (2009)), governance and country-level investor protection (Chen, Chen, and Wei (2009)), default risk (Chava and Purnanandam (2010)), shareholder rights (Chen, Chen, and Wei (2011)), and labor unionization (Chen, Kacperczyk, and Ortiz-Molina (2011)).

The paper is structured as follows: Section II develops our main hypothesis and related predictions. Section III describes our data and variables. Section IV reports the main empirical results. Section V studies the cross-sectional variation in the effect of real asset illiquidity on the cost of capital. Section VI presents several robustness tests. Section VII concludes.

II. Illiquid Real Assets and the Cost of Capital

Our conceptual framework is based on the corporate finance literature, which highlights the role of asset sales in firms' responses to changing economic conditions as well as on the asset pricing literature, which relates operating flexibility to equity risk. Sales of real assets in illiquid markets fetch large price discounts (e.g., Pulvino (1998)), which increases a firm's cost of reversing investment and reduces its ability to raise cash. Hence, real asset illiquidity makes firms' restructuring processes more difficult (e.g., Maksimovic and Phillips (1998)), which is especially costly to firms facing economic adversity (e.g., Lang, Poulsen, and Stulz (1995)). Such firms find it difficult to scale down operations and raise cash, and thus often remain burdened with unproductive assets. This increases the covariance of a firm's performance with macroeconomic conditions, especially during downturns. It is noteworthy that, in addition to reducing firms' ability to raise cash, illiquid real assets generate long-term obligations (e.g., fixed operating costs, wage contracts, and commitments to suppliers), and prior work (e.g., Lev (1974)) shows that operating leverage increases the cost of capital.[3]

This leads to our main hypothesis: Real asset illiquidity increases firms' cost of capital by decreasing their operating flexibility.

Our main hypothesis has three broad implications. The first implication should hold at the aggregate level. Specifically, there should be a positive spread in cost of capital between the high and low real asset illiquidity firms, that is, *a real asset illiquidity premium*. Moreover, real asset illiquidity is more harmful when economic conditions worsen and firms are more likely to need to sell assets, either to reduce fixed costs and thus operating risk or to raise the cash necessary to fund operations and avoid default. In sum, there should be a countercyclical aggregate real asset illiquidity premium. The second implication follows directly from the hypothesis: In firm-level multivariate tests, there should be a positive impact of real asset illiquidity on the cost of capital.

The third implication follows from Shleifer and Vishny (1992). They argue that buyers who operate outside the industry are willing to pay low prices due to little synergies and inexperience in operating the asset, while buyers who operate inside the industry can better redeploy the asset to productive uses and thus are willing to pay high prices. Supporting this view, financially constrained firms forced to sell assets to industry outsiders obtain much lower prices than those they would have obtained from industry insiders (e.g., Pulvino (1998)). This suggests that a weaker presence of inside buyers makes real asset markets more illiquid than a weaker presence of outside buyers and thus should have a stronger positive effect on firms' cost of capital.

We also develop predictions about what drives the variation across firms in the effect of real asset illiquidity. We first consider the role of a firm's competitive environment. Real asset illiquidity is likely to be more costly for firms in more competitive industries, where competition is more intense and thus firms that fail to quickly adapt to changes in the environment are drawn out of business.[4] It is also likely to be more costly for the smallest industry competitors, which are less able to endure economic hardship and are often exposed to competitive threats from larger rivals.[5] These arguments suggest that real asset illiquidity should

[3]In the same vein, the recent investment-based asset pricing literature, which aims to explain the value anomaly (e.g., Carlson et al. (2004)), argues that the returns of firms with more operating inflexibility load more on the state of the economy, which leads investors to require higher expected returns for their capital.

[4]Hou and Robinson (2006) empirically show that the stocks of firms operating in more competitive industries earn higher average returns and attribute this to their higher default risk.

[5]Smaller stocks are arguably more risky due to their higher distress risk (e.g., Chan and Chen (1991)), and the empirical evidence shows that small firms account for the majority of exits in industry restructurings.

increase the cost of capital more for firms in more competitive industries and for the smallest firms in each industry.

We then consider the role of a firm's access to capital and financial condition. Real asset illiquidity is likely to be more costly for firms with less access to external capital and for firms that are closer to financial distress, since such firms may be forced to raise cash with asset sales. Supporting the view, Campello, Graham, and Harvey (2010) report that during the recent financial crisis financially constrained firms have engaged in significantly more asset sales than have unconstrained firms. This suggests that real asset illiquidity should increase the cost of capital more for firms with less access to capital and for those with more default risk.

Last, we consider the role of a firm's business environment. Theory suggests that a firm's ability to sell its real assets is more valuable in bad times, when firms facing a low demand for their products may want to sell real assets to reduce their fixed costs or to raise cash (e.g., Kogan (2001), Zhang (2005)). This suggests that real asset illiquidity should increase the cost of capital more for firms with low valuations and for those in industries experiencing downturns.

These testable implications are summarized below:

Prediction 1. At the aggregate level, there should be a real asset illiquidity premium in the cost of capital that exhibits a countercyclical time-series variation.

Prediction 2. Firms with more illiquid real assets should have a higher cost of capital.

Prediction 3. Inside real asset illiquidity should increase a firm's cost of capital more than outside real asset illiquidity.

Prediction 4. Real asset illiquidity should increase the cost of capital more for:

i) firms in more competitive industries and the smallest firms in each industry,

ii) firms with less access to capital and firms with higher default risk, and

iii) firms with lower valuations and firms in industries experiencing downturns.

III. Data and Variables

A. Data Sources and Sample Selection

Our data come from the Center for Research in Security Prices (CRSP)-Compustat Merged Database, the Compustat Segment Database, the Institutional Brokers' Estimate System (IBES), the Securities Data Corporation (SDC), the St. Louis Federal Reserve Economic Data (FRED), and the Census of Manufactures. We start with the CRSP-Compustat Merged Database and exclude companies in the financial (Standard Industrial Classification (SIC) codes 6000–6999) and utilities (SIC codes 4900–4999) industries. We also drop companies not covered in IBES because we require analyst forecast data to calculate the implied cost of capital, and observations for which we are unable to compute the real asset illiquidity measures or our control variables. Our final sample includes

6,260 firms operating in 304 different 3-digit SIC industries and 33,788 firm-year observations during 1984–2006.

B. Measures of Asset Illiquidity

Given our conceptual framework, our main explanatory variables are *real* asset illiquidity measures, which capture only the illiquidity of fixed assets and a firm's ability to resell these assets to other firms in the industry. We also examine the effect of *total* asset illiquidity measures constructed at the firm level from firms' balance sheets, which capture not only the illiquidity of fixed assets but also the effect of how much cash or other liquid assets the firm holds.

1. Illiquidity of Firms' Real Assets

The measures of real asset illiquidity capture the "industry equilibrium" aspect of asset illiquidity highlighted by Shleifer and Vishny (1992), that is, the fact that the liquidity of a firm's fixed assets is intimately related to the presence and financial ability of other firms in the industry (the natural buyers) to act as acquirers. More recently, Gavazza (2011) and Benmelech and Bergman (2008), (2009) all highlight the importance of the set of potential buyers from within the industry in determining real asset liquidity. An additional advantage of the measures is that they are more likely to be exogenous to the firm and mitigate potential endogeneity concerns.

The liquidity of a firm's real assets (the extent to which the asset can be quickly sold at a fair price) depends on the existence of other firms with enough financial slack to purchase it and the extent to which the asset is transferrable to other firms. The existence of other firms with financial slack can be gauged empirically, but measuring the degree of asset specificity, and thus the transferability of assets across firms, is much more difficult. Still, the key source of asset specificity is the firm's industry affiliation (e.g., Kogan (2004)). Due to commonalities in production technologies, most assets are transferrable among firms in the same industry but much harder to transfer to firms outside the industry. Supporting this view, the bulk of asset sales occur between firms in the same or closely related industries (Maksimovic and Phillips (2001)).

We use three measures of real asset illiquidity based on industry definitions at the 3-digit SIC level. The first two capture the *absence of potential future buyers* from within the industry and are motivated by Shleifer and Vishny (1992) and Almeida et al. (2011). They assume that a firm's assets are transferrable to other firms in the industry, which are able to redeploy them to alternative uses, but not transferrable to firms outside the industry (i.e., they are industry specific).[6] Hence, financially flexible industry insiders are the likely future buyers of a firm's assets. Thus, a firm's real assets are more illiquid when the number of potential inside-industry buyers with financial slack is smaller.

[6]There might also be some heterogeneity in the transferability of assets across firms within the industry. Hence, in our tests we also include *firm-level* control variables, which capture the degree of specificity of each firm's assets.

Our first measure is similar to those used in Benmelech and Bergman (2008), (2009) and Gavazza (2011) for the airline industry.[7] This measure is *minus* the number of potential buyers for a firm's assets, *MNoPotBuy*, defined for each firm as minus the number of rival firms in the industry that have debt ratings.

Our second measure, denoted *NLPotBuy*, directly captures the financial slack of potential buyers, and for each firm it is defined as the average book leverage net of cash of rival firms in the industry, averaged over the last 5 years to minimize the impact of temporary changes in firms' financial situations. A firm's real assets are more illiquid for higher values of both *MNoPotBuy* and *NLPotBuy*. These measures have an important industry component (we identify rivals using SIC codes), but they vary across firms in the same industry.

Our third measure, *MTotM&A*, follows Schlingemann et al. (2002). It captures the *historical illiquidity* of a firm's assets using *minus* the value of M&A activity in the firm's industry scaled by industry assets (Sibilkov (2009) uses a similar measure). We obtain the value of all M&A deals involving publicly traded targets in each 3-digit SIC industry and year from SDC.[8] We include both mergers and acquisitions of assets (the latter comprise 75% of the deals). In industry-years with no reported transactions, we set the value equal to 0. We then multiply the value of transactions in the industry by -1, scale it by the book value of assets in the industry, and average this ratio over the past 5 years.[9] The last step smoothes temporary ups and downs in M&A activity to better capture the intrinsic salability of an industry's assets. Higher values of *MTotM&A* imply more illiquid real assets. This measure captures the salability of assets, regardless of whether it is driven by the presence of solvent rivals or by the asset's transferability. It uses transactions involving buyers both from inside and outside the industry, and thus it does not rely on assumptions about the transferability of assets across industries.

We decompose *MTotM&A* to discern between weaker acquisition activity by industry insiders (those who operate in the same 3-digit SIC industry as the target) and by industry outsiders (those who do not operate in the industry). We classify a purchase as made by an industry insider if the buyer has any segments in the same industry as the assets purchased, checking over each reported industry of the target if it reports multiple industries. *MInM&A* is *minus* the value of M&A activity in the industry involving acquirers that operate within the industry, scaled by the book value of the assets in the industry. *MOutM&A* is *minus* the value of M&A activity in the industry involving acquirers that operate outside the industry, scaled by the book value of the assets in the industry. Both of these variables are averaged over the past 5 years.

[7] They develop measures of illiquidity based on the idea that the potential secondary market buyers for any given type of aircraft are likely to be financially healthy airlines already operating the same type of aircraft.

[8] We focus on publicly traded targets because the Compustat firms for which we wish to measure real asset illiquidity are publicly traded, and because acquisitions of private targets are likely to be reported with significant noise.

[9] We calculate the value of assets in an industry by summing the assets in the industry of single-segment firms and the segment-level assets of multisegment firms, breaking up multisegment firms into their component industries.

2. Overall Asset Illiquidity

As in Gopalan et al. (2012), we construct four firm-level weighted measures of total asset illiquidity. These measures sum the liquidity scores assigned to each of the major asset classes in a firm's balance sheet (holdings of cash and equivalents, other noncash current assets, tangible fixed assets, and other assets) weighted by the importance of each asset class in the total assets of the firm (also see Berger and Bouwman (2009) for a similar approach). We only differ in that we multiply each measure by -1, so that we can interpret it as an asset illiquidity measure. The resulting weighted asset illiquidity measures are described below, where all measures of total assets and market assets in the denominator are lagged 1 year:

$$\begin{aligned}
\mathit{WAIL1} &= -\left(\frac{\text{Cash \& Equiv}}{\text{Total Assets}}\right), \\
\mathit{WAIL2} &= -\left[\left(\frac{\text{Cash \& Equiv}}{\text{Total Assets}}\right) + 0.5\left(\frac{\text{Noncash CA}}{\text{Total Assets}}\right)\right], \\
\mathit{WAIL3} &= -\left[\left(\frac{\text{Cash \& Equiv}}{\text{Total Assets}}\right) + 0.75\left(\frac{\text{Noncash CA}}{\text{Total Assets}}\right)\right. \\
&\qquad \left. + 0.5\left(\frac{\text{Tangible Fixed Assets}}{\text{Total Assets}}\right)\right], \\
\mathit{MWAIL} &= -\left[\left(\frac{\text{Cash \& Equiv}}{\text{Market Assets}}\right) + 0.75\left(\frac{\text{Noncash CA}}{\text{Market Assets}}\right)\right. \\
&\qquad \left. + 0.5\left(\frac{\text{Tangible Fixed Assets}}{\text{Market Assets}}\right)\right].
\end{aligned}$$

C. Measures of Cost of Capital

We use two ex ante measures of a firm's expected return. Our main measure is the implied cost of capital (*ICC*), which does not rely on noisy realized returns or on specific asset pricing models. Pástor et al. (2008) theoretically show that *ICC* is a good proxy for expected returns and that, unlike realized returns, it empirically identifies a positive risk-return tradeoff (see also Chava and Purnanandam (2010)). Sluggish adjustment or biases in analyst earnings forecasts might affect the *ICC* (Easton and Monahan (2005) and Guay et al. (2011)), but in Section IV.D we show that these issues do not drive our results. For robustness, we also use the Fama and French (1993) 3-factor model cost of capital (*FFCC*), but this measure is very imprecise (Fama and French (1997), Pástor and Stambaugh (1999)).

Following Gebhardt, Lee, and Swaminathan (2001), the *ICC* is defined as the discount rate that equates the present value of all expected future cash flows to shareholders to the current stock price. The calculation of a firm's *ICC* for year t starts with the dividend-discount model:

$$P_t = \sum_{i=1}^{\infty} \frac{\mathrm{E}_t(D_{t+i})}{(1+r_e)^i}, \tag{1}$$

where P is the stock price, D is dividends, r_e is the discount rate, and $\mathrm{E}(\cdot)$ is the expectation operator. Assuming clean-surplus accounting (change in book equity equals net income minus dividends) and using equation (1), we get the discounted residual income equity valuation model:

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{\mathrm{E}_t[(ROE_{t+i} - r_e)B_{t+i-1}]}{(1+r_e)^i}, \tag{2}$$

where ROE is the return on equity and B is the book value of equity. We then numerically solve for the implied cost of equity, r_e, from equation (2) using the current stock price, current book value of equity, and forecasts of future ROE and future book value of equity.

As in Gebhardt et al. (2001), we forecast earnings explicitly for the next 3 years using the analysts' forecasts of earnings per share (*EPS*) and *EPS* growth from IBES. We forecast earnings beyond year 3 implicitly assuming that ROE at period $t+3$ mean reverts to the industry median ROE by period $t+T$, and estimate a terminal value as the present value of period T residual income as a perpetuity. We set T equal to 12 years. The forecasts are obtained through linear interpolation between ROE at period $t+3$ and the industry median ROE at time t. The industry median ROE is a moving median of the past 10 year *ROE*s from all firms in the same 48 Fama and French (1997) industry. Last, assuming a clean-surplus accounting system and a constant dividend payout ratio, we forecast the future book value of equity using the forecasted future earnings.

We calculate the *FFCC* as a linear projection of returns based on the market, size, and value factors that we obtain from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). To estimate the factor loadings, for each stock j in year t (between 1984 and 2006), we estimate the following time-series regression using monthly data from year $t-4$ to t (we require a minimum of 36 months of data):

$$r_j - r_f = \alpha_j + \beta_j^{MKT}(r_M - r_f) + \beta_j^{HML} HML + \beta_j^{SMB} SMB + \varepsilon_j, \tag{3}$$

where $(r_j - r_f)$ is the monthly return on stock j minus the risk-free rate, $r_M - r_f$ is the excess return of the market portfolio over the risk-free rate, HML is the return difference between high and low book-to-market stocks, and SMB is the return difference between small and large capitalization stocks. We then construct the Fama-French (1993) cost of capital of firm j in year t as follows:

$$FFCC_{j,t} = r_f + \hat{\beta}_{j,t}^{MKT}(\overline{r_M - r_f}) + \hat{\beta}_{j,t}^{HML}\overline{HML} + \hat{\beta}_{j,t}^{SMB}\overline{SMB}, \tag{4}$$

where $(\overline{r_M - r_f})$, $\overline{HML}$, and $\overline{SMB}$ are the average annualized returns of the Fama-French (1993) factors calculated over the period 1926–2008, and the $\hat{\beta}$'s are the ordinary least squares (OLS) estimates of the β's from equation (3) using monthly stock price data for the past 3–5 years.

D. Control Variables

The control variables capture potential determinants of firms' cost of capital. *LogMCap* is the logarithm of market capitalization; *LogBM* is the logarithm of the book-to-market equity ratio; *DRP* is a firm's percentile ranking based on the yearly distribution of its default risk computed using the distance-to-default model as in Bharath and Shumway (2008); *BLev* is book leverage; *ROE* is return on equity; *VolRoe* is the standard deviation of *ROE* over the past 5 years; *FA/TA* is fixed assets scaled by total assets; *R&DExp* is research and development expenditures scaled by sales; *LogAge* is the logarithm of 1 plus the number of years since the firm was first listed in CRSP; *DivPay* equals 1 if the firm pays dividends, and 0 otherwise; *SalGrow* is sales growth; *LogInvPrice* is the logarithm of 1 divided by the stock price as of the estimation date of *ICC*; *RetPM* is the stock return over the past month; and *RetP12M* is the stock return over the past 12 months.

E. Summary Statistics for Main Variables

Table 1 gives summary statistics of the variables we use in our analyses. With the exception of *FFCC*, the statistics are calculated on the sample of firms we use in our main tests based on *ICC*. We calculate the summary statistics for *FFCC*

TABLE 1

Summary Statistics for the Main Variables

Table 1 reports summary statistics for the measures of cost of capital, the asset illiquidity measures, and the control variables. The sample spans the period 1984–2006 and excludes both financial firms and utilities. *ICC* is the implied cost of capital of Gebhardt et al. (2001) and *FFCC* is the Fama-French (1993) 3-factor model cost of capital. All measures of asset illiquidity are standardized to have a mean of 0 and a standard deviation of 1. The measures of *real* asset illiquidity use 3-digit SIC industry definitions: *MNoPotBuy* is *minus* the number of rival firms in the industry that have debt ratings (calculated for the period 1985–2006 because bond ratings become available in 1985); *NLPotBuy* is the average book leverage net of cash holdings of rival firms in the industry, averaged over the past 5 years; *MTotM&A* is *minus* the value of all M&A activity in the industry scaled by the book value of the assets in the industry, averaged over the past 5 years; *MInM&A* is *minus* the value of M&A activity in the industry involving acquirers that operate within the industry scaled by the book value of the assets in the industry, averaged over the past 5 years; *MOutM&A* is *minus* the value of M&A activity in the industry involving acquirers that operate outside the industry scaled by the book value of the assets in the industry, averaged over the past 5 years. The firm-level measures of *total* asset illiquidity are *WAIL1*, *WAIL2*, *WAIL3*, and *MWAIL*, all of which are defined in Section III.B.2 following Gopalan et al. (2012). Higher values of all these variables are associated with more illiquid real assets. The control variables we use throughout our tests are as follows: *LogMCap* is the logarithm of market capitalization; *LogBM* is the logarithm of the book-to-market equity ratio; *DRP* is a firm's percentile ranking based on the yearly distribution of default risk; *BLev* is book leverage; *ROE* is return on equity; *VolRoe* is the standard deviation of *ROE* over the past 5 years; *FA/TA* is fixed assets scaled by total assets; *R&DExp* is R&D expenditures scaled by sales; *LogAge* is the logarithm of 1 plus the number of years since the company was first listed in CRSP; *DivPay* equals 1 if the firm pays dividends, and 0 otherwise; *SalGrow* is the annual change in the logarithm of sales; *LogInvPrice* is the logarithm of 1 divided by the stock price as of the estimation date of *ICC*; *RetPM* is the stock return over the past month; and *RetP12M* is the stock return over the past 12 months. The summary statistics on the independent variables are calculated on the sample of firms for which we can calculate the *ICC*, which contains 6,260 firms and a total of 33,494 firm-year observations. The summary statistics for the *FFCC* are calculated using the larger sample of firms for which we are able to calculate *FFCC* during 1984–2006.

				Percentile	
Variables	Mean	Std. Dev.	Median	5th	95th
Panel A. Dependent Variables					
ICC	0.099	0.057	0.107	0.001	0.179
FFCC	0.142	0.091	0.137	0.004	0.301
Panel B. Standardized Real Asset Illiquidity Measures					
MNoPotBuy	0.000	1.000	0.382	−2.096	0.949
NLPotBuy	0.000	1.000	0.183	−1.838	1.464
MTotM&A	0.000	1.000	0.361	−2.246	1.002
MInM&A	0.000	1.000	0.415	−2.377	0.791
MOutM&A	0.000	1.000	0.389	−2.217	0.883

(continued on next page)

TABLE 1 (continued)

Summary Statistics for the Main Variables

				Percentile	
Variables	Mean	Std. Dev.	Median	5th	95th
Panel C. Standardized Total Asset Illiquidity Measures					
WAIL1	0.000	1.000	0.387	−1.847	0.697
WAIL2	0.000	1.000	0.217	−1.688	1.049
WAIL3	0.000	1.000	0.169	−1.600	1.133
MWAIL	0.000	1.000	0.184	−1.856	1.222
Panel D. Control Variables					
LogMCap	6.522	1.771	6.398	3.873	9.675
LogBM	−0.424	0.778	−0.394	−1.722	0.772
DRP	0.499	0.288	0.500	0.050	0.949
BLev	0.210	0.181	0.189	0.000	0.548
ROE	0.045	3.050	0.069	−0.235	0.194
VolRoe	0.087	0.127	0.050	0.009	0.266
FA/TA	0.300	0.225	0.242	0.037	0.768
R&DExp	0.068	0.207	0.005	0.000	0.253
LogAge	2.361	0.960	2.398	0.693	4.043
DivPay	0.431	0.495	0.000	0.000	1.000
SalGrow	0.156	0.254	0.118	−0.177	0.625
LogInvPrice	−2.989	0.818	−3.059	−4.193	−1.504
RetPM	0.036	0.142	0.026	−0.164	0.273
RetP12M	0.198	0.579	0.107	−0.513	1.230

using the larger sample of firms for which we are able to calculate them and have nonmissing values on the test and control variables. The mean and median *ICC* for the firms in our sample are close to 10%, with a standard deviation of 5.7%. For *FFCC*, the mean and median are about 14%, with a standard deviation of 9.1%.

Both estimates of expected returns are subject to measurement error (e.g., Guay et al. (2011) make the point for the *ICC,* and Fama and French (1997) make the point for the *FFCC*). Our summary statistics show that this measurement error is often reflected in values of these estimates below the 10-year risk-free rate, which averaged 6.5% during our sample period. In the case of the *ICC*, Gebhardt et al. (2001) and Easton and Monahan (2005) note that it is nevertheless very useful in capturing the *variation* in expected returns across firms and over time, even when it might give a biased estimate of the *mean* equity risk premium. Hence, it is widely used in studies like ours. Similarly, the *FFCC* helps capture the variation in expected returns across firms and over time, provided the 3 Fama-French (1993) factors indeed capture risk. In Section IV.D, we show that measurement error in the cost of capital does not affect our results.

To more easily compare the effect of the real and total asset illiquidity measures on the cost of capital, we standardize these measures to have a mean of 0 and a standard deviation of 1. Using the original (nonstandardized) real asset illiquidity variables, the mean value of *MNoPotBuy* is −13.4 firms, the mean value of *NLPotBuy* is 0.068, and the mean value of *MTotM&A* is −4.2%. Inside illiquidity (*MInM&A*) and outside illiquidity (*MOutM&A*) each account for about half of the total real asset illiquidity in the industry measured by *MTotM&A*. The summary statistics for the original (nonstandardized) total asset illiquidity variables are similar to those in Gopalan et al. (2012). Lastly, since we use firms with analyst-forecast data, the firms in our sample have mean book assets of $580

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million and are larger than those in the Compustat universe. Our asset illiquidity measures have low correlation with the control variables.

IV. Main Empirical Results

A. The Aggregate Real Asset Illiquidity Premium and Its Business-Cycle Variation

In Table 2 we relate a firm's cost of capital to real asset illiquidity using univariate tests. For each year, we sort firms into quintile portfolios based on the real asset illiquidity measure, where Q1 denotes the low and Q5 denotes the high real asset illiquidity quintiles. We then compute the average cost of capital for each quintile portfolio, and subsequently take the average for each quintile across years. The last two columns report the difference in the average cost of capital of the highest and lowest real asset illiquidity quintiles, and the corresponding *p*-value, respectively.

Panel A of Table 2 uses the *ICC* and shows that, for all measures of real asset illiquidity, there is a monotonically increasing pattern in the *ICC* as we move from Q1 to Q5. This relation is economically significant: Using the equal-weighted portfolios, the spread in the *ICC* between Q5 and Q1 is 4.29 percentage points when real asset illiquidity is measured with *MNoPotBuy,* 5.08 percentage points when it is measured with *NLPotBuy*, and 3.96 percentage points when it is

TABLE 2

Real Asset Illiquidity and the Cost of Capital: Univariate Tests

Table 2 reports the average cost of capital (*ICC* or *FFCC*) for quintile portfolios of firms formed using the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*). For each year we sort firms into quintile portfolios based on the real asset illiquidity measure. We then compute the average cost of capital for each quintile portfolio, and subsequently take the average for each quintile across years. Q1 denotes the least illiquid quintile and Q5 denotes the most illiquid quintile. The last column reports the *p*-value corresponding to the test of the difference in means between Q5 and Q1. Panel A uses the implied cost of capital (*ICC*) and Panel B uses the Fama-French (1993) 3-factor model cost of capital (*FFCC*).

	Real Asset Illiquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	*p*-Value
Panel A. ICC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity							
Sorted on MNoPotBuy							
Equal-weighted avg.	7.80%	9.39%	10.73%	11.76%	12.10%	4.29%	0.000
Value-weighted avg.	7.13%	8.90%	9.78%	9.23%	9.86%	2.73%	0.000
Sorted on NLPotBuy							
Equal-weighted avg.	7.25%	9.90%	11.29%	12.29%	12.33%	5.08%	0.000
Value-weighted avg.	5.06%	8.45%	9.56%	10.43%	11.58%	6.52%	0.000
Sorted on MTotM&A							
Equal-weighted avg.	8.59%	10.28%	10.39%	11.25%	12.54%	3.96%	0.000
Value-weighted avg.	6.92%	9.01%	9.01%	9.34%	10.73%	3.80%	0.000
Panel B. FFCC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity							
Sorted on MNoPotBuy							
Equal-weighted avg.	13.85%	14.31%	14.08%	14.67%	14.44%	0.59%	0.072
Value-weighted avg.	9.17%	10.48%	10.49%	10.95%	12.30%	3.13%	0.000
Sorted on NLPotBuy							
Equal-weighted avg.	13.26%	14.21%	14.16%	14.78%	14.77%	1.50%	0.000
Value-weighted avg.	7.09%	10.57%	11.33%	11.37%	11.45%	4.36%	0.000
Sorted on MTotM&A							
Equal-weighted avg.	13.60%	13.93%	14.27%	14.74%	14.63%	1.03%	0.000
Value-weighted avg.	8.73%	10.23%	10.36%	10.74%	11.56%	2.83%	0.000

measured with *MTotM&A*. All these differences are statistically significant at the 1% level. The value-weighted portfolios give similar results. Panel B uses the *FFCC,* which, as explained in Section III.C, does not rely on analysts' forecasts and is calculated for a larger sample but is more imprecise. For all measures of real asset illiquidity, the *FFCC* increases as we move from Q1 to Q5, providing further evidence of a real asset illiquidity premium.

In Table 3 we study the time-series variation in the aggregate real asset illiquidity premium, that is, in the spread between the (value-weighted) cost of capital for firms in the top and bottom illiquidity quintiles. We run univariate time-series regressions of the aggregate real asset illiquidity premium on alternative business-cycle indicators using the 23 annual observations in our sample period. These are the year-over-year growth in the fourth quarter's gross domestic product (*GDP Growth*), the utilization rate of capacity during the fourth quarter of the year (*Capacity Utilization*), the year-to-year change in December's Consumer Price Index (*Inflation*), the average 3-month Treasury bill rate during the year (*T-Bill Rate*), the average difference between the yield on Moody's Baa

TABLE 3

Business-Cycle Variation of the Real Asset Illiquidity Premium

Table 3 reports the results of OLS time-series univariate regressions of the annual average real asset illiquidity premium on various business-cycle indicators that we obtain from the St. Louis Federal Reserve Economic Data (FRED). In Panel A we measure a firm's expected return using the implied cost of capital (*ICC*), and in Panel B we measure it using the Fama-French (1993) 3-factor model cost of capital (*FFCC*). For the tests using both *ICC* and *FFCC*, we calculate three different versions of the real asset illiquidity premium using the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*). In all cases the real asset illiquidity premium is the difference between the value-weighted average cost of capital (in %) for firms in the highest and lowest real asset illiquidity quintiles. The regressions with the real asset illiquidity premium based on *MNoPotBuy* use the 22 annual observations during the period 1985–2006, and the regressions with real asset illiquidity premiums based on *NLPotBuy* and *MTotM&A* use the 23 annual observations during the period 1984–2006. *GDPGr* is the year-over-year growth in the fourth quarter's GDP; *CapUtil* is the utilization rate of the installed capacity in the manufacturing sector for the fourth quarter of each year; *Inflation* is the year-over-year change in December's Consumer Price Index; *T-Bill* is the average 3-month Treasury bill rate during the corresponding year; *DefSpr* is the average spread between the yield on Moody's Baa corporate bond index and the yield of 10-year government bonds during the year; *MktRet* is the annual return on the market portfolio (in %). The estimates of the intercept are omitted. The absolute values of *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors, which account for any significant autocorrelation. The R^2 of each regression is reported in square brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

			Panel A. Illiquidity Premium in the ICC			*Panel B. Illiquidity Premium in the FFCC*		
			Premium Based on					
			MNoPotBuy	*NLPotBuy*	*MTotM&A*	*MNoPotBuy*	*NLPotBuy*	*MTotM&A*
(1)	*GDPGr*	Coef.	−0.877**	−0.839***	−0.734***	−0.845**	−0.455***	−0.550***
		t-stat.	(2.81)	(6.64)	(5.45)	(2.30)	(4.66)	(5.53)
		R^2	[15.90%]	[25.85%]	[15.53%]	23.15%	13.41%	17.37%
(2)	*CapUtil*	Coef.	−0.351***	−0.305**	−0.464***	−0.483***	−0.140**	−0.234***
		t-stat.	(5.12)	(2.65)	(5.44)	(4.00)	(2.58)	(5.64)
		R^2	[19.11%]	[18.22%]	[33.14%]	56.93%	6.78%	16.72%
(3)	*Inflation*	Coef.	−1.066***	−0.445*	−0.954***	−0.474*	−0.884***	−0.398
		t-stat.	(4.95)	(1.77)	(3.99)	(1.85)	(6.18)	(1.32)
		R^2	[20.62%]	[4.65%]	[16.78%]	6.40%	32.40%	5.82%
(4)	*T-Bill*	Coef.	−0.939***	−0.732***	−0.937***	−0.525***	−0.391***	−0.333***
		t-stat.	(6.64)	(7.40)	(8.57)	(3.56)	(3.05)	(4.41)
		R^2	[46.84%]	[45.96%]	[59.20%]	23.00%	23.11%	14.91%
(5)	*DefSpr*	Coef.	1.652**	1.817*	2.783***	3.570***	1.120***	1.544***
		t-stat.	(2.23)	(2.06)	(4.34)	(5.91)	(4.45)	(4.50)
		R^2	[7.59%]	[11.81%]	[21.77%]	55.62%	7.92%	13.34%
(6)	*MktRet*	Coef.	−0.031*	−0.0484***	−0.045***			
		t-stat.	(1.96)	(4.87)	(3.92)			
		R^2	[3.27%]	[10.43%]	[7.21%]			

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corporate bonds and the yield of 10-year government bonds during the year (*Default Spread*), and the annual return on the market index (*Market Return*). The standard errors are calculated using the Newey-West (1987) procedure.

In Panel A of Table 3 we report the results using the *ICC*. The results are similar for all three measures of the aggregate real asset illiquidity premium: The premium is smaller when market conditions are stronger, that is, when the GDP growth, capacity utilization, inflation rate, T-bill rate, and market returns are higher, and when the default spread is lower. The vast majority of the coefficients on the business-cycle indicators are statistically significant in all models we consider. The R^2 for each regression, reported in square brackets below the t-statistics, suggests that business-cycle indicators explain a significant fraction of the time-series variation in the real asset illiquidity premium.

In Panel B of Table 3 we report the results using the *FFCC*. Note that we exclude the market return specification, which appeared in Panel A, as the Fama-French (1993) cost of capital has a sensitivity to the market return through market beta already built into the cost of capital. Once again, the results are similar for all three measures of the aggregate real asset illiquidity premium. Overall, the models show that the real asset illiquidity premium in the Fama-French cost of capital is also smaller when market conditions are stronger. Thus, both *ICC* and *FFCC* give consistent results.

To summarize, supporting our first prediction, there is an aggregate real asset illiquidity premium in firms' cost of capital that is strongly countercyclical. This finding suggests that the operating inflexibility associated with illiquid real assets increases firms' cost of capital and is more costly when economic activity is low and default risk is high. However, the results may be driven by cross-sectional differences in firm or industry characteristics correlated with both real asset illiquidity and the cost of capital. Hence, we now turn to a multivariate analysis.

B. Multivariate Evidence Relating Real Asset Illiquidity and the Cost of Capital

Our empirical tests regress firms' cost of capital (*ICC* or *FFCC*) on the measures of real asset illiquidity (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*) and controls for other potential determinants of the cost of capital defined in Section III.D, including *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*.

Our real asset illiquidity measures are designed to capture operating inflexibility and have the advantage of not directly depending on stock prices. Including *LogInvPrice* and *LogBM* in the regression eliminates the worry that the real asset illiquidity measures may be correlated with stock prices and mechanically drive the *ICC*. As noted by Lakonishok, Shleifer, and Vishny (1994), the book-to-market equity ratio is not a "clean" variable uniquely associated with an economically interpretable characteristic of a firm.[10] Yet, recent asset pricing work

[10]Berk (1995) argues that finding a relationship between average return and book-to-market equity is neither surprising nor informative in itself because, given expectations about security payoffs,

that aims to explain the value anomaly in stock returns (e.g., Zhang (2005)) suggests that it might be correlated with the same source of risk as real asset illiquidity (i.e., operating inflexibility). Including *LogBM* as a control variable implies that our estimates of the effect of real asset illiquidity on the *ICC* are conservative (i.e., net of any effect on the *ICC* they might have due to a correlation with *LogBM*).

Including *BLev* and *DRP* ensures that our results are not driven by a correlation of real asset illiquidity and firms' financial conditions. It also ensures that the estimated effect of *NLPotBuy* is not driven by the impact the leverage of industry rivals could have on the firm's own leverage. *RetPM* controls for the sluggishness of adjustments in analysts' forecasts (Chava and Purnanandam (2010)), that is, it ensures that a correlation of real asset illiquidity with such sluggishness does not affect our tests based on the *ICC*. *RetP12M* controls for momentum (results are similar if we use the past 3- or 6-month returns). Moreover, *MNoPotBuy* and *NLPotBuy* assume that a firm's assets are equally transferrable to other firms in the industry, but there might be heterogeneity in the transferability of assets within the industry. Including *R&DEx*p (which is related to the degree of specificity of a firm's assets) reduces the concern that this heterogeneity could affect our results. Last, in addition to *LogBM*, we include *LogAge* and *SalGrow* to alleviate the concern that a correlation of real asset illiquidity and growth options could drive the results.

Table 4 reports the results using the *ICC*. In columns 1, 3, and 5 we report the results of Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure with 6 lags.[11] These specifications rely solely on the cross-sectional variation in real asset illiquidity to identify its effect on a firm's cost of capital, and thus mitigate the concern that a correlation of the real asset illiquidity measures with the state of the economy could drive the results. For all measures of real asset illiquidity, we find highly statistically significant evidence that firms with more illiquid real assets have a higher cost of capital. The cross-sectional effect is economically significant: A 1-standard-deviation increase in real asset illiquidity increases the *ICC* by 1.4 percentage points if we measure real asset illiquidity with either *MNoPotBuy* or *NLPotBuy*, and by 0.9 percentage points if we measure it with *MTotM&A*.

In columns 2, 4, and 6 of Table 4 we run pooled (panel) OLS regressions with 3-digit SIC industry dummy variables and year dummy variables, and we thus use the time-series variation in real asset illiquidity within industries to identify our results. This approach reduces the concern that omitted industry factors correlated with both real asset illiquidity and the cost of capital (e.g., the specificity of the industry's assets or the industry's growth options) could drive our results. Throughout the paper we report conservative standard errors clustered by 3-digit SIC industry. We continue to find a positive and statistically significant

market value must be correlated with systematic risk across securities (i.e., because both variables use the stock price in their definitions).

[11]The results are highly similar if, instead, we run purely cross-sectional regressions based on the time-series averages of the variables for each firm over the sample period and we cluster the standard errors by 3-digit SIC industry.

effect of all real asset illiquidity measures on the *ICC*. These tests imply that a 1-standard-deviation increase in real asset illiquidity increases a firm's *ICC* by about 1.4 percentage points when it is measured by *MNoPotBuy*, by 1.1 percentage points when it is measured by *NLPotBuy*, and by 0.5 percentage points when it is measured by *MTotM&A*, respectively.

TABLE 4

Real Asset Illiquidity and the Implied Cost of Capital: Multivariate Analysis

Table 4 reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative measures of real asset illiquidity (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and the set of control variables (*LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM,* and *RetP12M*) defined in Table 1. In columns 1, 3, and 5 we report Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. In columns 2, 4, and 6 we report pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry. The estimates of the intercept, the year fixed effects, and the industry fixed effects are omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent Variables	1	2	3	4	5	6
MNoPotBuy	0.014***	0.014***				
	(3.51)	(2.86)				
NLPotBuy			0.014***	0.011***		
			(6.83)	(6.35)		
MTotM&A					0.009**	0.005**
					(2.40)	(2.53)
LogMCap × 100	−0.119***	−0.171***	−0.242***	−0.170***	−0.265***	−0.179***
	(6.46)	(3.23)	(4.75)	(3.62)	(4.46)	(3.73)
LogBM	0.021***	0.015***	0.018***	0.015***	0.020***	0.015***
	(34.19)	(13.48)	(38.90)	(12.80)	(54.89)	(13.09)
DRP	0.008**	0.013***	0.010***	0.013***	0.005***	0.013***
	(2.43)	(5.88)	(3.31)	(6.56)	(3.25)	(6.48)
BLev	0.023***	0.002	0.008	0.002	0.027***	0.003
	(11.17)	(0.24)	(1.67)	(0.33)	(13.35)	(0.40)
ROE × 100	1.748**	0.059***	2.127**	0.062***	2.104**	0.061***
	(2.39)	(5.69)	(2.48)	(5.74)	(2.52)	(5.67)
VolRoe	−0.047***	−0.020***	−0.052***	−0.021***	−0.053***	−0.022***
	(3.67)	(6.80)	(4.24)	(6.90)	(4.67)	(7.12)
FA/TA	−0.002	0.008*	−0.027***	0.008*	−0.019***	0.008*
	(0.28)	(1.71)	(10.91)	(1.76)	(5.48)	(1.75)
R&DExp	−0.050***	−0.010	−0.039**	−0.009	−0.060***	−0.010
	(2.81)	(0.73)	(2.67)	(0.71)	(3.00)	(0.79)
LogAge	−0.003***	−0.002***	−0.002	−0.002***	−0.003***	−0.002***
	(3.00)	(3.22)	(1.69)	(3.40)	(3.46)	(3.05)
DivPay	0.005***	0.004***	0.005***	0.004***	0.007***	0.004***
	(4.51)	(4.57)	(3.61)	(4.56)	(3.58)	(4.60)
SalGrow × 100	−0.050	0.391	−0.025	0.415	−0.059	0.416
	(0.18)	(1.44)	(0.06)	(1.43)	(0.15)	(1.44)
LogInvPrice × 100	0.140	0.167	0.108	0.122	0.020	0.107
	(0.71)	(1.33)	(0.54)	(1.03)	(0.09)	(0.91)
RetPM	−0.008	−0.013***	−0.005	−0.012***	−0.007	−0.012***
	(0.99)	(4.75)	(0.58)	(4.11)	(0.80)	(4.45)
RetP12M	0.004*	0.003***	0.003	0.003***	0.003	0.003***
	(1.99)	(3.79)	(1.70)	(3.86)	(1.64)	(3.80)
Constant	0.124***	0.144***	0.139***	0.167***	0.139***	0.166***
	(7.69)	(30.59)	(10.10)	(40.02)	(10.26)	(37.52)
No. of obs.	32,767	32,767	33,494	33,494	33,494	33,494
R^2		0.56		0.56		0.56
Year dummies	No	Yes	No	Yes	No	Yes
SIC3 dummies	No	Yes	No	Yes	No	Yes
Estimation	Fama-MacBeth	Panel	Fama-MacBeth	Panel	Fama-MacBeth	Panel
Newey-West 6 lags	Yes	No	Yes	No	Yes	No
Clustering by SIC3	No	Yes	No	Yes	No	Yes

Table 5 reports the results of regressions using the *FFCC*, but the coefficients of the control variables are omitted. In columns 1, 3, and 5 we run Fama-MacBeth (1973) regressions and calculate our standard errors using the Newey-West (1987) procedure with 6 lags. In columns 2, 4, and 6 we run purely cross-sectional regressions based on the time-series averages of the variables for each firm over the sample period, and we cluster the standard errors by 3-digit SIC industry. For both estimation approaches and for all measures of real asset illiquidity, firms with more illiquid real assets have a higher *FFCC*. These effects are statistically significant but smaller in magnitude than those reported in Table 4.[12] Depending on the specification, a 1-standard-deviation increase in real asset illiquidity increases the *FFCC* by 0.4 to 0.8 percentage points.

TABLE 5

Real Asset Illiquidity and the Fama-French Cost of Capital: Multivariate Analysis

Table 5 reports the results from regressions of the Fama-French (1993) 3-factor model cost of capital (*FFCC*) on the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. In columns 1, 3, and 5 we report Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. In columns 2, 4, and 6 we report an OLS purely cross-sectional regression using the time-series averages of the variables over the sample period for each firm, with standard errors clustered by 3-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent Variables	1	2	3	4	5	6
MNoPotBuy	0.005**	0.004**				
	(2.50)	(2.37)				
NLPotBuy			0.004***	0.006***		
			(6.03)	(2.73)		
MTotM&A					0.003*	0.008***
					(1.78)	(3.63)
No. of obs.	73,660	9,925	76,331	10,176	76,331	10,176
R^2		0.03		0.03		0.03
Empirical Model						
All control variables	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Fama-MacBeth	Cross-sectional	Fama-MacBeth	Cross-sectional	Fama-MacBeth	Cross-sectional
Newey-West 6 lags	Yes	No	Yes	No	Yes	No
Clustering by SIC3	No	Yes	No	Yes	No	Yes

In sum, we find a positive association between firms' cost of capital and the illiquidity of their real assets. This result holds for tests using the *ICC* and the noisier *FFCC*, and for three different measures of real asset illiquidity. This evidence supports our central hypothesis that real asset illiquidity is associated with more operating inflexibility. Given the evidence in this section and the previous one, in the interest of conciseness, in the remainder of the paper we focus on the *ICC* as the main measure of a firm's expected return and do not report further results for the *FFCC*.

[12]We use cross-sectional estimation, since by construction the *FFCC* has little time-series variation (factor loadings are based on 5-year rolling window regressions, and average factor returns are constant and common to all stocks).

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C. The Effect of Balance-Sheet Measures of Total Asset Illiquidity

Although our main focus is on the illiquidity of a firm's physical assets, in this section we further explore how the illiquidity of all assets in a firm's balance sheet affects the cost of capital. First, the illiquidity of other assets, such as cash holdings and other current assets, might also affect a firm's flexibility to operate and thus impact the cost of capital. For example, in their study of LA Gear's collapse, DeAngelo, DeAngelo, and Wruck (2002) argue that the firm's ability to liquidate working capital helped management maneuver in financial distress. Second, the balance-sheet measures of total asset illiquidity are computed at the firm level. Hence, they reflect each individual firm's illiquidity, although they do not capture the industry equilibrium aspect of asset illiquidity of Shleifer and Vishny (1992).

Table 6 reports the results of Fama-MacBeth (1973) regressions of the *ICC* on *WAIL1*, *WAIL2*, *WAIL3*, and *MWAIL*, all of which are standardized to have a mean of 0 and a standard deviation of 1, and all control variables defined in Table 1. The *t*-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. We find that the first three measures all have a positive and statistically significant impact on the cost of capital, but the fourth has no effect. *WAIL1* has the largest impact: A 1-standard-deviation increase in its value increases the *ICC* by 0.7 percentage points. For *WAIL2* and *WAIL3*, a 1-standard-deviation increase in their values is associated with a 0.2 and 0.3 percentage point increase in the *ICC*, respectively. In sum, we find that *total* asset illiquidity also increases the cost of capital and, in particular, that the effect of *WAIL1* (the negative of holdings of cash and equivalents scaled by lagged assets) is the most economically significant. This evidence complements our earlier

TABLE 6

Total Asset Illiquidity and the Implied Cost of Capital

Table 6 reports the results from regressions of the implied cost of capital (*ICC*) on the four alternative balance-sheet measures of total asset illiquidity from Gopalan et al. (2012) (*WAIL1, WAIL2, WAIL3,* and *MWAIL*) and the set of control variables (*LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*) defined in Table 1. The asset illiquidity measures are the original Gopalan et al. measures multiplied by −1 and standardized to have a mean of 0 and a standard deviation of 1. We report Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. The estimates of the intercept and the control variables are omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent Variables	1	2	3	4
WAIL1	0.007***			
	(12.31)			
WAIL2		0.002***		
		(5.92)		
WAIL3			0.003***	
			(3.88)	
MWAIL				0.000
				(0.06)
No. of obs.	33,333	32,442	24,502	24,431
R^2	0.05	0.05	0.04	0.24
Empirical Model				
All control variables	Yes	Yes	Yes	Yes
Estimation	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth
Newey-West 6 lags	Yes	Yes	Yes	Yes

results and reinforces the view that asset illiquidity is an important determinant of flexibility and thus of firms' cost of capital.

D. Measurement Error in the Expected Return Measures

The dependent variable in our regressions (the cost of capital estimates) might be measured with error and can be viewed as the firm's true (unobserved) cost of capital plus measurement error. If the measurement error is purely random (i.e., uncorrelated with the independent variables) as it is assumed in the classical measurement-error framework, then it should not affect the consistency of the parameter estimates. However, measurement error in the cost of capital might affect our inferences if it is not random. One potential source of measurement error in the *ICC* is that its calculation uses analyst earnings forecasts, since: i) revisions in analyst forecasts are sluggish, and ii) the forecasts are often biased. Below, we address the concern that these issues associated with the use of analyst earnings forecasts might affect our results.

We first address the issue of sluggish analyst forecast revisions. As noted by Guay et al. (2011), analyst earnings forecasts are an imperfect proxy for the market's expectation of future earnings. The reason is that analysts often fail to update their earnings forecasts in a timely fashion relative to the information contained in recent stock price changes. This induces a measurement error in the *ICC* estimates that is correlated with past stock price performance. In our regressions we address this issue, controlling for the stock returns over the past month and over the past 12 months (controlling for the past 3- or 6-month returns gives similar results).

In Panel A of Table 7 we repeat our main tests using *ICC* estimates that correct for the measurement error due to sluggish analyst forecast revisions using a method proposed by Guay et al. (2011). The idea behind their method is that analyst forecasts may only reflect information that was impounded in prices *earlier than the current price.* Hence, in essence, the method allows analysts extra time to impound the information in recent price movements into their forecasts. As suggested by those authors, we recalculate the *ICC* using the stock price measured 5 months earlier than in the previous calculation but using the same analyst forecasts. For both the Fama-MacBeth (1973) regressions and the pooled (panel) OLS regressions with 3-digit SIC industry dummy variables and year dummy variables, the results are similar to those in Table 4.

We also do tests that account for potential biases in analyst forecasts noted by Easton and Monahan (2005). The worry is that the calculation of *ICC* assumes that the consensus forecast is an unbiased estimate of investors' expectations, but analysts make biased forecasts. This should not affect our regressions of the *ICC* on real asset illiquidity if the forecasts are equally biased for all stocks, but it may affect our results if the bias is related to real asset illiquidity. For example, if the forecasts are biased in favor of firms with more illiquid real assets, then for these firms the *ICC* will be biased upward and the effect of real asset illiquidity on the *ICC* would be overstated.

Further investigation shows that biases in analysts' earnings forecasts do not drive our results. The correlations of the analyst forecast bias with the real asset

TABLE 7

Real Asset Illiquidity and the Implied Cost of Capital:
Sluggish Revisions of Analyst Earnings Forecasts and Analyst Forecast Biases

Table 7 reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative measures of real asset illiquidity (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. In Panel A, the dependent variable is the *ICC* corrected for sluggish analyst forecast revisions using the method of Guay et al. (2011), which allows analysts extra time to impound the information in recent price movements into their forecasts. Specifically, the correction is implemented by recalculating the *ICC* using the stock price measured 5 months earlier than in the original calculation but using the same analyst forecasts. In Panel B, the dependent variable is our original *ICC* estimate, but the sample excludes firms whose sample-average analyst earnings forecast bias is in the top 30% of the distribution. In columns 1, 3, and 5 we report Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. In columns 2, 4, and 6 we report pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are also omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent Variables	1	2	3	4	5	6
Panel A. ICC Corrected for Sluggish Revisions of Analyst Earnings Forecasts as Suggested by Guay et al. (2011)						
MNoPotBuy	0.013***	0.013***				
	(3.71)	(3.32)				
NLPotBuy			0.014***	0.009***		
			(9.45)	(5.45)		
MTotM&A					0.006**	0.004***
					(2.12)	(2.91)
No. of obs.	31,642	31,642	32,338	32,338	32,338	32,338
R^2		0.57		0.57		0.57
Panel B. Excluding Firms with Analysts' Forecast Errors in the Top 30% of Distribution						
MNoPotBuy	0.015***	0.015***				
	(4.56)	(3.00)				
NLPotBuy			0.014***	0.010***		
			(5.31)	(5.83)		
MTotM&A					0.008**	0.004**
					(2.13)	(2.13)
No. of obs.	22,072	22,072	22,559	22,559	22,559	22,559
R^2		0.61		0.61		0.61
Empirical Model (both panels)						
All control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	No	Yes	No	Yes	No	Yes
SIC3 dummies	No	Yes	No	Yes	No	Yes
Estimation	Fama-MacBeth	Panel	Fama-MacBeth	Panel	Fama-MacBeth	Panel
Newey-West 6 lags	Yes	No	Yes	No	Yes	No
Clustering by SIC3	No	Yes	No	Yes	No	Yes

illiquidity measures in our sample are low, suggesting that such biases are unlikely to affect our results. In Panel B of Table 7, we repeat our regressions of the *ICC* on real asset illiquidity variables after dropping from the sample those firms with forecast biases in the top 30% of the distribution. Once again, for both the Fama-MacBeth (1973) regressions and the pooled (panel) OLS regressions with 3-digit SIC industry dummy variables and year dummy variables, the results remain similar to those reported in Table 4.

Last, as noted in Section III.E, the *ICC* and *FFCC* often result in estimates of expected returns below the risk-free rate. The worry is that such estimates might be of lesser quality than those that are above the risk-free rate, and they might affect our results. To address this issue, we repeat our main tests after dropping all observations for which our cost of capital estimates are below the risk-free rate. We caution that discarding an important fraction of the observations on the left tail of the distribution of the dependent variables causes a significant reduction

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in their variation, which diminishes the statistical power of our tests. Nevertheless, we continue to find a positive and statistically significant relation between real asset illiquidity and both the *ICC* and the *FFCC*, albeit of a smaller economic significance (see Table A1 and Table A2 of the Online Appendix (www.jfqa.org)).

E. The Distinction Between Inside and Outside Illiquidity

To test our third prediction, in Table 8 we regress the *ICC* on inside-industry real asset illiquidity (*MInM&A*) and outside-industry real asset illiquidity (*MOutM&A*), which are defined in Section III.B. In columns 1 and 3 we report the results of Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure with 6 lags. In columns 2 and 4 we report the results of pooled (panel) OLS regressions with 3-digit SIC industry and year fixed effects, and standard errors clustered at the 3-digit SIC industry level.

TABLE 8

Inside versus Outside Real Asset Illiquidity and the Implied Cost of Capital

Table 8 reports the results from regressions of the implied cost of capital (*ICC*) on two measures of real asset illiquidity defined in Table 1 (*MInM&Q* and *MOutM&A*) and a set of control variables. In columns 1 and 3 we report Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags. In columns 2 and 4 we report pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are also omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Independent Variables	1	2	3	4
MInM&A	0.008*	0.005***		
	(2.03)	(2.62)		
MOutM&A			0.003***	0.002
			(3.71)	(1.50)
No. of obs.	33,494	33,494	33,494	33,494
R^2		0.56		0.56
Empirical Model				
All control variables	Yes	Yes	Yes	Yes
Year dummies	No	Yes	No	Yes
SIC3 dummies	No	Yes	No	Yes
Estimation	Fama-MacBeth	Panel	Fama-MacBeth	Panel
Newey-West 6 lags	Yes	No	Yes	No
Clustering by SIC3	No	Yes	No	Yes

There is a positive and statistically significant effect of both *MInM&A* and *MOutM&A* on the *ICC* in the cross-sectional tests. Similarly, both *MInM&A* and *MOutM&A* increase the *ICC* in the tests that rely on the time-series variation in asset illiquidity, but the effect of *MOutM&A* is not statistically significant. The new result is that inside illiquidity has a much larger effect on the cost of capital than outside illiquidity. The cross-sectional results in columns 1 and 3 imply that a 1-standard-deviation increase in *MInM&A* increases the *ICC* by 0.8 percentage points, but a similar increase in *MOutM&A* only increases it by 0.3 percentage points. This difference is statistically significant. For the time-series results in columns 2 and 4, such an increase in *MInM&A* reduces the cost of capital by 0.5 percentage points, but the same increase in *MOutM&A* reduces it by only 0.2 percentage points. This difference is statistically significant.

In sum, real asset illiquidity due to weak acquisition activity by industry insiders has a larger positive impact on the cost of capital than real asset illiquidity due to weak acquisition activity by industry outsiders. This suggests that inside-industry acquirers can better redeploy the asset than outside acquirers, and thus are willing to pay higher prices. By making real asset markets more illiquid, a weaker presence of inside buyers reduces firms' operating flexibility by more than a weaker presence of outside buyers, and thus has a larger positive effect on firms' cost of capital.

V. Cross-Sectional Variation in the Effect of Real Asset Illiquidity

To better understand the economic mechanism underlying our findings, we now explore what drives the variation across firms in the effect of real asset illiquidity on the cost of capital. The idea is to identify situations in which real asset illiquidity might cause a stronger covariance of fundamentals with the state of the economy and hence have a larger impact on firms' cost of capital. To this end, we run our main regression of the *ICC* on *MNoPotBuy*, *NLPotBuy*, or *MTotM&A* with 3-digit SIC fixed effects and year fixed effects separately for extreme subsamples and compare the effects. Our predictions 4i to 4iii state that the effect should be strictly larger in one subsample than in another. However, we use a conservative approach and compare the effects across groups using two-tailed tests of the null hypothesis that the effects are the same in both subsamples against the broader alternative hypothesis that they are different.

A. Product Market Competition and Relative Industry Position

In Table 9 we test the prediction that real asset illiquidity should increase the cost of capital more for firms in more competitive industries and for the smallest firms in each industry. In columns 1 and 2, we use the Herfindahl-Hirschman Index (*HHI*) of sales concentration to split the sample into firms in high-*HHI* industries (the least competitive) and in low-*HHI* industries (the most competitive). Since the Census only reports the *HHI* for manufacturing industries but our sample contains many nonmanufacturing industries, we calculate a predicted concentration index for all industries using the approach in Hoberg and Phillips (2010).[13] We then classify industries into those with a predicted *HHI* in the top tercile of the distribution (high *HHI*) and those with a predicted *HHI* in the bottom tercile of the distribution (low *HHI*). The coefficients of *MNoPotBuy* and *MTotM&A* are positive and statistically significant for firms in the low-*HHI* group, but they are much smaller and not significant or marginally significant for firms in the high-*HHI* group. The coefficient of *NLPotBuy* does not differ across the two groups.

[13]In short, we regress concentration indices in manufacturing industries on employment levels obtained from the Bureau of Labor Statistics as well as on Compustat-based concentration indices and other variables related to concentration. Since our predictors are available for all industries and not just manufacturing, we then use the estimated coefficients to predict the concentration indices for all industries in our data.

These differences in the coefficients of *MNoPotBuy* and *MTotM&A* are highly suggestive of a larger impact of real asset illiquidity for firms in the low-*HHI* group, but in both cases a two-tailed test is unable to reject the null that the effect of real asset illiquidity is the same in both groups.

TABLE 9

The Role of Industry Concentration and Industry Position

Table 9 reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. All specifications are pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry. Columns 1 and 2 split the sample into high-concentration industries and low-concentration industries according to whether the industry's predicted sales-based Herfindahl-Hirschman Index (*HHI*) of concentration is in the top or bottom tercile of the annual distribution, respectively. Columns 3 and 4 split the sample into industry leaders, defined as firms with at least a 15% market share in their 3-digit SIC industry, and industry followers, defined as those with market shares below 15%, respectively. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are also omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	High *HHI*	Low *HHI*	Leaders	Followers
	1	2	3	4
Panel A. The Measure of Real Asset Illiquidity Is MNoPotBuy				
MNoPotBuy	0.007*	0.020**	−0.005	0.014***
	(1.90)	(2.24)	(0.52)	(2.83)
No. of obs.	10,533	10,277	5,397	27,370
R^2	0.56	0.61	0.58	0.56
Panel B. The Measure of Real Asset Illiquidity Is NLPotBuy				
NLPotBuy	0.011***	0.010***	0.003**	0.012***
	(3.04)	(4.91)	(1.97)	(5.93)
No. of obs.	10,757	10,494	5,537	27,957
R^2	0.57	0.61	0.59	0.57
Panel C. The Measure of Real Asset Illiquidity Is MTotM&A				
MTotM&A	0.002	0.007**	0.000	0.006***
	(1.00)	(2.01)	(0.37)	(2.62)
No. of obs.	10,757	10,494	5,537	27,957
R^2	0.57	0.61	0.58	0.56
Empirical Model (all panels)				
All control variables	Yes	Yes	Yes	Yes
Estimation	Panel	Panel	Panel	Panel
Year dummies	Yes	Yes	Yes	Yes
SIC3 dummies	Yes	Yes	Yes	Yes
Clustering by SIC3	Yes	Yes	Yes	Yes

In columns 3 and 4 of Table 9, we split the sample into industry "leaders" and "followers." As in Campello (2006), we classify as "leaders" those firms with market shares of at least 15% in their 3-digit SIC industry and as "followers" those firms with market shares below 15%. We find that all of our measures of real asset illiquidity have a large positive and statistically significant impact on the cost of capital of followers, but they have little effect on the cost of capital of industry leaders. For leaders, the coefficients of *MNoPotBuy* and *MTotM&A* are close to 0 and are statistically insignificant, while the coefficient on *NLPotBuy* is statistically significant and positive but much smaller than for followers. Furthermore, in all cases two-tailed tests reject the null that the effect of real asset illiquidity is the same for followers and leaders, with *p*-values of 0.071 for *MNoPotBuy*, 0.001 for *NLPotBuy*, and 0.018 for *MTotM&A*, respectively.

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B. Access to Capital and Financial Situation

In Table 10 we test the prediction that real asset illiquidity should increase the cost of capital more for firms with less access to capital and for those with more default risk. Since Faulkender and Petersen (2006) highlight the importance of access to public debt markets, in columns 1 and 2 we split the sample into firms with unrated and rated debt. Both *MNoPotBuy* and *MTotM&A* have a positive and statistically significant effect on the cost of capital of firms with unrated debt and a slightly smaller effect for firms with rated debt, but the effect of *NLPotBuy* is marginally smaller for firms with unrated debt. In all cases we are unable to reject the null that the effects are the same for firms with rated and unrated debt.

TABLE 10

The Effect of Access to Debt Financing and Default Risk

Table 10 reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. All specifications are pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry. Columns 1 and 2 split the sample into firms with debt but no debt ratings and those whose debt is rated, respectively. Columns 3 and 4 split the sample into firms with high distress risk and low distress risk based on whether the distance of a firm's probability of default from the industry median is in the top or bottom tercile of the annual distribution across all firms, respectively. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are also omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Unrated Debt	Rated Debt	High Default Risk	Low Default Risk
	1	2	3	4
Panel A. The Measure of Real Asset Illiquidity Is MNoPotBuy				
MNoPotBuy	0.013**	0.012***	0.013***	0.007**
	(2.53)	(3.37)	(2.69)	(2.42)
No. of obs.	15,222	12,283	11,152	10,910
R^2	0.55	0.55	0.50	0.57
Panel B. The Measure of Real Asset Illiquidity Is NLPotBuy				
NLPotBuy	0.010***	0.011***	0.013***	0.009***
	(5.39)	(3.88)	(5.68)	(2.81)
No. of obs.	15,897	12,283	11,400	11,150
R^2	0.56	0.55	0.51	0.58
Panel C. The Measure of Real Asset Illiquidity Is MTotM&A				
MTotM&A	0.004**	0.003**	0.007***	0.002
	(2.09)	(2.00)	(3.24)	(1.14)
No. of obs.	15,897	12,283	11,400	11,150
R^2	0.56	0.54	0.50	0.58
Empirical Model (all panels)				
All control variables	Yes	Yes	Yes	Yes
Estimation	Panel	Panel	Panel	Panel
Year dummies	Yes	Yes	Yes	Yes
SIC3 dummies	Yes	Yes	Yes	Yes
Clustering by SIC3	Yes	Yes	Yes	Yes

In columns 3 and 4 of Table 10, we split the sample into firms with high and low default risk, based on whether the distance of a firm's probability of default from the industry median is in the top or bottom tercile of the annual distribution. Our approach to split the sample reflects the spirit of industry equilibrium models that highlight the importance of a firm's choices relative to those of its industry rivals (e.g., Williams (1995)). All measures of real asset illiquidity have a larger positive effect on the cost of capital in firms with high default risk than they do in firms with low default risk. The effect of *MTotM&A* is not statistically significant and is close to 0 for firms in the low default risk group. Two-tailed tests reject the null that the effect of real asset illiquidity is the same for firms with high and low default risk in the case of *NLPotBuy*, with a *p*-value of 0.048, and *MTotM&A*, with a *p*-value of 0.014. For *MNoPotBuy*, the two-tailed *p*-value is 0.153.

C. Business Environment

In Table 11 we test the prediction that real asset illiquidity should increase the cost of capital more for firms with low valuation and for those in industries experiencing downturns. In columns 1 and 2, we split the sample into firms with low and high market-to-book value of assets (*M*/*B*), based on whether the distance of a firm's *M*/*B* from the industry median is in the bottom or top tercile of the annual distribution. All measures of real asset illiquidity have a larger positive effect on the cost of capital for firms with low *M*/*B* than they do for firms with high *M*/*B*. Two-tailed tests reject the null that the effect of real asset illiquidity is

TABLE 11

The Effect of Market Valuations and Demand Shocks

Table 11 reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. All specifications are pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry (except columns 3 and 4 which have no industry fixed effects). Columns 1 and 2 split the sample into low and high market-to-book value of assets ratios (*M*/*B*) based on whether the distance of a firm's *M*/*B* from the industry median is in the bottom or top tercile of the annual distribution across all firms, respectively. Columns 3 and 4 split the sample into firms in 3-digit SIC industries experiencing an economic downturn and firms in industries that are not experiencing a downturn, respectively. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogMCap*, *LogBM*, *DRP*, *BLev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, *RetPM*, and *RetP12M*. The estimates of the intercept, the year fixed effects, and the industry fixed effects are also omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low *M*/*B*	High *M*/*B*	Industry Downturn	Not Industry Downturn
	1	2	3	4
Panel A. The Measure of Real Asset Illiquidity Is MNoPotBuy				
MNoPotBuy	0.015**	0.013***	0.012*	0.016***
	(2.55)	(2.74)	(1.68)	(4.69)
No. of obs.	10,824	11,152	854	31,913
R^2	0.57	0.54	0.33	0.38
Panel B. The Measure of Real Asset Illiquidity Is NLPotBuy				
NLPotBuy	0.013***	0.010***	0.032***	0.017***
	(5.85)	(5.12)	(5.20)	(6.21)
No. of obs.	11,064	11,400	862	32,632
R^2	0.58	0.55	0.39	0.39
Panel C. The Measure of Real Asset Illiquidity Is MTotM&A				
MTotM&A	0.006***	0.004**	0.024***	0.011***
	(2.76)	(2.07)	(4.77)	(5.04)
No. of obs.	11,064	11,400	862	32,632
R^2	0.57	0.55	0.40	0.36
Empirical Model (all panels)				
All control variables	Yes	Yes	Yes	Yes
Estimation	Panel	Panel	Panel	Panel
Year dummies	Yes	Yes	Yes	Yes
SIC3 dummies	Yes	Yes	No	No
Clustering by SIC3	Yes	Yes	Yes	Yes

the same for firms with high and low *M/B* in the case of *NLPotBuy* (the *p*-value is 0.002) and *MTotM&A* (the *p*-value is 0.044). The two-tailed test cannot reject the null that the effect of *MNoPotBuy* is the same in both groups.

In columns 3 and 4 of Table 11, we split the sample into firms in industries experiencing a downturn and those in industries that are not. As in Opler and Titman (1994), we identify a 3-digit SIC industry to be in a downturn in a given year when its median sales growth is negative and its median stock return is below −30%. We do not include the 3-digit SIC industry dummy variables in the regressions because few industries remain in the downturn group for more than 1 year. All real asset illiquidity measures are positively related to the cost of capital and are statistically significant in both samples. The effects of *NLPotBuy* and *MTotM&A* are much larger for firms in industries experiencing downturns than they are for firms in industries that are not. Two-tailed tests reject the null that the effect of real asset illiquidity is the same in both groups with *p*-values of 0.018 for *NLPotBuy* and of 0.001 for *MTotM&A*, respectively. The effect of *MNoPotBuy* is smaller during downturns, but the difference is small and statistically insignificant.

VI. Additional Tests

We now briefly discuss additional tests whose results are omitted from the main text for brevity but are contained in the paper's Online Appendix. Unless otherwise noted, we run both Fama-MacBeth (1973) regressions with *t*-statistics adjusted for autocorrelation using the Newey-West (1987) procedure based on 6 lags and pooled (panel) OLS regressions with 3-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by 3-digit SIC industry.

A. Real Asset Illiquidity and the Illiquidity or Systematic Liquidity Risk of Firms' Stock

There is a potential concern that our results could be capturing liquidity risk as more illiquid stocks (e.g., Amihud and Mendelson (1986)) and stocks with more systematic liquidity risk (e.g., Pástor and Stambaugh (2003)) have higher expected returns. To address this concern, we measure systematic liquidity risk using *PSLiqBeta*, defined following Pastor and Stambaugh (2003) as the sensitivity of a stock's return to their liquidity factor,[14] and we measure a stock's illiquidity using the square root version of Amihud's (2002) measure, *AmihudIll*.[15] The

[14]For each firm, the loading (β^{LIQ}) on the liquidity factor (*LIQ*) is estimated with monthly data using 5-year rolling windows (with at least 36 observations): $r - r_f = \alpha + \beta^{MKT}MKT + \beta^{SMB}SMB + \beta^{HML}HML + \beta^{LIQ}LIQ + \varepsilon$.

[15]For each firm i and year t,

$$AmihudIll_{i,t} \quad = \quad \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \sqrt{|R_{i,j}|/VolD_{i,j}},$$

where $N_{i,t}$ is the number of trading days for stock i during year t, $R_{i,j}$ is the return on day j, and $VolD_{i,j}$ is the trading volume on day j in millions of dollars.

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effect of real asset illiquidity on the *ICC* is robust to controlling for *PSLiqBeta* and *AmihudIll* or their 3-digit SIC industry value-weighted averages (see Tables A3 and A4).

B. Controlling for Industry Valuation

To explore whether a correlation between the measures of real asset illiquidity and industry valuations could drive our results, we repeat our analyses after controlling for two alternative measures of industry valuations constructed at the 3-digit SIC industry level. The first is the logarithm of the average market-to-book equity ratio in the industry (*LogIndMB*). The second is the industry's valuation relative to historical values (*RelIndVal*). As in Hoberg and Phillips (2010), we construct this variable as the difference between the industry's log market-to-book equity ratio and its predicted value from the benchmark specification in Pástor and Veronesi (2003). Including these industry valuation measures in our regression models does not significantly affect the coefficients on *MNoPotBuy*, *NLPotBuy*, or *MTotM&A* (see Table A5).

C. Unlevered Cost of Capital

We study whether an association between real asset illiquidity and financial leverage could drive our results. To this end, we repeat our tests using the *unlevered* cost of capital, which we estimate by delevering the *ICC* using the Modigliani-Miller formula with taxes, and all the control variables, except that we omit financial leverage.[16] The estimated coefficients on *MNoPotBuy*, *NLPotBuy*, or *MTotM&A* are similar in magnitude and statistical significance to those in regression models estimated using the *ICC* and controlling for leverage (see Table A6).

D. Industry-Level Tests

Our main analyses are based on firm-level regressions of the *ICC* on measures of real asset illiquidity that are largely measured at the industry level. An alternative estimation approach is to convert the *ICC* and the control variables into 3-digit SIC industry-level (equal-weighted) averages and then estimate the regressions at the industry level. Hence, we estimate industry-level regression models using weighted least squares (WLS), wherein the weight on each industry-year observation is the number of firms in the industry. We run pooled (panel) OLS

[16]In addition to market debt-to-equity ratios and the top corporate tax rate, the formula requires each firm's cost of debt. We estimate the cost of debt for each firm-year in our sample by mapping a firm's Standard & Poor's (S&P) debt rating to the average bond yield in its rating category. Since only a limited number of firms have credit ratings, we estimate missing credit ratings for other firms. For the subset of companies with credit ratings, we estimate an ordered logit model that predicts the S&P debt rating. Our predictors are the natural logarithm of a firm's assets, financial leverage, profitability, interest coverage, the natural logarithm of a firm's age, and the volatility of excess returns. Next, we use the estimated coefficients from this model to predict the debt rating for all the companies whose ratings are missing, but have the complete set of predictors. For each year, we match a firm's debt rating to the average bond yield in its rating category, based on individual yields on new debt issues obtained from SDC.

regressions with year fixed effects and with both 3-digit SIC industry fixed effects and year fixed effects. In all models we cluster the standard errors by 3-digit SIC industry. We continue to find a positive and statistically significant effect of real asset illiquidity on the cost of capital (see Table A7).

E. Real Asset Illiquidity and Equity Values

Our results suggest that, through its effect on the discount rate, real asset illiquidity has a large impact on firm value. To better gauge the magnitude of this impact, we regress the logarithm of the book-to-market equity ratio on the real asset illiquidity measures and control variables. Using alternative estimation approaches, we find that all three measures of real asset illiquidity have a negative impact on firm value that is statistically and economically significant after controlling for cash flow effects. These tests, which do not rely on asset pricing models as the *FFCC* does or on assumptions like those used to calculate the *ICC*, provide further evidence that real asset illiquidity affects firms' cost of capital and thus their values (see Table A8).

F. Multisegment Firms

Our measures of real asset illiquidity require that we identify each firm's industry, which we do using firms' primary SIC codes. We further refine the measures to incorporate the segments of multiple-segment firms. We calculate the real asset illiquidity of a multiple-segment firm as the weighted average real asset illiquidity of each of its 3-digit SIC industry segments, with weights equal to the fraction of a firm's total assets accounted for by each segment's assets. For *MNoPotBuy* and *NLPotBuy*, which depend on identifying a firm's industry rivals, we consider all rivals, including the secondary segments of multiple-segment firms. Tests using segment-weighted measures of real asset illiquidity give results similar to those reported (see Table A9).

VII. Summary and Conclusions

We examine whether a more illiquid market for real (or physical) assets increases a firm's cost of unwinding its capital stock and decreases its ability to raise cash, hence reducing the firm's flexibility in responding to a changing business environment. Operating inflexibility can be costly in downturns (a point that has become very evident during the recent financial crisis). Thus, we hypothesize that real asset illiquidity reduces a firm's operating flexibility, and as a result it increases the cost of capital.

Using measures of real asset illiquidity that capture the industry equilibrium aspect of illiquidity highlighted by Shleifer and Vishny (1992), we find an aggregate real asset illiquidity premium in firms' cost of capital that is strongly countercyclical. We also show that firms with more illiquid real assets have a higher cost of capital both in cross-sectional and time-series tests. These results are robust to the worry that measurement error in the cost of capital, which could arise due to biases or sluggish revisions in the analyst earnings forecasts used to calculate the implied cost of capital, might drive the results. They are also similar if we measure expected returns using the more noisy Fama-French (1993) 3-factor model cost of capital. For robustness, we also use firm-level measures, which capture the overall illiquidity of all assets in a firm's balance sheet, and we continue to find a positive impact of these measures on the cost of capital.

Consistent with Shleifer and Vishny (1992), who model how buyers who operate inside the industry are willing to pay higher prices for an asset than buyers who operate outside the industry, we find that weaker acquisition activity by industry insiders increases a firm's cost of capital more than weaker acquisition activity by firms of industry outsiders. The effect of real asset illiquidity on the cost of capital also exhibits sensible variation across firms: It is stronger for firms that face more competitive risk in product markets, that have less access to external capital or are closer to default, and for those facing negative demand shocks. These effects are robust to controlling for the systematic liquidity risk of a firm's stock.

Taken together, our results suggest that real asset illiquidity is a major determinant of a firm's operating flexibility, and that it has an economically significant impact on a firm's cost of equity capital. Combined with the evidence in Benmelech and Bergman (2009), which shows that real asset illiquidity increases the cost of debt, our results also suggest that, by increasing firms' overall cost of capital, real asset illiquidity might affect firms' investment decisions.

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