Real Asset Illiquidity and the Cost of Capital*

Hernán Ortiz-Molina
University of British Columbia
Email: ortizmolina@sauder.ubc.ca

Gordon M. Phillips
University of Maryland and NBER
Email: gphillips@rhsmith.umd.edu

Current Version: March, 2011

Abstract

We study the effect of real (or physical) asset illiquidity on a firm's cost of capital. We find an aggregate real asset illiquidity premium in firms' cost of capital that is strongly countercyclical. At the firm level, we find that real asset illiquidity affects firms' cost of capital both in the cross section and in the time series: Firms with more illiquid real assets and during periods of high real asset illiquidity have higher cost of capital. This effect is stronger when the real asset illiquidity is due to less purchasing activity by firms operating within the industry. In addition, we find that real asset illiquidity reduces firm value and it increases the loading of a firm's stock return on the value factor. Last, the effect of real asset illiquidity is robust to controlling for the illiquidity and systematic liquidity risk of the stock of firms in the industry. Our results suggest that the operating inflexibility caused by real asset illiquidity is an important source of risk.

Key words: real asset illiquidity; cost of capital; operating inflexibility; financial flexibility.

* We thank Heitor Almeida, Murray Carlson, Jason Chen, Lorenzo Garlappi, Itay Goldstein (Western Finance Association Meetings discussant), Marcos Fabricio Perez (Wilfrid Laurier Finance Conference discussant), N. R. Prabhala, Avri Ravid, and Jason Schloetzer, as well as seminar participants at Georgetown University, the Pacific North West Finance Conference 2008, the Western Finance Association Meetings 2009, the Wilfrid Laurier Finance Conference 2010, and the Northern Finance Association Meetings 2010 for their helpful comments. Ortiz-Molina acknowledges the financial support from the Social Sciences and Humanities Research Council of Canada.

Real Asset Illiquidity and the Cost of Capital

Current Version: March, 2011

Abstract

We study the effect of real (or physical) asset illiquidity on a firm's cost of capital. We find an aggregate real asset illiquidity premium in firms' cost of capital that is strongly countercyclical. At the firm level, we find that real asset illiquidity affects firms' cost of capital both in the cross section and in the time series: Firms with more illiquid real assets and during periods of high real asset illiquidity have higher cost of capital. This effect is stronger when the real asset illiquidity is due to less purchasing activity by firms operating within the industry. In addition, we find that real asset illiquidity reduces firm value and it increases the loading of a firm's stock return on the value factor. Last, the effect of real asset illiquidity is robust to controlling for the illiquidity and systematic liquidity risk of the stock of firms in the industry. Our results suggest that the operating inflexibility caused by real asset illiquidity is an important source of risk.

Key words: real asset illiquidity; cost of capital; operating inflexibility; financial flexibility.

1. Introduction

Understanding what are the underlying sources of risk that drive the cross-sectional and time-series variation in firms' cost of capital is of fundamental interest in financial economics. Previous work, including recent studies by Pástor, Sinha, and Swaminathan (2008) and Chava and Purnanandam (2010) which highlight the importance of using ex-ante measures of the cost of capital, shed light on this question. However, very little is known about how the cost of capital may be affected by the illiquidity of a firm's real (or physical) assets. Yet, real asset illiquidity directly 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, Diamond and Rajan (2009) argue that during the recent financial crisis firms may have been unwilling to sell real assets at the prevailing fire-sale prices.

The importance of the constraints that illiquid real asset markets impose on a firm's ability to restructure its operations are illustrated in a recent article in the Wall Street Journal.[1] In early June 2009 Quest Communications was soliciting bids for its long-distance business, with the objectives of exiting an unprofitable business and raising cash to pay down some of its debt. Naturally, the potential buyers for this highly industry-specific asset were other telecom firms (e.g., Level 3 Communications, XO Communications, and TW Telecom). However, the potential bids were coming at a 50% discount from the target price set by Quest. At that time, Quest faced the choice of calling off the auction or accepting a significant price discount.

In this paper we examine whether more illiquid real asset markets increase a firm's cost of capital by decreasing its operating flexibility. Our study is motivated by recent studies in both corporate finance and asset pricing. The corporate finance literature emphasizes the significant frictions firms face in redeploying their real assets to their best alternative use. The problem is that, because assets are often industry or firm specific, it is difficult to find a suitable buyer (Shleifer and Vishny (1992)). This issue is the focus of a recent study by Almeida, Campello and Hackbarth (2009) who show that, when assets are industry specific but transferable to other firms in the industry, solvent firms can provide liquidity to distressed firms by buying their assets even in the absence of operational

[1] See Amol Sharma, "Quest's Long-Distance Arm Draws Bids Below Targets", *Wall Street Journal*, June 5, 2009.

synergies. Furthermore, other studies have shown that asset sales in illiquid markets are associated with a significant price discount (Pulvino (1998); Ramey and Shapiro (2001); and Gavazza (2010)). This implies that the cost a firm faces in reversing a real investment and its ability to raise cash in an asset sale when distressed depend on the liquidity of the market for its real assets. In sum, this literature suggests that real asset illiquidity is a main determinant of a firm's operating flexibility and that as a result real asset illiquidity should affect a firm's cost of capital.

The growing investment-based theoretical asset pricing literature directly links a firm's cost of reversing its real investments, which is higher when real assets are more illiquid, to its cost of capital (e.g., Kogan (2004), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Cooper (2006), and Gala (2007)). The argument is that firms with significant costs of reversing their real investments will be unable to scale down their operations during times of low demand for their products. As a result, they will be unable to cut their fixed costs and will remain burdened with unproductive capital. This, in turn, increases the covariance of a firm's performance with macroeconomic conditions, especially during economic downturns. This literature suggests that, through this operating flexibility channel, the returns of firms with more illiquid real assets load more on the state of the economy, leading investors to require higher expected returns for their capital.

For the purposes of our study we need to measure real asset illiquidity for firms in a broad number of industries and over a long period of time. Throughout the paper, we use three different measures of real asset illiquidity: minus the number of industry rivals with access to debt markets, the average leverage net of cash of industry rivals, and minus the value of M&A activity in a firm's industry.[2] The first two measures capture the absence of potential buyers from within the industry and are motivated by Shleifer and Vishny (1992) and recently by Almeida, Campello and Hackbarth (2009). The intuition behind these measures is that a firm's assets are more valuable to other firms in the industry, which are better able to redeploy them to alternative uses. As a result, industry insiders with financial slack are the most likely buyers of the assets. The third measure follows Schlingemann,

[2] We multiply the number of industry rivals with access to debt markets and the value of M&A in the industry by minus one so that higher values of all measures are associated with more illiquid real assets.

Stulz and Walkling (2002), who argue that a low volume of M&A activity in an industry is evidence of asset illiquidity because price discounts are larger in less active resale markets.

We measure a firm's expected return primarily using the implied cost of capital (*ICC*), which Pástor, Sinha, and Swaminathan (2008) theoretically and empirically show is a good proxy for a stock's conditional expected return. An advantage of *ICC* is that it does not rely on noisy realized returns or on specific asset pricing models. Elton (1999) forcefully argues against using realized returns in asset pricing tests and highlights that the relation between realized returns and risk can be anomalously negative even for long periods.[3] Similarly, the simulations in Lundblad (2007) show 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, Sinha, and Swaminathan (2008)) and a positive relation between distress risk and expected returns (Chava and Purnanandam (2010)).[4] Although measures of expected returns based on standard models are very imprecise (Fama and French (1997), and Pástor and Stambaugh (1999)), for robustness, in our main tests we also measure expected returns using Fama and French's (1993) three-factor model (*FFCC*).

Using a large-scale dataset containing firms in 304 different three-digit SIC industries during the period 1984-2006, 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 firm-level and industry-level univariate tests using both the implied cost of capital and the Fama-French cost of capital as well as alternative measures of real asset illiquidity, we find a *real asset illiquidity premium*, i.e., the cost of capital is higher for firms in the highest versus the lowest real asset illiquidity quintiles. Moreover, supporting the theoretical argument that operating inflexibility causes time-varying equity risk, we find that the real asset illiquidity premium is strongly countercyclical. Thus, our initial evidence shows that there is a real asset illiquidity premium which is likely driven by costly reversibility of investment.

Consequently, in firm-level tests we further examine the relation between real asset illiquidity and the cost of capital by exploiting the rich panel structure of our data. Our cross-sectional tests show

[3] For example, the average realized return on the market was lower than the risk-free rate during the ten-year period 1973–1984 and the risky long-term bonds on average underperformed the risk-free rate during the period 1927–1981.
[4] While the *ICC* uses analysts' forecasts, Campello, Chen, and Zhang (2008) derive a measure of ex-ante expected returns based on bond yields, but its empirical execution is constrained by the limited availability of bond yield data.

that firms with more illiquid real assets have a higher implied cost of capital and a higher Fama-French cost of capital than firms with less illiquid real assets. Our time-series tests show that during periods of high real asset illiquidity a firm's implied cost of capital is higher than it is during periods of low real asset illiquidity. These tests imply that a one-standard deviation increase in real asset illiquidity across firms increases the implied cost of capital by 1.4 to 1.9 percentage points and that a similar increase in real asset illiquidity over time increases it by 0.5 to 1.5 percentage points. The results are qualitatively similar if we do the tests using industry averages of the variables.

Our measure of real asset illiquidity based on M&A activity allows us to distinguish between "inside" real asset illiquidity, defined as minus the value of M&A activity involving acquirers that operate within the industry, and "outside" real asset illiquidity, defined as minus the value of M&A activity involving acquirers that operate outside the industry. As argued by Shleifer and Vishny (1992), buyers from inside the industry can better redeploy the asset to a productive use and are willing to pay higher prices. In contrast, buyers from outside the industry are willing to pay lower prices due to a lack of synergies and of experience in using the asset. Suggesting that less acquisition activity by industry insiders makes real asset markets more illiquid than less acquisition activity by industry outsiders, we find that inside illiquidity increases firms' implied cost of capital by more than outside illiquidity. These results support those in Almeida, Campello and Hackbarth (2009), who find that when industry asset specificity is high financially distressed firms often can sell their assets to more financially flexible firms in their industries instead of selling them to industry outsiders.

Using large-sample regressions of the book-to-market equity ratio on the real asset illiquidity measures and control variables we show that, consistent with our results based on measures of expected returns, real asset illiquidity also has a large negative impact on firm value. These tests, which do not rely on asset pricing models or on the assumptions implicit in the calculation of the implied cost of capital, provide further evidence that real asset illiquidity affects firms' discount rates.

The asset pricing literature argues that B/M is correlated with risk because value firms are less flexible than growth firms in adjusting their physical capital in response to worsening economic conditions and thus load more on the state of the economy (e.g., Zhang (2005)). The theory suggests that, if real asset illiquidity increases the cost of capital by making investments more costly to reverse, then the returns of firms with more illiquid real assets should load more on the value factor. To explore this issue we decompose the Fama-French cost of capital into the loadings on the market, size, and value factors. Supporting the argument above, we find that real asset illiquidity increases the Fama-French cost of capital mainly by increasing the loading of a firm's return on the value factor.

Our results are not driven by issues related to the illiquidity of the firm's stock. Specifically, if firms with more illiquid real assets also have more illiquid stocks or their stocks are more exposed to systematic liquidity risk (both of which are associated with higher expected returns), then firms with more illiquid real assets would spuriously appear to have a higher cost of capital. We find that real asset illiquidity is indeed negatively related to an industry measure of stock liquidity based on share turnover and positively related to an industry measure of systematic liquidity risk based on Pástor and Stambaugh (2003). However, the effect of real asset illiquidity on the cost of capital is robust to controlling for the illiquidity and systematic liquidity risk of the stock of firms in the industry.

All our results hold controlling for firm value, growth options, or asset specificities, and thus they are not driven by a correlation between real asset illiquidity and these firm characteristics. In further tests we show that the effect of real asset illiquidity on the implied cost of capital holds in pure cross-sectional tests, as well as in cross-sectional and time-series tests 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 are not driven by biases in analysts' forecasts. They also hold if we measure real asset illiquidity using minus the average acquisition premium in the industry, and if we use segment-weighted measures of real asset illiquidity.

Last, in additional tests we document cross-sectional variation in the effect of real asset illiquidity on the cost of capital which is broadly consistent with the operating inflexibility channel. Specifically, we find that higher real asset illiquidity increases the cost of capital by more for firms that face more competitive risk in product markets (i.e., for firms in low concentration industries and for the smaller firms within the industry), have less access to external capital or are closer to default, and for those facing negative demand shocks (i.e., for firms with low valuations or in industry downturns).

Our paper fits in the literature which suggests that a firm's ability to sell assets enhances its operating and financial flexibility. Maksimovic and Phillips (1998) show that asset sales are at the core of firms' restructuring processes, and Schlingemann, Stulz, and Walkling (2002) show that asset liquidity determines firms' ability to restructure. Lang, Poulsen, and Stulz (1995) find that sellers of assets are usually poor performers and Weiss and Wruck (1998) show that asset liquidity helps managers maneuver in distress.[5] Almeida, Campello, and Hackbarth (2009) show that, if assets are transferrable within the industry, then industry insiders buy distressed assets purely due to liquidity reasons. Last, Benmelech and Bergman (2009) find that debt tranches of airlines secured with more redeployable collateral have higher ratings and lower spreads. We add to this work by showing that the operating inflexibility caused by real asset illiquidity significantly increases a firm's cost of equity.

Our paper is also related to the asset pricing literature which examines whether the liquidity of a firm's stock as a characteristic affects expected returns (e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), and Datar, Naik, and Radcliffe (1998), among others) and to the work of Pastor and Stambaugh (2003) who examine whether a stock's market-wide liquidity risk is priced. These studies focus on the liquidity of a firm's financial claims on firm value and on a mechanism which operates through the liquidity risk to which investors are exposed if they need to sell their shares. In contrast, we focus on the liquidity of real assets – property, plant, and equipment – and on a mechanism which operates through the firm's business risk and financial risk associated with a higher cost of reversing its real investments. We add to this literature by showing that the illiquidity of a firm's real assets also affects its expected returns.

The article is structured as follows. Section 2 develops our main hypothesis and related empirical predictions. Section 3 describes our data and variables. Section 4 reports the main empirical results. Section 5 and the Appendix present additional robustness tests. Section 6 concludes.

---

[5] In addition, DeAngelo, DeAngelo, and Wruck (2002) find that LA Gear's ability to liquidate working capital to fund operations allowed the firm to implement various business strategies and delay distress.

2. Illiquid Real Assets and the Cost of Capital

Our framework is based on the corporate finance and investment-based asset pricing literatures that emphasize the significant frictions firms face in redeploying their real assets to their best alternative uses, and in recovering the undepreciated value of their original investments. The central idea is that the liquidity of the market for a firm's real assets determines the difference between the market price for those assets and their fundamental value, and thus it determines the firm's cost of unwinding its capital stock as well as its ability to raise cash with asset sales. Highlighting that real asset illiquidity makes capital investments more costly to reverse, Pulvino (1998) and Ramey and Shapiro (2001) document significant price discounts for asset sales in illiquid markets. Hence, our point of departure is that real asset illiquidity is a key determinant of firms' operating flexibility.

The corporate finance literature suggests that real asset illiquidity reduces a firm's operating flexibility and thus it may increase the cost of capital by making firms' restructuring processes more difficult (e.g., Maksimovic and Phillips (1998), and Schlingemann, Stulz, and Walkling (2002)), which is especially costly to firms facing economic adversity (e.g., Lang, Poulsen, and Stulz (1995), Weiss and Wruck (1998), and Almeida, Campello, and Hackbarth (2009)). The asset pricing literature (e.g., Kogan (2004), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Cooper (2006), and Gala (2007)) suggests that the returns of firms with more operating inflexibility load more on the state of the aggregate economy, especially during times of economic contraction, which leads equity investors to require higher expected returns for their capital. If the firm has significant flexibility to scale down its capital stock, after a negative productivity shock it will disinvest to reduce the impact on its cash flow. In this case the firm's dividend stream will not strongly covary with business cycles and its return will not be too risky. In contrast, if the firm has little flexibility to scale down its capital stock, after the shock it will disinvest much less and will be less able to reduce the impact on its cash flow. The resulting dividend stream will strongly covary with business cycles and its return will be much more risky.[6] This leads to our main hypothesis:

[6] Note that these theories suggest that real inflexibility due to illiquid asset markets affects the loading of a firm's return on the state of the economy and not the loading on a specific aggregate "real asset illiquidity factor". However, as we discuss and empirically examine in Section 4.5, real asset illiquidity may affect the loading on the book-to-market factor, which previous theoretical work associates with risk through the operating inflexibility channel.

Main Hypothesis: Real asset illiquidity increases firms' cost of capital by decreasing their operating flexibility.

Our main hypothesis has three broad implications. At the aggregate level, 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, the growing theoretical literature which directly links a firm's operating inflexibility to its cost of capital provides a rationale for countercyclical time-series variation in equity risk. The argument is that 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. This suggests that the aggregate real asset illiquidity premium should be countercyclical. In multivariate tests at the firm level, there should be a positive association between real asset illiquidity and the cost of capital.

As noted by Shleifer and Vishny (1992), inside buyers (who operate in the same industry as the target) can better redeploy the real asset to a productive use and thus are willing to pay higher prices. In contrast, outside buyers (who do not operate in the industry) are willing to pay lower prices due to reduced synergies and inexperience in operating the asset. Supporting this view, Pulvino (1998) and Ramey and Shapiro (2001) show that financially constrained firms that are forced to sell their assets to industry outsiders obtain prices that are substantially below the prices they would have obtained had they been able to sell them to industry insiders. This suggests that a weaker presence of inside buyers makes the market for real assets more illiquid than does a weaker presence of outside buyers, and thus should have a stronger positive effect on firms' cost of capital.

These implications are summarized below:

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

<u>*Prediction 2:*</u> *Firms with more illiquid real assets should have a higher cost of capital.*

<u>*Prediction 3:*</u> *Inside real asset illiquidity should increase a firm's cost of capital more than outside real asset illiquidity.*

3. Data and Variables

3.1 Data Sources and Sample Selection

Our data come from the Merged CRSP-Compustat Database, the Compustat Segment Database, the Institutional Broker Estimates System (IBES), the Securities Data Corporation (SDC), the St. Louis Federal Reserve Economic Database (FRED), and the Census of Manufactures. We start with the Merged CRSP-Compustat Database and exclude companies in the financial (SIC codes 6000 to 6999) and utilities (SIC codes 4900 to 4999) industries. We also drop companies not covered in IBES because we require analyst forecasts data to calculate the implied cost of capital, as well as observations for which we are unable to compute the real asset illiquidity measures or our main control variables. Our final sample includes 6,260 firms operating in 304 different three-digit SIC industries and 33,788 firm-year observations during the period 1984-2006.[7]

3.2. Measures of Real Asset Illiquidity

Our measures of real asset illiquidity aim to capture differences in the cost of reversing investments across firms, and thus to allow us to empirically examine the impact of operating inflexibility on the cost of capital within the conceptual framework described in Section 2. Previous work on how real asset illiquidity affects resale values relies on small samples and on specific industries where specific attributes of the assets can be identified precisely (e.g., Pulvino (1998), Ramey and Shapiro (2001), and Gavazza (2010)). Given that we aim to study whether real asset illiquidity affects firms' cost of capital, it is important that we measure real asset illiquidity for firms in a broad number of industries and over a long sample period. We now discuss our approach.

The liquidity of a firm's real asset – the extent to which the real asset can be quickly sold at a fair price – depends both on the existence of other firms with enough financial slack to purchase it and on the extent to which the real asset is transferrable to other firms, i.e., on its degree of specificity. The existence of other firms with financial slack to buy a transferrable real asset can be gauged empirically, but measuring the degree of asset specificity – and consequently the transferability of

---

[7] We did not impose restrictions on the number of firms in each three-digit SIC industry for inclusion in our sample. However, our results are robust to excluding firms in industries with less than three or five firms.

assets across firms – is much more difficult, especially for a large sample of firms. Nevertheless, the key source of asset specificity is the firm's industry affiliation (e.g., Kogan (2004)). Specifically, as a result of commonalities in production technologies, most assets are easily transferrable among the firms operating in the same industry, but much harder to transfer (or not transferrable at all) to firms operating outside the industry. Supporting this view, previous work shows that the bulk of asset sales occur between firms in the same or in closely related industries (e.g., Maximovic & Phillips (2001)).

We use three measures of real asset illiquidity which rely on industry definitions at the three-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, Campello, and Hackbarth (2009). Consistent with the common wisdom that industry affiliation is the key determinant of transferability, the intuition behind these measures is that a firm's assets are valuable mostly to other firms in the industry. Specifically, these measures assume that a firm's real assets are equally 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., that assets are industry specific.[8] Hence, financially-flexible industry insiders are the most likely future buyers of a firm's assets. It then follows that a firm's real assets are more illiquid when there is a smaller number of potential inside-industry buyers with financial slack.

Our first measure is similar to those used in Benmelech and Bergman (2009) and Gavazza (2010) for the airline industry. 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 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. Given these definitions, a firm's real assets are more illiquid for higher values of both *MNoPotBuy* and *NLPotBuy*. Note that these measures have an important industry component (we identify a firm's rivals using SIC codes), but they also vary across firms within the same industry.

[8] This assumption is reasonable because industry affiliation is the main determinant of asset specificity. But there might also be some heterogeneity in the transferability of assets across firms within the industry. To ensure that this does not affect our results, our tests include *firm-level* control variables which capture the degree of specificity of each firm's assets.

Our third measure follows Schlingemann, Stulz, and Walkling (2002) and it captures the *historical illiquidity* of a firm's assets using *minus* the value of past M&A activity in the firm's industry. Shleifer and Vishny (1992) argue that a high volume of transactions in an industry is evidence of high liquidity because the discounts that sellers must offer to attract buyers are smaller in more active resale markets. Consequently, we obtain the value of all M&A activity involving publicly traded targets in each three-digit SIC industry and in each year from SDC.[9] We include both mergers and acquisitions of assets (the latter comprise approximately 75% of the deals). If SDC does not report transactions in an industry-year, we set the value equal to zero. We then multiply the value of transactions in the industry by minus one, we scale it by the book value of assets in the industry, and average this ratio over the past five years. To compute the value of the assets in each industry, we sum the assets in the industry reported by single-segment firms and the segment level assets reported by multiple-segment firms in the Compustat Segment data, breaking up the multiple-segment firms into their component industries. Averaging over past years smoothes the temporary ups and downs in M&A activity and allows us to better capture the intrinsic salability of an industry's assets. The resulting measure is denoted *MTotM&A*, and higher values imply more illiquid real assets.[10] An advantage of this measure is that it captures the salability of assets, regardless of whether it is driven by the presence of solvent rivals, the degree of the asset's transferability, or a combination of both. In addition, it uses transactions involving buyers of industry assets both from inside and outside the industry, and thus it does not rely on assumptions about the transferability of assets across industries.

We also decompose *MTotM&A* to distinguish between a weaker acquisition activity by industry insiders – those who operate in the same three-digit SIC industry as the target – and by industry outsiders – those who do not currently 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 the target reports multiple industries. *MInsM&A* is *minus* the value of M&A activity in the industry involving acquirers that operate within the industry, scaled

---

[9] 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.

[10] Our analyses based on this and related M&A measures are unaffected if we exclude from the sample firms that are undergoing M&A activity in a particular year.

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 five years. Since assets are easier to transfer to industry insiders than they are to industry outsiders, a weaker presence of inside-industry buyers makes a firm's real assets more illiquid than a weaker presence of outside-industry buyers.

To facilitate the comparison of the effect of *MNoPotBuy, NLPotBuy, MTotM&MA, MInsM&A,* and *MOutM&A* on the cost of capital, we standardize all of these variables by subtracting their sample mean and dividing by their sample standard deviation. With this transformation all the measures have mean zero and standard deviation of one, and hence in regressions of the cost of capital on real asset illiquidity, the coefficient of any real asset illiquidity measure can be interpreted as the change in the cost of capital for a one-standard-deviation increase in the measure's value.

3.3. Measures of Cost of Capital

Instead of relying on noisy realized returns, which often portray an anomalous negative relation to risk even over large sample periods (e.g., Elton (1999) and Lundblad (2007)), our tests use two different *ex-ante* measures of a firm's expected return. Our main measure, which we use throughout our tests, is the implied cost of capital (*ICC*) developed by Gebhardt, Lee, and Swaminathan (2001). Our second measure, which we use solely to assess the robustness of our main results based on the *ICC*, is the cost of capital that arises from the three-factor model of Fama and French (1993).

The advantage of the *ICC* is that it does not rely on noisy realized returns or on specific asset pricing models. Pástor, Sinha, and Swaminathan (2008) show that if both dividend growth and conditional expected returns follow AR(1) processes, then *ICC* is a perfect proxy for expected returns. They also show that, unlike tests based on market returns, those based on *ICC* can identify a positive intertemporal risk-return tradeoff. Chava and Purnanandam (2010) further show that the *ICC* detects a positive relation between distress risk and expected returns instead of the puzzling negative relation observed using realized returns.[11] Ex-ante measures, such as *ICC*, are used in various other recent studies of the cost of capital (e.g., Kaplan and Ruback (1995), Claus and Thomas

[11] Earlier studies have discussed in some detail the noisy nature of average realized returns in a number of different contexts (see, for example, Blume and Friend (1973), Sharpe (1978), and Miller and Scholes (1982)).

(2001), Fama and French (2002), Lee, Ng, and Swaminathan (2009), Brav, Lehavy, and Michaely (2005), Chen, Petkova, and Zhang (2008), and Chen, Kacperczyk, and Ortiz-Molina (2009)).

While the *ICC* has its merits as noted above, some recent papers (e.g., Easton and Monahan (2005)) have raised the concern that analysts make biased earnings forecasts. In Section 5.1 we show that biases in analysts' forecasts do not drive the results of our tests based on the *ICC*. We nevertheless assess the robustness of our main results using the Fama-French Cost of Capital (*FFCC*) as an alternative measure of expected returns. This measure derives from the Fama and French (1993) three-factor model and thus it does not rely on analysts' earnings forecasts. However, tests based on the *FFCC* are likely to have low statistical power and are less reliable than those based on the *ICC*, as it is well known that measures of expected returns based on standard asset pricing models are highly imprecise (e.g., Fama and French (1997) and 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. Specifically, the calculation of a firm's *ICC* for year *t* starts with the dividend-discount model:

$$P_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r_e)^i} \qquad (1)$$

where *P* is the stock price, *D* is dividends, r_e is the discount rate, and *E(.)* is the expectation operator. Using equation (1) and assuming clean surplus accounting (change in book equity equals net income minus dividends), we get the discounted residual income equity valuation model:

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e)B_{t+i-1}]}{(1+r_e)^i} \qquad (2)$$

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.

To implement the method, we require forecasts of future earnings and equity values. As in Gebhardt, Lee, and Swaminathan (2001), we forecast earnings explicitly for the next three years using the analysts' forecasts of *EPS* and *EPS* growth which we obtain from IBES. We forecast earnings beyond year 3 implicitly by assuming that the *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 simple 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 ten year *ROE*s from all firms in the same 48 Fama and French industry. Last, by 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. [12]

We calculate the *FFCC* as a linear projection of returns based on the market, size, and value factors which we obtain from Kenneth French's website. 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):

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

where the $(r_j - r_f)$ is the monthly return on stock *j* minus the risk-free rate, $r_M - r_f$ denotes 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 cost of capital of firm *j* in year *t* as follows:

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

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

3.4. Control Variables

In our analyses we include control variables that capture various other potential determinants of a firm's cost of capital. *LogAssets* is the logarithm of total assets (AT); *M/B* is the market-to-book

[12] Following recent work in finance (e.g., Pástor, Sinha, and Swaminathan (2008) and Chava and Purnanandam (2010)), we calculate the *ICC* as in Gebhardt, Lee, and Swaminathan (2001). However, other approaches exist which differ in how they use the analyst forecasts (e.g., residual income or abnormal earnings) and in their assumptions (e.g., on growth rates and forecasting horizons). All approaches give rise to measures of the *ICC* that are highly correlated, and Hail and Leuz (2009) show that the results of tests based on alternative measures or indices that aggregate them are qualitatively similar.

assets ratio ((CSHO * PRCC_F + DLTT + DLC + PSTKL – TXDITC) / AT))*; DRP* is a firm's percentile ranking based on the yearly distribution of its default risk computed using the distance-to-default model [13]; *Blev* is book leverage ((DLTT + DLC) / AT); *ROE* is return on equity (NI / (AT – DLTT – DLC)); *VolRoe* is the standard deviation of *ROE* over the past five years; *FA/TA* is fixed assets (PPENT) scaled by total assets (AT); *R&DExp* is R&D expenditures (XRD) scaled by sales (SALE); *LogAge* is the logarithm of one plus the number of years since the company was first listed in CRSP; *DivPay* equals one if the firm pays dividends (DVC is positive) and zero otherwise; *SalGrow* is the annual change in the logarithm of sales (SALE); *LogInvPrice* is the logarithm of one divided by the stock price as of the estimation date of *ICC*; and *RetPM* is the stock return over the past month.

3.5. Summary Statistics for Main Variables

Table 1 shows 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* using the larger sample of firms for which we are able to calculate it and have non-missing values on the test and control variables. The mean and median *ICC* for the firms in our sample is 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%.[14] All standardized real asset illiquidity variables (*MNoPotBuy, NLPotBuy, MTotM&MA, MInsM&A,* and *MOutM&A*) have by construction mean zero and standard deviation of one. Using the original (non standardized) 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%. We split *MTotM&A* into inside illiquidity (*MInsM&A*) and outside illiquidity (*MOutM&A*), which each roughly account for half of the total real asset illiquidity in the industry. Since we focus on the firms with analyst-forecast data, the firms in our sample have average book assets of $580 million and thus are larger than those in the Compustat universe. Our asset illiquidity measures exhibit low correlation with the control variables (not tabulated).

---

[13] We rely on the Merton distance to default model, which is based on Merton's (1974) bond pricing model. Specifically, we estimate the likelihood of default using the simple approach suggested by Bharath and Shumway (2008).

[14] The summary statistics for *FFCC* are similar if we focus on the smaller sample for which we can calculate *ICC*.

We further inspect the sources of variation in our real asset illiquidity measures by estimating a regression of each measure on three-digit SIC industry dummies. We find that 76.5% of the total variation in *MNoPotBuy,* 78.2% of the total variation in *NLPotBuy*, and 40.4% of the total variation in *MTotM&A* is due to differences across industries. Hence, our three measures have a strong time-invariant industry component, even the first two measures which also exhibit a small variation across firms within the industry, but also exhibit substantial variation in the time series. We use both of these sources of variation to identify our results in the subsequent sections.

In Table 2 we report selected firm characteristics (*LogAssets*, *M/B*, *DRP*, *Blev*, and *ROE*) averaged across quintile portfolios sorted alternately on each of the three measures of real asset illiquidity. Specifically, in each year we sort firms into quintiles based on the measure, compute the average characteristic for each quintile, and then take the average for each quintile across all years. The patterns of the firm characteristics as we move from the lowest (Q1) to the highest real asset illiquidity quintile (Q5) differ across measures of real asset illiquidity, but there are some regularities. Firms in the highest quintiles tend to be larger than those in the lowest quintiles, except when the quintiles are formed using *MNoPotBuy* in which case the pattern is flat across quintiles, and to have lower market-to-book ratios. Default risk tends to increase as we move from the lowest to the highest quintiles, except when the quintiles are formed using *MNoPotBuy* in which case the pattern is flat across quintiles. Last, firms in the highest quintiles tend to carry more debt (the exception is when the quintiles are based on *MNoPotBuy*) and to be more profitable than those in the lowest quintiles. Since these firm attributes are associated with real asset illiquidity and may have an impact on firms' cost of capital, we control for these and other firm attributes in our multivariate analyses.

4. Main Empirical Results

4.1. The Aggregate Real Asset Illiquidity Premium and its Business-Cycle Variation

Our hypothesis suggests that firms with more illiquid real assets should have a higher cost of capital. In Table 3 we relate a firm's implied cost of capital (*ICC*) – our main measure of expected returns – to our three measures of real asset illiquidity using a univariate approach. In Panel A we form portfolios using firm-level observations and in Panel B we form the portfolios using industry-level observations (after collapsing all data to the value-weighted three-digit SIC industry average). In both panels, for each year we sort firms or industries 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 *ICC* of the highest and lowest asset illiquidity quintiles, and the corresponding p-value, respectively.

Panel A shows that, for all three measures of real asset illiquidity, there is a monotonically increasing pattern in the *ICC* as we move from the lowest quintile to the highest quintile. This relation is economically significant: Using the equal-weighted portfolios, the spread in the cost of capital 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 measured with *MTotM&A*. All of these differences are statistically significant at the 1% level. The value-weighted portfolios provide similar results. Panel B shows that the results are qualitatively similar when the portfolios are formed using the industry-level observations. Thus, consistent with our first prediction, the univariate evidence suggests that there is an economically important real asset illiquidity premium in firms' implied cost of capital.

Albeit the evidence in Fama and French (1997) and Pástor and Stambaugh (1999) that measures of expected returns based on standard asset pricing models are very imprecise, in Table 4 we repeat our portfolio-sort analysis using the Fama-French cost of capital (*FFCC*), both at the firm level (Panel A) and the industry level (Panel B). The advantages of using *FFCC* are that it does not rely on the earnings forecasts of analysts, which have been shown to contain biases, and that we are able to calculate it for a larger sample of stocks (including those not covered in IBES). In both panels, for all three measures of real asset illiquidity we find an increasing pattern in the *FFCC* as we move from the lowest real asset illiquidity quintile to the highest real asset illiquidity quintile. The differences in the *FFCC* between the top and bottom quintiles are both statistically and economically significant, but slightly smaller in magnitude than those reported in Table 3 which are based on the *ICC*. In sum, tests based on the Fama-French cost of capital provide results that are qualitatively similar to those based on the implied cost of capital and provide further evidence of a real asset illiquidity premium.

Since the literature on operating flexibility provides a rationale for countercyclical time-series variation in equity risk (e.g., Zhang (2005), and Cooper (2006)), our first prediction also relates the aggregate real asset illiquidity premium to the business cycle. If real asset illiquidity increases firms' cost of capital because it decreases firms' operating flexibility, we should expect the real asset illiquidity premium to be larger in periods of low economic activity. Thus, we also study the time-series variation in the aggregate real asset illiquidity premium, that is, in the yearly spread between the cost of capital for firms in the top and bottom asset illiquidity quintiles.

In Table 5 we report the results of univariate time-series regressions of the aggregate real asset illiquidity premium on alternative business-cycle indicators. For both the *ICC* and the *FFCC* we conduct our tests using the three different measures of the real asset illiquidity premium based on *MNoPotBuy*, *NLPotBuy*, and *MTotM&A*, respectively. We proxy for macroeconomic conditions using the year-over-year growth in the fourth quarter's GDP (*GDP Growth*), the utilization rate of installed capacity during the fourth quarter of the year (*Capacity Utilization*), the year-to-year change in the December's Consumer Price Index (*Inflation*), the average three-month Treasury Bill Rate during the year (*T-Bill Rate*), the average difference between the yield on Moody's Baa corporate bonds and the yield of ten-year government bonds during the year (*Default Spread*), and the annual return on the market index (*Market Return*). The regressions with the real asset illiquidity premium based on *MNoPotBuy* use the 22 annual observations in the period 1985-2006 and those with premiums based on *NLPotBuy* and *MTotM&A* use the 23 annual observations in the period 1984-2006. Our standard errors are corrected for autocorrelation using the Newey-West procedure.

In Panel A 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 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 of the models we consider. Moreover, the R^2

for each regression, reported in 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 we report the results using the Fama-French cost of capital. Note that we exclude the market return specification which appeared in Panel A, as the Fama-French 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, consistent with 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 which can be correlated with both real asset illiquidity and the cost of capital. Hence, we now turn to a multivariate analysis.

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

We now test our second prediction of a negative association between real asset illiquidity and cost of capital at the firm level. Our empirical model regresses firms' cost of capital (*ICC* or *FFCC*) on the measures of real asset illiquidity (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*) and controls for potential determinants of the cost of capital including firm size (*LogAssets*), the market-to-book assets ratio (*M/B*), the percentile ranking of a firm's default risk (*DRP*), financial leverage (*Blev*), profitability (*ROE*), equity risk (*VolROE*), asset tangibility (*FA/TA*), R&D expenditures (*R&DEx*p), firm age (*LogAge*), whether the firm pays dividends (*DivPay*), sales growth (*SalGrow*), the logarithm of the inverse of price (*LogInvPrice*), and the stock return over the last month (*RetPM*). Since the real asset illiquidity variables have a strong industry component, we cluster the standard errors by three-digit SIC industry. However, note that clustering by both industry and year, by firm, by year, and by both firm and year, gives t-statistics that are similar or larger than those reported.

Including a comprehensive list of control variables helps ensure our results are not driven by a correlation of real asset illiquidity with other firm attributes which could affect the cost of capital. Noteworthy, including *LogInvPrice* and *M/B* eliminates the worry that the real asset illiquidity measures may be correlated with stock prices and mechanically drive the *ICC*.[15] The inclusion of *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. As noted by Chava and Purnanandam (2010), including *RetPM* controls for the potential sluggishness of analysts' forecasts, i.e., it ensures that a correlation between the sluggishness of adjustments in analysts' forecasts and real asset illiquidity does not affect our results based on the *ICC* (results are similar if we use the past three-, six-, and twelve-month returns). Moreover, *MNoPotBuy*, *NLPotBuy* assume that a firm's assets are equally transferrable to all firms in the industry, but there might be some heterogeneity in the transferability of assets across firms within the industry. The inclusion of *R&DEx*p – which is related to the degree of specificity of a firm's assets – alleviates the concern that this heterogeneity could affect our results. Last, in addition to *M/B*, we include *LogAge* and *SalGrow*, which addresses the concern that a correlation of real asset illiquidity and growth options could drive the results.

Table 6 reports the results of regressions using the *ICC* as the dependent variable. The coefficients of the control variables are omitted in the interest of space. The regressions in Panel A are based on firm-level observations. In columns (1), (3), and (5) we report the results of Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure with 6 lags. 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 spuriously drive the results.[16] 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

[15] For example, in Carlson, Fisher, and Giammarino (2004) investments are irreversible (assets are completely illiquid) but (through an operating leverage effect) higher firm values are associated with a lower cost of capital. Hence, a correlation of real asset illiquidity with firm value could cause a spurious correlation of real asset illiquidity and the cost of capital.
[16] 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 three-digit SIC industry.

significant: A one-standard deviation increase in real asset illiquidity increases the cost of capital by 1.5 percentage points if we measure real asset illiquidity with *MNoPotBuy*, by 1.6 percentage points if we measure it with *NLPotBuy*, and by 0.9 percentage points if we measure it with *MTotM&A*.[17]

In columns (2), (4), and (6) we run pooled (panel) OLS regressions with three-digit SIC industry dummies and year dummies, and thus we use the time-series variation in real asset illiquidity within industries to identify our results.[18] This advantage of this approach is that it 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. The cost, however, is that it ignores the large variation in real asset illiquidity across industries, which diminishes the power of our tests. Yet, we continue to find a positive and statistically significant relation between all measures of real asset illiquidity and the cost of capital. These tests imply that a one-standard deviation increase in real asset illiquidity increases a firm's cost of capital by about 1.5 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.

Since our real asset illiquidity measures have a strong industry component, Panel B reports the industry-level results (i.e., after converting all data into value-weighted three-digit SIC industry averages). This substantially reduces our sample size and hence the power of our tests. Nevertheless, we continue to find a positive relation between real asset illiquidity and the *ICC* in the industry-level tests, but the relation is less economically significant than in the firm level tests and it becomes statistically insignificant in the case of *MTotM&A*.

Table 7 reports the results of regressions using the *FFCC* as the dependent variable. The coefficients of the control variables are omitted in the interest of space. In columns (1), (3), and (5) we run Fama-MacBeth regressions and calculate our standard errors using the Newey-West 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 cluster the

---

[17] The measure *NoPotBuy*, which varies across firms within the industry, has a -50% correlation with the sales-based Herfindahl-Hirschman Index of three-digit SIC industry concentration (*HHI*), which Hou and Robinson (2006) identify as a predictor of stock returns. However, the effect of *NoPotBuy* on the *ICC* is highly robust to controlling for *HHI*.

[18] For our first two measures, we also use the smaller variation across the firms within the industry.

standard errors by three-digit SIC industry. The regressions in Panel A are based on firm-level observations and those in Panel B are based on industry-level observations. The firm-level tests in Panel A show that, for both estimation approaches and for all measures of real asset illiquidity, firms more illiquid real assets have a higher Fama-French cost of capital. These effects are highly statistically significant, although smaller in magnitude than those reported in Panel A of Table 6.[19] Depending on the specification, a one-standard deviation increase in real asset illiquidity increases the cost of capital by about 0.4 to 0.8 percentage points. The industry-level tests in Panel B are also suggestive of a positive effect of real asset illiquidity on the cost of capital, but the results in most specifications are statistically insignificant. This is likely the result of a smaller sample size as well as of a noisier measurement of the cost of capital through the Fama-French three-factor model.

In sum, we find a positive association between firms' cost of capital and the illiquidity of their real assets. This key relation holds for tests using the implied cost of capital and the noisier Fama-French cost of capital, and for three different measures of real asset illiquidity. This evidence lends support for 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 our analyses we focus on the implied cost of capital as the main measure of a firm's expected return and do not report further results for the Fama-French cost of capital.

4.3. The Distinction Between Inside and Outside Illiquidity

To test our third prediction that inside real asset illiquidity should increase firms' cost of capital by more than outside real asset illiquidity we split our measure of real asset illiquidity *MTotM&A* into two components. These are the previously defined inside industry real asset illiquidity (*MInsM&A*) and outside industry real asset illiquidity (*MOutM&A*). For this purpose, in Table 8 we run regressions relating these two measures of real asset illiquidity to firms' cost of capital. In columns (1) and (3) we report the results of Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure with 6 lags. In columns (2) and (4) we report the

[19] We use only 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).

results of pooled (panel) OLS regressions with three-digit SIC industry and year fixed effects. In all models we cluster the standard errors at the three-digit SIC industry level.

There is a positive and statistically significant effect of both inside and outside real asset illiquidity on the cost of capital in the cross-sectional tests. Similarly, both inside and outside real asset illiquidity increase the cost of capital in the tests which rely on the time-series variation in asset illiquidity, but the effect of outside illiquidity is not statistically significant. The striking new result is that inside illiquidity has a much larger effect on the cost of capital than outside illiquidity. The pure cross-sectional results reported in columns (1) and (3) imply that a one-standard deviation increase in inside illiquidity increases the cost of capital by 0.9 percentage points, but a similar increase in outside illiquidity only increases it by 0.4 percentage points. This difference is statistically significant. For the time-series results reported in columns (2) and (4), such an increase in inside illiquidity reduces the cost of capital by 0.6 percentage points, but the same increase in outside illiquidity reduces it by only 0.2 percentage points. This difference is also statistically significant.

In sum, we find that 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 supports the view 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 stronger positive effect on firms' cost of capital.

4.4. Real Asset Illiquidity and Equity Values

The results in Section 4.2 show that, through its effect on the discount rate, real asset illiquidity has a large impact on firm value. To better gauge the impact of real asset illiquidity on firm value, in Table 9 we regress the logarithm of the book-to-market equity ratio on each of the real asset illiquidity measures and control variables including the previously defined *LogAssets*, *ROE*, *VolROE*, *LogAge*, *DivPay*, and *SalGrow*, as well as *MShr*, defined as the firm's market share in the three-digit SIC industry, and *Rated*, which equals one if the firm has rated debt and zero otherwise. These tests also help assets the robustness of our results based on the implied or Fama-French costs of capital.

Since these tests do not require the availability of analyst forecasts, we use the larger sample of firms for which we can calculate the Fama-French cost of capital, but the results are similar if we restrict attention to the sample of firms for which we can calculate the implied cost of capital. In columns (1), (3), and (5) we report Fama-MacBeth regressions with t-statistics which are adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2), (4), and (6) we report OLS purely cross-sectional regressions using the time-series averages of the variables for each firm, with standard errors clustered by three-digit SIC industry.

Consistent with the operating inflexibility argument and with our prior evidence from the tests using the implied or Fama-French costs of capital, we find that all three measures of real asset illiquidity have a negative impact on firm values which is both statistically and economically significant. Specifically, the estimated coefficients from the multivariate Fama-MacBeth regressions suggest that a one standard deviation increase in *MNoPotBut* / *NLNoPotBuy* / *MTotM&A* decreases equity values by 10.3% / 19.5% / 10.8%, respectively. These tests, which do not rely on asset pricing models or assumptions like those implicit in the calculation of the implied cost of capital, provide further evidence that real asset illiquidity affects firms' cost of capital and thus their values.

4.5. Real Asset Illiquidity and the Loadings of Returns on the three Fama-French Factors

The investment-based asset pricing literature discussed in Section 2 seeks to understand the source of the value premium – the difference in the returns of high and low B/M stocks. This literature argues that B/M is correlated with risk because value firms are less flexible than growth firms in adjusting their physical capital in response to worsening economic conditions and thus load more on the state of the economy. Noteworthy, Zhang (2005) theoretically argues that costly reversibility and countercyclical price of risk cause assets in place to be harder to reduce, and hence assets in place are riskier than growth options, especially in bad times when the price of risk is high. This suggests that the effect of real asset illiquidity on the cost of capital is intimately related to the value premium and more specifically to the loading of a firm's stock return on the value factor.

Measures of expected returns based on standard asset-pricing models are highly imprecise (e.g., Fama and French (1997) and Pástor and Stambaugh (1999)), but nevertheless the tests using the

Fama-French three-factor model cost of capital (*FFCC*) reported in Tables 4 and 7 show that the real asset illiquidity variables are related to at least some of the loadings on these factors. To shed further light on the nature of the effects we document, we further decompose the *FFCC* into its three components - market beta, size beta, and value beta - and study how they are affected by real asset illiquidity. In particular, to the extent that the B/M ratio is positively related to the loading of returns on the value factor and that B/M indeed captures risk, if real asset illiquidity increases the cost of capital by making investments less costly to reverse, then the returns of firms with more illiquid real assets should load more strongly on the value factor.

Table 10 reports the results from regressions of the loadings on the market factor (β^{MKT}), small-minus-big factor (β^{SMB}), and high-minus-low factor (β^{HML}) on the three alternative measures of real asset illiquidity (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and the same set of control variables used throughout the paper which are defined in Table 1 (*LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*). Panels A, B, and C report the results using β^{MKT}, β^{SMB}, and β^{HML}, respectively. In columns (1), (3), and (5) we report the results of Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2), (4), and (6) we report the results of purely cross-sectional OLS regressions based on the time-series averages of the variables over the sample period for each firm with t-statistics adjusted for the clustering of observations at the three-digit SIC industry level.

The results in Panel A provide some weak evidence of a negative relation between real asset illiquidity and β^{MKT}, but the results are not consistent across asset illiquidity measures and estimation approaches (they are statistically significant at the 5% level only when we use *NLPotBuy*). Panel B shows that there is no reliable effect of the real asset illiquidity measures on β^{SMB} (the effect is statistically significant only in the specification in column (6)). In contrast, in Panel C we find strong evidence that real asset illiquidity increases β^{HML} which is statistically significant and highly consistent across real asset illiquidity measures and estimation approaches. Thus, we conclude that real asset illiquidity ultimately affects the Fama-French cost of capital primarily through the B/M channel. This further supports the view that real asset illiquidity increases firms' cost of capital because it increases firms' cost of reversing their investments and hence reduces their operating flexibility.

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

Previous work shows that more illiquid stocks or those more exposed to systematic liquidity risk are associated with higher expected returns (see, for example, Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) for evidence on stock illiquidity, and Pástor and Stambaugh (2003) for evidence on systematic liquidity risk). It is conceivable that firms with more illiquid real assets may also have more illiquid stocks or that their stock may be more exposed to systematic liquidity risk. For example, it could be argued that in good times real assets are easier to sell and at the same time stocks are more liquid or less exposed to liquidity shocks. If for whatever reason that is indeed the case, then firms with more illiquid real assets could appear to have a higher cost of capital, but this would be driven by the lower liquidity or the higher liquidity risk of their stock.

To this end, in Table 11 we examine the correlation of the real asset illiquidity measures (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*) with market-wide liquidity risk and stock liquidity measures calculated for three-digit SIC industries. As in Pastor and Stambaugh (2003), we measure systematic liquidity risk using *IndPSLiqBeta*, which is defined as the average sensitivity of stock returns to their liquidity factor across all stocks in the industry.[20] We measure stock liquidity using *IndShrTurn*, defined as the average share turnover across all stocks in the industry (our results are also similar if we measure stock liquidity using the average Amhihud measure across all stocks in the industry). We find a positive and statistically significant correlation of *IndPSLiqBeta* with both *MNoPotBuy* and *NLPotBuy*, but no significant correlation with *MTotM&A*. We also find a negative and statistically significant correlation between all real asset illiquidity measures and *IndShrTurn*. In sum, firms with more illiquid real assets have more illiquid stocks and their stocks face more systematic liquidity risk.

In Table 12 we expand our empirical models which regress the *ICC* on the real asset illiquidity measures to further include *IndPSLiqBeta* and *IndShrTurn* as control variables. Panels A, B, and C report the results for each of the real asset illiquidity measures *MNoPotBuy*, *NLPotBuy*, and

---

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

MTotM&A, respectively, using both the Fama-MacBeth approach and the OLS (panel) approach with industry and year fixed effects. Consistent with prior work, using the cross-sectional approach we find that firms whose stocks face more systematic liquidity risk have a higher cost of capital. The effect of *IndPSLiqBeta* is not statistically significant in column (2) due to a lack of power, since by construction this variable exhibits little variation over time due to the use of five-year rolling windows to estimate the loadings on the liquidity factor for each firm. We find no effect of stock liquidity on *ICC*, but this is due to the inclusion of highly correlated variables (the univariate correlation between the *ICC* and *IndShrTurn* is -35.3%). More importantly, in all panels we find that including these additional control variables in the regression has no impact on the estimated effect of real asset illiquidity on the cost of capital. Hence, the effect of a firm's real asset illiquidity on its cost of capital is not driven by the liquidity or systematic liquidity risk of the firm's stock.

5. Additional Tests

We now briefly discuss further tests which help assess the robustness of our main results and also the results of an exploration of the cross-sectional variation in the effect of real asset illiquidity on the implied cost of capital. The results from these analyses are omitted from the paper but the key ones are reported and discussed in detail in the Online Appendix.

5.1. Robustness of Main Results

We explore whether a correlation between our measures of real asset illiquidity and industry valuations could drive our results. During periods of high industry valuation, new firms may enter the industry or acquire debt ratings, which would affect *MNoPotBuy*, and industry rivals may change their leverage, which would affect *NLPotBuy*. Moreover, our tests using *MTotM&A* may suffer from reverse causality: during periods of low industry valuation firms have a high cost of capital, which may lead to less M&A activity in the industry and thus to higher values of *MTotM&A*. In prior tests we address this issue by controlling for a firm's market-to-book ratio and stock price, and show that our results hold in cross-sectional tests which do not use the time-series variation in asset illiquidity.

For robustness, we repeat our analyses after controlling for two alternative measures of industry valuations constructed at the three-digit SIC industry level: the logarithm of the average market-to-book equity ratio in the industry and the industry's valuation relative to historical values. As in Hoberg and Phillips (2010), we construct the latter 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). In both Fama-MacBeth regressions and pooled (panel) OLS regressions with three-digit SIC industry and year fixed effects (reported in the Online Appendix), the coefficients on the real asset illiquidity measures remain positive and statistically significant, and of similar magnitudes. Hence, the variation in industry valuations over time is unlikely to drive our results.

We also study whether an association between real asset illiquidity and financial leverage could drive our results. Real asset illiquidity may affect debt capacity (Shleifer and Vishny (1992) and Morellec (2001)) and it could affect the cost of capital through this leverage channel rather than through the operating flexibility channel. In addition, our asset illiquidity measure based on the net leverage of industry rivals could predict the cost of capital because the firm's own leverage is correlated with that of its rivals. In prior tests we address this issue by including financial leverage as a control variable but, for robustness, we also repeat our tests using the *unlevered* implied cost of capital. The Online Appendix explains the calculation of the unlevered cost of capital using the Modigliani-Miller formula with taxes and reports the results. For all measures of real asset illiquidity and estimation approaches, the estimated coefficients are similar in both magnitude and statistical significance to those reported in Table 6. Hence, financial leverage does not drive our results.

We also explore whether our tests using the *ICC* are affected by biases in analysts' earnings forecasts (but note we obtain similar results using the *FFCC* which does not rely on these forecasts). The calculation of *ICC* assumes that the consensus forecast is an unbiased estimate of investors' expectations, but analysts make biased forecasts (e.g., Easton and Monahan (2005)). This should not affect our results if the forecasts are equally biased for all stocks. However, the bias may be systematically related to real asset illiquidity. For example, if the forecasts are biased in favor of firms with more illiquid real assets, then the estimate of the *ICC* will be biased upwards for these firms. This would lead to an overstatement of the effect of real asset illiquidity on the *ICC*. Our evidence suggests that the biases in analysts' earnings forecasts do not drive our results. First, the correlations between the forecast bias and the real asset illiquidity measures are fairly low. Second, adding the forecast bias as a control variable in our regressions or dropping from the sample those firms with forecast biases in the top 30% or the 50% of the annual distribution has no effect on our results.

We also examine a measure of real asset illiquidity based on the premiums paid to targets in the M&A market (a firm's assets are more likely to be illiquid when targets operating in the industry are sold at lower premiums). Using all merger deals involving publicly traded targets recorded in SDC, we calculate this measure as *minus* the average acquisition premium for each three-digit SIC industry over the past five years (higher values imply more illiquid assets).[21] The correlation between our previous measure *MTotM&A* and the negative of the average acquisition premium is 53%, and thus a lower volume of transactions is associated with more illiquid transactions. Noteworthy, using this measure based on the average acquisition premium, we continue to find that real asset illiquidity increases the implied cost of capital (the magnitude of the effect is similar to that of *MTotM&A*).

Our measures of real asset illiquidity require that we identify each firm's industry affiliation, which we do using firms' primary SIC codes. We further refine the measures to incorporate the individual segments of multiple-segment firms. Specifically, we calculate the real asset illiquidity of a multiple-segment firm as the weighted-average real asset illiquidity of each of its three-digit SIC industry segments, with weights equal to the fraction of a firm's total assets accounted for by each segment's assets. In the case of *MNoPotBuy* and *NLPotBuy*, which depend on identifying a firm's industry rivals, we also consider all rivals, including the secondary segments of multiple-segment firms. For all three revised measures of real asset illiquidity the results are similar to those reported.

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

We now briefly discuss results which are suggestive of what drives the variation across firms in the strength of the effect of real asset illiquidity on the implied cost of capital (the Online Appendix contains the results and detailed explanations). The idea is to identify situations in which real asset

[21] For each industry and year with at least one transaction, we average the premium across all targets in the same industry. The premium is (bidder's offer price – target's pre-bid price) / target's pre-bid price, where the target's pre-bid price is recorded 30 days before the announcement. For industry-years with no transactions, we set the premium to be equal to the minimum premium recorded across all industries in that year.

illiquidity may cause a stronger covariance of fundamentals with the state of the economy and hence have a larger impact in firms' cost of capital. To this end, we run our benchmark regression with three-digit SIC and year fixed effects separately for extreme subsamples and compare the effects.

The operating inflexibility caused by real asset illiquidity is likely to be more costly for firms in more competitive industries, where firms that fail to quickly adapt to changes in the environment are drawn out of business. 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. Our results generally suggest that real asset illiquidity increases the *ICC* mostly for firms in low concentration industries (sales Herfindahl in the bottom tercile) and for firms with market shares in the industry below 15% (i.e., the firms classified as industry "followers" as in Campello (2006)).

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. Since Faulkender and Petersen (2006) highlight the importance of access to public debt markets, we split the sample into firms with unrated and rated debt. We find that the effect of real asset illiquidity on the cost of capital is larger for firms with unrated debt. We also 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. We find that real asset illiquidity has a stronger positive effect on the cost of capital in firms with high default risk.

Theory suggests that a firm's ability to sell its real assets is more valuable in bad times, when firms may want to sell real assets to reduce their fixed costs or to raise cash (e.g., Kogan (2001) and Zhang (2005)). We find two results which support this view. First, real asset illiquidity increases the cost of capital more for firms with low valuations than it does for firms with high valuations (high and low valuations are defined according to whether the distance of a firm's market-to-book value of assets from the industry median is in the bottom or top tercile of the annual distribution). Second, real asset illiquidity increases the cost of capital by more for firms in industries experiencing downturns (defined as in Opler and Titman (1994)) than it does for firms in industries that are not.

6. Summary and Conclusions

We argue that a more illiquid market for real assets increases a firm's cost of unwinding its capital stock and it decreases its ability to raise cash, hence reducing the firm's flexibility in responding to a changing business environment. This operating inflexibility is especially costly in bad times – a point which 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 firm's cost of capital.

Consistent with this hypothesis, we find an aggregate real asset illiquidity premium in firms' cost of capital that is strongly countercyclical. Moreover, we show that firms with more illiquid real assets have a much higher cost of capital both in cross-sectional and time-series tests. These results are robust to using different measures of potential and historical real asset illiquidity, as well as to measuring a firm's expected returns using the implied cost of capital and the Fama-French three-factor model cost of capital. In further support of the hypothesis, we also show that, through its effect on the discount rate, real asset illiquidity has a large negative impact on firm value.

Supporting theories which suggest that 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 by industry outsiders. Consistent with the implications of the investment-based asset pricing literature which argues that value firms have less flexible operations than growth firms, we also show that real asset illiquidity significantly increases the loading of a firm's stock return on the value factor. Last, we find that the effect of real asset illiquidity on the cost of capital is very robust to controlling for the stock liquidity and the systematic stock liquidity risk of firms in the industry.

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 capital. More generally, our study highlights the importance of real-side fundamentals as important drivers of the required return on equity as well as the importance of industry factors in asset pricing.

References

Almeida, H., M. Campello, and D. Hackbarth, 2009, Liquidity mergers, Working Paper, University of Illinois.

Amihud, Y., and H. Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Benmelech, E., and N. K. Bergman, 2009, Collateral Pricing, Working Paper, Harvard University.

Bharath, S. T., and T. Shumway, 2008, Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339-1369.

Blume, M. E., and I. Friend, 1973, A new look at the capital asset pricing model, *Journal of Finance* 28: 19-33.

Brav, A., R. Lehavy, and R. Michaely, 2005, Using expectations to test asset pricing models, *Financial Management* 34, 5-38.

Brennan, M. J., and A. Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Brennan, M. J., T. Chordia, and A. Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345-373.

Campello, M., 2006, Debt financing: Does it boost or hurt firm performance in product markets?, *Journal of Financial Economics* 82, 135-172.

Campello, M., L. Chen, and L. Zhang, 2008, Expected returns, yield spreads, and asset pricing tests, *Review of Financial Studies* 21, 1297-1338.

Carlson, M., A. Fisher, and R. Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577-2603.

Chan, K.C., and N-F Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467-1484.

Chava, S., and A. K. Purnanandam, 2010, Is default risk negatively related to stock returns?, *Review of Financial Studies* 23, 2523-2559.

Chen, H., M. Kacperczyk, and H. Ortiz-Molina, 2009, Labor unions, operating flexibility, and the cost of equity, *Journal of Financial and Quantitative Analysis*, forthcoming.

Chen, L., R. Petkova, and L. Zhang, 2008, The expected value premium, *Journal of Financial Economics* 87, 269-280.

Claus, J., and J. Thomas, 2001, Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets, *Journal of Finance* 56, 1629-1666.

Cooper, I., 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment, *Journal of Finance* 61, 139-170.

Datar, V. T., N. Y. Naik, and Robert Radcliffe, 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203-219.

DeAngelo, H., L. DeAngelo, and K. H. Wruck, 2002, Asset liquidity, debt covenants, and managerial discretion in financial distress: The collapse of L.A. Gear, *Journal of Financial Economics* 64, 3-34.

Diamond, D. W., and R. G. Rajan, 2009, Fear of fire sales and the credit freeze, Working Paper, University of Chicago.

Easton, P. D., and S. J. Monahan, 2005, An evaluation of accounting-based measures of expected returns, *Accounting Review* 80, 501-538.

Elton, E. J., 1999, Expected return, realized return, and asset pricing tests, *Journal of Finance* 54, 1199-1220.

Fama, E. F. and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E. F., and K. R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fama, E. F., and K. R. French, 2002, The equity premium, *Journal of Finance* 57, 637–659.

Faulkender, M., and M. A. Petersen, 2006, Does the source of capital affect capital structure?, *Review of Financial Studies* 19, 45-79.

Gala, V. D., 2007, Investment and returns, Working Paper, London Business School.

Gavazza, A., 2010, The role of trading frictions in real asset markets, *American Economic Review*, forthcoming.

Gebhardt, W. R., C. M. C. Lee, and B. Swaminathan, 2001, Toward an implied cost of capital, *Journal of Accounting Research* 39, 135-176.

Gomes, J., L. Kogan, and L. Zhang, 2003, Equilibrium cross-section of returns, *Journal of Political Economy* 111, 693-732.

Hail, L., and C. Leuz, 2009, Cost of capital effects and changes in growth expectations around U.S. cross-listings, *Journal of Financial Economics* 93, 428-454.

Hoberg, G., and G. Phillips, 2010, Real and financial industry booms and busts, *Journal of Finance* 65, 45-86.

Hou, K., and D. T. Robinson, 2006, Industry concentration and average stock returns, *Journal of Finance* 61, 1927-1956.

Kaplan, S. N., and R. S. Ruback, 1995, The valuation of cash flow forecasts: An empirical analysis, *Journal of Finance* 50, 1059–1093.

Kogan, L., 2001, An equilibrium model of irreversible investment, *Journal of Financial Economics* 62, 201-245.

Kogan, L., 2004, Asset prices and real investment, *Journal of Financial Economics* 73, 411-431.

Lang, L., A. Poulsen, and R. M. Stulz, 1994, Asset sales, firm performance, and the agency costs of managerial discretion, *Journal of Financial Economics* 37, 3–37.

Lee, C. M. C., D. Ng, and B. Swaminathan, 2009, Testing international asset pricing models using implied cost of capital, *Journal of Financial and Quantitative Analysis* 44, 307-305.

Lundblad, C., 2007, The risk return tradeoff in the long-run: 1836–2003, *Journal of Financial Economics* 85, 123–150.

Maksimovic, V., and G. Phillips 1998, Asset efficiency and the reallocation decisions of bankrupt firms, *Journal of Finance* 53, 1495-1532.

Maksimovic, V., and G. Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?, *Journal of Finance* 61, 2019-2065.

Merton, R. C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449-470.

Miller, M. H., and M. S. Scholes, 1982, Dividends and Taxes: Some empirical evidence, *Journal of Political Economy* 90, 1118-1141.

Morellec, E., 2001, Asset liquidity, capital structure, and secured debt, *Journal of Financial Economics* 61, 173-206.

Opler, T. C., and S. Titman, 1994, Financial distress and corporate performance, *Journal of Finance* 49, 1015-1040.

Pástor, L., and P. Veronesi, 2003, Stock valuation and learning about profitability, *Journal of Finance* 58, 1749-1789.

Pástor, L., and R. F. Stambaugh, 1999, Costs of equity capital and model mispricing, *Journal of Finance* 54, 67–121.

Pástor, L., and R. F. Stambaugh, 2003, Stock Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642-685.

Pástor, L., M. Sinha, and B. Swaminathan, 2008, Estimating the intertemporal risk-return tradeoff using the implied cost of capital, *Journal of Finance* 63, 2859-2897.

Pulvino, T. C., 1998, Do asset fire sales exist? An empirical investigation of commercial aircraft transactions, *Journal of Finance* 53, 939-975.

Ramey, V. A., and M. D. Shapiro, 2001, A study of aerospace plant closings, *Journal of Political Economy* 109, 958-992.

Schlingemann, F. P., R. M. Stulz, and R. A. Walkling, 2002, Divestitures and the liquidity of the market for corporate assets, *Journal of Financial Economics* 64, 117-144.

Sharpe, W. F., 1978, New evidence on the capital asset pricing model: Discussion, *Journal of Finance* 33, 917-920.

Shleifer, A., and R. W. Vishny, 1992, Liquidation values and debt capacity: A market equilibrium approach, *Journal of Finance* 47, 1343-1366.

Weiss, L. A., and K. H. Wruck, 1998, Information problems, conflicts of interest, and asset stripping: Chapter 11's failure in the case of Eastern Airlines, *Journal of Financial Economics* 48, 55-9.

Zhang, L., 2005, The value premium, *Journal of Finance* 60, 67-103.

Table 1
Summary Statistics for the Main Variables

The table reports summary statistics for the measures of cost of capital, the real asset illiquidity measures, and the variables that serve as controls in our analyses. The dependent variables in our tests are *ICC*, the implied cost of capital of Gebhardt, Lee, and Swaminathan (2001), and *FFCC*, the Fama-French three-factor model cost of capital. The summary statistics on the independent variables are calculated on the sample of firm for which we can calculate the *ICC*, which covers the period 1984-2006 and contains 6,260 firms and a total of 33,788 firm-year observations (financial institutions and utilities are excluded from the sample). 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. The measures of real asset illiquidity use three-digit SIC industry definitions and are standardized to have mean zero and standard deviation of one. These measures are as follows: *MNoPotBuy* is *minus* the number of rival firms in the industry that have debt ratings, and is calculated for the period 1985-2006 because bond ratings become available in 1985 (the tests which use this variable rely on 6,180 firms and 33,052 firm-year observations); *NLPotBuy* is the average book leverage net of cash holdings of rival firms in the industry, averaged over the past five 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 five years; *MInsM&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 five 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 five years. Higher values of all these variables are associated with more illiquid real assets. The control variables we use throughout our tests are as follows: *LogAssets* is the logarithm of total assets; *M/B* is the market-to-book assets 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 five years; *FA/TA* is fixed assets scaled by total assets; *R&DExp* is R&D expenditures scaled by sales; *LogAge* is the logarithm of one plus the number of years since the company was first listed in CRSP; *DivPay* equals one if the firm pays dividends and zero otherwise; *SalGrow* is the annual change in the logarithm of sales; *LogInvPrice* is the logarithm of one divided by the stock price as of the estimation date of *ICC*; and *RetPM* is the stock return over the past month.

	Mean	Std. Dev.	Median	5^{th} Pctile	95^{th} Pctile
Dependent Variables					
ICC	0.099	0.057	0.107	0.001	0.179
FFCC	0.142	0.091	0.137	0.004	0.301
Standardized Real Asset Illiquidity Measures					
MNoPotBuy	0.000	1.000	0.383	-2.098	0.950
NLPotBuy	0.000	1.000	0.182	-1.831	1.461
MTotM&A	0.000	1.000	0.361	-2.243	1.002
MInsM&A	0.000	1.000	0.413	-2.376	0.792
MOutM&A	0.000	1.000	0.390	-2.216	0.884
Control Variables					
LogAssets	6.363	1.792	6.215	3.705	9.604
M/B	1.870	1.712	1.350	0.601	4.936
DRP	0.500	0.288	0.500	0.050	0.950
Blev	0.210	0.182	0.189	0.000	0.549
ROE	0.045	3.037	0.069	-0.236	0.194
VolROE	0.087	0.128	0.050	0.009	0.267
FA/TA	0.300	0.225	0.242	0.036	0.767
R&DExp	0.068	0.207	0.005	0.000	0.254
LogAge	2.349	0.966	2.303	0.693	4.043
DivPay	0.429	0.495	0.000	0.000	1.000
Salgrow	0.157	0.255	0.119	-0.177	0.629
LogInvPrice	-2.986	0.819	-3.056	-4.191	-1.504
RetPM	0.036	0.142	0.026	-0.165	0.273

Table 2
Average Firm Characteristics of Quintile Portfolios Sorted on Real Asset Illiquidity

The table reports the averages of selected firm characteristics for quintile portfolios of firms formed using the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*). In each year, we first sort firms into quintiles based on the measure of real asset illiquidity, compute the average characteristic for each quintile, and then take the average for each quintile across all years. Q1 denotes the least illiquid quintile and Q5 denotes the most illiquid quintile. The firm characteristics are defined in Table 1 and include *LogAssets*, *M/B*, *DRP*, *Blev*, and *ROE*. The sample includes all firms for which we are able to compute the *ICC*.

	Real Asset Illiquidity Quintile				
	Q1	Q2	Q3	Q4	Q5
Sorted on MNoPotBuy					
LogAssets	6.40	6.27	6.38	6.52	6.30
M/B	2.26	2.09	1.80	1.60	1.66
DRP	0.50	0.48	0.50	0.52	0.50
Blev	0.20	0.18	0.23	0.23	0.21
ROE	-0.02	0.01	0.04	0.04	0.15
Sorted on NLPotBuy					
LogAssets	5.73	5.86	6.33	7.01	6.96
M/B	2.76	2.15	1.68	1.44	1.39
DRP	0.42	0.46	0.50	0.54	0.59
Blev	0.13	0.14	0.21	0.26	0.31
ROE	-0.02	0.02	0.13	0.06	0.04
Sorted on MTotM&A					
LogAssets	5.84	6.27	6.44	6.49	6.84
M/B	2.43	1.92	1.89	1.70	1.48
DRP	0.43	0.50	0.52	0.53	0.53
Blev	0.16	0.21	0.21	0.23	0.24
ROE	-0.01	0.01	0.11	0.04	0.06

Table 3
Real Asset Illiquidity and the Implied Cost of Capital: Univariate Tests

The table reports the average implied cost of capital (*ICC*) for quintile portfolios of firms formed using the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy*, *NLPotBuy*, and *MTotM&A*). In Panel A we form portfolios using firm-level observations and in Panel B we first collapse all data to the value-weighted three-digit SIC industry average and then form portfolios using the industry-level observations. In both panels, for each year we sort firms or industries 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 p-value corresponding to the test of the difference in means between Q5 and Q1.

Panel A: ICC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity – Firm Level

	Real Asset Illiquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
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: ICC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity – Industry Level

	Real Asset Illiquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
Sorted on MNoPotBuy							
Equal-Weighted Avg.	10.79%	11.66%	12.02%	12.11%	12.31%	1.51%	0.000
Value-Weighted Avg.	8.76%	9.30%	10.43%	10.24%	10.04%	1.28%	0.000
Sorted on NLPotBuy							
Equal-Weighted Avg.	10.65%	11.09%	11.93%	12.23%	12.99%	2.34%	0.000
Value-Weighted Avg.	6.21%	9.39%	10.46%	10.29%	12.76%	6.56%	0.000
Sorted on MTotM&A							
Equal-Weighted Avg.	11.42%	11.44%	11.71%	12.36%	11.94%	0.53%	0.084
Value-Weighted Avg.	7.18%	9.12%	9.39%	10.80%	10.17%	2.99%	0.000

Table 4
Real Asset Illiquidity and the Fama-French Cost of Capital: Univariate Tests

The table reports the average Fama-French three-factor model cost of capital (*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*). In Panel A we form portfolios using firm-level observations and in Panel B we first collapse all data to the value-weighted three-digit SIC industry average and then form portfolios using the industry-level observations. In both panels, for each year we sort firms or industries 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 p-value corresponding to the test of the difference in means between Q5 and Q1.

Panel A: FFCC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity – Firm Level

	Real Asset Illiquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
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

Panel B: FFCC for Quintile Portfolios Sorted on Measures of Real Asset Illiquidity – Industry Level

	Real Asset Illiquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
Sorted on MNoPotBuy							
Equal-Weighted Avg.	11.22%	11.90%	12.25%	12.40%	11.98%	0.76%	0.000
Value-Weighted Avg.	9.31%	10.22%	11.48%	11.83%	10.13%	0.82%	0.000
Sorted on NLPotBuy							
Equal-Weighted Avg.	11.04%	11.95%	11.96%	12.16%	12.65%	1.61%	0.000
Value-Weighted Avg.	7.81%	10.69%	10.80%	10.30%	11.39%	3.58%	0.000
Sorted on MTotM&A							
Equal-Weighted Avg.	11.27%	11.68%	12.04%	12.49%	12.27%	1.00%	0.000
Value-Weighted Avg.	8.14%	9.47%	10.22%	11.20%	10.63%	2.49%	0.000

Table 5
Business-Cycle Variation of the Real Asset Illiquidity Premium

The table 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 Database (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 three-factor model (*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 average cost of capital (in %) for firms in the highest and lowest real asset illiquidity quintiles (equal-weighted for *ICC* and value-weighted for *FFCC*). 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 the December's Consumer Price Index; *T-Bill* is the average three-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 ten-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 standard errors which account for any significant autocorrelation. The R^2 of each regression is reported in brackets. *, **, and *** indicate statistical significance at 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.	-0.876***	-0.845***	-0.750***	-0.845**	-0.455***	-0.550***
		t-stat	(2.86)	(6.50)	(5.50)	(2.30)	(4.66)	(5.53)
		R^2	[19.88%]	[26.27%]	[16.27%]	23.15%	13.41%	17.37%
(2)	CapUtil	Coef.	-0.230***	-0.299**	-0.463***	-0.483***	-0.140**	-0.234***
		t-stat	(4.14)	(2.60)	(5.45)	(4.00)	(2.58)	(5.64)
		R^2	[10.33%]	[17.61%]	[33.11%]	56.93%	6.78%	16.72%
(3)	Inflation	Coef.	-0.656***	-0.450*	-0.972***	-0.474*	-0.884***	-0.398
		t-stat	(3.42)	(1.81)	(4.12)	(1.85)	(6.18)	(1.32)
		R^2	[9.80%]	[4.78%]	[17.51%]	6.40%	32.40%	5.82%
(4)	T-Bill	Coef.	-0.748***	-0.728***	-0.935***	-0.525***	-0.391***	-0.333***
		t-stat	(3.67)	(7.33)	(8.85)	(3.56)	(3.05)	(4.41)
		R^2	[37.32%]	[45.68%]	[59.20%]	23.00%	23.11%	14.91%
(5)	DefSpr	Coef.	0.748	1.802**	2.789***	3.570***	1.120***	1.544***
		t-stat	(0.75)	(2.08)	(4.39)	(5.91)	(4.45)	(4.50)
		R^2	[1.95%]	[11.67%]	[21.95%]	55.62%	7.92%	13.34%
(6)	MktRet	Coef.	-0.038***	-0.049***	-0.045***			
		t-stat	(3.10)	(4.87)	(3.66)			
		R^2	[6.25%]	[10.67%]	[7.06%]			

Table 6
Real Asset Illiquidity and the Implied Cost of Capital: Multivariate Analysis

The table 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. Panel A reports the results of firm-level regressions and Panel B reports the results of industry-level regressions based on the value-weighted averages of the variables across all firms in the three-digit SIC industry. In columns (1), (3), and (5) we report Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2), (4), and (6) we report pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*. 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 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Empirical Model (All 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
Panel A: Regressions of ICC on Real Asset Illiquidity Measures and Control Variables – Firm-Level Tests						
MNoPotBuy	0.015***	0.015***				
	(3.73)	(2.97)				
NLPotBuy			0.016***	0.011***		
			(6.44)	(6.36)		
MTotM&A					0.009**	0.005***
					(2.50)	(2.64)
Observations	33052	33052	33788	33788	33788	33788
R-squared		0.54		0.55		0.54
Panel B: Regressions of ICC on Real Asset Illiquidity Measures and Control Variables – Industry-Level Tests						
MNoPotBuy	0.005*	0.009**				
	(1.98)	(2.43)				
NLPotBuy			0.006***	0.003*		
			(5.10)	(1.66)		
MTotM&A					0.001	0.001
					(0.52)	(1.37)
Observations	4793	4793	4793	4793	4793	4793
R-squared		0.71		0.71		0.71

Table 7
Real Asset Illiquidity and the Fama-French Cost of Capital: Multivariate Analysis

The table reports the results from regressions of the Fama-French Three-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. Panel A reports the results of firm-level regressions and Panel B reports the results of industry-level regressions based on the value-weighted averages of the variables across all firms in the three-digit SIC industry. In columns (1), (3), and (5) we report Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West 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 three-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*. 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 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Empirical Model (All Panels)						
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
Panel A: Regressions of FFCC on Real Asset Illiquidity Measures and Control Variables – Firm-Level Tests						
MNoPotBuy	0.005**	0.004**				
	(2.75)	(2.29)				
NLPotBuy			0.005***	0.006***		
			(5.03)	(3.03)		
MTotM&A					0.004**	0.008***
					(2.19)	(3.76)
Observations	73893	9930	76575	10180	76575	10180
R-squared		0.03		0.03		0.03
Panel B: Regressions of FFCC on Real Asset Illiquidity Measures and Control Variables – Industry-Level Tests						
MNoPotBuy	0.007*	0.008				
	(2.05)	(1.50)				
NLPotBuy			0.002			
			(1.50)			
MTotM&A				0.006	0.001	0.004
				(1.25)	(0.81)	(0.88)
Observations	5725	333	5725	333	5725	333
R-squared		0.15		0.15		0.15

Table 8
Inside vs. Outside Real Asset Illiquidity and the Implied Cost of Capital

The table reports the results from regressions of the implied cost of capital (*ICC*) on two measures of real asset illiquidity defined in Table 1 (*MInsM&Q* and *MOutM&A*) and a set of control variables. In columns (1) and (3) we report Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2) and (4) we report pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*. 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 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
MInsM&A	0.009**	0.006***		
	(2.08)	(2.78)		
MOutM&A			0.004***	0.002
			(3.95)	(1.53)
Observations	33788	33788	33788	33788
R-squared		0.55		0.54
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

Table 9
Effect of Real Asset Illiquidity on Equity Values

The table reports the results from regressions of the logarithm of book-to-market equity ratio 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 regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2), (4), and (6) we report OLS purely cross-sectional regressions using the time-series averages of the variables over the sample period for each firm, with standard errors clustered by three-digit SIC industry. We also include but do not report the coefficients of the following control variables: *LogAssets*, *Blev*, *ROE*, *VolRoe*, *LogAge*, *DivPay*, and *SalGrow* (defined in Table 1) as well as *MShr*, defined as the firm's market share in the three-digit SIC industry, and *Rated*, which equals one if the firm has rated debt and zero otherwise. The estimates of the intercept, the year fixed effects, and the coefficients of the control variables are omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
MNoPotBuy	0.103***	0.146***				
	(6.16)	(3.28)				
NLPotBuy			0.195***	0.221***		
			(14.36)	(5.99)		
MTotM&A					0.108***	0.100***
					(6.55)	(5.29)
Observations	73893	9930	76575	10180	76575	10180
Empirical Model						
All Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Fama-MacBeth	Cross-Sectional	Fama-MacBeth	Cross-Sectional	Fama-MacBeth	Cross-Sectional
Clustering by SIC3	No	Yes	No	Yes	No	Yes
Newey-West 6 lags	Yes	No	Yes	No	Yes	No

Table 10
Real Asset Illiquidity and the Loadings on the Fama-French Factors

The table reports the results from regressions of the loadings of stock returns on the market factor (β^{MKT}), small-minus-big factor (β^{SMB}), and high-minus-low factor (β^{HML}) on the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) and a set of control variables. Panels A, B, and C report the results using β^{MKT}, β^{SMB}, and β^{HML}, respectively. In columns (1), (3), and (5) we report Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West 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 three-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*. The estimates of the intercept, the year fixed effects, and the coefficients of the control variables are omitted. The absolute values of the *t*-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Empirical Model (All Panels)						
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
Observations	73893	9930	76575	10180	76575	10180
Panel A: The Dependent Variable is the Loading on the Market Factor (β^{MKT})						
MNoPotBuy	-0.010	-0.046*				
	(0.70)	(1.80)				
NLPotBuy			-0.026***	-0.052**		
			(3.03)	(2.42)		
MTotM&A					-0.002	-0.003
					(0.61)	(0.23)
Panel B: The Dependent Variable is the Loading on the Small-Minus-Big Factor (β^{SMB})						
MNoPotBuy	0.029	0.021				
	(0.88)	(1.28)				
NLPotBuy			-0.029	-0.029		
			(1.43)	(1.63)		
MTotM&A					0.006	0.054***
					(0.53)	(3.73)
Panel C: The Dependent Variable is the Loading on the High-Minus-Low Factor (β^{HML})						
MNoPotBuy	0.107***	0.140***				
	(3.12)	(2.83)				
NLPotBuy			0.159***	0.214***		
			(8.42)	(5.25)		
MTotM&A					0.073*	0.135***
					(1.94)	(2.88)

Table 11
Correlation of Real Asset Illiquidity with the Systematic Liquidity Risk and Liquidity of Firms' Stock

The table reports the pair-wise correlations of the three alternative measures of real asset illiquidity defined in Table 1 (*MNoPotBuy, NLPotBuy,* and *MTotM&A*) with a measure of the average market-wide liquidity risk of stocks in the industry (*IndPSLiqBeta*) and a measure of the average liquidity of stocks in the industry (*IndShrTurn*). *IndPSLiqBeta* is the average sensitivity of stock returns to the Pastor and Stambaugh (2003) liquidity factor across all stocks in the three-digit SIC industry; and *IndShrTurn* is the average share turnover across all stocks in the three-digit SIC industry. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	MNoPotBuy	NLPotBuy	MTotM&A	IndPSLiqBeta	IndShrTurn
MNoPotBuy	1.000				
NLPotBuy	0.324***	1.000			
MTotM&A	0.294***	0.376***	1.000		
IndPSLiqBeta	0.072***	0.126***	0.008	1.000	
IndShrTurn	-0.408***	-0.446***	-0.276***	0.056***	1.0000

Table 12
Real Asset Illiquidity and the Implied Cost of Capital:
Controlling for the Liquidity and Systematic Liquidity Risk of Firms' Stock

The table 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*), a measure of the average market-wide liquidity risk of stocks in the industry (*IndPSLiqBeta*), a measure of the average liquidity of stocks in the industry (*IndShrTurn*), and a set of control variables. In columns (1) and (3) we report Fama-MacBeth regressions with t-statistics adjusted for autocorrelation using the Newey-West procedure based on 6 lags. In columns (2) and (4) we report pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. *IndPSLiqBeta* is the average sensitivity of stock returns to the Pastor and Stambaugh (2003) liquidity factor across all stocks in the three-digit SIC industry; and *IndShrTurn* is the average share turnover across all stocks in the three-digit SIC industry. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *Blev*, *ROE*, *VolRoe*, *FA/TA*, *R&DExp*, *LogAge*, *DivPay*, *SalGrow*, *LogInvPrice*, and *RetPM*. 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 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Empirical Model (All Panels)				
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
Panel A: The measure of real asset illiquidity is MNoPotBuy				
MNoPotBuy	0.014***	0.015***	0.015***	0.015***
	(3.25)	(3.01)	(4.13)	(3.03)
IndPSLiqBeta	0.013***	-0.004		
	(3.40)	(0.93)		
IndShrTurn			0.001	0.001*
			(0.94)	(1.71)
Panel B: The measure of real asset illiquidity is NLPotBuy				
NLPotBuy	0.015***	0.010***	0.015***	0.011***
	(6.28)	(6.19)	(7.82)	(6.31)
IndPSLiqBeta	0.011**	-0.004		
	(2.30)	(0.88)		
IndShrTurn			0.001	0.001
			(1.09)	(1.51)
Panel C: The measure of real asset illiquidity is MTotM&A				
MTotM&A	0.009**	0.005***	0.009**	0.005**
	(2.77)	(2.78)	(2.41)	(2.56)
IndPSLiqBeta	0.013***	-0.005		
	(3.46)	(1.12)		
IndShrTurn			0.000	0.000
			(0.02)	(0.93)