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ABSTRACT

We study the effect of real asset liquidity on a firm's cost of capital. We find an aggregate asset-liquidity discount in firms' cost of capital that is strongly counter-cyclical. At the firm-level we find that asset liquidity affects firms' cost of capital both in the cross section and in the time series: Firms in industries with more liquid assets and during periods of high asset liquidity have lower cost of capital. This effect is stronger when the asset liquidity is provided by firms operating within the industry. We also find that higher asset liquidity reduces the cost of capital by more for firms that face more competitive risk in product markets, have less access to external capital or are closer to default, and for those facing negative demand shocks. Our results suggest that asset liquidity is valuable to firms and, more generally, that operating inflexibility is an economically important source of risk.

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I. 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 (2009) 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 liquidity of a firm's physical assets. Yet, asset liquidity 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 assets at the prevailing fire-sale prices.

The importance of the constraints that illiquid 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 discount.

In this paper we examine whether more liquid asset markets reduce a firm's cost of capital by increasing 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

[1] See Amol Sharma, "Quest's Long-Distance Arm Draws Bids Below Targets", Wall Street Journal, dateMonth6Day5Year2009June 5, 2009.

even in the absence of operational 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 (2008)). This implies that the cost a firm faces in reversing an 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 asset liquidity is a main determinant of a firm's operating flexibility and that as a result asset liquidity should affect a firm's cost of capital ex-ante.

In asset pricing, a growing theoretical literature directly links a firm's cost of reversing its real investment to its cost of capital (e.g., Kogan (2004), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006)). 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, and thus it leads investors to require higher returns for the capital they provide.

For the purposes of our study it is important that we measure asset liquidity for firms in a broad number of industries and over a long period of time. Throughout the paper, we use three different measures of asset liquidity: the number of industry rivals with access to debt markets, the average leverage net of cash of industry rivals, and the value of M&A activity in a firm's industry. The first two measures capture the presence 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, Stulz and Walkling (2002), who argue that a high volume of M&A activity in an industry is evidence of high asset liquidity because price discounts are smaller in more active resale markets.

We measure a firm's expected return using two alternative methods. The primary measure we use in our analyses is the implied cost of capital (ICC), which Pástor, Sinha, and Swaminathan (2008) show is a good proxy for a stock's conditional expected return under plausible conditions. An advantage of using ICC is that it does not rely on noisy realized returns or on specific asset pricing models. Specifically, Elton (1999) forcefully argues against using realized returns in asset pricing tests, and Fama and French (1997) show that measures based on standard models are imprecise. Moreover, unlike tests based on returns, the ICC detects a positive risk-return tradeoff (Pástor, Sinha, and Swaminathan (2008)) and a positive relation between distress risk and expected returns (Chava and Purnanandam (2009)).[2] 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 asset liquidity 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. In our initial univariate tests using both the implied cost of capital and the Fama-French cost of capital as well as alternative measures of asset liquidity, we find an *asset-liquidity discount*, that is, the cost of capital is lower for firms in the highest versus the lowest asset-liquidity quintiles. Our estimates range from 2.72 to 6.52 percentage points lower depending on the measure of asset liquidity. Moreover, consistent with the theoretical argument that operating inflexibility causes time-varying equity risk, in time-series tests we find that the asset-liquidity discount is strongly counter-cyclical. Thus, our initial evidence shows that there is an asset-liquidity discount which is likely to be driven by costly reversibility of investment.

Consequently, in firm-level tests we further examine the relation between asset liquidity and the cost of capital by exploiting the rich panel structure of our data. Our cross-sectional multivariate tests show that firms with higher asset liquidity have a lower implied cost of capital and a lower Fama-French cost of capital than firms with lower asset liquidity. Our within-industry time-series tests show that during periods of high asset liquidity in the industry a firm's implied cost of capital is lower

[2] While the ICC uses analysts' forecasts, Campello, Chen, and Zhang (2009) 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.

than it is during periods of low asset liquidity. These tests imply that a one-standard deviation increase in asset liquidity across firms decreases the implied cost of capital by 1.4 to 1.9 percentage points and a similar increase in an industry's asset liquidity over time decreases the implied cost of capital by 0.5 to 1.5 percentage points.

Our measure of asset liquidity based on M&A activity allows us to further distinguish between inside asset liquidity, the value of M&A activity involving acquirers that operate within the industry, and outside asset liquidity, 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 operating the asset. Suggesting that inside buyers provide more liquidity in asset markets than outside buyers, we find that inside liquidity reduces firms' implied cost of capital by more than outside liquidity. These findings are consistent with the recent results for mergers in Almeida, Campello and Hackbarth (2009), who show that when industry-level asset specificity is high financially distressed firms are often able to sell their assets to more financially flexible firms in their industries instead of selling them to industry outsiders.

We also explore which competitive factors affect the importance of asset liquidity in explaining firms' cost of capital. We first study the role of the competitive risk a firm faces in product markets. Asset liquidity should be more valuable for firms in more competitive industries, where competition is fiercer due to lower barriers to entry. It should also be more valuable for the smallest firms in an industry, since these firms are more exposed to competitive threats from larger rivals and have a higher likelihood of exit in industry restructurings. Supporting these predictions, we find that asset liquidity decreases the implied cost of capital mostly for firms in competitive industries and for firms with smaller market shares.

Our arguments suggest that asset liquidity is valuable because it allows firms to scale down their operations and to raise cash with asset sales. This suggests that the effect of asset liquidity on the cost of capital should depend on a firm's access to external financing, its financial situation, its investment opportunities, and its economic environment. Supporting this view, we find that the negative effect of asset liquidity on the implied cost of capital is stronger for firms with no debt ratings, with higher probability of default, with lower market-to-book value of assets, and for those operating during industry downturns.

In further robustness tests we show that the effect of asset liquidity 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 suggests that our findings are not biased by a correlation between our measures of asset liquidity and changes in industry valuation or the supply of capital. Moreover, our main results hold in industry-level tests, they are robust to measuring expected returns using the unlevered implied cost of capital, and are not driven by biases in analysts' forecasts. They also hold if we measure asset liquidity using the average acquisition premium in the industry, when we use segment-weighted measures of asset liquidity, and if we control for stock liquidity or cash holdings.

Our paper is closely related to 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. Moreover, 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 financial distress.[3] Similarly, Almeida, Campello, and Hackbarth (2009) show that when assets are transferrable within the industry inside-industry buyers purchase 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 credit ratings and lower credit spreads. We add to this literature by showing that the flexibility provided by asset liquidity significantly reduces a firm's cost of equity capital.

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 presents additional robustness tests. Section 6 concludes.

[3]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.

II. The Value of Asset Liquidity and the Cost of Capital

Our framework is based on the recent corporate finance and 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 the role of asset liquidity, Pulvino (1998) and Ramey and Shapiro (2001) document significant price discounts for asset sales in illiquid markets.

The corporate finance literature suggests that asset liquidity enhances a firm's operating flexibility and thus it may reduce the cost of capital by facilitating firms' restructuring processes (e.g., Maksimovic and Phillips (1998), and Schlingemann, Stulz, and Walkling (2002)), which is especially valuable to firms facing economic adversity (e.g., Lang, Poulsen, and Stulz (1995), Weiss and Wruck (1998), and Almeida, Campello, and Hackbarth (2009)). Moreover, the asset pricing literature (e.g., Kogan (2004), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006)) also suggests that firms facing illiquid asset markets are unable to sell unproductive assets to cut their fixed costs in times of low demand, and thus the higher operating risk leads investors to require higher returns for the capital they provide. These arguments lead to our central hypothesis:

Main Hypothesis: Asset liquidity reduces firms' cost of capital by increasing their operating flexibility.

To guide our analysis we develop several testable predictions that follow from our main hypothesis. First, note that our hypothesis has two broad implications that should hold *at the aggregate level*. Specifically, there should be a negative spread in cost of capital between the high and low asset-liquidity firms, that is, an asset-liquidity discount. 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 asset liquidity is more valuable 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 asset-liquidity discount should be counter-cyclical. These implications are summarized below:

Prediction 1: At the aggregate level, there should be an asset-liquidity discount in the cost of capital that exhibits a counter-cyclical time-series variation.

We now derive several predictions that can be tested in multivariate analyses *at the firm level* by exploiting the rich panel structure of our data. The first prediction relates asset liquidity to the cost of capital and follows directly from our main hypothesis:

Prediction 2: Firms with a more liquid market for their assets should have a lower 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 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 the presence of inside buyers provides more liquidity in the market for corporate assets than does the presence of outside buyers, and thus should have a stronger effect on firms' cost of capital. This intuition leads to our third prediction:

Prediction 3: Inside asset liquidity should decrease a firm's cost of capital more than outside asset liquidity.

Our remaining predictions deal with the question of what may drive the *cross-sectional* variation in the strength of the effect of asset liquidity on the cost of capital. We first focus on the roles of competition in product markets and a firm's competitive position. Previous research in industrial organization shows that product market competition is more intense in more competitive industries. At the one extreme, in highly concentrated markets barriers to entry entrench incumbent firms in their market positions. At the other extreme, the free entry of firms in competitive industries makes markets highly contestable, and firms that fail to quickly adapt to a changing environment are drawn out of business. Consistent with this view, Hou and Robinson (2006) empirically show that the stocks of firms operating in more competitive industries earn higher average returns. This logic suggests that the operating flexibility provided by a more liquid market for assets is more valuable to firms in more competitive industries because they face higher competitive risk.

In addition, a firm's relative position in the industry is also an important determinant of its competitive risk. Unlike the largest firms in the industry (the "industry leaders"), who have well-established industry positions, the smallest firms in an industry (the "followers") have a higher competitive risk due to their weaker industry positions in terms of market share, customer and supplier loyalty, and ability to endure economic hardship. Moreover, previous work shows that small firms are more exposed to competitive threats from larger rivals, and that they account for the majority of exits in industry restructurings.[4] Thus, higher asset liquidity should also be more valuable for the smallest firms in the industry. The arguments above give rise to the following two predictions:

Prediction 4.a: Asset liquidity should reduce the cost of capital more for firms in more competitive industries.

Prediction 4.b: Asset liquidity should reduce the cost of capital more for the smallest firms in each industry.

Our remaining predictions focus on the roles of a firm's access to financing, its financial situation, and its business environment. First, asset liquidity should be more valuable for firms with less access to external capital and for firms that are closer to financial distress. The reason is that such firms may be forced to raise cash with asset sales, for example, to fund new investment in the case of financially constrained firms or to fund existing operations and avert bankruptcy in the case of distressed firms. Supporting the view, Campello, Graham, and Harvey (2009) report that during the recent financial crisis financially constrained firms have engaged in significantly more asset sales than have unconstrained firms. Second, as discussed

[4]Moreover, the empirical evidence suggests that one reason smaller stocks are more risky is because they are associated with higher distress risk (e.g., Chan and Chen (1991)).

before asset pricing theory suggests that a firm's ability to sell its assets is more valuable in bad times, such as when firms have low market-to-book ratios or during industry-wide recessions (e.g., Kogan (2001) and Zhang (2005)). The reason is that it is in bad times when firms may want to sell assets to reduce their fixed costs and operating risk or to raise cash. These predictions are summarized as follows:

Prediction 5.a: Asset liquidity should reduce the cost of capital more for firms with less access to capital and for firms that are closer to default.

Prediction 5.b: Asset liquidity should reduce the cost of capital more for firms with lower valuations and for firms facing negative demand shocks.

III. Data and Variables

A. 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 asset liquidity 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.[5]

B. Measures of Asset Liquidity

Previous work on how asset liquidity 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 (2008)). Given that we aim to study whether asset liquidity affects firms' cost of capital it is important

[5]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.

that we measure asset liquidity for firms in a broad number of industries and over a long sample period.

Throughout the paper we use three main measures of asset liquidity. The first two capture the presence of *potential future buyers* from within the industry and are motivated by Shleifer and Vishny (1992) and 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, financially-flexible industry insiders are the most likely buyers of a firm's assets in the event the firm wishes to sell them in the near future. It then follows that a firm's assets are more liquid when there is a larger number of potential inside-industry buyers with financial slack.

Specifically, our first measure of asset liquidity is similar to those used in Benmelech and Bergman (2009) and Gavazza (2008) for the airline industry. This measure is the number of potential buyers for a firm's assets, *NoPotBuy*, defined as the number of rival firms in the three-digit SIC industry that have debt ratings. In a similar vein, our second measure, denoted *MNLPotBuy*, directly captures the financial slack of potential buyers, and is defined as *minus* the average book leverage net of cash of rival firms in the three-digit SIC industry, averaged over the last 5 years to minimize the impact of temporary changes in firms' financial situations. Given the definition of these variables, a firm's assets are more liquid for higher values of both *NoPotBuy* and *MNLPotBuy*.

Our third measure of asset liquidity follows Schlingemann, Stulz, and Walkling (2002) and it captures the *historical liquidity* of a firm's assets using 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 the Securities Data Corporation (SDC).[6] We include both mergers and acquisitions of assets. Ac-

[6] We focus on transactions involving publicly traded targets because the Compustat firms for which we wish to measure asset liquidity are publicly traded. Moreover, transactions involving private targets are likely to be reported with noise due to the weaker disclosure requirements for these transactions.

quisitions of assets are particularly important as they comprise approximately 75% of the total deals. If SDC does not report corporate transactions in an industry-year, we set the value of transactions equal to zero. We then scale the value of transactions in the industry by the total book value of assets in the industry, and further 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 smooths 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 asset-liquidity measure is denoted *TotM&A*.[7]

We further decompose our third measure of asset liquidity to distinguish between inside buyers of assets – those who operate in the same three-digit SIC industry as the target – and outside buyers – those who do not currently operate in the industry. Again we use the Compustat Segment tapes to further refine this calculation. We classify a purchase as an inside purchase if the buyer has any segments with the same there-digit SIC code as the assets purchased – checking over each reported SIC code of the target if the target reports multiple SIC codes. *InsM&A* is 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. *OutM&A* is 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.

To facilitate the comparison of the effect of *NoPotBuy, MNLPotBuy, TotM&MA, InsM&A,* and *OutM&A* on the cost of capital, we standardize all original asset liquidity variables by subtracting their sample mean and dividing by their sample standard deviation. With this transformation all measures of asset liquidity have mean zero and standard deviation of one. Hence, in regressions of the cost of capital on asset liquidity the coefficient of any asset liquidity variable can be interpreted as the change in the cost of capital for a one-standard-deviation increase in the measure of

[7] 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.

asset liquidity.

C. Measures of Cost of Capital

We construct two different measures of a firm's cost of equity capital. Our main measure is the implied cost of capital (*ICC*) developed by Gebhardt, Lee, and Swaminathan (2001) and our second measure, which we use to assess the robustness of the results based on *ICC*, is the cost of capital that arises from the three-factor model of Fama and French (1993). While we report results for both measures, we focus mainly on the *ICC* as a proxy for expected returns for several reasons. Its main advantage is that it does not rely on potentially noisy realized asset returns or on specific asset pricing models. Moreover, in a recent study Pástor, Sinha, and Swaminathan (2008) show that if both dividend growth and conditional expected returns follow AR(**??**) 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 risk-return tradeoff. In addition, Chava and Purnanandam (2009) show that the *ICC* detects a positive relation between distress risk and expected returns instead of the puzzling negative relation that is obtained using realized returns.[8] Due to these attractive features, ex-ante measures of expected returns, such as *ICC*, are used in various other recent studies of the cost of capital (e.g., Kaplan and Ruback (1995), Claus and Thomas (2001), Fama and French (2002), Lee, Ng, and Swaminathan (2003), Brav, Lehavy, and Michaely (2005), Chen, Petkova, and Zhang (2008), and Chen, Kacperczyk, and Ortiz-Molina (2009)).

Following Gebhardt, Lee, and Swaminathan (2001), the implied cost of capital 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:

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

where P is the stock price, D is dividends, r_e is the discount rate, and $E(.)$ is the

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

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*:

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

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

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 ROEs 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. We refer the reader to Gebhardt, Lee, and Swaminathan (2001) for more detail on the calculation of *ICC*.

We follow recent research in finance (e.g., Pástor, Sinha, and Swaminathan (2008) and Chava and Purnanandam (2009)) and calculate the *ICC* using the approach in Gebhardt, Lee, and Swaminathan (2001), but other approaches are also used in the literature. These approaches are also consistent with the discounted dividend valuation model, and also obtain the *ICC* as the discount rate that equates the current stock price to the present value of expected future cash flows derived from analyst forecasts. However, they differ in how they use the analyst forecast data (e.g., residual income or abnormal earnings) and in their assumptions (e.g., on growth rates and forecasting horizons). Nevertheless, the various implementations give rise to measures of the implied cost of capital that are highly correlated. Moreover, previous work shows that the results of empirical tests based on alternative measures or indices that aggregate them are qualitatively similar (e.g., Hail and Leuz (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 we show that biases in analysts' forecasts do not drive the results in our tests based on the *ICC*. In addition, we assess the robustness of our 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.

Specifically, 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):

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

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 (month and year subscripts omitted for brevity). We then construct the Fama-French cost of capital of firm j in year t as follows:

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

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.

D. Control Variables

In addition to asset liquidity, in our analyses we include control variables that capture well-known determinants of a firm's cost of capital. *LogAssets* is the logarithm of total assets (AT); *M/B* is the market-to-book 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 [9]; *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.

E. 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%.[10] All standardized asset liquidity variables (*NoPotBuy, MNLPotBuy, TotM&MA, InsM&A,* and *OutM&A*) have by construction mean zero and standard deviation of one. Using the original (non standardized) asset liquidity variables, the mean value of *NoPotBuy* is 13.4 firms, the mean value of *MNLPotBuy* is -0.068, and the mean value of *TotM&A*

[9] 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).

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

is 4.2%. We split *TotM&A* into inside liquidity (*InsM&A*) and outside liquidity (*OutM&A*), which each roughly account for half of the total asset liquidity 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. Moreover, although not tabulated, our asset liquidity measures exhibit low correlation with the control variables.

We further inspect the sources of variation in our asset liquidity measures by estimating a regression of each measure on three-digit SIC industry dummies. This approach allows us to decompose the total variation in each asset liquidity variable into the variation due to time-invariant differences across industries and within-industry time-series variation. We find that 76.5% of the total variation in *NoPotBuy* is across industries and 23.5% is time-series variation; 78.2% of the total variation in *MNLPotBuy* is across industries and 21.8% is time-series variation; and 40.4% of the total variation in *TotM&A* is across industries while 59.6% is time-series variation. Hence, industry asset liquidity measures exhibit substantial variation both in the cross section and in the time series. We use both of these sources of variation to identify our results in the subsequent sections.

IV. Main Empirical Results

A. *The Aggregate Asset-Liquidity Discount and its Business-Cycle Variation*

Our hypothesis suggests that firms with more liquid markets for their real assets should have a lower cost of capital. In Table 2 we start our investigation of this issue by relating our three alternative measures of asset liquidity to a firm's cost of capital using a univariate approach. For this purpose, in each year we sort firms into quintiles according to the asset liquidity of their industries, where Q1 denotes the low and Q5 denotes the high asset-liquidity quintiles. We then calculate the average asset liquidity and the average cost of capital for each quintile across all years. The last two columns report the difference in asset liquidity and cost of capital between the highest and lowest asset-liquidity quintiles, and the corresponding p-value, respectively.

In Panels A, B, and C we measure a firm's expected return using the implied cost of capital (*ICC*) and asset liquidity using *NoPotBuy*, *MNLPotBuy*, and *TotM&A*, respectively. For all three measures of asset liquidity, we observe a monotonically decreasing pattern in the implied cost of capital as we move from the lowest asset-liquidity quintile to the highest asset-liquidity quintile. This relation is economically significant: Using the equal-weighted portfolios, the negative spread in the cost of capital between asset-liquidity quintiles 5 and 1 is 4.29 percentage points per year when asset liquidity is measured with *NoPotBuy,* 5.08 percentage points per year when it is measured with *MNLPotBuy*, and 3.96 percentage points when it is measured with *TotM&A*. All of these differences are statistically significant at the 1% level. The value-weighted portfolios provide similar results. Thus, consistent with our first prediction, the univariate evidence suggests that there is an economically important asset-liquidity discount in firms' cost of capital.

Albeit the evidence in Fama and French (1997) showing that measures of expected returns based on standard asset pricing models are noisy and imprecise, in Panel D we repeat our portfolio-sort analysis using the Fama-French cost of capital (*FFCC*). 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). For all three measures of asset liquidity, we find a monotonically decreasing pattern in the value-weighted Fama-French cost of capital as we move from the lowest asset-liquidity quintile to the highest asset-liquidity 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 Panels A-C 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 an asset-liquidity discount.

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 asset-liquidity discount to the business cycle. If asset liquidity decreases firms' cost of capital because it increases firms' operating flexibility, we should expect the asset-liquidity discount to be larger in periods of low economic activity. Thus, we also study the time-series variation in the aggregate asset-liquidity discount, that is, in the spread between the cost of capital for firms in the top and bottom asset-liquidity quintiles.

In Table 3 we report the results of univariate time-series regressions of the aggregate asset-liquidity discount on alternative business-cycle indicators. For both the implied cost of capital and the Fama-French cost of capital we conduct our tests using the three different measures of the asset-liquidity discount, which are based on *NoPotBuy*, *MNLPotBuy*, and *TotM&A*, respectively. Following the asset pricing literature, we proxy for macroeconomic conditions using GDP growth, capacity utilization, inflation rate, T-bill rate, stock market returns, and default spread on corporate bonds. *GDP Growth* is the year-over-year growth in the fourth quarter's GDP; *Capacity Utilization* is the utilization rate of installed capacity during the fourth quarter of the year; *Inflation* is the year-to-year change in the December's Consumer Price Index; *T-Bill Rate* is the average three-month Treasury Bill Rate during the year; *Default Spread* is the average difference between the yield on Moody's Baa corporate bonds and the yield of ten-year government bonds during the year; and *Market Return* is the annual return on the market index. The regressions with the asset-liquidity discount based on *NoPotBuy* use the 22 annual observations in the period 1985-2006 and those with discounts based on *MNLPotBuy* and *TotM&A* use the 23 annual observations in the period 1984-2006. Our standard errors are corrected for potential autocorrelation using the Newey-West (1987) adjustment. Note that because the asset-liquidity spread is negative, a positive coefficient on any indicator implies that a higher value decreases the magnitude of the asset-liquidity discount.

In Panel A we report the results using the implied cost of capital. The results are similar for all three measures of the aggregate asset-liquidity discount. They show that the discount 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 *R2* 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 asset-liquidity discount.

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 asset-liquidity discount. Overall, the models show that the asset-liquidity discount 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 asset-liquidity discount in firms' cost of capital that is strongly counter-cyclical. This finding is consistent with the view that the operating flexibility provided by a liquid market for corporate assets is more valuable 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 asset liquidity and the cost of capital. Hence, we now turn to a multivariate analysis that exploits the panel structure of our data to address these issues.

B. *Multivariate Evidence Relating Asset Liquidity and the Cost of Capital*

In this section we test our second prediction of a negative association between asset liquidity and cost of capital at the firm level. In our benchmark empirical model we regress firms' cost of capital (*ICC* or *FFCC*) on each of the three measures of asset liquidity (*NoPotBuy*, *MNLPotBuy*, and *TotM&A*) and control for well-known 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*).

Throughout the paper we estimate our empirical models using the conservative method of running pooled (panel) OLS regressions and calculating the standard errors by clustering at the three-digit SIC industry level (using our 304 SIC industry groupings). This approach specifically addresses the concern that our asset-liquidity measures are constructed at the industry level but the cost of capital and the controls are firm-level variables. The worry is that the errors, conditional on the independent variables, are correlated within three-digit SIC industry groupings. One reason why this may occur is that industry factors may have a similar effect on the equity risk of all firms in the industry. Clustered errors assume that observations are independent across industries, but not necessarily independent within industries. The clustering method makes weak assumptions about the correlation structure of the error term, and thus is likely to provide the most conservative standard errors.

Panel A of Table 4 reports the results of regressions of the implied cost of capital (*ICC*) on the three measures of asset liquidity (*NoPotBuy*, *MNLPotBuy*, and *TotM&A*) and the control variables. Noteworthy, including *LogInvPrice* and *M/B* in the regression eliminates the concern that our measures of asset liquidity may be correlated with stock prices and thus mechanically drive the *ICC*. We include *RetPM* to control for the potential sluggishness of analysts forecasts, but the results are similar if we control for the past three-, six-, and twelve-month stock returns. We estimate our empirical models using two approaches.

In columns (1),(3), and (5) we run purely cross-sectional regressions based on the time-series averages of the variables for each firm over the sample period. Thus, we rely solely on the variation in asset liquidity across industries to identify its effect on a firm's cost of capital. For all three measures of asset liquidity, we find that firms in industries with a more liquid market of corporate assets have a lower cost of capital. These effects are highly statistically significant. Since our asset liquidity measures are standardized, the coefficient estimate on each measure gives the percentage-point change in the *ICC* for a one standard-deviation increase in asset liquidity. The cross-sectional effect is also economically significant: A one-standard deviation increase in asset liquidity decreases the cost of capital by 1.8 percentage points per year if we measure asset liquidity using *NoPotBuy*, by 1.9 percentage points if we measure it using *MNLPotBuy*, and by 1.4 percentage points if we measure it using *TotM&A*, respectively.[11]

In columns (2), (4), and (6) we run pooled (panel) OLS regressions with three-

[11] The results are similar in both magnitude and statistical significance if we estimate our empirical model using pooled OLS regressions with year dummies or using the Fama-MacBeth approach.

digit SIC industry dummies and year dummies, and thus use the time-series variation in the measures of asset liquidity within industries to identify our results. The advantage of this approach is that it diminishes the concern that omitted industry factors correlated with both asset liquidity and cost of capital could drive our results. The cost, however, is that it ignores the large variation in asset liquidity across industries and thus it diminishes the power of our tests. Nevertheless, we continue to find a negative and statistically significant relation between all three measures of asset liquidity and the cost of capital. These time-series tests imply that a one-standard deviation increase in an industry's asset liquidity decreases the cost of capital for firms in that industry by about 1.5 percentage points per year when asset liquidity is measured by *NoPotBuy*, by 1.1 percentage points when it is measured by *MNLPotBuy*, and by 0.5 percentage points when it is measured by *TotM&A*, respectively.

In Panel B we report the results of regressions of the Fama-French cost of capital (*FFCC*) on the three measures of asset liquidity (*NoPotBuy*, *MNLPotBuy*, and *TotM&A*) and all the control variables. We omit the coefficients for the control variables in the interest of space. In columns (1), (3), and (5) we run purely cross-sectional regressions based on the time-series averages of the variables for each firm over the sample period. In these regressions we cluster the standard errors by three-digit SIC industry. In columns (2), (4), and (6) we run Fama-MacBeth regressions and calculate our standard errors using the Newey-West procedure with 6 lags. For both estimation approaches and for all three measures of asset liquidity, we find that firms in industries with a more liquid market of corporate assets have a lower Fama-French cost of capital. These effects are highly statistically significant, although smaller in magnitude than those reported in Panel A.[12] Depending on the specification, a one-standard deviation increase in asset liquidity decreases the cost of capital for firms in that industry by about 0.4 to 0.8 percentage points per year.

In sum, we find a negative association between firms' cost of capital and the liquidity of their assets. This relation holds for tests using the implied cost of capital

[12] We focus on purely cross-sectional estimation approaches because by construction the FFCC exhibits a small time-series variation. The reason is that factor loadings for each firm are based on 5-year rolling window regressions and the average factor returns are constant and common to all stocks.

and the Fama-French cost of capital, and for three different measures of asset liquidity. This evidence lends support for our central hypothesis that asset liquidity is associated with increased operating flexibility. Given the evidence in this section and the previous section, in the remainder of our analyses in the interest of conciseness we concentrate on the implied cost of capital as the main measure of a firm's expected return and do not report additional results for the Fama-French cost of capital.

C. The Distinction Between Inside and Outside Liquidity

To test our third prediction that inside asset liquidity should decrease firms' cost of capital by more than outside asset liquidity we split our measure of asset liquidity based on M&A activity into two components. These are inside industry asset liquidity (*InsM&A*), which captures the value of M&A activity in the industry involving acquirers that operate within the industry, and outside industry asset liquidity (*OutM&A*), which captures the value of M&A activity in the industry involving acquirers that operate outside the industry. For this purpose, in Table 5 we run regressions relating these two measures of asset liquidity to firms' cost of capital. In columns (1) and (3) we report the results of purely cross-sectional regressions based on the time-series averages of the variables for each firm over the sample period. In columns (2) and (4) we report the 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.

The table shows that there is a negative and statistically significant effect of both inside and outside liquidity on the cost of capital in the cross-sectional tests. Similarly, both inside and outside liquidity have reduce the cost of capital in the tests which rely in the within-industry time-series variation in asset liquidity, but the effect of outside liquidity is not statistically significant. The striking new result in this table is that inside liquidity has a much larger effect on the cost of capital than outside liquidity. The pure cross-sectional results reported in columns (1) and (3) imply that a one-standard deviation increase in inside liquidity decreases the cost of capital by 1.6 percentage points per year, but a similar increase in outside liquidity only decreases it by 0.7 percentage points per year. This difference is statistically significant. For the within-industry results reported in columns (2) and (4), such an increase in inside liquidity reduces the cost of capital by 0.6 percentage points, but the same increase in outside liquidity reduces it by only 0.2 percentage points. This difference is also statistically significant.

In sum, consistent with our second prediction, we find that inside industry asset liquidity has a much larger negative impact on the cost of capital than outside industry liquidity. This is consistent with the view that inside-industry acquirers can better redeploy the asset than outside acquirers, and thus are willing to pay higher prices. By making asset markets more liquid, the presence of inside buyers better enhances firms' operating flexibility than outside liquidity, and thus has a stronger negative effect on firms' cost of capital.

D. *Cross-Sectional Variation in the Effect of Asset Liquidity on the Cost of Capital*

In this section, we seek to better understand the economic mechanism underlying our previous findings. For this purpose, we explore whether the importance of asset liquidity in explaining firms' cost of capital varies across firms in ways that are consistent with the predictions derived from our main hypothesis.

D.1. Product Market Competition and Relative Industry Position

In Table 6 we test our predictions about how the nature of competition in product markets and a firm's competitive position may affect the value of operating flexibility. In columns (1) and (2) we test prediction 4.a that the operating flexibility provided by a more liquid market for assets is more valuable to firms in more competitive industries. Since the Census only reports the Herfindahl-Hirschman Index (*HHI*) of sales concentration for manufacturing firms but our sample contains a large number of non-manufacturing firms, we calculate a predicted concentration index for all firms in our sample using the approach in Hoberg and Phillips (2009).[13] We then split the sample into firms that operate in a high *HHI* industry (with a predicted *HHI* in the top tercile of the distribution) and those that operate in a low *HHI* industry (with

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

a predicted *HHI* in the bottom tercile of the distribution), and run our benchmark regression with three-digit SIC industry fixed effects and year fixed effects separately for firms in each group. Consistent with our prediction 4.a, the coefficients on both *NoPotBuy* and *TotM&A* are negative and statistically significant for firms in the low *HHI* group, but they are much smaller and not statistically significant or only marginally significant for firms in the high *HHI* group. The p-values for a formal one-tailed test of the null that the effect of asset liquidity is larger in the low *HHI* group than it is in the high *HHI* group are 0.081 for *NoPotBuy* and 0.109 for *TotM&A*, respectively. However, the effect of *MNLPotBuy* does not differ across firms in the high and low *HHI* groups.

In columns (3) and (4) we test prediction 4.b that higher asset liquidity is more valuable for the smallest firms in the industry. The industrial organization literature commonly denotes as "market leaders" those firms whose sales account for a sizable percentage of the total gross sales in their industries. Following Haskel and Scaramozzino (1997) and Campello (2006), we classify as "leaders" firms with market shares of at least 15% in their three-digit SIC industry and classify as "followers" firms with market shares below 15%. We then run our benchmark regression with three-digit SIC industry fixed effects and year fixed effects separately for firms in each group. Consistent with our prediction 4.b, we find that all of our measures of asset liquidity have a large negative and statistically significant impact on the cost of capital of followers, but they have little effect on the cost of capital of industry leaders. For leaders, the coefficients of *NoPotBuy* and *TotM&A* are close to zero and are statistically insignificant, while the coefficient on *MNLPotBuy* is statistically significant and negative but much smaller than it is for followers. The p-values for a formal one-tailed test of the null that the effect of asset liquidity is larger for followers than it is for leaders are 0.046 for *NoPotBuy*, 0.001 for *MNLPotBuy*, and 0.006 for *TotM&A*, respectively.

D.2. Access to Capital, Financial Situation, and Business Environment

In Table 7 we test our predictions that asset liquidity should be more valuable for firms with less access to external financing and higher default risk (prediction 5.a). For this purpose, we first run our benchmark regression with three-digit SIC industry fixed effects and year fixed effects separately for firms high and low access to financing, as well as for firms with high and low probability of default. Since the evidence in Faulkender and Petersen (2006) highlights the importance of having access to public debt markets, in columns (1) and (2) we split the sample into firms with unrated and rated debt. Consistent with prediction 5.a, we find that both *NoPotBuy* and *TotM&A* have a negative and statistically significant effect on the cost of capital of firms with unrated debt, but that this effect is slightly smaller for firms with rated debt. These differences in the effect of asset liquidity across rated and unrated firms are suggestive, but not statistically significant. There is no difference in the effect of *MNLPotBuy* across rated and unrated firms.

In columns (3) and (4) we then split the sample into firms with high default risk 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 across all firms. Our approach in splitting the sample reflects the spirit of industry equilibrium models which highlight the importance of a firm's choices relative to those of its industry rivals (e.g., Williams (1995)). Also supporting prediction 5.a, we find that all measures of asset liquidity have a stronger negative effect on the cost of capital in firms with high default risk than they do in firms with low default risk. In fact, the effect of *TotM&A* is not statistically significant and is close to zero for firms in the low default risk group. The p-values for a formal one-tailed test of the null that the effect of asset liquidity is larger for firm with high default risk than it is for firms with low default risk are 0.102 for *NoPotBuy*, 0.017 for *MNLPotBuy*, and 0.005 for *TotM&A*, respectively.

In Table 8 we examine the predictions that the effect of asset liquidity on firms' cost of capital should be stronger for firms with lower market-to-book ratios and for those facing negative demand shocks (prediction 5.b). To this end, in columns (1) and (2) we split the sample into firms with low and high market-to-book value of assets (V/A), according to whether the distance of a firm's V/A from the industry median is in the bottom or top tercile of the annual distribution across all firms. We then run our benchmark regression with three-digit SIC industry fixed effects and year fixed effects separately for firms in each sample. Consistent with prediction 5.b, for all measures of asset liquidity we find that their negative effect on the cost of capital is larger for firms with low market-to-book ratios than it is for firms with high market-to-book ratios. The p-values for a formal one-tailed test of the null that the effect of asset liquidity is larger for firm with low market-to-book ratios than it is for firms with high market-to-book ratios are 0.154 for *NoPotBuy*, 0.001 for *MNLPotBuy*, and 0.004 for *TotM&A*, respectively.

Last, we examine whether asset liquidity is more valuable for firms in industries experiencing economic downturns. For this purpose, we follow Opler and Titman (1994) and identify a three-digit SIC industry to be experiencing a downturn in a given year when its median sales growth is negative and when its median stock return is below -30%. In columns (3) and (4) we run our benchmark OLS regression with year fixed effects separately for firms in industries experiencing a downturn and those in industries that are not. We do not include the three-digit SIC industry dummies because industry downturns are not long lasting and so few industries remain in the downturn group for more than one year. We find that our measures of asset liquidity are negatively related to the cost of capital and are statistically significant for both samples of firms. Moreover, consistent with prediction 5.b, the effects of *MNLPotBuy* and *TotM&A* are substantially larger in magnitude for firms in industries experiencing downturns than they are for firms in industries that are not. One-tailed tests show that these differences are statistically significant (with p-values 0.008 and 0.001, respectively). For *NoPotBuy*, we find a smaller effect of asset liquidity during downturns, but the difference is small and not statistically significant.

V. Additional Robustness Tests

A. Controlling for Industry Valuation

In this section we explore whether a correlation between our measures of asset liquidity and industry valuations could drive our results. Our first two measures, *NoPotBuy* and *MNLPotBuy* rely only on information on the existence and access to capital of a firm's industry *rivals*, which is largely outside the firm's control. In addition, they are not directly related to stock prices or industry valuations. However, industry valuations could indirectly affect *NoPotBuy* if during periods of high industry valuation new firms enter the industry or acquire debt ratings, and they could affect *MNLPotBuy* if during these periods industry rivals change their capital structures.

More importantly, it is conceptually possible that our tests using *TotM&A* may suffer from reverse causality: during periods of high industry valuations firms in the industry have a low cost of capital, which in turn may lead to increased M&A activity in the industry. In our prior analyses we address this issue by controlling for a firm's market-to-book ratio and stock price. We also show that our results hold in pure cross-sectional tests which do not use the time-series variation in asset liquidity.

We further explore whether our results are driven by the time-series variation in industry valuations. For this purpose, in Table 9 we repeat our analyses after explicitly controlling for two alternative measures of industry valuations constructed at the three-digit SIC industry level. The first is the logarithm of the average market-to-book equity ratio in the industry (*LogIndMB*). The second is the industry's valuation relative to historical values (*IndRelVal*). As in Hoberg and Phillips (2009), we construct this variable as the difference between the industry's log market-to-book equity ratio and its predicted value from the benchmark specification in Pástor and Veronesi (2003). In columns (1) and (3) we run purely cross-sectional OLS regressions using the time-series averages of the variables over the sample period for each firm and in columns (2) and (4) we run pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects. In columns (1) and (2) we control for *LogIndMB* and in columns (3) and (4) we control for *IndRelVal*, respectively.

Including these industry valuation and miss-valuation measures in our regression models does not have a significant effect on the coefficients on *NoPotBuy*, *MNLPotBuy*, or *TotM&A*, which remain negative and statistically significant for both estimation approaches. The results suggest that a correlation between our measures of asset liquidity with industry valuations does not drive our results. They also suggest that a reverse causality driven by changes in industry valuations over time does not explain our results based on *TotM&A*.

B. Industry-Level Tests

Our main analyses are based on firm-level regressions of the cost of capital on measures of asset liquidity which are largely measured at the industry level. An alternative estimation approach is to convert the cost of capital and our control variables into three-digit SIC industry-level medians and then estimate the regressions at the industry level. Hence, in Table 10 we report the results of industry-level regression models estimated by weighted least squares (WLS), wherein the weights on each industry-year observation are the number of firms in the industry. The coefficient estimates obtained using the cross-sectional approach are reported in columns (1), (3), and (5) and those obtained using the within-industry time-series variation are reported in columns (2), (4), and (6). As we did before, we cluster the standard errors by three-digit SIC industry. In our industry-level tests we continue to find a negative and statistically significant relation between all three measures of asset liquidity and the cost of capital.

C. Tests Based on the Unlevered Cost of Capital

Since previous work suggests that asset liquidity may affect debt capacity (Shleifer and Vishny (1992) and Morellec (2001)), which in turn affects firms' cost of capital, we investigate whether an association between asset liquidity and financial leverage could drive our results. Throughout the paper we deal with this issue by including financial leverage as a control variable in all our tests. In this section, we repeat our tests using the *unlevered* cost of capital, which eliminates any concerns that financial leverage might alter our results.

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

Table 11 reports regressions of the unlevered implied cost of capital on our three measures of asset liquidity. In columns (1), (3), and (5) we run purely cross-sectional OLS regressions using the time-series averages of the variables over the sample period for each firm. In columns (2), (4), and (6) we run pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects. We cluster the standard errors by three-digit SIC industry in all models. The control variables are identical to those we use before, except that we omit financial leverage. Our results show that financial leverage does not explain the effect of asset liquidity on the cost of capital. For all measures of asset liquidity and estimation approaches, we find that the estimated coefficients are similar in both magnitude and statistical significance to those reported in Table 4.

D. Robustness to Biases in Analyst Earnings Forecasts

While the *ICC* is very attractive because it is a forward-looking measure of a firm's expected return, a potential weakness is that it relies on analyst forecasts. In calculating the *ICC* we assume that analysts' consensus forecast is an unbiased estimate of investors' expectations. However, as pointed out by some recent papers (e.g. Easton and Monahan (2005)), one problem with this assumption is that there is evidence that analysts make biased earnings forecasts. This raises the question of whether biased analyst forecasts could in turn bias our inferences.

If analyst forecasts are equally biased for all stocks, then this average bias would not have any effect on our results. However, our analyses could be affected if the bias in analysts' forecasts is related to asset liquidity. If the forecasts are systematically biased in favor of firms with higher asset liquidity, then the estimate of the *ICC* will be biased upwards for these firms. This would lead to an understatement of the effect of asset liquidity on the *ICC*. Conversely, if the forecasts are systematically biased against firms with higher asset liquidity, then the estimate of the *ICC* will be biased downwards for these firms. This would lead to an overstatement of the effect of asset liquidity on the *ICC*.

To address this issue, we first examine whether the bias in analysts' forecasts is related to our asset liquidity measures. The pair-wise correlations between the forecast bias and *NoPotBuy*, *MNLPotBuy*, or *TotM&A* are fairly low (less than 4% in absolute value). We then add the forecast bias to our regressions and repeat our analyses, but consistent with the low correlation between the forecast bias and the asset liquidity variables this has no effect on our results. Last, we re-run our main analyses after dropping from the sample those firms with analysts' forecasts biases in the top 30% or the 50% of the annual distribution. Again, this has no effect on our results. In sum, there is no indication that our results could be driven by the biases in analysts' earnings forecasts.

E. Tests Using a Measure of Asset Liquidity Based on Acquisition Premiums

We examine an additional fourth measure of asset liquidity which also comes from the M&A market. This measure captures the idea that firm's assets are more liquid when targets operating in the industry are sold at higher premiums. Put differently, higher acquisition premiums are likely to be associated with more competition by buyers of a firm's assets.[14]

We calculate this measure using information on all merger deals involving publicly traded targets recorded in SDC. For each deal, we first compute the acquisition premium as (bidder's offer price – target's pre-bid price) / target's pre-bid price, where the target's pre-bid price is its share price 30 days prior to the announcement. For each industry and year with at least one transaction, we compute an average premium across all targets in the same three-digit SIC industry. For industry-years with no transactions, we set the premium to be equal to the minimum premium recorded across all industries in that year. We use this approach because the assets in industries with no transactions are likely to be the least liquid and thus the potential premiums they could obtain if sold are very low. In fact, on average the premium we impute is -34%, that is, a significant price discount.[15] The final measure, *IndPrem*,

[14] We thank Itay Goldstein for this suggestion.

[15] What is the premium that should be assigned to industries with no mergers is not entirely obvious and our approach is not without flaws. However, the key issue is that an imputation is necessary, as otherwise we would be forced to drop from our analysis industries with no merger transactions. Since these industries are likely to be those with the most illiquid assets, dropping

results from averaging the acquisition premium for each industry over the past five years.

We find that a higher value of M&A deals is associated with higher acquisition premiums (the correlation between *TotM&A* and *IndPrem* is 53%). This counters the argument that a higher volume of transactions could in fact be associated with illiquid transactions. Moreover, in analyses that are available upon request, we run our cross-sectional and time-series regressions of the implied cost of capital on *IndPrem* and the control variables in our benchmark empirical model. As we did before, we cluster our standard errors by three-digit SIC industry. For all specifications we consider, we find a negative and statistically significant effect of *IndPrem* on the implied cost of capital. The economic significance of the effect of *IndPrem* is similar to that we obtain using *TotM&A*.

F. Measurement of Asset Liquidity for Multi-Segment Firms

Two of our measures of asset liquidity, *NoPotBuy* and *MNLPotBuy*, depend on identifying the rivals a firm faces in its industry. In our main tests, we assign competitors to each firm based on their primary SIC code. We now further refine these measures to incorporate the individual segments multiple-segment firms operate. The industry-level measures now consider all competitors a firm faces, including the secondary segments of multiple-segment firms.

Using these updated measures of asset liquidity which incorporate multi-segment firms, for each firm we compute a weighted average measure of industry asset liquidity that takes into account the industries in which it operates. We calculate the industry asset liquidity a multiple-segment firms faces as the weighted-average asset liquidity 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. We do this last step for the asset liquidity measure *TotM&A* as well. For all three measures of asset liquidity the results are similar in signficance to those reported.

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those industries would cause a serious sample-selection bias.

G. Controlling for Stock Liquidity and Cash Holdings

It is possible that the liquidity of a firm's assets could be empirically related with a high volume of trading in the firm's stock. Since firms with more liquid stocks tend to have a lower cost of capital, a positive correlation between the liquidity of a firm's real assets and the liquidity of its stock could explain our results. However, the effect of asset liquidity on the cost of capital is unaffected if we control for stock liquidity using a firm's share turnover or the average share turnover of firms in the three-digit SIC industry.

Recent work argues that cash holdings allow a firm to fund investment and to endure negative cash flow shocks (e.g., Opler, Pinkowitz, Stulz, and Williamson (1999), Almeida, Campello, and Weisbach (2004), and Acharya, Almeida, and Campello (2007)). As a result, higher cash holdings are likely to reduce default risk and thus the cost of capital. It then follows that a positive correlation of our measures of real asset liquidity with cash holdings could drive our findings. To address this issue, we repeat our regressions of the implied cost of capital on asset liquidity and further include a firm's raw or excess cash holdings[16] as an additional control variable. However, this does not affect our results.

H. Alternative Methods to Assess Statistical Significance

Since the key test variables in our regression analyses (*MNLPotBuy*, *NoPotBuy*, and *TotM&A*) are measured at the three-digit SIC industry-level, throughout the paper we cluster the standard errors by three-digit SIC industry. For robustness, we re-estimate our main specifications clustering our standard errors by both industry and year, by firm, by year, and by both firm and year, but all of these alternative approaches give t-statistics that are similar or larger than those reported. Hence, the approach we use to assess the statistical significance of our results is conservative.

[16]Excess cash holdings are the residual of a regression of log cash holdings scaled by assets (net of cash) on various predictors identified in previous research (e.g., Opler, Pinkowitz, Stulz, and Williamson (1999)) as well as year and firm fixed effects.

VI. Conclusions

We argue that a more liquid market for real assets reduces a firm's cost of unwinding its capital stock and it increases its ability to raise cash, both of which provide the firm with flexibility in responding to a changing business environment and are especially valuable in bad times - a point that has been shown to be especially true during the recent financial crisis. Thus, we hypothesize that asset liquidity increases a firm's operating flexibility and as a result it reduces the firm's cost of capital.

Consistent with this hypothesis, we find an aggregate asset-liquidity discount in firms' cost of capital that is strongly counter-cyclical. Moreover, we show that firms operating in industries with high asset liquidity have a much lower cost of capital both in cross-sectional and time-series tests. These results are robust to using different measures of potential and historical asset liquidity within an industry, 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.

Our tests also show that the effect of asset liquidity on the cost of capital varies across and within industries in ways that are consistent with operating flexibility being an important determinant of firms' cost of capital. Consistent with theories suggesting that buyers who operate in the same industry are willing to pay higher prices for an asset than buyers who operate outside the industry, we also find that higher asset liquidity from within the industry lowers a firm's cost of capital more than asset liquidity from outside the industry. In addition, asset liquidity lowers the cost of capital more for firms that face more competitive risk in product markets, have less access to external financing, are closer to default, have lower valuations, and face negative demand shocks.

Taken together, our results suggest that asset liquidity 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.

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Table 1
Summary Statistics for Main Variables

The table reports summary statistics for the measures of cost of capital, the asset liquidity measures defined for three-digit SIC industries, 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 implied cost of capital, 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). However, 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. We use various measures of asset liquidity which, for ease of comparison, are standardized to have mean zero and standard deviation of one by subtracting the sample mean and dividing by their sample standard deviation. These measures are as follows: *NoPotBuy* is 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); *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the industry, averaged over the past five years; *TotM&A* is 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; *InsM&A* is 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; *OutM&A* is 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 higher asset liquidity. 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	5th Pctile	95th 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 Asset Liquidity Measures					
NoPotBuy	0.000	1.000	-0.383	-0.950	2.098
MNLPotBuy	0.000	1.000	-0.182	-1.461	1.831
TotM&A	0.000	1.000	-0.361	-1.002	2.243
InsM&A	0.000	1.000	-0.413	-0.792	2.376
OutM&A	0.000	1.000	-0.390	-0.884	2.216
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
Asset Liquidity and the Cost of Capital: Univariate Tests

The table reports the average cost of capital for quintile portfolios of firms formed using three alternative measures of asset liquidity defined for three-digit SIC industries: *NoPotBuy*, *MNLPotBuy*, and *TotM&A*. These measures are standardized to have mean zero and standard deviation of one. *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. For each year we sort firms into quintile portfolios based on the asset liquidity measure in their three-digit SIC industry. We then compute the average cost of capital for each quintile portfolio, and subsequently take the average for each quintile across years. The last column reports p-value corresponding to the test of the difference in means between Quintile 5 and Quintile 1. In Panels A, B, and C we measure a firm's expected return using the implied cost of capital (*ICC*) and rely on the sample described in Table 1. In Panel D we measure a firm's expected return using the Fama-French three-factor model (*FFCC*) and rely on the sample of all firms for which we are able to calculate *FFCC* during 1984-2006.

Panel A: ICC for Quintile Portfolios Based on (standardized) NoPotBuy

	Asset Liquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
Mean NoPotBuy	-0.88	-0.68	-0.36	0.23	1.17	2.05	0.000
Equal-Weighted ICC	12.10%	11.76%	10.73%	9.39%	7.80%	-4.29%	0.000
Value-Weighted ICC	9.86%	9.23%	9.78%	8.90%	7.13%	-2.73%	0.000

Panel B: ICC for Quintile Portfolios Based on (standardized) MNLPotBuy

	Asset Liquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
Mean NLPotBuy	-1.23	-0.65	-0.16	0.50	1.20	2.43	0.000
Equal-Weighted ICC	12.33%	12.29%	11.29%	9.90%	7.25%	-5.08%	0.000
Value-Weighted ICC	11.58%	10.43%	9.56%	8.45%	5.06%	-6.52%	0.000

Panel C: ICC for Quintile Portfolios Based on (standardized) TotM&A

	Asset Liquidity Quintile						
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
Mean TotM&A	-0.92	-0.62	-0.30	0.15	1.24	2.17	0.000
Equal-Weighted ICC	12.54%	11.25%	10.39%	10.28%	8.59%	-3.96%	0.000
Value-Weighted ICC	10.73%	9.34%	9.01%	9.01%	6.92%	-3.80%	0.000

Panel D: Value-Weighted FFCC for Quintile Portfolios Based on (standardized) Asset Liquidity

	Asset Liquidity Quintile						
Asset Liquidity Measure	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	p-value
(1) NoPotBuy	12.30%	10.95%	10.49%	10.48%	9.17%	-3.13%	0.000
(2) MNLPotBuy	11.45%	11.37%	11.33%	10.57%	7.09%	-4.36%	0.000
(3) TotM&A	11.56%	10.74%	10.36%	10.23%	8.73%	-2.83%	0.000

Table 3
Business-Cycle Effects on the Asset-Liquidity Discount

The table reports the results of OLS time-series univariate regressions of the annual average asset-liquidity discount 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 asset-liquidity discount using three alternative measures of asset liquidity defined for three-digit SIC industries which are standardized to have mean zero and standard deviation of one. In all cases the asset-liquidity discount is the difference between the average cost of capital (in %) for firms in the highest and lowest asset-liquidity quintiles. The first asset-liquidity discount is calculated using standardized *NoPotBuy*, which is the number of rival firms in the industry that have debt ratings. The second asset-liquidity discount is calculated using standardized *MNLPBuy*, which is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years. The third asset-liquidity discount is calculated using standardized *TotM&A*, which is defined as 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. Higher values of all three variables are associated with higher asset liquidity. The regressions with the asset liquidity discount based on *NoPotBuy* are based on the 22 annual observations during the period 1985-2006 and the regressions with asset liquidity discounts based on *MNLPotBuy* and *TotM&A* are based on the 23 annual observations during the period 1984-2006 and. *GDP Growth* is the year-over-year growth in the fourth quarter's GDP; *Capacity Utilization* 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 Rate* is the average three-month Treasury Bill Rate during the corresponding year; *Default Spread* 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; *Market Return* 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 calculated using standard errors obtained from a Newey-West procedure that accounts for any significant autocorrelation. The R^2 of each univariate regression is reported in brackets. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Discount in the ICC

			The Dep. Var. is the Asset-Liquidity Discount Based on:		
			NoPotBuy	MNLPotBuy	TotM&A
(1)	GDP Growth	Coef.	0.876***	0.845***	0.750***
		t-stat	(2.86)	(6.50)	(5.50)
		R^2	[19.88%]	[26.27%]	[16.27%]
(2)	Capacity Utilization	Coef.	0.230***	0.299**	0.463***
		t-stat	(4.14)	(2.60)	(5.45)
		R^2	[10.33%]	[17.61%]	[33.11%]
(3)	Inflation	Coef.	0.656***	0.450*	0.972***
		t-stat	(3.42)	(1.81)	(4.12)
		R^2	[9.80%]	[4.78%]	[17.51%]
(4)	T-Bill Rate	Coef.	0.748***	0.728***	0.935***
		t-stat	(3.67)	(7.33)	(8.85)
		R^2	[37.32%]	[45.68%]	[59.20%]
(5)	Default Spread	Coef.	-0.748	-1.802**	-2.789***
		t-stat	(0.75)	(2.08)	(4.39)
		R^2	[1.95%]	[11.67%]	[21.95%]
(6)	Market Return	Coef.	0.038***	0.049***	0.045***
		t-stat	(3.10)	(4.87)	(3.66)
		R^2	[6.25%]	[10.67%]	[7.06%]

Panel B: Discount in the FFCC

			The Dep. Var. is the Asset-Liquidity Discount Based on:		
			NoPotBuy	MNLPotBuy	TotM&A
(1)	GDP Growth	Coef.	0.845**	0.455***	0.550***
		t-stat	(2.30)	(4.66)	(5.53)
		R^2	23.15%	13.41%	17.37%
(2)	Capacity Utilization	Coef.	0.483***	0.140**	0.234***
		t-stat	(4.00)	(2.58)	(5.64)
		R^2	56.93%	6.78%	16.72%
(3)	Inflation	Coef.	0.474*	0.884***	0.398
		t-stat	(1.85)	(6.18)	(1.32)
		R^2	6.40%	32.40%	5.82%
(4)	T-Bill Rate	Coef.	0.525***	0.391***	0.333***
		t-stat	(3.56)	(3.05)	(4.41)
		R^2	23.00%	23.11%	14.91%
(5)	Default Spread	Coef.	-3.570***	-1.120***	-1.544***
		t-stat	(5.91)	(4.45)	(4.50)
		R^2	55.62%	7.92%	13.34%

Table 4
Asset Liquidity and the Cost of Capital: Multivariate Analysis

The table reports the results from regressions of the implied cost of capital (*ICC*) and the Fama-French three-factor model cost of capital (*FFCC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A,*) and a set of control variables. Panel A reports the results using *ICC*. In columns (1), (3), and (5) 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. In columns (2), (4), and (6) we report a pooled (panel) OLS regression with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. Panel B reports the results using *FFCC*. In columns (1), (3), and (5) 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. In columns (2), (4), and (6) we report Fama-MacBeth regressions and report t-statistics which are adjusted for autocorrelation using the Newey-West procedure based on 6 lags. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. The control variables 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. 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.

Panel A: The Dependent Variable is the Implied Cost of Capital (ICC)

	(1)	(2)	(3)	(4)	(5)	(6)
NoPotBuy	-0.018***	-0.015***				
	(5.65)	(2.97)				
MNLPotBuy			-0.019***	-0.011***		
			(7.08)	(6.36)		
TotM&A					-0.014***	-0.005***
					(9.40)	(2.64)
LogAssets	-0.005***	-0.001	-0.008***	-0.001	-0.007***	-0.001
	(4.48)	(1.12)	(7.83)	(1.18)	(7.08)	(1.36)
M/B	-0.008***	-0.004***	-0.008***	-0.004***	-0.009***	-0.004***
	(5.63)	(5.19)	(5.75)	(5.02)	(5.52)	(5.28)
DRP	0.036***	0.023***	0.040***	0.022***	0.029***	0.023***
	(7.24)	(9.60)	(8.51)	(10.52)	(5.72)	(10.61)
Blev	0.020*	-0.009	0.003	-0.008	0.033***	-0.008
	(1.94)	(1.18)	(0.26)	(1.08)	(2.74)	(1.07)
ROE	0.002*	0.000***	0.002*	0.000***	0.002*	0.000***
	(1.74)	(3.66)	(1.77)	(3.75)	(1.82)	(3.69)
VolROE	-0.051***	-0.026***	-0.059***	-0.027***	-0.062***	-0.027***
	(6.10)	(8.47)	(6.62)	(8.65)	(8.04)	(9.02)
FA/TA	0.002	0.006	-0.031***	0.006	-0.021*	0.006
	(0.17)	(1.30)	(2.63)	(1.30)	(1.76)	(1.30)
R&DExp	-0.012	-0.012	-0.007	-0.012	-0.017*	-0.013
	(0.85)	(0.90)	(0.58)	(0.89)	(1.75)	(0.97)
LogAge	-0.001*	-0.002**	-0.001	-0.002**	-0.001	-0.002**
	(1.80)	(2.36)	(0.69)	(2.48)	(1.34)	(2.11)
DivPay	0.013***	0.004***	0.016***	0.004***	0.017***	0.004***
	(5.80)	(3.74)	(6.78)	(3.79)	(7.28)	(3.82)
SalGrow	-0.016***	0.003	-0.020***	0.003	-0.015**	0.003
	(3.93)	(0.97)	(3.29)	(0.97)	(2.31)	(1.00)
LogInvPrice	-0.003	0.005***	-0.006***	0.004***	-0.004*	0.004***
	(1.42)	(3.88)	(3.03)	(3.87)	(1.75)	(3.63)
RetPM	-0.025***	-0.011***	-0.030***	-0.009***	-0.030***	-0.010***
	(2.84)	(3.57)	(2.97)	(2.99)	(3.28)	(3.21)
Constant	0.117***	0.148***	0.141***	0.171***	0.141***	0.169***
	(10.72)	(31.53)	(15.68)	(42.33)	(15.99)	(38.02)
Year Dummies	No	Yes	No	Yes	No	Yes
SIC3 Dummies	No	Yes	No	Yes	No	Yes
Estimation	Cross-Sectional	Panel	Cross-Sectional	Panel	Cross-Sectional	Panel
Clustering by SIC3	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6180	33052	6260	33788	6260	33788
R-squared	0.36	0.54	0.34	0.55	0.32	0.54

Panel B: The Dependent Variable is the Fama-French Cost of Capital (FFCC)

	(1)	(2)	(3)	(4)	(5)	(6)
NoPotBuy	-0.004**	-0.005**				
	(2.29)	(2.77)				
MNLPotBuy			-0.006***	-0.005***		
			(3.03)	(5.03)		
TotM&A					-0.008***	-0.004**
					(3.78)	(2.20)
All Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Estimation	Cross-Sectional	Fama-MacBeth	Cross-Sectional	Fama-MacBeth	Cross-Sectional	Fama-MacBeth
Clustering by SIC3	Yes	No	Yes	No	Yes	No
Newey-West 6 lags	No	Yes	No	Yes	No	Yes
Observations	9930	73893	10180	76575	10180	76575

Table 5
Inside Vs. Outside Asset Liquidity and the Implied Cost of Capital

The table reports the results from regressions of the implied cost of capital (*ICC*) on two standardized measures of asset liquidity defined at the three-digit SIC industry level (*InsM&Q* and *OutM&A*) and a set of control variables. In columns (1) and (3) 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. In columns (2) and (4) we report a pooled (panel) OLS regression with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *InsM&A* is 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; *OutM&A* is 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 three variables are associated with higher asset liquidity. 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)
InsM&A	-0.016***	-0.006***		
	(9.09)	(2.78)		
OutM&A			-0.007***	-0.002
			(2.80)	(1.51)
All Control Variables	Yes	Yes	Yes	Yes
Year Dummies	No	Yes	No	Yes
SIC3 Dummies	No	Yes	No	Yes
Estimation	Cross-Sectional	Panel	Cross-Sectional	Panel
Clustering by SIC3	Yes	Yes	Yes	Yes
Observations	6260	33788	6260	33788
R-squared	0.33	0.55	0.29	0.54

Table 6
The Role of Industry Concentration and Industry Position

The table reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A,*) and a set of control variables. All specifications are pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. Columns (1)-(2) split the sample into high concentration industries and low concentration industries according to whether the industry's predicted sales-based Herfindahl-Hirschman Index of concentration (*HHI*) is in the top or bottom tercile of the annual distribution, respectively. Columns (3)-(4) split the sample into industry leaders, defined as firms with at least a 15% market share in their three-digit SIC industry, and industry followers, defined as those with market shares below 15%, respectively. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. 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.

	High HHI (1)	Low HHI (2)	Leaders (3)	Followers (4)
Panel A: The measure of asset liquidity is NoPotBuy				
NoPotBuy	-0.007*	-0.021**	0.003	-0.015***
	(1.94)	(2.33)	(0.32)	(2.94)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	10626	10362	5412	27640
R-squared	0.55	0.60	0.57	0.55
Panel B: The measure of asset liquidity is MNLPotBuy				
MNLPotBuy	-0.011***	-0.010***	-0.004**	-0.012***
	(2.97)	(4.87)	(2.16)	(5.68)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	10853	10582	5552	28236
R-squared	0.56	0.60	0.57	0.55
Panel C: The measure of asset liquidity is TotM&A				
TotM&A	-0.002	-0.007**	-0.000	-0.006***
	(1.02)	(2.10)	(0.32)	(2.74)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	10853	10582	5552	28236
R-squared	0.55	0.60	0.57	0.55

Table 7
The Effect of Access to Debt Financing and Default Risk

The table reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A,*) and a set of control variables. All specifications are pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. Columns (1)-(2) split the sample into firms with debt but no debt ratings and those whose debt is rated, respectively. Columns (3)-(4) split the sample into firms with high distress risk and low distress risk based on whether the distance of a firm's probability of default from the industry median is in the top or bottom tercile of the annual distribution across all firms, respectively. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. 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.

	Unrated Debt (1)	Rated Debt (2)	High Default Risk (3)	Low Default Risk (4)
Panel A: The measure of asset liquidity is NoPotBuy				
NoPotBuy	-0.014**	-0.013***	-0.014***	-0.008***
	(2.55)	(3.65)	(2.78)	(2.75)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	15400	12331	11250	10968
R-squared	0.54	0.54	0.49	0.55
Panel B: The measure of asset liquidity is MNLPotBuy				
MNLPotBuy	-0.010***	-0.011***	-0.014**	-0.009***
	(5.65)	(3.90)	(5.65)	(2.94)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	16079	12331	11501	11211
R-squared	0.55	0.54	0.49	0.56
Panel C: The measure of asset liquidity is TotM&A				
TotM&A	-0.005**	-0.003**	-0.007***	-0.002
	(2.27)	(2.11)	(3.44)	(1.34)
Includes all control variables, year dummies, and SIC3 dummies; standard errors are clustered by SIC3				
Observations	16079	12331	11501	11211
R-squared	0.55	0.53	0.49	0.56

Table 8
The Effect of Market Valuations and Demand Shocks

The table reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A,*) and a set of control variables. All specifications are pooled (panel) OLS regressions with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry (except columns (3) and (4) which have no industry fixed effects). Columns (1)-(2) split the sample into low and high market-to-book value of assets ratios (V/A) based on whether the distance of a firm's V/A from the industry median is in the bottom or top tercile of the annual distribution across all firms, respectively. Columns (3)-(4) split the sample into firms in three-digit SIC industries experiencing an economic downturn and firms in industries that are not experiencing a downturn, respectively. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. 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.

	Low V/A (1)	High V/A (2)	Industry Downturn (3)	Non Industry Downturn (4)
Panel A: The measure of asset liquidity is NoPotBuy				
NoPotBuy	-0.015**	-0.012***	-0.013*	-0.017***
	(2.43)	(2.76)	(1.79)	(4.90)
Includes all control variables and year dummies; standard errors are clustered by SIC3				
SIC3 Dummies	Yes	Yes	No	No
Observations	10915	11250	860	32192
R-squared	0.57	0.54	0.32	0.35
Panel B: The measure of asset liquidity is MNLPotBuy				
MNLPotBuy	-0.013***	-0.009**	-0.034***	-0.019***
	(5.89)	(4.82)	(5.77)	(6.06)
Includes all control variables and year dummies; standard errors are clustered by SIC3				
SIC3 Dummies	Yes	Yes	No	No
Observations	11158	11501	868	32920
R-squared	0.58	0.54	0.38	0.36
Panel C: The measure of asset liquidity is TotM&A				
TotM&A	-0.007***	-0.004**	-0.024***	-0.012***
	(3.04)	(2.01)	(4.78)	(5.23)
Includes all control variables and year dummies; standard errors are clustered by SIC3				
SIC3 Dummies	Yes	Yes	No	No
Observations	11158	11501	868	32920
R-squared	0.57	0.54	0.39	0.33

Table 9
Asset Liquidity and the Implied Cost of Capital: Controlling for Industry Valuation

The table reports the results from regressions of the implied cost of capital (*ICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A*), measures of industry valuation (*LogIndMBE*) or miss-valuation (*IndRelVal*) also defined for three-digit SIC industries, and a set of control variables. In columns (1) and (3) 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. In columns (2) and (4) we report a pooled (panel) OLS regression with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. *LogIndMBE* is the logarithm of the mean market-to-book equity ratio in the firm's industry and *IndRelVal* is the industry's relative valuation, computed as the difference between the industry market-to-book equity ratio and its predicted value based on the benchmark Pastor and Veronesi (2003) specification. 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)
All Control Variables	Yes	Yes	Yes	Yes
Year Dummies	No	Yes	No	Yes
SIC3 Dummies	No	Yes	No	Yes
Estimation	Cross-Sectional	Panel	Cross-Sectional	Panel
Clustering by SIC3	Yes	Yes	Yes	Yes
Panel A: The measure of asset liquidity is NoPotBuy				
NoPotBuy	-0.014***	-0.015***	-0.018***	-0.015***
	(4.51)	(2.98)	(5.69)	(3.00)
LogIndMBE	-0.024***	0.002		
	(5.15)	(1.31)		
IndRelVal			0.006	-0.004
			(1.19)	(1.36)
Panel B: The measure of asset liquidity is MNLPotBuy				
MNLPotBuy	-0.013***	-0.011***	-0.019***	-0.011***
	(5.78)	(6.38)	(7.30)	(6.70)
LogIndMBE	-0.025***	0.003		
	(6.39)	(1.51)		
IndRelVal			0.016**	-0.001
			(2.42)	(0.41)
Panel C: The measure of asset liquidity is TotM&A				
TotM&A	-0.011***	-0.005***	-0.014***	-0.005***
	(8.81)	(2.62)	(9.62)	(2.65)
LogIndMBE	-0.031***	0.002		
	(9.45)	(1.17)		
IndRelVal			0.004	-0.003
			(0.54)	(0.96)

Table 10
Asset Liquidity and the Implied Cost of Capital: Industry-Level Tests

The table reports the results from industry-level regressions of the implied cost of capital (*ICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A,*) and a set of control variables. For this purpose, all firm-level variables are converted into three-digit SIC industry medians for each year. In columns (1), (3), and (5) we report an OLS purely cross-sectional industry-level regression using the time-series averages of the variables over the sample period for each industry, with standard errors clustered by three-digit SIC industry. In columns (2), (4), and (6) we report a pooled (panel) industry-level OLS regression with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. 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)	(5)	(6)
NoPotBuy	-0.012**	-0.015**				
	(2.27)	(2.33)				
MNLPotBuy			-0.016***	-0.013***		
			(3.24)	(5.78)		
TotM&A					-0.011**	-0.003*
					(2.47)	(1.81)
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	Cross-Sectional	Panel	Cross-Sectional	Panel	Cross-Sectional	Panel
Clustering by SIC3	Yes	Yes	Yes	Yes	Yes	Yes
Observations	303	4631	304	4793	304	4793
R-squared	0.59	0.86	0.58	0.85	0.58	0.85

Table 11
Asset Liquidity and Unlevered Implied Cost of Capital

The table reports the results from regressions of the *unlevered* implied cost of capital (*UNLICC*) on the three alternative standardized measures of asset liquidity calculated for three-digit SIC industries (*NoPotBuy, MNLPotBuy,* and *TotM&A*) and a set of control variables. In columns (1), (3), and (5) 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. In columns (2), (4), and (6) we report a pooled (panel) OLS regression with three-digit SIC industry fixed effects and year fixed effects, and standard errors clustered by three-digit SIC industry. The following measures of asset liquidity are standardized to have mean zero and standard deviation of one: *NoPotBuy* is the number of rival firms in the three-digit SIC industry that have debt ratings; *MNLPotBuy* is *minus* the average book leverage net of cash holdings of rival firms in the three-digit SIC industry, averaged over the past five years; and *TotM&A* is 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. Higher values of all three variables are associated with higher asset liquidity. We also include but do not report the coefficients of the following control variables defined in Table 1: *LogAssets*, *M/B*, *DRP*, *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)	(5)	(6)
NoPotBuy	-0.015***	-0.012**				
	(4.33)	(2.49)				
MNLPotBuy			-0.016***	-0.009***		
			(7.35)	(6.29)		
TotM&A					-0.013***	-0.004**
					(8.52)	(2.25)
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	Cross-Sectional	Panel	Cross-Sectional	Panel	Cross-Sectional	Panel
Clustering by SIC3	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6180	33052	6260	33788	6260	33788
R-squared	0.36	0.56	0.36	0.57	0.34	0.57