Two Essays on Corporate Finance: Financing Frictions and Corporate Decisions

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Abstract

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My dissertation focuses on the effect of financial market frictions on firm value in the context of corporate mergers, capital structure and growth. The first chapter explores how financing frictions faced by potential buyers of industry specific real assets affect the transaction value of merger targets that consist of such assets. I find that shareholders of target firms with highly specialized assets receive a significantly smaller premium than targets with generic assets when industry peer firms are financially constrained. Further investigation reveals that firms with specialized assets reduce leverage more than other firms when the risk of liquidation loss is high. The second chapter explores how frictions in the financial market affect corporate capital structure and growth. I present evidence that firms that have experienced financing frictions prior to entering the public debt market undergo significant changes in capital structure and investment as they gain access to the new sources of capital. Overall, the findings in this dissertation highlight the importance of financing frictions as key determinants of capital structure and firm value.

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Chapter 1: Asset Specificity and Firm Value: Evidence from Mergers

1.1 Introduction

Real assets built for specific purposes have few alternative uses. When facing financial distress, owners of such assets may be forced to raise funds through quick asset deployment into an illiquid asset market, causing inefficient allocation of the assets at a price below the assets' fundamental value. Rational owners of specialized assets foresee the potential private cost of such distressed sales and adjust their leverage to mitigate their exposure to such risk.

Prior studies in the literature have focused on identifying the value effect of real asset liquidity on the asset price in specific industries, such as airlines, (Pulvino (1998) and Gavazza (2011)), aerospace manufacturing (Ramey and Shapiro (2001)), and housing (Campbell, Giglio and Pathak (2011)).

The main purpose of this paper is to examine the effect of real asset specificity on the value of the entire firm in a merger. I use a comprehensive sample of completed merger deals between publicly traded targets and publicly traded acquiring firms across industries over a 30-year period to examine the sensitivity of proxies for target firms' premiums to the degree of target firms' asset specificity.

I derive my testable implications from the predictions of the asset liquidity model in Shleifer and Vishny (1992). Shleifer and Vishny define asset liquidity (or illiquidity) as the difference between the realized sales price of an asset and its fundamental value in best use. They highlight two key components that jointly determine the liquidity of an asset. The first component is the degree of asset specificity, which is essentially the difference between the asset's value in best use and its value in second best use. The second component of asset liquidity is the degree of financial constraints faced by potential high valuation buyers, e.g. within-industry peers, at the time of sales. Shleifer and Vishny theoretically show that the combination of a high degree of target firms' asset specialization and the inability of highest valuation buyers to finance the purchase of the assets leads to a sales discount for financially distressed sellers of the assets and inefficient asset reallocation.

Empirically measuring asset liquidity as defined by Shleifer and Vishny (1992) is challenging for two reasons. First, sellers' valuation on their assets is unobservable. Second, direct estimation of the gap between sellers' valuation on the assets and the actual sales price requires detailed transaction records of the assets, which are largely private information. For this reason, the literature has been mostly limited to specific industries in which sales data is publically available (Pulvino (1998), Gavazza (2011), Ramey and Shapiro (2001) and Campbell, Giglio and Pathak (2011)).

This paper takes a different approach. Rather than attempting to directly measure asset liquidity for a single industry, I use proxies that can measure asset specificity for all industries as well as proxies for the degree of buyers' financial constraints separately. With these proxies, I then show that liquidity discount is a common phenomenon and can occur in any industries where these two components of asset illiquidity along with selling firms' financial distress are jointly at work.

To generate a proxy for the degree of asset specificity, I follow the method by Kim and Kung (2011) using the US Bureau of Economic Analysis (BEA) industry survey data on new capital asset leases and purchases. This measure is constructed by first estimating the potential valuation gap among the 123 user industries on the 180 fixed asset types tracked in the BEA report. I proxy for this potential valuation gap by gauging how narrow the demand for each fixed asset type is across using industries. Then, I generate a weighted average of this cross-industry demand for all fixed asset types within each using industry based on the dollar amount spent on each fixed asset type by the industry. This measure is designed to capture the degree of specialization of assets for each using industry.

As for the second component of asset liquidity, which is the degree of financial constraints faced by potential highest valuation buyers, I use the following three proxies drawn from Shleifer and Vishny (1992) and Harford (2005): annual median industry cash flows, the average annual commercial and industrial (C&I) loan spread over the Federal Funds rate, and recessions. Lastly, I use firm interest coverage ratio and Altman Z-score from Almeida, Campello and Hackbarth (2011) and Altman (1968, 2000), as the proxies for target firms' financial condition. I then empirically examine the joint effect of target firms' asset specificity and the financing capability of potential highest valuation buyers on target shareholder returns of financially distressed targets using three-day cumulative abnormal returns (CAR) as the primary measure of the purchase price paid to sellers. To address the concern that the stock market may anticipate sales of firms with specialized assets and adjust the firm value before merger deals are made public, I also use the total offer premium paid to target shareholders as the secondary proxy.

The empirical results strongly support the hypothesis that these components of asset liquidity and target firms' financial condition are important determinants of the target firm price. In particular, multiple regression results show that a move from the 25th to 75th percentile in the targets' asset specificity distribution combined with targets' financial distress is associated with an 8% discount in target announcement abnormal returns. Likewise, a move from the 25th to 75th percentile in the targets' asset specificity distribution combined with tight financial market conditions is associated with an 8.3% announcement return discount; and during recessions, a 4.1% discount. When targets are financially distressed *and* potential high valuation buyers are financially constrained, a move from the 25th to 75th percentile in the targets' asset specificity accounts for an announcement return discount of 12.2%. A robustness test result shows that acquirer announcement returns are positively but statistically insignificantly associated with target asset specificity, inconsistent with the alternative explanation that merger deals involving high target asset specificity are value destroying for both firms.

Another important and related prediction made by Shleifer and Vishny (1992) and also by Williamson (1988) is that firms with specialized assets, when faced with the prospect of real asset sales at a large discount due to asset illiquidity, reduce leverage more than firms with generic assets in order to mitigate the risk of such loss. I empirically test this hypothesis as an additional check, and the test results are consistent with their prediction. Multiple regression results show that a move from the 25th to 75th percentile in the targets' asset specificity distribution combined with tight financial market conditions is associated with a 2.2% annual reduction in book leverage. Finally, I present evidence supporting Shleifer and Vishny (1992)'s prediction in a time-series context that the sales price of real assets is closely related to the overall capital liquidity in the economy.

There are a few studies in the literature that explore the joint effect of asset specificity and the availability of highest valuation buyers on the liquidation price (Pulvino (1998), Gavazza (2011), Ramey and Shapiro (2001) and Campbell, Giglio and Pathak (2011)) but the scope of the literature is mostly limited to particular industries due to difficulty in measuring the valuation differences among sellers and potential buyers of assets. While Brown, James and Mooradian (1994) and Lang, Poulsen and Stulz (1995) find a link between target firms' asset illiquidity and their announcement returns on asset sales, they do not separate the valuation effect from other information affecting stock market reactions to merger announcements. One key contribution of this paper is that it offers a way of isolating the valuation effect from other determinants of the target price through a measure of asset specificity. To my knowledge, this is the first paper that documents direct evidence of the joint effect between real asset specificity and the degree of potential buyers' financial capacity on asset price using the comprehensive US merger sample. This paper adds to the literature related to optimal capital structure and asset redeployability (Almeida and Campello (2007) and Sibilkov (2009)) by providing a link between firms' optimal leverage and the firms' sales value. Finally, the implications from this study are also linked to the findings by Custódio, Ferreira and Matos (2012) who examine the effect of CEOs' human capital specificity on CEO pay in light of their relative bargaining power in the labor market.

The rest of the paper is outlined as follows. Section 1 derives testable implications. Section 2 explains empirical methods and provides descriptive statistics. Section 3 reports main empirical results and robustness checks. Section 4 concludes.

1.2 Hypothesis

In this section, I briefly motivate the main predictions and testable implications of this study using the Shleifer and Vishny (1992) model.

In their model, Shleifer and Vishny consider a firm that consists of highly specialized assets. The specific nature of the firm's assets limits the size of the highest valuation buyer pool. The firm faces two possible industrywide states of the world for the future period, prosperity and depression. The firm's shareholders determine the optimal capital structure based on the balance between the benefits and the costs of leverage. In their model, debt is beneficial because it reduces the agency costs of free cash flow in a prosperous state. The cost of using debt is the potential private cost from forced partial or complete liquidation of the firm to raise funds for creditors when the depression state occurs. Specifically, the expected cost of debt is equal to the probability of occurrence of the depression state times the difference between the future cash flows generated by the firm assets in best use and the firm's liquidation price to potential buyers.

An increase in the probability of future financial distress affects the firm's cost of using leverage in two ways. First, a high probability of financial distress means a high probability of forced asset sale. Second, if the reason for financial distress is not idiosyncratic but industrywide, the potential highest valuation buyers of the firm's assets, e.g. industry insiders, are also likely to be financially constrained, unable to buy the selling firm. Then the firm may be sold to lower valuation buyers, e.g. industry outsiders, who place a low value on the firm's assets because of 1) the adverse selection problem from lacking knowledge necessary to properly value the assets, or 2) the potential agency costs from having to hire specialists to manage the acquired firm's assets. This prospect undermines the potential sales price of the firm's assets and drives up the ex ante cost of leverage further.

If the depression state occurs, the firm may raise funds for the creditors by either issuing new securities, rescheduling debt payments or selling its real assets. The opportunity cost of selling the assets declines in the degree of financial distress because potential investors for new securities will demand a reward for taking extra risk from potential asset substitutions (Jensen and Meckling (1976)) and the adverse selection problem (Myers and Majluf (1984)), or because coordinating creditors with varying seniorities and conflicting interests to reschedule debt is difficult (Gertner and Scharfstein (1991)). Potential debt overhang problems may further increase the cost of debt (Myers (1977)).

When the financially distressed firm is sold, two factors determine the extent of the discount in the sales price. First, if the firm assets are so specialized that very few potential highest valuation buyers exist and that the gap between primary and secondary user valuation on the assets is wide, the sale will fetch a price below fundamental value on average. On the other hand, if the firm consists of generic assets with many alternative uses, the price of the assets will be close to the fundamental value. Second, the financing capability of highest valuation buyers at the time of firm sales affects the sales price because they are willing to match or pay more than the price the low valuation buyers are willing to pay, if they are financially unconstrained to acquire the assets.

I apply these predictions to the context of full firm mergers and construct the following testable hypotheses. First, the prediction that asset specificity of the firm's assets limits the size of the highest valuation buyer pool leads to the first hypothesis of this study.

Ha1: *Target announcement returns are negatively related to the target firms' degree of asset* *specificity.*

The opportunity cost of selling a firm declines in the severity of financial distress because the cost of raising funds through alternative channels increases as financial distress deepens. Distressed firms with highly specialized assets are more likely to be sold at a discount because there are fewer high valuation buyers competing for the assets. Pulvino (1998) makes a similar argument that an increasing default probability raises the airline firms' cost of external capital and this in turn makes the airlines more willing to liquidate their airplanes at a deeper discount. Also, if the financial distress is rooted in industrywide factors, the potential high valuation buyers of the assets may be in financial distress as well and so unable to buy the target assets. This prediction leads to the second hypothesis of the study.

Ha2: *The negative sensitivity of target announcement returns to target firms' asset specificity is more pronounced when targets are in financial distress.*

Shleifer and Vishny (1992, 2011) highlight debt capacity of potential high valuation buyers as one of the key determinants for sellers' liquidation prices. The low borrowing cost increases debt capacity of highest valuation buyers and their ability to invest, and competition among the financially unconstrained buyers drives up the prices of specialized assets, narrowing the gap between fundamental value and the sales price. Similarly, Harford (2005) provides evidence that overall capital liquidity in the economy facilitates the clustering of real asset transactions.

Besides low costs of external financing, internally generated funds are another source of financing for potential highest valuation buyers of the target assets. Low overall industry cash flows indicate that potential highest valuation buyers of specialized assets are likely to be financially constrained and unable to finance mergers. These arguments lead to the third hypothesis.

Ha3: *The negative sensitivity of target announcement returns to target firms' asset specificity is more pronounced when the potential highest valuation buyers are financially constrained.*

The fourth hypothesis naturally follows the predictions in Ha2 and Ha3.

Ha4: *The negative sensitivity of target announcement returns to target firms' asset specificity is most pronounced when the two following conditions are jointly met: (1) targets are in financial distress; (2) the potential highest valuation buyers are financially constrained.*

In addition to these main hypotheses, I test for the following implications regarding ex ante leverage response to increased risk of distressed asset sales. When the potential buyers of the assets with highest valuation are financially constrained, the prospect of firms with high asset specificity being sold at a discount increases and this increased risk causes the firms to lower their optimal leverage.

Ha5: *Changes in a firm's leverage are negatively related to the firm's asset specificity when the potential buyers of the firm assets are financially constrained.*

1.3 Data

1.3.1 Asset specificity measure

The key variable in this study is the measure of asset specificity. I follow the procedure by Kim and Kung (2011) to construct an asset specificity measure. The data come from the 1997 Capital Flow Table (CFT) published by the US Bureau of Economic Analysis (BEA).[1] The BEA produced one CFT every 5 years from 1967 to 1997 except for 1987. Among them, the 1997 CFT provides the most complete estimation for purchases and leases of fixed asset types by using industries. CFT differs from the Input-Output Use tables (IOT), also published by the BEA, in that CFT follows each industry's fixed capital investment while IOT tracks general flows of materials and services not limited to fixed assets. This particular feature

[1] The data are available at www.bea.gov/industry/index.htm and the full description of the data, including the detailed comparisons between CFT and IOT, can be found at the following link: www.bea.gov/scb/pdf/2003/11November/1103%20Investment.pdf.

makes CFT more relevant to this study than IOT because the predictions in this paper involve asset specificity of pledgeable assets.

The CFT columns consist of 123 industry classifications that include not only manufacturing sectors but also mining, retail, service, financial, utility and public sectors. The table rows cover 180 different types of fixed assets that include equipment, vehicles, buildings and structures. Land is not included in the CFT table.[2] Each cell in the table shows the total dollar amount of a particular fixed asset type paid by the using industry in producers' prices. If a fixed asset type is not used by an industry, then the corresponding cell is left blank. There is a substantial variation in terms of how widely each asset type is used across different industries. For example, a fixed asset class associated with "drilling gas and oil wells" is used only by two out of the 123 industry categories ("Oils and gas extraction" and "Support activities for mining" sectors), while the "computer terminal" asset class is widely used across industries, 110 out of the 123 industries in total.

As in Kim and Kung (2011), I use the following formula to construct the asset specificity score for each industry:[3]

$$Industry\ asset\ specificity_i = \sum_{a}^{A} \omega_{i,a}(ASpecificity_a)$$

where i represents each of the 123 industries and a represents each of the 180 fixed asset types. $ASpecificity_a$ gauges how narrow the demand for fixed asset type a by different industries is, and the measure is constructed by dividing the number of industries that *do not*

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[2] Kim and Kung (2011) use a second measure of asset specificity that includes land owned by firms. The formula is as below:

$$Specificity_{j,with\ land} = \left(1-\alpha_j^{land}\right)Specificity_{ind}$$

where $Specificity_{j,with\ land}$ is the firm-level asset specificity measure for firm j; $Specificity_{ind}$ is the industry-level asset specificity measure; and α_j^{land} is the sum of the value of land divided by the sum of the value of properties, plant, and equipment (PP&E) for firm j. Repeating all the tests in this paper using this alternative measure in place of the original variable yields results almost identical to the initial results and so I do not report them.

[3] A minor difference between the method used in Kim and Kung (2011) and the one used in this paper is that they exclude an asset from a using industry if the industry's expenditure on the given asset constitutes less than 1% of the total expenditure in the asset in the economy while I do not exclude any asset based on industries' relative expenditure size.

use commodity *a* by the total number of industries, which is 123. For example, $ASpecificity_a$ for the fixed asset type “drilling gas and oil wells” is 121/123 or 0.98 (= (123-2)/123) which indicates a high degree of specificity, while $ASpecificity_a$ for “computer terminal” is only 13/123 or 0.10, which indicates that computer terminals are generic assets. In essence, $ASpecificity_a$ conveys information about how specialized an asset type is to a particular using industry, indirectly capturing the extent of the gap between the asset’s value in best use and value in second best use. $\omega_{i,a}$ measures the relative importance of fixed asset type *a* to the industry *i* and is constructed by dividing industry *i*’s dollar expenditure on *a* by its total dollar expenditures on all fixed asset types in a given year. Finally, $Industry\ asset\ specificity_i$ is the asset specificity score for industry *i*, and it captures how much of industry *i*’s resources is allocated to industry-specific assets. As the final step in compiling the asset specificity score, I convert the BEA industry specification into the 2-digit SIC code by using the concordance tables provided by the BEA and the US Census Bureau in order to make the variable compatible to other data used in this study.[4]

Next, in order to construct a firm level asset specificity measure, I use the firm segment data provided by COMPUSTAT. Specifically, a firm’s asset specificity score is compiled as the weighted average of the segments’ industry asset specificity score, with the ratio of each segment’s book asset value to the firm’s total book value used as the weight for the segment.[5] I remove firm observations from the sample if a firm has segments operating in financial and utility sectors (SIC in 6000s and 4900s) because of the concern that government regulations may affect shareholders’ or management’s incentives surrounding asset liquidation. I also

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[4] I first convert the BEA industry code into the North American Industry Classification System (NAICS) code using the concordance tables provided by the BEA. Then, the 1997 NAICS – 1987 SIC concordance table provided by the US Census Bureau allows me to map the code to the two-digit SIC code. The concordance table can be found at www.census.gov/eos/www/naics/concordances/concordances.html.

[5] I implicitly assume that the true real asset specificity of firm segments is correlated with real asset specificity of segment industries at the two-digit SIC level.

exclude observations if acquirers are operating in financial and utility sectors for the same reason.

The 1997 CFT data is based on new investment in that year rather than assets already in use, and I make two assumptions in using this measure as the proxy for asset specificity of assets-in-place over time. The first assumption is that the types of assets in which an industry invests are similar to the assets the industry already has in place for operation.[6] Another assumption I make about the measure is that an industry's asset specificity does not vary substantially over time. I argue that this is a reasonable assumption, because what determines asset specificity is asset composition and not the total volume of assets used. For example, when demand for crude oil falls and the low demand state continues, the oil extraction industry's total output will be reduced and along with it the absolute volume of fixed assets used for operation, e.g. oil rigs. However, the industry's asset specificity will change little over time as long as the industry shrinks the amount of other types of fixed assets, e.g. office buildings for staff, roughly in the same proportion. Similarly, Ahern (2012) assumes time invariability of buyer-seller industry bargaining power for his time-invariant measure of industry interdependence, constructed from the 1997 BEA Use and Makes tables.

As an indirect way of testing my assumptions on the asset specificity measure, I construct the industry asset specificity measure using the 1992 CFT table and estimate the correlation coefficient between the scores compiled using the 1992 table and the 1997 table.[7] The correlation coefficient between the two scores is over 84% and statistically different from zero at the 0.1% level, even though the BEA used different definitions for commodities and industries to produce these two tables. This result provides support for my argument that industries' asset composition is persistent over time. The results of this paper do not change

[6] Almeida and Campello (2007) make a similar assumption in their study of asset tangibility and financial constraints. My assumption is a bit stronger than theirs in that my sample includes firms in non-manufacturing sectors whereas their study concerns manufacturing firms only.

[7] The 1992 CFT table is available at www.bea.gov/industry/index.htm. BEA does not provide 1987 data.

qualitatively even if I use the asset specificity score generated using the 1992 data instead of the 1997 data, or use the average score of the two scores from the 1992 and 1997 tables. Throughout this paper, I use the asset specificity score from the 1997 data as the time-invariant measure of industry asset specificity for the sample period because the 1997 table provides the most comprehensive industry coverage.

One may argue that while the concept of asset specificity in mining, manufacturing, construction, and retail industries are straightforward to grasp, the concept of asset specificity in service sectors and how it may affect firms' sales price may not be as clear. To address this concern, I conduct all tests in the paper using a subset of the data excluding firms in the service industry (SIC in 7000s and 8000s). The test results are robust to this alternative sampling. I also repeat the same tests on the data excluding any a one-digit SIC sector, one at a time, from the initial sample. The results and the implications still hold qualitatively.[8]

Table 1 reports a list of non-service industry categories and their asset specificity score, sorted by the score. The ranking is intuitive in that the machine-intensive industries such as mining, manufacturing and transportation are assigned a high asset specificity score while other industries such as retailing and farming rank low, consistent with the assumptions made in the literature (Almeida, Campello and Hackbarth (2011)).

As a further check, I repeat the regression tests in this study using the asset redeployability measure similar to the one used in Almeida and Campello (2007) as the key independent variable (results not tabulated). They construct the measure by compiling the ratio of used to total fixed depreciable capital expenditures in industries based on the four-digit SIC code.[9] I replicate their measure using the 1997 data at the three-digit SIC level to make it comparable to the asset specificity measure of this paper and use it in model

[8] I acknowledge and emphasize that there is no reason to believe that the "real" asset specificity measure used in this paper is correlated with the specificity of firms' intangible assets, which is another substantial source of firm value. All results and implications presented in this paper are strictly limited to tangible fixed assets.

[9] The data is from the Bureau of Census' Economic Census and available at www.census.gov/econ/aces /historic_releases_ace.html.

estimation. The resulting coefficient estimates on the variable are consistent with the results from using the asset specificity measure of this paper, although estimates with their measure show weaker statistical significance. I argue that the measure used in this paper is a more direct representation of asset specificity and thus produces sharper results because this measure captures how specialized each fixed asset type is to the using industries and also how each industry distributes its resources among the fixed asset types with the varying degree of specialization.

1.3.2 Sample data and summary statistics

The merger data is from the Securities Data Corporation (SDC) US Mergers and Acquisitions database. The initial sample includes all completed mergers between publicly traded acquirers and publicly traded targets with deal announcement dates between January 1, 1980 and December 31, 2011. Repurchases, recapitalizations, minority share purchases, exchange offers, spin-offs and privatizations are all excluded from the sample. Deals with transaction values less than $10 million or deals involving bankrupt targets are also excluded from the sample.[10] These restrictions give 2,324 unique completed merger deals as the initial sample. The sample used in the actual analysis has smaller size due to missing stock returns and data on firm characteristics.

The goal of this study is to examine the effect of target firms' asset specificity on their sales prices in mergers. I use two proxies to measure the target returns in merger deals. The primary proxy is the three-day cumulative abnormal returns (CAR) surrounding merger announcements estimated using the standard CAPM market model as in Brown and Warner

[10] I drop bankrupt targets to avoid unobserved institutional details of the auction process affecting the results. However, inclusion of the firms makes little difference.

(1985).[11] I also use the total offer premium paid to target shareholders, developed by Schwert (1996), as the secondary proxy for target shareholder returns to address the concern that the stock market may anticipate sales of firms with specialized assets and adjust the firm value before merger deals are made public. The measure is constructed in the following way. First, I estimate a market model for a (-316, -64) estimation period, requiring minimum 200 non-missing days for the estimation. The next step generates *Runup,* which consists of cumulative target abnormal returns from day -42 to day -1 relative to the announcement date and also *Markup,* which is cumulative target abnormal returns from day 0 through the day of delisting or day 126, whichever comes first. The total premium paid to target shareholders by an acquirer is equal to the sum of *Runup* and *Markup*.[12]

Table 2 reports initial summary statistics for the target returns. Row (1) shows the average CAR and total offer premium for all target firms. Both values are statistically different from zero at the 0.01% level. I split the sample into two groups by the median asset specificity score of the COMPUSTAT universe over the sample period and report each group's average returns in rows (2) and (3). The result shows that targets with highly specialized assets receive a lower announcement return and offer premium compared to the targets with low asset specificity, and the difference is statistically significant at the 1% and 5% levels, respectively.

Table 3 presents the average target returns based on a more detailed sample breakdown by target size. The first row shows target returns without size breakdown. Consistent with Table

[11] I use (-239, -6) days relative to the announcement days as the estimation window and require 100 minimum non-missing observations. The estimation uses CRSP daily stock return data and the value-weighted market index.

[12] I repeat all the tests in the paper using two more proxies for target shareholder returns but do not report the results in the interest of space; the third proxy is the difference between the final target share price paid to target shareholders by an acquirer and target share price 4-weeks prior to the deal announcement day, divided by the target share price 4-weeks prior to the deal announcement day. I construct the proxy using the variables provided by SDC. The test results from using this proxy are statistically and economically similar to those obtained from using the total offer premium. The fourth proxy tested is the measure for the division of merger gains developed by Ahern (2012). The results with this proxy are consistent with the results from using the other three proxies but statistical significance is weaker.

2, high target asset specificity is associated with low target returns. The target returns for the lowest asset specificity group are significantly larger than those for the highest specificity group at the 1% level, as indicated by the difference-in-means test results in the far right column. The table also shows that targets with low asset specificity are generally smaller than the firms with high asset specificity, consistent with the notion that large firms in capital-intensive industries use specialized assets.

Moeller, Schlingemann and Stulz (2003) present evidence that there is a persistent size effect associated with merger returns. To control for the target size effect, I split the target firms by quartiles for beginning-of-year market equity size and then further divide each size group into four subgroups by asset specificity. The table shows that target returns for the lowest asset specificity groups are still higher than the returns for the highest asset specificity groups in all cases even after controlling for target size, and the statistical significance still holds in three out of eight tests despite the low statistical power due to reduced sample size.

The initial summary statistics support Ha1 but there are many other factors that affect target merger returns. The next section presents multiple regression results.

1.4 Empirical Results

1.4.1 Test results for liquidity discount

For the regression analysis, I use two model specifications to control for firm and deal characteristics that are known in the literature to be associated with target shareholder returns. The base model is from Moeller, Schlingemann and Stulz (2003), and I include the target asset specificity measure in it. This base setting contains deal characteristic variables reflecting payment methods, existence of toeholds, competing deals and target termination fees, whether the deal is a tender offer, whether it is a diversifying merger, and relative deal size. It also includes firm specifics such as acquirer and target market capitalization and proxies for Q. The "extended" model includes all the variables in the base model plus an additional set of variables that might be correlated with target asset specificity and returns. Firms with highly specialized assets are typically machine intensive (Almeida, Campello and Hackbarth (2011)) and tend to hold a greater portion of their assets in tangible form. Because the main interest of this study is to test the effect of asset specificity on target returns rather than the effect of size of specialized assets, I include the ratio of tangible assets to total assets as a control variable.

Shleifer and Vishny (1992) suggest that assets owned by technology-intensive firms may be illiquid. This view also implies that asset specificity may be correlated with the firm's growth opportunities, which in turn is likely to be correlated with target announcement returns for reasons other than the specificity of the firm assets. To address this issue, I include the ratio of target R&D expenditures to target assets as a proxy for the firms' growth opportunities. I also include the R&D ratio of acquiring firms to capture the synergy effect correlated with growth opportunities not picked up by the target R&D ratio.

Industries using specialized assets such as natural resource extraction or durable goods manufacturing may require high startup costs and this feature may work as an entry barrier, causing some of these industries to be concentrated. Consequently, the level of target industry concentration may affect target shareholder returns for reasons related to industrial organization (Kim and Singal (1993), Singal (1996) and Hackbarth and Miao (2011)), but unrelated to target asset specificity. I control for target industry concentration using the eight-firm concentration ratio provided by the US Census Bureau from the same year as the data used for the asset specificity measure. I also include the eight-firm concentration ratio for acquirer industries to control for the possibility that acquirer industries are closely related to target industries and reflect target industry concentration. Finally, all models control for year and Fama-French twelve industry fixed effects for both acquirer and target industries. The regression model used in this section is as follows:

$$Proxy\ for\ Target\ SH\ Premium = \phi \times Target's\ asset\ specificity\ score + Xb + \varepsilon \qquad (1)$$

Table 4 presents the estimation results. The three-day abnormal returns of target firm stocks surrounding merger announcements is the dependent variable for column (1) and (2) and the total offer premium received by target shareholders is the dependent variable for Column (3) and (4).[13] The coefficient estimates on target asset specificity across all models are negative and statistically significant, consistent with the prediction in Ha1. Based on the estimate in column (2), an increase in targets' asset specificity from the 25th to 75th percentile accounts for a 3.3% smaller target announcement return, or a 6.1% smaller total offer premium if based on the column (4) results, holding other variables constant. Estimates for other coefficients are consistent with the estimates reported in Moeller et al (2003) and the literature.

The models for Table 5 test Ha2 that predicts that the negative sensitivity of target announcement returns to target firms' asset specificity is more pronounced when targets are in financial distress. I follow Almeida, Campello and Hackbarth (2011) and classify a financially distressed target firm as a firm with its interest coverage ratio lower than the industry-year median interest coverage ratio.[14] The odd-numbered columns in Table 5 report the estimation results for the deals involving financially distressed targets, and the even-numbered columns report the results for the rest of the sample.

The estimation results are consistent with Ha2. Across all model settings, the coefficients for target asset specificity in the odd-numbered columns are all negative and their absolute values greater than the estimates for financially healthy target firm groups. The differences in

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[13] Note that the sample size for estimation using the premium as the dependent variable is a bit smaller than the sample size for estimation using the CAR. This is because estimation of the premium requires more stock return data and this leads to more observations with missing values.

[14] Pulvino (1998) identifies financially constrained firms as firms with book leverage higher than the industry-year median book leverage and their current ratio lower than the industry-year median current ratio. Tests based on the Pulvino's classification yield similar results.

the target asset specificity coefficients between the distressed target group and the healthy group are statistically significant for the results with the three-day CAR as the dependent variable, as reported in the coefficient comparison test P-values next to each set of estimation. The results based on the total offer premium as the dependent variable in column (5) and (7) show economically significant but statistically insignificant coefficients. This may be so because the size of standard errors in the long-run return measure is large enough so that the effect of target distress is lost in the noise.

The economic magnitude of the coefficients is substantial. Results in column (3) indicate that a financially distressed target firm whose assets are more specialized (i.e. the 75th percentile relative to 25th percentile in the target asset specificity score distribution) will experience an 8.6% lower announcement return. We can also interpret the result in a different light; even if a firm is financially distressed, if the firm consists of generic assets, the firm owners experience a minimal price discount because generic assets have many potential high valuation buyers inside or outside the target's own industry. These buyers will compete for the firm assets and drive up the sales price close to the fundamental value. This is precisely one of the central predictions made by Shleifer and Vishny (1992).

As an alternative classification, I define a financially distressed target firm to be a target firm with an Altman Z-score below 2.99 at the beginning of the announcement year.[15] As in the previous part, I estimate the regression models for the subgroup separately from the rest of the sample. The odd-numbered columns in Table 6 report estimation results for the firms with a low Altman Z-score, and the even-numbered columns report estimates for the rest of the sample.

The results in Table 6 show the same pattern as in Table 5 that the coefficients on target asset specificity for the distressed firm group are negative and their absolute values are

[15] Altman (1968) suggests the Z-score 2.99 as the threshold that divides healthy firms from firms with some probability of default in the near future. Using 1.81, another threshold under which Altman calls the "distressed" zone, as the cutoff point does not change the results qualitatively.

greater than the counterparts for the financially healthy group. As in Table 5, the differences in the target asset specificity coefficients between the distressed group and the healthy group are statistically significant for the results based on the three-day CAR. As in Table 5, the results based on the total offer premium as the dependent variable in column (5) and (7) show economically significant but statistically insignificant coefficients. This may be so because the size of standard errors in the long-run return measure is large enough so that the effect of target distress is lost in the noise. Overall, these results are consistent with the prediction in Ha2 and also with the implications from Table 5.

The result in column (3) suggests that the shareholders of a financially distressed target firm consisting of specialized assets (i.e. the 75th percentile relative to 25th percentile with respect to the target asset specificity score) will experience a 7.2% lower merger announcement return than shareholders of targets with generic assets.

There is a concern that the sensitivity of the target merger announcement return to target asset specificity may be positive if an eventual target firm is in deep financial distress and the market anticipates with near certainty that the firm will go through bankruptcy and subsequent costly restructuring. To address this possibility, I repeat the tests for Ha2 with a sample excluding deals involving target firms with the interest coverage or the Z-score below the 10^{th} percentile of each industry year. The results do not change qualitatively from using the original sample.

According to Ha3, the negative sensitivity of target announcement returns to target firms' asset specificity is more pronounced when the potential highest valuation buyers are financially constrained. Following Harford (2005), I use the spread between the average interest rate on commercial and industrial loans and the Federal Funds rate (C&I loan spread) as a proxy for the overall capital liquidity in the economy. I define high C&I loan spread regimes as the periods when the C&I loan spread is above the 67th percentile (i.e. the spread greater than 1.75) in its time series over the sample period and consider potential buyers in the regimes to be financially constrained.[16]

Table 7 presents the estimation results. The odd-numbered columns report estimation results for target returns in the high C&I loan spread regimes and the even-numbered columns report the results for the rest of the sample. The results are consistent with the prediction in Ha3. The coefficients on target asset specificity are significantly negative and their absolute values are greater in the high C&I loan spread than those in the low spread regimes. The results from coefficient comparison tests between the two regimes reject the null hypothesis that the two estimates are the same, except for one case.

The results also show that the impact of asset illiquidity on the target price is economically substantial. The coefficient estimate in Column (3) suggests that when the credit market tightens, firms with more highly specialized assets (i.e. the 75th percentile relative to 25th percentile in the target asset specificity score distribution) will experience an 8.2% lower announcement return and an 11.1% smaller premium, according to column (7).

Two key implications emerge from the results. The first implication is that when low borrowing costs increase the financing capacity of highest valuation potential buyers, the shareholders of target firms consisting of highly specialized assets will experience a minimal merger discount because competition among the buyers will drive up the asset price. The statistically insignificant coefficients of target asset specificity in the even-numbered columns highlight this point. The second implication is that even if the credit market tightens and high valuation potential buyers of the target firm are financially constrained, there will be little price discount on target firms consisting of generic assets that have very little gap between value in best use and value in second best use. These two implications are consistent with the

[16] This cutoff point allocates about a one third of the sample into the high cost of external financing regime. The results are robust to alternative cutoff points such as the time series median or the 75th percentile. In a separate test, I divide the sample into the tightening capital market regimes and the loosening capital market regimes according to whether the concurrent changes in the C&I spread are positive or negative, and then I estimate the regression models separately for each subgroup. The results still hold qualitatively under this classification scheme.

central prediction by Shleifer and Vishny (1992) and provide direct evidence to their theory of asset illiquidity and liquidation discount.

As an alternative classification for financially constrained buyers, I define low industry cash flow regimes as the periods when the annual median cash flow of a target industry is below the 25th percentile in its time series over the sample period.[17]

Table 8 presents the estimation results. The odd-numbered columns report the results for target firms in the low target industry cash flow regimes and the even-numbered columns report the results for the rest of the sample. The coefficients on target asset specificity in the low industry cash flow regimes are negative and statistically significant, and their absolute values are greater than the coefficients for the rest of the sample across all the model settings. The results from coefficient comparison tests between the two regimes reject the null hypothesis that the two estimates are the same in all cases. Overall, the results presented in Table 8 are consistent with the prediction in Ha3 and the implications from Table 7.

The economic implication based on the asset specificity coefficients in column (3) and column (7) is that when the cash flow of a target firm's industry is low and the target's asset specificity is high (i.e. the 75th percentile relative to 25th percentile with respect to the target asset specificity score), the target shareholders are to experience a 8.4% lower announcement return and a severe discount of 23.2% in the total offer premium.

The results in Table 8 and Table 7 show two different channels through which asset liquidity of specialized assets can be realized. Table 7 provides evidence that the ease of external financing increase the highest valuation buyers' financial capacity, allowing them to compete over target firms. On the other hand, table 8 provides evidence that an increase in the internally generated funds within the target industries can also relieve the financial constraints of the highest valuation buyers and drive up the targets' asset price close to the

[17] This cutoff point allocates about a one third of the sample into the low industry cash flow regimes. The results are robust to alternative cutoff points such as the time series median or the 33rd percentile. The results are also unaffected to using industry cash flows at the three-digit SIC level instead of the two-digit level.

highest fundamental value. Shleifer and Vishny (1992) suggest that these two effects can reinforce each other. High industry cash flows increase the financing ability of highest valuation users. Competition among such buyers over the specialized assets pushes up the liquidation price of these assets. For the holders of these assets, this means that the potential cost of using leverage drops partly because the liquidation price increases but also because the assets' fundamental value itself increases, opening up more debt capacity. The low borrowing costs allow the firms to invest more in these assets, knowing that there will be other financially unconstrained high valuation buyers of their assets available when it is optimal for the firms to sell their assets.

As another classification for financially distressed potential buyers, I follow the definition of The National Bureau of Economic Research (NBER) to identify merger deals during the recession years, which are 1980, 1981, 1982, 1990, 1991, 2001, 2008 and 2009 in my sample period.[18] I estimate the regression models for the recession group separately from the rest of the sample. The odd-numbered columns in Table 9 report estimation results for the recession group, and the even-numbered columns report results for the rest of the sample.

The coefficients on target asset specificity for the recession group are negative and statistically significant, and their absolute values are greater than the coefficients for the off-recession group. The results from coefficient comparison tests between the two regimes reject the null hypothesis that the two estimates for asset specificity are the same in one case with another P-value being close to the 10% level at 11.1%. The rejection rate being lower than the ones in other previous tests is not surprising considering that the sample size for the recession group is small. Besides, as implied in Mitchell and Mulherin (1996), slowdowns in industrywide real asset transactions can occur not only during the economywide recession periods but also outside recessions as well, and this may explain the negative and statistically significant coefficients on target asset specificity in some of the off-recession columns.

[18] A year is identified as a recession year if at least three months of the calendar year is in recession periods.

Nevertheless, the estimation results are generally consistent with the prediction in Ha3.

One alternative explanation for the Ha2 and Ha3 test results so far is that perhaps the merger deals involving targets with specialized assets are shareholder value destroying for both target and acquiring firms. That is, some unobserved factors may be positively correlated with target firms' asset specificity and negatively correlated with perceived deal quality. To check this possibility, I estimate the models using acquiring firms' announcement returns as the dependent variable (results not reported). If this alternative explanation is driving the original results, the test outcome should reveal a negative relation between targets' asset specificity and the acquirers' announcement returns. Instead, the test results indicate that acquirer returns are positively related with target firms' asset specificity, although the coefficients are mostly statistically insignificant. In fact, the sensitivity of acquiring firms' returns to target firms' asset specificity is also positive for subgroups of all target financial distress and constrained financing classifications tested earlier in this section. This result provides some support to the argument that value is transferred from target shareholders to acquiring shareholders when such targets are in financial distress and the liquidity of target assets is low.

Another possible explanation is that the results may be driven by other firm and industry characteristics not included in the models tested. In untabulated tests, I augment the initial models to further include additional target firm and industry variables such as firm profitability, firm book leverage, firm age, industry profitability, industry interest coverage ratio, industry cash flow volatility and average industry book leverage. The results are not qualitatively different from the original results, with the implications from the original tests mostly unchanged.

Lastly, I test whether the results in this section are dependent on the way the regression tests are set up (results not tabulated). For example, in testing Ha2, instead of dividing the initial sample into two groups according to the target firms' financial condition and estimating the model separately for each subgroup, I create a dummy variable reflecting the target firms' financial condition and include the variable as a stand-alone control along with an interaction term between the variable and target asset specificity. I set up a model for the Ha3 tests involving financially constrained buyers in the same way. The results using the three-day CAR as the dependent variable show that the coefficients on the interaction terms are all negative and statistically significant at the conventional level, consistent with the predictions in Ha2 and Ha3. This outcome suggests that the initial results are not conditional on the test setting.

1.4.2 Test results for asset illiquidity and financial distress

The tests in the previous section examined the joint effect of target firms' asset specificity and financial distress on target shareholder returns and the joint effect of target firms' asset specificity and financially constrained potential buyers on target shareholder returns, separately. However, the Shleifer and Vishny model predicts that the discount effect of asset illiquidity on target shareholder value is the greatest when the following three conditions are jointly met: (1) a target firm is financially distressed; (2) the target firm consists of highly specialized assets; and (3) the potential high valuation buyers are financially constrained. This section tests the prediction in Ha4.

First, I split the initial sample into four subgroups. Subgroup 1 includes merger deals involving financially distressed target firms (e.g. the target interest coverage ratio below the industry-year median or the target Altman Z-score below 2.99) with financially constrained potential buyers (e.g. the C&I spread above the time series median or the annual target industry median cash flows below their time series medians). Subgroup 2 includes deals involving financially distressed targets with financially unconstrained potential buyers. Subgroup 3 includes deals involving financially healthy targets with financially constrained potential buyers. Lastly, Subgroup 4 includes deals involving financially healthy targets with financially unconstrained potential buyers. The prediction is that the target announcement return should be most negatively associated with target asset specificity in subgroup 1 and least negatively associated with it in subgroup 4. I estimate the extended regression model (1) on the four subgroups.

Table 10 presents the regression results for each group. I only report the coefficient estimates on target asset specificity in the interest of space. Both tables in Panel A use targets' industry-year median interest coverage ratio to classify financially distressed targets. In the upper table of Panel A, potential high valuation buyers are considered financially constrained if the C&I spread is above its time series median and unconstrained otherwise. In the lower table of Panel A, potential high valuation buyers are considered financially constrained if the annual target industry median cash flows are below their time series median and unconstrained otherwise. As before, the dependent variable is the target firms' three-day CAR on merger announcements. Tests using the total offer premium as the dependent variable yield results with essentially the same implications. The four columns (1) through (4) in each table correspond to the estimation results for the four subgroups with the same number.

Inspecting the coefficients across the four subgroups confirms the prediction that the target announcement return is most negatively associated with target asset specificity both when a target firm is financially distressed and the potential buyers are financially constrained, as shown in column (1). The results are also consistent with the prediction that the target announcement return is least negatively associated with target asset specificity when a target firm is financially healthy and when the potential buyers are financially unconstrained, as shown in column (4). In fact, the coefficient comparison test results reported in the far right column confirm that the estimates in column (1) and column (4) are statistically different at the 1% level.

Models in Panel B use the Altman Z-score instead of the targets' interest coverage ratio to classify financially distressed target group and healthy target group. The rest of the test setting is the same as the models in Panel A. The results reported in Panel B are consistent with the prediction and also with the results in Panel A.

Note that coefficients in odd-numbered columns are generally more negative and more statistically significant than the coefficients in even-numbered columns. This suggests that potential highest valuation buyers' financing capacity, rather than target firms' financial condition, may be the primary factor determining the sales price of specialized assets. This implication is intuitive in that when many potential high valuation buyers of the target assets are financially unconstrained, competition among the buyers over the target firms will drive up the price regardless of target firms' financial conditions, and vice versa.

1.4.3 Test results for changes in optimal leverage

The results on target shareholder returns so far provide evidence supporting the prediction that targets' high asset specificity combined with financially constrained potential high valuation buyers severely undermines the target price in mergers. Shleifer and Vishny (1992) hypothesize that the prospect of such ex post liquidation loss gives ex ante incentives for the firms to reduce leverage to mitigate the possibility of such loss, because the expected costs of using leverage becomes greater than the benefits of using leverage. I draw Ha5 from this prediction.

To test this hypothesis, I construct a dataset containing target firms' annual changes in leverage over the entire sample period before the years in which they are acquired. The dataset also includes control variables that the capital structure literature identifies as key determinants of changes in firm leverage.[19] I classify subgroups of asset illiquidity based on

[19] The control variables used in this section are similar to the ones in Sibilkov (2009).

the three different conditions in which potential highest buyers are financially constrained, estimate the regression models separately for each group, and compare the estimation results from these groups with the results from subsamples with financially unconstrained buyers. To ensure the firms have little financial slack, I require all firms in the subgroups to have book leverage greater than the industry-year medians. The test uses the following regression model:

$$Changes\ in\ leverage = \phi \times Firm\ asset\ specificity\ score + \mathrm{X}\beta + \varepsilon \quad (2)$$

As in Sibilkov (2009), I include industry-year adjusted book leverage as an independent variable to control for the leverage level prior to changes. Table 11 presents the estimation results for the regression model (2). Columns (1), (2), (5) and (6) in Panel A and columns (1) and (2) in Panel B report the estimation results using changes in leverage from the current year to the following year as the dependent variable. Columns (3), (4), (7) and (8) in Panel A and columns (3) and (4) in Panel B report the results using changes in leverage over a two-year period starting the current year as the dependent variable. The subgroups for which the models are estimated appear at the table header. All models include year fixed effects and industry fixed effects with the Fama-French 12 industry specifications.

The results in Panel A of Table 11 are consistent with Shleifer and Vishny (1992)'s predictions that firms facing the prospect of a liquidity loss due to high asset specificity adjust leverage more to reduce such risk. The estimation results for illiquid groups are presented in columns (1), (3), (5) and (7) in Panel A and they report that the coefficients on asset specificity are all negative and statistically significant, except for one case. Their absolute values are greater than those of the healthy counterparts reported in the even-numbered columns, and the coefficient comparison tests reject the null hypothesis that the coefficients on asset specificity of the two groups are the same in two out of four cases. The regression results for the recession sample presented in Panel B are not as consistent with the prediction as the results in Panel A, and I argue that this is because slowdowns in industrywide asset transactions can occur outside the economywide recession periods, adding noise to the results. Finally, the results hold qualitatively when the models are tested on the entire sample of COMPUSTAT firm year observations with the required data.

The central implications from the ex ante leverage change results in this section combined with the ex post liquidity discount results in the previous section are the following. The coefficient estimates for asset specificity in the even-numbered columns being mostly statistically insignificant and greater than the estimates in odd-numbered columns suggest that even if a firm consists of highly specialized assets, as long as there are many financially unconstrained highest valuation users of the assets ready to compete for the firm assets, the firm's asset specificity plays no role in determining its optimal leverage. The negative coefficient estimates on asset specificity in the odd-numbered columns provide support to the prediction that when the market condition changes so that the high valuation users of the assets are no longer available as potential buyers, the firm's expected liquidation value drops in the degree of the firm's asset specificity. Facing the increasing cost of holding leverage, the firm adjusts its leverage lower to mitigate the probability of a loss from selling its assets when the market is illiquid.

1.4.4 Cyclicality of asset liquidity

For this final section, I briefly discuss the procyclicality of asset liquidity proposed by Shleifer and Vishny (1992). They predict that liquidity of specialized assets is pro-cyclical because the financial capacity of the assets' highest valuation potential buyers is procyclical.

There have been a few studies in the literature that tested this procyclicality prediction of asset liquidity in light of the clustering of asset transactions. Mitchell and Mulherin (1996) relate merger waves to industrywide economic and regulatory shocks. Harford (2005) provides evidence that merger waves are triggered by industrywide economic and regulatory shocks and are facilitated by overall capital liquidity in the economy. Eisfeldt and Rampini (2005) show that the amount of capital reallocation is procyclical. Dittmar and Dittmar (2008) and Rau and Stouraitis (2011) also highlight the importance of industry and economywide shocks for occurrence of merger waves.

Expanding on the findings of these papers, I provide some evidence that sales prices for specialized assets may follow a cyclical pattern as well. First, I estimate the base model (1) for each year separately over the sample period. Because some years have only a small number of completed mergers, I combine two consecutive years to form a unit subperiod. For example, merger observations in 1992 and in 1993 are combined to form a subgroup for year 1993, and the next period subgroup for year 1994 is formed by combining observations from 1993 and 1994, and so on. This process yields thirty one initial subgroups and I drop the groups between 1980 and 1984 because the sample size is too small.

The model estimation using each subgroup gives one estimate for the coefficient on target asset specificity for each of the 26 sample groups. I plot the point estimate values in Figure 1 and call the time series *price coefficient*. A low price coefficient value indicates that there is an overall price discount on asset specificity. The caveat is that only a few coefficient estimates plotted in the graphs are statistically significant at the conventional level, due partially to small sample size. I also exclude the industry fixed effects for acquirers and targets because their inclusion further reduces sample size.

Panel A in Figure 1 displays the price coefficient along with the annual average C&I spread. Panel B plots the price coefficient along with the annual median cash flow over book assets. Panel C plots the price coefficients along with and the annual average GDP growth rate.

The price cyclicality hypothesis predicts that there is a negative relation between the price coefficient and the C&I spread. Tests for unit roots on the variables indicate that the C&I spread has a unit root. An Engle-Granger test on the residuals from regressing the price coefficient on the C&I spread and a time trend indicates that the price coefficient and the C&I spread are cointegrated.[20] This result is consistent with the prediction that real asset price is determined in equilibrium and the level of financial constraints faced by potential buyers of the assets is an important determinant of the price. A Durbin-Watson test on the residuals rejects the serial correlation hypothesis. The OLS estimation result is shown below:

$$Price\ coefficient = -26.434 - 0.309^{*} \times C\ \&\ I\ spread + 0.013 \times Time\ trend$$

The * indicates a statistical significance at the 10% level. The adjusted R^2 is 0.06. The coefficient suggests that a one standard deviation increase in the annual C&I spread accounts for a 0.150 drop in the price coefficient. Economically, this means that every one standard deviation increase in the C&I spread is associated with a 2.74% additional asset specificity discount on target announcement returns, based on the coefficient estimate reported in Column (2) of Table 4.[21]

Similar tests on the annual median cash flow show that the variable and the price coefficient are also cointegrated and the residual not serially correlated. Regressing the price coefficient on the annual median cash flow yields the estimation results below:

$$Price\ coefficient = -15.276 + 7.405^{*} \times Median\ CF + 0.007 \times Time\ trend$$

The adjusted R^2 is 0.04. The coefficient on *Median CF* is positive and statistically significant and the result indicates that a one standard deviation increase in the annual median cash flow accounts for a 0.118 increase in the price coefficient. Economically, this means that every one standard deviation decrease in the overall median cash flow is associated with a 2.15% additional asset specificity discount on target returns. These results from the two regressions are consistent with the argument that the price discount on asset specificity is

[20] To conduct the Engle-Granger test, I first estimate the residuals from an OLS estimation of the price coefficient on the C&I spread and a time trend, and then I test for a unit root on the residuals using the augmented Dickey-Fuller test. The resulting test statistic is -4.630 and it rejects the unit root hypothesis on the residuals at the 1% level.

[21] The standard deviation of the annual C&I spread for the sample period is 0.487, and so - 0.309 $\times$ 0.487 = -0.150. Multiplying this by 0.183, the difference in the specificity scores between the 25th percentile and the 75th percentile, gives the said - 2.74%.

large when the overall financing in the economy is tight and small when there is an overall financial slack in the economy. This provides some support to the prediction that the asset liquidation value for specialized assets is procyclical.

Interestingly, a similar test on the real GDP growth rate reveals a positive but statistically insignificant relation between the price coefficient and the GDP growth rate. This result may be consistent with the findings by Harford (2005) that overall capital liquidity in the economy is a necessary condition for the clustering of asset transactions and a liquid asset market to form. This result is not conclusive and warrants further investigation.

1.5 Conclusion

The main purpose of this paper is to examine the effect of asset specificity on firms' sales value in mergers. Using US merger data, I identify two key factors that jointly determine the extent of liquidity discount of target firms: target firms' asset specificity and the degree of financial constraints faced by highest valuation buyers of target assets at the time of liquidation.

The empirical results strongly support the prediction that the target announcement returns are negatively related to the target firms' degree of asset specificity. In particular, multiple regression results show that a move from the 25th to 75th percentile in targets' asset specificity distribution accounts for a 3.4% smaller target announcement abnormal returns. Results also indicate that the asset specificity discount in target premium is more pronounced if target firms are financially distressed or high valuation buyers of target assets are financially constrained. The average economic magnitude of the target firm price effect is -7.7% at merger announcements when targets' high asset specificity is combined with financial distress of the target firms or with tight financing conditions for potential buyers, or -12.2% when *both* target firms and potential high valuation buyers are in tight financial conditions.

Another important and related prediction made by Shleifer and Vishny (1992) and Williamson (1988) is that firms with specialized assets, when faced with the prospect of an illiquid asset market condition, reduce leverage rapidly in an attempt to mitigate the risk. The test results are consistent with their prediction. After controlling for other factors, the results show that a one standard deviation increase in targets' asset specificity combined with illiquid market conditions is associated with a 2.2% annual reduction in book leverage. Finally, I present evidence supporting the Shleifer and Vishny (1992)'s prediction that the degree of asset liquidity of specialized assets is pro-cyclical. Overall, the results presented in this paper are consistent with the hypothesis that asset liquidity plays an important role in determining an asset's selling value as well as its value as pledgeable collateral.

Table 1: Summary statistics: Asset specificity by industry (non-service sectors)

This table presents asset specificity score for each of the two-digit industry specification excluding banking, utility and service sectors. The industry asset specificity score is constructed using the following formula:

$$Industry\ asset\ specificity_i = \sum_{a}^{A} \omega_{i,a} (ASpecificity_a)$$

where i represents each of the 123 industries and a represents each of the 180 fixed asset types provided in the 1997 Capital Flow Table published by the US Bureau of Economic Analysis. $ASpecificity_a$ measures the intensity of demand for fixed asset type a by different industries and is constructed by dividing the number of industries that *do not* use commodity a by the total number of industries. $\omega_{i,a}$ measures the relative importance of fixed asset type a to the industry i and is constructed by dividing industry i's dollar expenditure on a by its total dollar expenditures on all fixed asset types in the survey year.

2-digit SIC	Industry description	Asset specificity score
13	Oil and gas extraction	0.786
40	Railroad transportation	0.638
44	Water transportation	0.599
09	Fishing, hunting, trapping	0.596
07	Agricultural services	0.478
30	Rubber and misc. plastics products	0.470
12	Coal mining	0.454
10	Metal mining	0.418
22	Textile mill products	0.394
23	Apparel and other textile products	0.394
26	Paper and allied products	0.367
24	Lumber and wood products	0.362
25	Furniture and fixtures	0.336
14	Nonmetallic minerals, except fuels	0.324
45	Air transportation	0.319
39	Misc. manufacturing industries	0.310
46	Pipelines, except natural gas	0.296
51	Wholesale trade - nondurable goods	0.296
33	Primary metal industries	0.291
20	Food and kindred products	0.291
36	Electronic & other electric equipment	0.283
34	Fabricated metal products	0.281
32	Stone, clay, and glass products	0.262
29	Petroleum and coal products	0.258
35	Industrial machinery and equipment	0.255
37	Transportation equipment	0.250
48	Communication	0.242
38	Instruments and related products	0.236
08	Forestry	0.231
31	Leather and leather products	0.206
01	Agricultural production crops	0.203
52	Building materials & garden supplies	0.200
02	Agricultural production - livestock	0.199
28	Chemicals and allied products	0.173
27	Printing and publishing	0.165
21	Tobacco products	0.162
50	Wholesale trade - durable goods	0.150
42	Trucking and warehousing	0.149
53	General merchandise stores	0.103
56	Apparel and accessory stores	0.103
59	Miscellaneous retail	0.103
54	Food stores	0.100
55	Automotive dealers & service stations	0.100
58	Eating and drinking places	0.100
41	Local and interurban passenger transit	0.097
15	General buildling contractors	0.061
16	Heavy construction, except building	0.061
17	Special trade contractors	0.061
47	Transportation services	0.028

Table 2: Summary statistics: Merger returns for target shareholders

This table reports three-day average target cumulative abnormal return (CAR) at announcement and total offer premium received by target (Premium). The three-day cumulative target abnormal return is constructed following Brown and Warner (1985). Total offer premium received by target is constructed using the method by Schwert (1996). The median asset specificity score of the COMPUSTAT firms over the sample period splits the target firms into the high asset specificity group and the low asset specificity group. The asterisks report test results for a differences-in-means test for the announcement return variables between the two sample groups. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

		Mean	Standard Deviation	25th	Median	75th	Number of obs.
(1) All target firms	CAR	0.248	0.255	0.083	0.201	0.357	1,896
	Premium	0.418	0.533	0.104	0.371	0.694	1,807
(2) Low asset specificity	CAR	0.265	0.274	0.087	0.207	0.373	1,055
	Premium	0.445	0.568	0.111	0.383	0.703	1,000
(3) High asset specificity	CAR	0.226***	0.227	0.079	0.194	0.335	841
	Premium	0.386**	0.485	0.097	0.358	0.681	807

Table 3: Summary statistics: Target returns by target size and asset specificity

This table reports three-day average target cumulative abnormal return (CAR) at announcement and total offer premium received by target (Premium). The three-day cumulative target abnormal return is constructed following Brown and Warner (1985). Total offer premium received by target is constructed using the method by Schwert (1996). The table splits the sample of the target firms into four groups by their market value of common equity outstanding at the beginning of the merger announcement year, and each size group is further divided into four subgroups by the asset specificity score. The table at the top shows the sample statistics without breakdown by equity size. The last column reports results from the difference-in-means test of the target return values between the least specific group and the most specific group. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

		Asset specificity				
	Variables	Least specific	Group 2	Group 3	Highly specific	Q1-Q4 (Ha:Q1-Q4>0)
All sample:						
	Specificity score	0.052	0.189	0.267	0.489	
	CAR	0.259	0.270	0.238	0.214	0.044***
	Premium	0.462	0.429	0.415	0.354	0.107***
	Target Mkt cap ($ Mil)	320.45	605.61	710.84	1,076.83	
	Number of Obs.	506	552	434	407	
By target size group:						
Smallest	Specificity score	0.047	0.186	0.270	0.468	
	CAR	0.682	0.483	0.492	0.573	0.109
	Premium	0.339	0.302	0.245	0.276	0.063
	Target Mkt cap ($ Mil)	31.14	30.38	36.29	24.95	
	Number of Obs.	135	170	117	104	
Group 2	Specificity score	0.047	0.180	0.268	0.499	
	CAR	0.452	0.521	0.514	0.275	0.177***
	Premium	0.256	0.300	0.269	0.198	0.057**
	Target Mkt cap ($ Mil)	112.57	120.48	112.41	103.61	
	Number of Obs.	137	165	117	92	
Group 3	Specificity score	0.047	0.177	0.267	0.482	
	CAR	0.461	0.331	0.336	0.350	0.110**
	Premium	0.238	0.246	0.223	0.205	0.033
	Target Mkt cap ($ Mil)	325.70	325.48	301.65	347.61	
	Number of Obs.	129	158	111	117	
Largest	Specificity score	0.071	0.205	0.271	0.536	
	CAR	0.281	0.352	0.355	0.218	0.063
	Premium	0.197	0.230	0.231	0.182	0.015
	Target Mkt cap ($ Mil)	1,833.14	3,271.90	2,778.14	2,180.02	
	Number of Obs.	139	138	128	127	

Table 4: Target returns and target asset specificity

This table reports the test results for Ha1. The model used for estimation is

$$\textit{Proxy for Target SH Premium} = \phi \times \textit{Target's asset specificity score} + Xb + \varepsilon \text{ .}$$

Columns (1) and (2) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Columns (3) and (4) use the total offer premium received by target (Schwert (1996)) as the dependent variable. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR	Target 3-day CAR	Target premium	Target premium
Target subgroup:	All targets	All targets	All targets	All targets
	(1)	(2)	(3)	(4)
Constant	0.128***	0.254***	0.357***	0.978***
	(2.685)	(3.275)	(5.786)	(5.650)
Target asset specificity	**-0.090****	**-0.185*****	**-0.266***	**-0.338****
	(-2.005)	**(-3.130)**	**(-1.900)**	**(-2.401)**
Paid in cash	0.034***	0.040**	-0.014	0.013
	(2.842)	(2.516)	(-0.479)	(0.391)
Toehold	-0.028	-0.035	0.016	0.006
	(-0.724)	(-0.824)	(0.330)	(0.129)
LN(Acquirer mkt equity)	0.032***	0.030***	0.041***	0.040**
	(3.691)	(3.165)	(2.888)	(2.502)
LN(Target mkt equity)	-0.036***	-0.038***	-0.073***	-0.065***
	(-4.467)	(-3.595)	(-5.322)	(-1.209)
Tender offer	0.045***	0.044**	0.013	0.015
	(2.866)	(2.480)	(0.377)	(0.429)
Focused	0.026*	0.014	-0.004	-0.022
	(1.868)	(0.921)	(-0.186)	(-0.848)
Acquirer Q	0	-0.002	-0.016	-0.016
	(0.043)	(-0.536)	(-1.365)	(-1.011)
Target Q	-0.018***	-0.020***	-0.062***	-0.064***
	(-3.870)	(-3.456)	(-5.674)	(-4.835)
Competed	-0.076***	-0.091***	0.036	0.027
	(-2.614)	(-2.892)	(0.754)	(0.525)
Relative size	0.014	0.018	0.116***	0.113**
	(0.643)	(0.634)	(2.617)	(2.295)
Target termination fee	0.026	0.040*	0.100***	0.121***
	(1.255)	(1.916)	(2.710)	(3.480)
Acquirer R&D / assets		-0.032		0.045
		(-0.396)		(0.302)

Target R&D / assets		0.088		0.170
		(1.138)		(1.201)
Acquirer tangible assets		0.052		0.092
		(0.850)		(0.685)
Target tangible assets		0.011		-0.016
		(0.271)		(-0.134)
Acquirer industry concentration		-0.001		-0.001
		(-1.437)		(-1.414)
Target industry concentration		0		0.001
		(1.163)		(0.951)
Acquiter ind. fixed effects	Yes	Yes	Yes	Yes
Target ind. fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,573	1,300	1,501	1,251
Adj. R^2	0.130	0.131	0.142	0.131

Table 5: Joint effect of low interest coverage and asset specificity on target returns

This table reports the test results for Ha2. The model used for estimation is: *Proxy for Target SH Premium* = ϕ × *Target asset specificity score* + *Xb* + ε. Columns (1)-(4) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Columns (5)-(8) use the total offer premium received by target (Schwert (1996)) as the dependent variable. Columns (1), (3), (5) and (7) report estimation results for the low interest coverage ratio group. Columns (2), (4), (6) and (8) reports estimation for the rest of the sample. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR			Target 3-day CAR			Target premium			Target premium		
Target subgroup:	Low int. coverage	High int. coverage	(1)-(2) P-value	Low int. coverage	High int. coverage	(3)-(4) P-value	Low int. coverage	High int. coverage	(5)-(6) P-value	Low int. coverage	High int. coverage	(7)-(8) P-value
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)	
Constant	0.205**	0.101	0.438	0.317**	0.128***	0.150	0.442	0.297***	0.721	-0.166	0.445***	0.036**
	(2.255)	(1.567)		(2.367)	(4.127)		(1.536)	(2.759)		(-0.469)	(3.658)	
Target asset specificity	**-0.297***	**0.015**	**0.006***	**-0.479***	**-0.070**	**0.010**	**-0.280**	**-0.088**	**0.447**	**-0.375**	**-0.196**	**0.584**
	(-3.094)	**(0.307)**		**(-3.057)**	**(-1.015)**		**(-1.018)**	**(-0.691)**		**(-1.434)**	**(-1.281)**	
Paid in cash	0.036	0.061***	0.502	0.024	0.086***	0.137	-0.027	0.019	0.525	0.003	0.043	0.618
	(0.957)	(3.340)		(0.576)	(3.123)		(-0.410)	(0.434)		(0.041)	(0.823)	
Toehold	0.006	-0.047	0.454	-0.004	-0.041	0.650	0.047	0.090	0.69	0.034	0.110	0.524
	(0.084)	(-1.397)		(-0.046)	(-0.948)		(0.586)	(1.379)		(0.360)	(1.292)	
LN(Acquirer mkt equity)	0.040**	0.023***	0.225	0.037**	0.020**	0.225	0.040	0.049***	0.72	0.020	0.056***	0.204
	(2.456)	(3.472)		(2.065)	(2.247)		(1.276)	(3.534)		(0.583)	(3.938)	
LN(Target mkt equity)	-0.036***	-0.024***	0.363	-0.038**	-0.023**	0.328	-0.081**	-0.046***	0.195	-0.068*	-0.040**	0.349
	(-2.595)	(-3.063)		(-2.270)	(-2.443)		(-2.525)	(-3.075)		(-1.712)	(-2.517)	
Tender offer	0.057*	0.016	0.286	0.071**	0.008	0.120	0.062	-0.013	0.281	0.077	-0.013	0.225
	(1.930)	(0.790)		(2.435)	(0.321)		(1.072)	(-0.311)		(1.230)	(-0.268)	
Focused	0.030	0.013	0.593	0.010	0	0.785	-0.038	-0.028	0.893	-0.082	-0.054	0.716
	(0.811)	(0.759)		(0.237)	(-0.003)		(-0.549)	(-0.841)		(-1.237)	(-1.159)	

Acquirer Q	0.006	-0.004	0.143	0.004	0.001	0.721	0.001	-0.007	0.735	0.011	-0.010	0.400
	(1.632)	(-1.206)		(0.651)	(0.170)		(0.045)	(-0.312)		(0.633)	(-0.332)	
Target Q	-0.032***	-0.016**	0.088*	-0.039***	-0.017**	0.053*	-0.107***	-0.054***	0.043**	-0.132***	-0.053***	0.009***
	(-4.250)	(-2.345)		(-3.977)	(-2.096)		(-3.779)	(-5.690)		(-4.336)	(-4.399)	
Competed	-0.082	-0.121***	0.477	-0.060	-0.147***	0.135	-0.160	0.060	0.091*	-0.075	-0.011	0.645
	(-1.257)	(-4.980)		(-0.952)	(-5.652)		(-1.057)	(1.023)		(-0.512)	(-0.189)	
Relative size	-0.002	0.013	0.732	0.010	0.019	0.864	0.049	0.134***	0.455	0.039	0.154***	0.348
	(-0.035)	(0.736)		(0.177)	(0.746)		(0.385)	(3.009)		(0.285)	(2.935)	
Target termination fee	0.039	0.020	0.625	0.074**	0.039	0.414	0.093	0.101**	0.926	0.189**	0.114**	0.405
	(1.390)	(0.750)		(2.137)	(1.381)		(1.222)	(2.551)		(2.217)	(2.581)	
Acquirer R&D / assets				-0.033	-0.074	0.825				-0.224	-0.085	0.762
				(-0.228)	(-0.722)					(-0.718)	(-0.248)	
Target R&D / assets				0.126	0.026	0.534				0.337	0.225	0.760
				(1.031)	(0.334)					(1.042)	(1.029)	
Acquirer tangible assets				0.054	0.013	0.757				0.379	-0.025	0.147
				(0.438)	(0.181)					(1.157)	(-0.225)	
Target tangible assets				-0.042	0.040	0.549				-0.043	0.029	0.780
				(-0.324)	(0.475)					(-0.170)	(0.262)	
Acquirer industry concentration				0	-0.001**	0.101				0.002	-0.003***	0.008***
				(0.409)	(-2.295)					(1.126)	(-2.953)	
Target industry concentration				0	0.001*	0.200				0.001	0.001**	0.718
				(-0.346)	(1.746)					(0.351)	(2.269)	
Acquiter ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Target ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	492	782		404	637		459	759		383	621	
Adj. R^2	0.178	0.092		0.150	0.096		0.165	0.100		0.156	0.113	

Table 6: Joint effect of low Altman Z-score and asset specificity on target returns

This table reports the test results for Ha2. The model used for estimation is: *Proxy for Target SH Premium* = $\phi \times$ *Target asset specificity score* + $Xb + \varepsilon$. Models (1)-(4) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Models (5)-(8) use the total offer premium received by target (Schwert (1996)) as the dependent variable. Models (1), (3), (5) and (7) report estimation results for the low Altman Z-score group. Models (2), (4), (6) and (8) reports estimation for the rest of the sample. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR			Target 3-day CAR			Target premium			Target premium		
Target subgroup:	Low Altman Z (1)	High Altman Z (2)	(1)-(2) P-value	Low Altman Z (3)	High Altman Z (4)	(3)-(4) P-value	Low Altman Z (5)	High Altman Z (6)	(5)-(6) P-value	Low Altman Z (7)	High Altman Z (8)	(7)-(8) P-value
Constant	0.314***	0.224***	0.558	0.226	-0.002	0.170	0.590**	0.532***	0.875	0.204	0.919***	0.006***
	(3.271)	(3.127)		(1.196)	(-0.036)		(2.123)	(5.389)		(0.633)	(6.261)	
Target asset specificity	**-0.188****	**0.012**	**0.054***	**-0.306*****	**-0.068**	**0.074***	**-0.353**	**-0.189**	**0.458**	**-0.402**	**-0.205**	**0.446**
	(-2.268)	**(0.174)**		**(-3.211)**	**(-0.694)**		**(-1.213)**	**(-1.347)**		**(-1.259)**	**(-1.325)**	
Paid in cash	0.026	0.045***	0.575	0.008	0.060***	0.187	0.011	-0.047	0.420	0.024	-0.014	0.633
	(0.901)	(2.804)		(0.242)	(3.583)		(0.194)	(-1.266)		(0.388)	(-0.342)	
Toehold	-0.031	-0.006	0.707	-0.045	-0.011	0.674	0.026	0.025	0.995	-0.007	0.051	0.632
	(-0.445)	(-0.136)		(-0.504)	(-0.242)		(0.312)	(0.432)		(-0.096)	(0.901)	
LN(Acquirer mkt equity)	0.050***	0.017***	0.005***	0.048**	0.018***	0.031**	0.058**	0.031**	0.224	0.052*	0.028**	0.322
	(3.242)	(3.018)		(2.435)	(3.317)		(2.518)	(2.128)		(1.867)	(2.120)	
LN(Target mkt equity)	-0.048***	-0.021***	0.025**	-0.046***	-0.025***	0.154	-0.101***	-0.049***	0.032**	-0.089***	-0.039**	0.057*
	(-3.486)	(-2.719)		(-3.390)	(-3.294)		(-4.327)	(-3.183)		(-3.592)	(-2.410)	
Tender offer	0.042	0.045**	0.928	0.073*	0.031	0.313	-0.028	0.03	0.423	0.037	0.001	0.650
	(1.367)	(2.335)		(1.729)	(1.497)		(-0.401)	(0.835)		(0.446)	(0.028)	
Focused	0.001	0.053***	0.081*	-0.015	0.045**	0.086*	-0.025	0.034	0.320	-0.077	0.025	0.128
	(0.041)	(3.115)		(-0.434)	(2.216)		(-0.437)	(0.944)		(-1.480)	(0.626)	

Acquirer Q	-0.009	0	0.181	-0.01	-0.002	0.287	-0.042	-0.012	0.211	-0.044*	-0.009	0.173
	(-1.429)	(0.022)		(-1.470)	(-0.791)		(-1.596)	(-1.318)		(-1.817)	(-0.855)	
Target Q	-0.042***	-0.013***	0.008***	-0.049***	-0.013***	0.012**	-0.109***	-0.048***	0.021**	-0.113***	-0.055***	0.053*
	(-4.559)	(-3.589)		(-4.546)	(-3.098)		(-5.410)	(-5.095)		(-5.636)	(-4.550)	
Competed	-0.084	-0.080***	0.924	-0.089	-0.106***	0.743	-0.128	0.137**	0.013**	-0.088	0.081	0.149
	(-1.454)	(-3.216)		(-1.406)	(-4.277)		(-1.333)	(2.223)		(-0.930)	(1.339)	
Relative size	0.055	-0.029	0.031**	0.065	-0.025	0.069*	0.228***	0.03	0.036**	0.292***	-0.004	0.006***
	(1.452)	(-1.161)		(1.297)	(-0.866)		(2.913)	(0.573)		(3.226)	(-0.089)	
Target termination fee	0.045	0.004	0.275	0.063	0.016	0.259	0.152*	0.05	0.188	0.197**	0.055	0.095*
	(1.524)	(0.137)		(1.566)	(0.519)		(1.893)	(1.189)		(2.240)	(1.294)	
Acquirer R&D / assets				0.028	-0.06	0.539				0.018	0.029	0.974
				(0.153)	(-0.694)					(0.054)	(0.230)	
Target R&D / assets				0.126	0.071	0.714				0.354	0.126	0.479
				(1.007)	(1.058)					(1.448)	(0.717)	
Acquirer tangible assets				0.145	-0.029	0.163				0.315	-0.049	0.143
				(1.020)	(-0.396)					(1.178)	(-0.365)	
Target tangible assets				-0.095	0.127	0.079*				-0.123	-0.049	0.757
				(-0.985)	(1.582)					(-0.540)	(-0.433)	
Acquirer industry concentration				-0.002	0	0.130				-0.001	-0.001*	0.554
				(-1.645)	(-0.529)					(-0.417)	(-1.806)	
Target industry concentration				0	0.001	0.486				0	0.002*	0.318
				(0.252)	(1.405)					(-0.097)	(1.791)	
Acquiter ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Target ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	616	939		486	799		597	885		473	762	
Adj. R²	0.185	0.089		0.166	0.098		0.19	0.089		0.177	0.077	

Table 7: Joint effect of high C&I loan spread and asset specificity on target returns

This table reports the test results for Ha3. The model used for estimation is: *Proxy for Target SH Premium* = $\phi \times$ *Target asset specificity score* + $Xb + \varepsilon$. Columns (1)-(4) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Columns (5)-(8) use the total offer premium received by target (Schwert (1996)) as the dependent variable. Columns (1), (3), (5) and (7) report estimation results for the high C&I spread regimes. Columns (2), (4), (6) and (8) reports estimation for the rest of the sample. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR			Target 3-day CAR			Target premium			Target premium		
Target subgroup:	High CI spread	Low CI spread	(1)-(2) P-value	High CI spread	Low CI spread	(3)-(4) P-value	High CI spread	Low CI spread	(5)-(6) P-value	High CI spread	Low CI spread	(7)-(8) P-value
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)	
Constant	0.199**	-0.067	0.382	0.459	-0.227***	<0.001***	0.924**	0.243	0.017**	0.568**	0.939***	0.189
	(1.972)	(-1.410)		(0)	(-3.987)		(2.584)	(0)		(2.095)	(5.203)	
Target asset specificity	**-0.217*****	**0.018**	**0.019****	**-0.448*****	**-0.005**	**0.001*****	**-0.522*****	**-0.103**	**0.072***	**-0.611*****	**-0.192**	**0.151**
	(-2.815)	**(0.400)**		**(-4.970)**	**(-0.095)**		**(-2.740)**	**(-0.546)**		**(-3.004)**	**(-1.018)**	
Paid in cash	0.036	0.033**	0.924	0.039	0.040	0.985	0.006	-0.055	0.386	0.034	-0.036	0.353
	(1.528)	(2.065)		(1.565)	(1.630)		(0.100)	(-1.473)		(0.576)	(-0.761)	
Toehold	-0.049	-0.005	0.537	-0.081	0.009	0.271	0.101	-0.029	0.282	0.135	-0.070	0.106
	(-0.616)	(-0.133)		(-0.990)	(0.175)		(0.856)	(-0.451)		(1.494)	(-0.873)	
LN(Acquirer mkt equity)	0.025	0.037***	0.255	0.027	0.033***	0.629	0.039	0.055***	0.511	0.043	0.062***	0.442
	(1.424)	(6.370)		(1.402)	(3.691)		(1.266)	(4.590)		(1.560)	(3.959)	
LN(Target mkt equity)	-0.036**	-0.034***	0.870	-0.038**	-0.032***	0.681	-0.078***	-0.083***	0.846	-0.074***	-0.075***	0.973
	(-2.080)	(-4.225)		(-2.391)	(-2.819)		(-3.774)	(-4.558)		(-3.821)	(-3.509)	
Tender offer	0.037	0.043*	0.871	0.045*	0.031	0.717	-0.089	0.089**	0.009***	-0.073	0.082*	0.031**
	(1.584)	(1.813)		(1.957)	(0.907)		(-1.499)	(2.196)		(-1.285)	(1.667)	
Focused	0.060**	0.018	0.116	0.046**	0.019	0.351	0.037	-0.002	0.479	0.078**	-0.011	0.132
	(2.394)	(1.093)		(2.475)	(1.027)		(1.159)	(-0.081)		(2.212)	(-0.265)	

Acquirer Q	0	0	0.962	-0.012	0.001	0.135	-0.025	-0.010	0.424	-0.032^{**}	-0.007	0.252
	(0.013)	(0.303)		(-1.299)	(0.333)		(-1.555)	(-0.856)		(-2.047)	(-0.485)	
Target Q	-0.011	-0.020^{***}	0.193	-0.013	-0.021^{***}	0.357	-0.052^{***}	-0.061^{***}	0.665	-0.061^{***}	-0.059^{***}	0.917
	(-1.528)	(-3.813)		(-1.473)	(-2.813)		(-4.172)	(-4.555)		(-4.938)	(-3.560)	
Competed	-0.07	-0.088^{***}	0.714	-0.111^{**}	-0.088^{**}	0.655	-0.019	0.035	0.595	0.006	0.004	0.986
	(-1.373)	(-2.670)		(-2.449)	(-2.055)		(-0.279)	(0.606)		(0.082)	(0.067)	
Relative size	-0.028	0.034^{**}	0.132	-0.054	0.034	0.046^{**}	0.105	0.158^{***}	0.628	0.120	0.167^{***}	0.684
	(-0.582)	(1.984)		(-1.123)	(1.166)		(1.391)	(3.945)		(1.619)	(3.086)	
Target termination fee	0.002	0.035^{*}	0.364	0.041	0.042^{**}	0.982	0.065^{*}	0.114^{**}	0.511	0.116^{***}	0.121^{***}	0.950
	(0.061)	(1.660)		(0.888)	(2.042)		(1.703)	(2.274)		(2.654)	(2.990)	
Acquirer R&D / assets				0.140	-0.057	0.139				0.403	-0.113	0.101
				(0.611)	(-1.298)					(1.122)	(-0.857)	
Target R&D / assets				0.100	0.056	0.731				0.597^{***}	-0.134	0.028^{**}
				(0.700)	(0.652)					(3.204)	(-1.179)	
Acquirer tangible assets				0.289^{***}	-0.052	0.004^{***}				0.331	-0.022	0.179
				(3.099)	(-0.983)					(1.268)	(-0.194)	
Target tangible assets				0.027	0.035	0.952				0.092	-0.082	0.479
				(0.294)	(0.558)					(0.348)	(-0.633)	
Acquirer industry concentration				-0.001	0	0.555				-0.001	-0.001	0.826
				(-0.892)	(-0.717)					(-1.176)	(-1.123)	
Target industry concentration				0	0	0.729				0.002	0	0.460
				(0.532)	(0.461)					(0.855)	(0.347)	
Acquiter ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Target ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	611	884		515	715		597	827		507	675	
Adj. R^2	0.121	0.137		0.151	0.121		0.169	0.112		0.181	0.09	

Table 8: Joint effect of low industry cash flow and asset specificity on target returns

This table reports the test results for Ha3. The model used for estimation is: *Proxy for Target SH Premium* = ϕ × *Target asset specificity score* + *Xb* + *ε*. Columns (1)-(4) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Columns (5)-(8) use the total offer premium received by target (Schwert (1996)) as the dependent variable. Columns (1), (3), (5) and (7) report estimation results for targets when their annual industry median cash flow is low. Columns (2), (4), (6) and (8) reports estimation for the rest of the sample. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR			Target 3-day CAR			Target premium			Target premium		
Target subgroup:	Low industry CF	High industry CF	(1)-(2) P-value	Low industry CF	High industry CF	(3)-(4) P-value	Low industry CF	High industry CF	(5)-(6) P-value	Low industry CF	High industry CF	(7)-(8) P-value
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)	
Constant	0.511***	0.134***	0.011**	0.422***	0.184**	0.234	1.039*	0.173*	0.096*	1.034***	-0.123	0.002***
	(3.215)	(2.986)		(3.081)	(2.102)		(1.837)	(1.729)		(2.646)	(-0.659)	
Target asset specificity	**-0.349***	**-0.019**	**0.006***	**-0.459***	**-0.104**	**0.022**	**-1.082***	**0.057**	**<0.001***	**-1.273***	**0.073**	**<0.001***
	(-3.912)	**(-0.405)**		**(-4.290)**	**(-1.486)**		**(-3.926)**	**(0.477)**		**(-4.340)**	**(0.595)**	
Paid in cash	0.014	0.049***	0.343	-0.011	0.065***	0.060*	0.063	-0.042	0.162	0.016	0.006	0.902
	(0.572)	(3.028)		(-0.373)	(2.870)		(0.930)	(-0.986)		(0.213)	(0.133)	
Toehold	-0.018	-0.026	0.921	-0.072	-0.018	0.559	0.122	-0.01	0.324	0.055	-0.015	0.641
	(-0.220)	(-0.561)		(-0.754)	(-0.357)		(1.345)	(-0.164)		(0.665)	(-0.221)	
LN(Acquirer mkt equity)	0.027*	0.031***	0.770	0.032**	0.027***	0.713	0.004	0.058***	0.023**	0.02	0.052***	0.211
	(1.901)	(3.783)		(2.029)	(2.815)		(0.117)	(4.922)		(0.565)	(4.157)	
LN(Target mkt equity)	-0.045***	-0.030***	0.266	-0.048***	-0.031***	0.262	-0.073**	-0.077***	0.885	-0.068**	-0.069***	0.979
	(-3.001)	(-4.207)		(-3.324)	(-3.679)		(-2.439)	(-4.646)		(-2.099)	(-4.143)	
Tender offer	0.052**	0.023	0.452	0.056**	0.022	0.407	-0.023	0.027	0.495	0.036	0.011	0.758
	(2.136)	(1.206)		(2.153)	(0.915)		(-0.276)	(0.631)		(0.437)	(0.252)	
Focused	0.041	0.013	0.367	0.030	0.003	0.414	-0.008	0.009	0.799	-0.034	0.001	0.631
	(1.312)	(0.906)		(0.893)	(0.184)		(-0.121)	(0.351)		(-0.442)	(0.041)	

Acquirer Q	-0.001	0	0.911	-0.005	0.001	0.231	-0.023**	0.003	0.095*	-0.035**	0.007	0.022**
	(-0.150)	(-0.011)		(-0.931)	(0.381)		(-2.581)	(0.260)		(-2.356)	(0.591)	
Target Q	-0.01	-0.023***	0.074	-0.014*	-0.021***	0.481	-0.042***	-0.065***	0.289	-0.042*	-0.069***	0.263
	(-1.617)	(-4.328)		(-1.672)	(-3.485)		(-2.840)	(-5.091)		(-1.886)	(-4.835)	
Competed	-0.02	-0.095**	0.161	-0.038	-0.113**	0.220	0.068	0.02	0.691	0.126	-0.01	0.322
	(-0.387)	(-2.559)		(-0.743)	(-2.549)		(0.573)	(0.675)		(0.922)	(-0.227)	
Relative size	-0.009	0.022	0.474	-0.013	0.027	0.383	0.039	0.133***	0.413	0.051	0.125**	0.541
	(-0.201)	(1.007)		(-0.278)	(1.005)		(0.316)	(3.335)		(0.436)	(2.349)	
Target termination fee	0.026	0.031*	0.893	0.033	0.048**	0.730	0.125*	0.058	0.413	0.156**	0.096**	0.492
	(0.590)	(1.671)		(0.817)	(2.343)		(1.838)	(1.635)		(2.454)	(2.578)	
Acquirer R&D / assets				-0.07	-0.007	0.591				0.099	-0.064	0.567
				(-0.548)	(-0.082)					(0.307)	(-0.449)	
Target R&D / assets				0.17	-0.02	0.120				0.236	0.02	0.512
				(1.571)	(-0.225)					(0.705)	(0.155)	
Acquirer tangible assets				0.151	0.025	0.366				0.336	0.005	0.291
				(1.056)	(0.368)					(0.971)	(0.054)	
Target tangible assets				-0.055	0.037	0.517				0.002	-0.044	0.864
				(-0.414)	(0.670)					(0.012)	(-0.350)	
Acquirer industry concentration				-0.001	0	0.463				-0.002	0	0.513
				(-0.984)	(-0.386)					(-0.897)	(-0.648)	
Target industry concentration				0.001	0	0.314				0.003	0.001	0.305
				(0.860)	(0.289)					(1.203)	(0.616)	
Acquiter ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Target ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	544	1025		468	831		523	975		451	799	
Adj. R²	0.119	0.131		0.131	0.113		0.168	0.127		0.141	0.113	

Table 9: Joint effect of recessions and asset specificity on target returns

This table reports the test results for Ha3. The model used for estimation is: *Proxy for Target SH Premium* = ϕ × *Target asset specificity score* + *Xb* + ε. Columns (1)-(4) use the three-day cumulative target abnormal return around the merger announcement day as the dependent variable. Columns (5)-(8) use the total offer premium received by target (Schwert (1996)) as the dependent variable. Columns (1), (3), (5) and (7) report estimation results for targets during recessions. Columns (2), (4), (6) and (8) reports estimation for the rest of the sample. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Target 3-day CAR			Target 3-day CAR			Target premium			Target premium		
Target subgroup:	Recession	Off-recession	(1)-(2) P-value	Recession	Off-recession	(3)-(4) P-value	Recession	Off-recession	(5)-(6) P-value	Recession	Off-recession	(7)-(8) P-value
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)	
Constant	0.394***	0.099**	0.034**	0.548***	0.014	0.002***	1.441***	0.557***	0.001***	1.319**	0.459***	0.047**
	(2.662)	(2.228)		(4.383)	(0.298)		(3.127)	(3.235)		(2.477)	(3.843)	
Target asset specificity	**-0.287*****	**-0.056**	**0.111**	**-0.233***	**-0.165****	**0.778**	**-0.927*****	**-0.191**	**0.032****	**-0.650**	**-0.307****	**0.520**
	(-3.729)	**(-1.155)**		**(-1.687)**	**(-2.525)**		**(-2.896)**	**(-1.324)**		**(-1.295)**	**(-1.998)**	
Paid in cash	0.069	0.032***	0.404	0.087**	0.033**	0.266	0.017	-0.014	0.730	-0.008	0.009	0.867
	(1.527)	(2.834)		(2.126)	(2.102)		(0.201)	(-0.424)		(-0.063)	(0.260)	
Toehold	-0.249**	0.004	0.002***	-0.291**	0.007	0.004***	0.159*	0.003	0.200	0.154	-0.004	0.296
	(-2.321)	(0.106)		(-2.504)	(0.147)		(1.797)	(0.046)		(1.152)	(-0.063)	
LN(Acquirer mkt equity)	0.041	0.028***	0.283	0.043	0.027***	0.318	-0.01	0.049***	0.060*	0.011	0.052***	0.245
	(1.452)	(3.905)		(1.346)	(3.211)		(-0.160)	(6.185)		(0.238)	(5.123)	
LN(Target mkt equity)	-0.066**	-0.030***	0.009***	-0.063**	-0.035***	0.082*	-0.064	-0.075***	0.718	-0.055**	-0.076***	0.535
	(-2.146)	(-4.292)		(-2.408)	(-4.136)		(-1.443)	(-5.864)		(-2.210)	(-5.980)	
Tender offer	0.073**	0.036**	0.456	0.066**	0.037*	0.555	-0.055	0.022	0.407	-0.067	0.031	0.313
	(2.103)	(2.323)		(2.369)	(1.933)		(-0.573)	(0.579)		(-0.467)	(0.831)	
Focused	0.018	0.025**	0.891	0.004	0.025	0.712	-0.101	0.003	0.274	0.067	0.011	0.679
	(0.251)	(2.052)		(0.080)	(1.549)		(-0.714)	(0.151)		(0.640)	(0.354)	

Acquirer Q	0.001	0	0.844	0	-0.002	0.738	0	-0.018	0.378	0.001	-0.021	0.389
	(0.226)	(0.052)		(-0.063)	(-0.695)		(0.060)	(-1.386)		(0.093)	(-1.172)	
Target Q	-0.011	-0.019***	0.323	-0.018	-0.018***	0.932	-0.069***	-0.058***	0.742	-0.071***	-0.056***	0.669
	(-1.278)	(-3.297)		(-1.184)	(-2.883)		(-3.765)	(-4.675)		(-3.460)	(-3.711)	
Competed	-0.081**	-0.081**	0.997	-0.150***	-0.083**	0.329	-0.052	0.044	0.578	0.109***	0.016	0.637
	(-2.078)	(-2.458)		(-3.350)	(-2.212)		(-1.038)	(0.793)		(2.680)	(0.272)	
Relative size	-0.033	0.009	0.500	-0.019	0.013	0.662	-0.123	0.142***	0.142	-0.047	0.150***	0.314
	(-0.330)	(0.558)		(-0.149)	(0.528)		(-0.595)	(4.462)		(-0.234)	(4.678)	
Target termination fee	0.107*	0.017	0.092*	0.152***	0.033	0.066*	0.016	0.102***	0.517	0.124	0.116***	0.960
	(1.957)	(0.814)		(3.177)	(1.446)		(0.120)	(2.677)		(0.860)	(3.328)	
Acquirer R&D / assets				-0.066	-0.019	0.792				-0.502**	0.191	0.059*
				(-0.300)	(-0.203)					(-2.212)	(1.220)	
Target R&D / assets				0.280	0.014	0.106				1.042***	-0.072	0.007***
				(1.205)	(0.221)					(4.661)	(-0.745)	
Acquirer tangible assets				-0.252	0.074	0.109				-0.746	0.186*	0.067*
				(-1.201)	(1.187)					(-0.906)	(1.763)	
Target tangible assets				-0.238	0.008	0.206				0.362	-0.101	0.290
				(-1.639)	(0.171)					(0.618)	(-1.109)	
Acquirer industry concentration				-0.001	0	0.631				0	-0.001	0.701
				(-0.726)	(-0.971)					(0.097)	(-1.304)	
Target industry concentration				0.001	0.001	0.968				-0.003	0.001*	0.192
				(0.436)	(1.450)					(-1.648)	(1.798)	
Acquiter ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Target ind. fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	239	1,334		193	1,107		223	1,278		182	1,069	
Adj. R^2	0.183	0.106		0.202	0.104		0.091	0.127		0.022	0.125	

Table 10: Joint effect of low interest coverage and asset liquidity on target returns

This table reports the test results for Ha4. The model used for estimation is

$$Proxy\ \ for\ Target\ SH\ \ Premium = \phi \times Target's\ asset\ specificity\ score + Xb + \varepsilon$$

The dependent variable for all regressions is the three-day cumulative target abnormal return around the merger announcement day. In Panel A, a target firm with its interest coverage ratio below the industry-year median is classified as financially distressed. In Panel B, a target firm with its Altman Z-score below 2.99 is classified as financially distressed. All models include year fixed effects and target and acquirer industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A: with targets' interest coverage

Dependent variable: 3-day cummulative return

	Distressed & high CI spread (1)	Distressed & low CI spread (2)	Not distressed & high CI spread (3)	Not distressed & low CI spread (4)	(1)-(4) P-value
Target asset specificity	-0.796***	-0.168	-0.215	-0.086	0.002***
	(-3.043)	(-0.840)	(-1.641)	(-0.697)	
Observations	199	185	306	297	
Adj. R²	0.223	0.023	0.084	0.101	

	Distressed & low ind.CF (1)	Distressed & high ind.CF (2)	Not distressed & low ind.CF (3)	Not distressed & high ind.CF (4)	(1)-(4) P-value
Target asset specificity	-0.514*	-0.341	-0.183*	-0.029	0.007***
	(-1.913)	(-1.017)	(-1.758)	(-0.211)	
Observations	241	163	360	277	
Adj. R²	0.096	0.240	0.085	0.040	

Panel B: with targets' Altman Z-score

Dependent variable: 3-day cummulative return

	Distressed & high CI spread (1)	Distressed & low CI spread (2)	Not distressed & high CI spread (3)	Not distressed & low CI spread (4)	(1)-(4) P-value
Target asset specificity	-0.407***	-0.001	-0.268	-0.017	0.015**
	(-4.085)	(-0.004)	(-1.625)	(-0.140)	
Observations	328	157	459	340	
Adj. R²	0.173	0.164	0.096	0.129	

	Distressed & low ind.CF (1)	Distressed & high ind.CF (2)	Not distressed & low ind.CF (3)	Not distressed & high ind.CF (4)	(1)-(4) P-value
Target asset specificity	-0.451***	-0.076	-0.301*	-0.017	0.022**
	(-4.027)	(-0.765)	(-1.673)	(-0.163)	
Observations	268	184	386	380	
Adj. R²	0.183	0.134	0.133	0.085	

Table 11: Changes in leverage and asset illiquidity

This table reports the test results for Ha5. The regression model used for estimation is: *Change in Leverage* $= \theta \times$ *Target asset specificity score* $+ X\beta + \varepsilon$ Columns (1), (2), (5) and (6) in Panel A and columns (1) and (2) in Panel B report model estimation using changes in leverage from the current year to the following year as the dependent variable. Columns (3), (4), (7) and (8) in Panel A and columns (3) and (4) in Panel B report model estimation using a two-year leverage change starting the current year as the dependent variable. The subgroups for which the models are estimated appear at the table header. All models include year fixed effects and industry fixed effects with the Fama-French 12 industry specifications. Student t-statistics from standard errors clustered by the acquirer identifier is reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively

Panel A.

Dependent variable:	Δ Leverage [0 +1]			Δ Leverage [0 +2]			Δ Leverage [0 +1]			Δ Leverage [0 +2]		
Target subgroup:	Low ind. CF (1)	High ind. CF (2)	(1)-(2) P-value	Low ind. CF (3)	High ind. CF (4)	(3)-(4) P-value	High CI spread (5)	Low CI spread (6)	(5)-(6) P-value	High CI spread (7)	Low CI spread (8)	(7)-(8) P-value
Constant	0.012	-0.025	0.305	0.022	-0.027	0.919	-0.040	-0.060	0.379	-0.044	-0.052	0.427
	-0.387	(-0.855)		-0.452	(-0.659)		(-1.036)	(-1.637)		(-0.613)	(-1.013)	
Asset specificity	**-0.067****	**-0.002**	**0.089***	**-0.085****	**-0.008**	**0.399**	**-0.072***	**0.006**	**0.059***	**-0.066**	**-0.012**	**0.115**
	(-2.332)	**(-0.066)**		**(-2.295)**	**(-0.207)**		**(-1.957)**	**-0.202**		**(-1.383)**	**(-0.269)**	
LN(Book assets)	0.006***	0.005**	0.043**	0.010***	0.003	0.035**	0.009***	0.002	0.615	0.013***	0.003	0.075*
	-2.855	-2.538		-3.442	-1.227		(3.643)	(0.774)		(4.025)	(0.775)	
Profitability	-0.057*	0.03	0.174	-0.117**	0.05	0.676	0.03	-0.038	0.064*	-0.029	-0.058	0.010**
	(-1.681)	-0.866		(-2.429)	-1.075		(0.784)	(-1.105)		(-0.635)	(-1.074)	
Q	-0.007**	-0.002	0.269	-0.010***	-0.005	0.029**	-0.005**	-0.001	0.251	-0.011***	0.002	0.394
	(-2.300)	(-0.565)		(-3.015)	(-1.116)		(-1.982)	(-0.207)		(-3.586)	(0.398)	
R&D /assets	-0.105*	-0.016	0.143	-0.241***	0.005	0.476	0.031	-0.089	0.218	0.034	-0.059	0.034**
	(-1.650)	(-0.430)		(-2.939)	-0.08		(0.580)	(-1.370)		(0.410)	(-0.576)	
Advert. / assets	0.078	-0.026	0.136	-0.136	0.16	0.900	0.093	-0.113	0.290	-0.036	-0.006	0.075**
	-0.854	(-0.409)		(-0.922)	-1.302		(0.750)	(-1.471)		(-0.181)	(-0.047)	
Tangible assets / assets	-0.018	0.002	0.050**	-0.03	0.001	0.070*	-0.035	0.034	0.408	-0.048	0.049	0.440
	(-0.946)	-0.136		(-1.018)	-0.03		(-1.303)	(1.451)		(-1.220)	(1.295)	
Marginal tax rate	-0.01	-0.077	0.008***	-0.006	-0.045	0.013**	-0.116	0.061	0.305	-0.051	0.048	0.724
	(-0.155)	(-1.201)		(-0.063)	(-0.535)		(-1.645)	(0.730)		(-0.573)	(0.432)	
Industry adjusted leverage	-0.209***	-0.168***	0.099*	-0.360***	-0.341***	0.480	-0.209***	-0.105***	0.448	-0.357***	-0.225***	0.762
	(-6.410)	(-7.057)		(-8.027)	(-9.769)		(-7.191)	(-4.137)		(-9.994)	(-5.384)	
Industry fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	1,600	2,804		1,393	2,495		1,300	1,523		1,117	1,357	
Adj. R²	0.117	0.061		0.188	0.132		0.102	0.037		0.203	0.061	

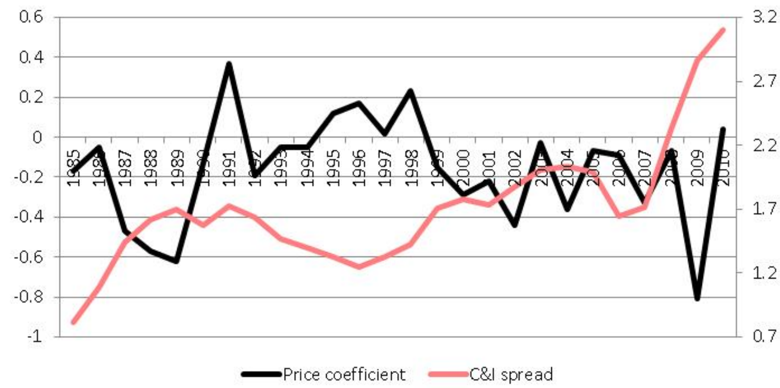
Panel B.

Dependent variable:	Δ Leverage [0 +1]			Δ Leverage [0 +2]		
Target subgroup:	Recession	Off-recession	(1)-(2) P-value	Recession	Off-recession	(3)-(4) P-value
	(1)	(2)		(3)	(4)	
Constant	-0.029	0.044*	0.100	0.047	-0.02	0.427
	(-0.738)	(1.922)		(0.754)	(-0.652)	
Asset specificity	**-0.017**	**-0.040****	**0.476**	**-0.077***	**-0.047**	**0.497**
	(-0.583)	**(-2.147)**		**(-1.918)**	**(-1.481)**	
LN(Book assets)	0.003	0.007***	0.178	0.003	0.009***	0.092*
	(1.479)	(5.196)		(1.015)	(4.461)	
Profitability	-0.070*	0.016	0.108	-0.120**	0.011	0.043**
	(-1.761)	(0.471)		(-2.233)	(0.271)	
Q	-0.006	-0.007***	0.702	-0.006	-0.010***	0.417
	(-1.644)	(-2.993)		(-1.130)	(-3.406)	
R&D /assets	0.056	-0.027	0.399	-0.445***	0.017	<0.001***
	(0.603)	(-0.895)		(-3.741)	(0.356)	
Advert. / assets	-0.056	0.069	0.247	-0.09	0.151	0.070*
	(-0.735)	(0.888)		(-0.741)	(1.178)	
Tangible assets / assets	-0.003	0.002	0.846	0.004	-0.015	0.577
	(-0.118)	(0.184)		(0.122)	(-0.715)	
Marginal tax rate	0.033	-0.109**	0.556	-0.028	-0.068	0.662
	(0.366)	(-2.201)		(-0.215)	(-1.051)	
Industry adjusted leverage	-0.155***	-0.180***	0.153	-0.352***	-0.331***	0.780
	(-4.223)	(-9.938)		(-8.171)	(-12.507)	
Industry fixed effects	Yes	Yes		Yes	Yes	
Year fixed effects	Yes	Yes		Yes	Yes	
Observations	1,349	12,473		1,265	11,179	
Adj. R^2	0.116	0.048		0.095	0.033	

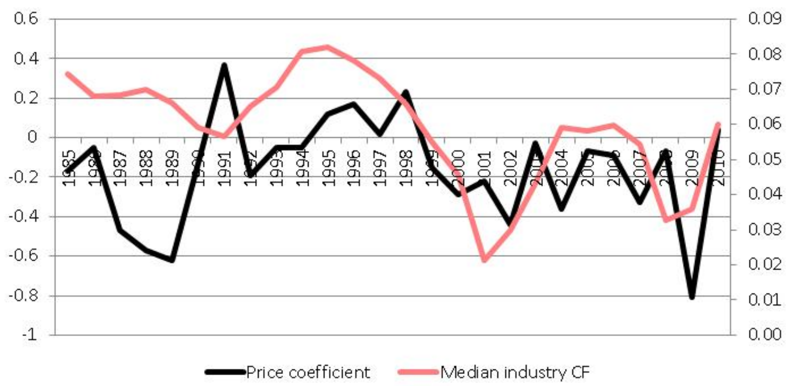
Figure 1: Cyclicality of liquidity discount

These graphs display a time series of asset specificity discount coefficients over the 1985-2010 period, shown as the black line. In Panel A, the red line is the annual average C&I spread; in Panel B, the red line is the median value of median industry free cash flow divided by book assets; in Panel C, the red line is the median value of annual average real GDP growth. The vertical axis on the left shows the price coefficient scale and the axis on the left show the scales for the economic variables.

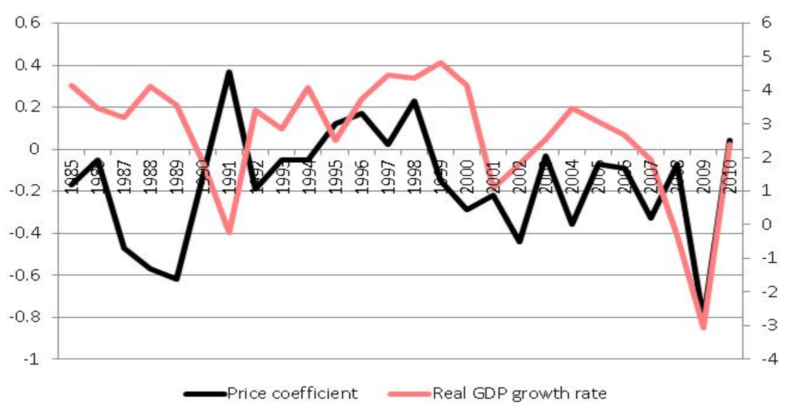
Panel A.



Panel B.



Panel C.



Chapter 2: Debt Financing Frictions and Access to Public Debt

2.1 Introduction

Imperfect and segmented financial markets create frictions in the supply of external capital, and these frictions affect corporate activities that require external financing. The objective of this study is to investigate a causal relationship between debt financing frictions and their effects on corporate capital structure and firm growth.

The main predictions of this paper have three parts. First, firms having characteristics associated with greater information asymmetries between firm insiders and outside investors, e.g. small firm size and weak third-party information production, are more likely to be unable to access public debt and so remain in the private debt market. Second, firms that were previously unable to access public debt due to such debt financing frictions undergo a substantial increase in leverage once the firms gain access to public debt. Third, because their growth has been constrained due to costly private financing, firms entering the public debt market, experience a rapid increase in asset size as the new financing source for growth becomes available to them.

The identification strategy of this paper comes from relating firms' *ex post* reaction to the reduction in financial constraints to the *ex ante* extent of financing frictions. Following Faulkender and Peterson (2006), I use the event of unrated firms' securing a public debt rating for the first time as a proxy for the firms' gaining access to a cheaper means of financing, which eases the firms' financial constraints through reduction in borrowing costs.

This approach differs from studies using true natural experiments in a few aspects. The advantage of using the securing of a debt rating as the event of the study is that the events are scattered across time so that it is possible to draw time-controlled implications. On the other hand, unlike a true natural experiment that provides an exogenous event that randomly assigns treatment to the population, the securing of a debt rating occurs only to firms that both choose to participate and are qualified to participate, i.e. only the firms that have access and seek access to public debt. In order to mitigate this endogeneity issue I use fixed effects and the Heckman two-step selection model. The empirical results support the existence of a causal relation between financing frictions and the post-rating changes in capital structure and firm growth even after addressing the endogeneity issues.

The constrained investment literature has shown that firm size is strongly correlated with the extent of financial constraints (Gilchrist and Himmelberg (1995), Erickson and Whited (2000)). Basing on this finding, I divide the pre-rating sample firms into two groups, *ex ante* small firm group consisting of more financially constrained firms and *ex ante* large firm group consisting of less constrained firms, by firms' total book asset size measured one year prior to their rating years.[22] For another proxy for financing frictions, I follow Chang, Dasgupta and Hilary (2007) and Lang and Lundholm (1993) and use the annual average number of analyst following to capture the intensity of third-party information production surrounding each sample firm. As in the firm size variable, I divide the sample firms into two groups, *ex ante* less analyst coverage group and *ex ante* more coverage group, based on the number of analyst reports on year prior to the firms' rating year.

The empirical results strongly support the causal relation between debt financing frictions and capital structure and also firm growth. First, a multivariate probit regression reveals that the likelihood of gaining access to the debt market is significantly greater for firms having asset size greater than the median size of firms accessing public debt for the first time and having analyst coverage greater than the median amount of coverage on the firms entering the debt market.

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[22] Hadlock and Pierce (2007) find firm size and age are the two measures that perform consistently well in identifying financially constrained firms. The findings of Whited and Wu (1996) also confirm that firm size is one of the most reliable measures of financial constraints. Similarly, Beck, Demirgüç-Kunt and Maksimovic (2005)'s survey study shows that firm size is perceived by firm management as a variable most strongly associated with financial and legal constraints, not only in the United States but in other countries as well.

Second, a multivariate regression test on changes in leverage reveals that firms accessing public debt for the first time sharply increase leverage in the rating years and more so if the firms are from more constrained groups, e.g. small and less covered firms, by 27% and by 11% of the total asset, respectively.

Third, a test result from a panel data regression indicates that the leverage increase in the rating years explains more about firm growth in that year if the firms were exposed to greater financing frictions before they entered the public debt market. For example, for firms in the small *and* less analyst coverage group, each unit of debt increase is responsible for that of asset growth by 0.6 in the rating year. As for firms in the large *and* more coverage group, the sensitivity is -0.04. I present evidence that this discrepancy is at least partially because unconstrained firms distribute the raised cash to investors rather than use it to finance growth.

While the literature on stock IPO is extensive, studies on firms' initial access to public debt is relatively rare. To my knowledge, this paper is one of few attempts to document the effect of financial market segmentation on corporate financing and growth by investigating the changes the firms undergo entering the public debt market. Hale and Santos (2008) explore firms' timing of entering the public bond market for the first time. Datta, Iskandar-Datta, and Patel (2000) study the stock market reactions to the news of firms entering the debt market in the agency context. This paper is also closely related to the literature on debt supply frictions (Faulkender and Peterson (2006), Sufi (2009), Lemmon and Roberts (2010) and others).

Implications from my paper are also related to the findings of Chang, Dasgupta and Hilary (2006). Motivating their study in the context of information asymmetry and market timing surrounding seasoned equity offerings, the authors empirically show that small firms with low analyst coverage are financially more constrained because of high cost of equity stemming from severe information asymmetry. They find that such firms less frequently issue equity and time the market more, but when the market conditions change so that equity issuance is available at a low cost, they raise funds through large SEOs.

The rest of the paper is outlined as follows. Section 1 derives testable implications. Section 2 provides descriptive statistics. Section 3 reports empirical test results. Section 4 concludes.

2.2 Hypothesis

In this section, I develop a simple two-period model in order to illustrate how firm size and third-party information production may affect firms' ability to finance their growth. The model's main implication is that financing frictions impede firms' ability to draw private financing as well as their access to public debt financing, and the wedge between the optimal amount of external financing to support firms' investment opportunities and the firms' inability to fully raise the amount through equity, internal financing and private loans forces firms to forgo a part of positive net present value (NPV) projects.

A firm with an investment technology $g(\cdot)$ invests an amount I at the beginning of a period and receives $g(I)$ at the end of the period. There are largely two sources for I: W, a non-debt financing source; D, debt financing that includes bank debt B and public debt sources A (public bond market and certified syndicate bank loans (Sufi, 2007, 2009)), such that $D = B + A$.[23]

To simplify the analysis, I make the following assumptions regarding bank debt B and arm's length financing A. First, a firm can borrow an optimal bank loan B from its banks at a price that fairly reflects the riskiness of the firm's investment as long as B is below a certain value $\overline{B}$, a maximum loan amount due to credit rationing (Stiglitz and Weiss (1981)).

[23] This setting is applicable to both the pecking order and the trade-off contexts depending on how one interprets W; in the pecking order context, W is an internal financing source with the least information asymmetry costs; in the trade-off context, W reflects some optimized combination of internal and equity financing before the firm considers debt financing as an additional source for next investment projects in an attempt to maximize firm value.

$\overline{B}$ is an inverse function of a firm-level variable f that negatively affects the firm's credit status to potential lenders, such that and $\frac{\partial \overline{B}}{\partial f} < 0$. Examples of such "friction variables" could be proxies for credit worthiness or for the level of information opacity. We may also resort to Faulkender and Peterson (2006) to interpret the inverse relation in another way: information production that reduces adverse selection and moral hazard for borrowing firms is a prerequisite for attracting outside investors. Information production through private intermediaries such as banks is costly and the expense is imposed on the borrowing firms in the form of increased borrowing costs. In that context, f is correlated with the unit cost of producing information about the firm to attract additional dollar of external financing from potential investors.

A firm issues public debt through an investment bank. There are two types of underwriting costs: the fixed cost ϕ and the variable cost $c(A, f)$ such that $\frac{\partial c}{\partial f} > 0$ and $\frac{\partial^2 c}{\partial A \partial f} > 0$. The variable cost is a function of both the amount raised and the firm's friction variable, reflecting the implications from Altinkihc and Hansen (2000). I use $c(A, f) = A \cdot f$ to simplify the model and assume $0 < f < 1$. The underwriting market is competitive and each investment bank earns a zero economic profit from their underwriting service. For simplicity, I assume a zero discount rate, no implicit underpricing cost, and no incremental distress cost from increasing leverage. The model does not distinguish the events of a firm's entering a public debt market for the first time and of a firm's securing its credit debt rating for the first time separately, as in Faulkender and Peterson (2006).

Let us assume first that the firm used up all other means of financing and is to finance its investment opportunity entirely with the public debt A. The firm hires an investment bank for its debt issuance and looks to enter the debt market for the first time. The cost of underwriting, which will be fully paid by the issuing firm, is the sum of the fixed and the variable cost of underwriting service, $C = A \cdot f + \phi$. The investment bank is a price taker and charges a service fee at a fixed market rate $0 < \dot{\alpha} < 1$ such that its service generates $A \cdot \dot{\alpha}$ for the investment bank. Assuming zero economic profit, the bank will not contract unless $A \geq \dfrac{\phi}{\dot{\alpha} - f}$. Let $\overline{A} \equiv A = \dfrac{\phi}{\dot{\alpha} - f}$, the minimum target issue amount for which the bank is willing to contract. Then, it follows that $\dfrac{\partial \overline{A}}{\partial f} > 0$ and $\dfrac{\partial^2 \overline{A}}{\partial f^2} > 0$.

The issuing firm's goal is to maximize the following objective function:

$$\max_{A} g(A) - A - (A \cdot f + \phi),$$

$$s.t.\ \ g(A) - A - A \cdot f \geq \phi, \ \text{and} \qquad (1)$$

$$A \geq \frac{\phi}{\dot{\alpha} - f} \qquad (2)$$

The constraint term (1) captures the firm's incentive to not participate if investing through public debt financing results in negative profit, and term (2) is the investment bank's participation condition. Which one of the two conditions binds depends on the relative size of $g(A)$ and $(1+\dot{\alpha})A$. If the condition (1) binds, the optimal A^* for the issuing firm is such that $g'(A^*) = 1 + f$ and it follows that $\dfrac{\partial A^*}{\partial f} < 0$. If the left-hand side of (1) is less than ϕ at A^*, then the firm opts not to borrow and forgoes the investment opportunity. There is a maximum threshold for f, $\overline{f}$, for a given investment technology $g(\cdot)$ that makes $g(A^*) - A^* - A^* \cdot \overline{f} = \phi$. If the condition (2) binds, then the maximum $\overline{f}$ for the given $g(\cdot)$ forms not at A^* but at $\overline{A}$, such that $g(A) - \overline{A} - \overline{A} \cdot \overline{f} = \phi$, where $\overline{A} > A^*$.

Several implications emerge from the model. First, firm size is an important determinant for whether an unrated firm's investment is financially constrained. If the issuing firm is too small or the issue size is not large enough so that the investment bank can not cover the fixed cost with the service revenue, it may be difficult for an issuer to hire an investment bank for underwriting and distribution service even if the issuing firm has firm characteristics desirable to investors.

Second, firm characteristics f that is correlated with the firm's internalized information production cost is another important determinant of constrained financing. Firms perceived to be opaque, i.e. with high f such that $f > \overline{f}$ for a given size and investment technology $g(\cdot)$, will face issue costs not low enough to make the investment profitable, and thus forgo the investment.

Third, exogenous shocks such as technological or economic conditions can affect $g(\cdot)$, W or the overall f in the economy as well as firms' ability and incentives to access public debt. Specifically, if the marginal cost of debt issuance is a function of γ such that $f(\gamma)$, instead of just f, where γ reflects the financial market conditions such as overall illiquidity in the market, then $\frac{\partial \overline{f}}{\partial \gamma} < 0$ and $\frac{\partial \overline{A}}{\partial \gamma} > 0$, i.e. poor financial market conditions reduce firms' likelihood of tapping into public debt.

Let us relax the restricting assumption on other financing means and allow the firm to finance through equity, internal and bank loans. To determine changes in the firm when rated, I examine a two-period world in which the firm is unrated in the first period and rated and thus financially unconstrained in the second period. The subscript 1 and 2 denotes the first and the second periods.

If a firm's optimal investment in the first period, I_1^*, is financially unconstrained due to high $\overline{B}(f_1)$, abundant internal funding W_1 or low investment opportunities, so that $I_1^* \leq W_1 + \overline{B}(f_1)$, the changes in the firm's leverage in the second period does not reflect the existence of any credit supply frictions because the firm was not constrained in the first period.

On the other hand, if the firm's financing in the first period is constrained because its funding needs for investment is greater than the maximum internal and external funds the firm is able to raise, i.e. $f_1 > \overline{f}_1$ and $I_1^* > W_1 + \overline{B}(f_1)$, then changes in leverage observed in the second period should reflect the financing frictions during the first period because the second period shift in leverage is equal to $D_{12} \equiv D_2 - D_1 = B_2 + A_2 - \overline{B}(f_1)$. Because of the earlier assumption $\frac{\partial \overline{B}_1}{\partial f_1} < 0$, it follows that $\frac{\partial D_{12}}{\partial f_1} > 0$, i.e. the sensitivity of the leverage shift in the second period to the *ex ante* friction variable is positive. Similarly, because $I_2 = W_2 + D_2 = W_2 + \left(D_1 + D_{12}\right)$, it follows that $\frac{\partial I_2}{\partial (D_{12} \mid f_1)} > 0$.

The overall implication is that corporate financing and growth may be constrained by small size and the high cost of information production. Guided by the implications from the model, I construct the following propositions:

- P1-1: Small firm size and weak information production negatively affects firms' likelihood of accessing public debt.
- P1-2: Poor financial market conditions make the negative relation in P1-1 more pronounced.

- P2-1: $\frac{\partial D_{12}}{\partial S_1} < 0$, i.e. the effect of *ex ante* small firm size on the leverage shift after securing access to public debt is positive.
- P2-2: $\frac{\partial D_{12}}{\partial f_1} > 0$, i.e. the effect of *ex ante* weak third –party information production on the leverage shift after securing access to public debt is positive.

- P3-1: $\frac{\partial I_2}{\partial (D_{12} \mid -S_1)} > 0$, i.e. the marginal effect of an increased borrowing in the rating year on firm growth is positive and the effect is more pronounced with *ex ante* small firm size.

- P3-2: For *ex ante* financially unconstrained firms, $\frac{\partial I_2}{\partial(D_{12} \mid f_1)} > 0$, i.e. the marginal effect of an increased borrowing in the rating year on firm growth is positive and the effect is more pronounced with weak third-party information production.

The model I present in this paper only focuses on supply side implications in a static two-period world and assumes away important determinants of financing decisions such as growth, tax and financial distress cost. I also acknowledge that the effect of financing frictions alone certainly does not fully explain firms' capital structure decisions and growth. The point of this exercise is to show two possible sources of frictions, i.e., firm size that implies an economically feasible minimum issue size for underwriters and the cost of information production that affect the firms' borrowing ability.

2.3 Data

The test sample consists of publically traded firms that obtain their issuer credit ratings for the first time during the 1987-2011 period. COMPUTSTAT began populating Standards and Poor's (S&P) issuer credit rating (item 288) from 1986, which I set as the beginning year of my sample period. COMPUSTAT maintains the firm-level credit rating record every month since 1986. From the dataset, I indentify the month and the year in which a firm receive a rating score for the first time and consider it as the time of entering the public debt market. If the matching calendar year's fiscal year end date comes after the rating month, the year is set as the fiscal year that links to the annual COMPUSTAT data. If a fiscal year end date comes before the rating month, then the next fiscal year is set as the firm's rating year.

One of the key explanatory variables in this paper is the number of analyst following. I compile this variable using the analyst coverage data from Thomson Reuters I/B/E/S Historical Summary. To construct the variable, I take a fiscal-year average of the monthly analyst count reporting on earning-per-share and use it as the extent of analyst coverage for that year. As in Chang, Dasgupta and Hilary (2007), I use the raw count or a binary variable throughout this paper without log-transforming it. I also treat missing analyst following value as not having coverage.[24]

I discard firms that already have issuer ratings entering year 1986 because there is no way of verifying from the dataset whether these firms received the ratings in 1986 for the first time or did so before 1986. Following the literature convention, I exclude firms in the financial (SIC in 6000s) and utility sectors (SIC in 4900-4999) and also firms with book asset value smaller than 10 million dollars.

I consider missing values in R&D expenditure, advertising expenditure, capital expenditure, short term and long term debt as zero. Following the literature, I winsorize the variables at the 1% and 99% level in order to prevent a few extreme values from driving the test results. I also winsorize the book and market leverage ratios exceeding 1.00.

The constrained investment literature implements various approaches to assign firms into financially constrained and unconstrained groups. Almeida and Campello (2007, p.1441) give a good review of the methods used in the literature. I divide the pre-rating sample firms into two groups, *ex ante* small firm group for more financially constrained firms and *ex ante* large firm group for less constrained firms, by firms' total book asset size measured one year prior to their rating years. For a proxy for the *ex ante* unit cost of information production, I follow Chang, Dasgupta and Hilary (2007) and Lang and Lundholm (1993) and use the annual average number of analyst forecasts on a firm to capture the intensity of third-party information producing activities surrounding each sample firm. As in the firm size variable, I divide the sample firms into two groups, *ex ante* less analyst coverage group and *ex ante* more coverage group, based on the annual average number of analyst reports on the years

[24] The regression results are qualitatively unaffected when log-transformed values are used or when observations with missing analyst coverage are excluded from the tests.

prior to the firms' rating years.

Panel A in Table 12 compares the firm characteristics of the firms accessing public debt for the first time prior to the rating years (shown in column (2)) to those of the two other firm groups, one consisting of unrated firms (shown in column (1)) and the other group consisting of rated firms (shown in column (3)). A mean comparison test and a Wilcoxon rank-sum test among the firm groups show that firms entering the public debt market grow faster than the firms in the other two groups, and the growth rate accelerates significantly in the rating year (from 0.56 to 0.59) while firms in the other groups display diminishing growth rates (from 0.33 to 0.19 for group (1) and from 0.10 to 0.06 for group (3)). Firms entering the public debt market also accelerate the annual rate of leverage increase (from 0.01 to 0.07) and the amount of net debt issued (from 0.13 to 0.25), while other groups show little year-to-year changes for the same variables. Firms entering the public debt market have larger asset size and greater analyst coverage than unrated firms, consistent with the prediction that the likelihood of accessing public debt is positively correlated with firm size and also with the intensity of third-party information production. Rated firms are older, larger, more levered, have lower Q and grow slower than firms entering the public debt market. The unrated firms are smaller, less levered, with higher Q and more R&D intensive than the firms being rated.

Panel B compares the cost of issuing public bonds to firms entering the public debt market to the cost to the rated firms. I use the bond yield spread over the treasury yield of the same maturity, provided by the Thomson Reuters' Securities Data Corporation (SDC) new security data service, as a proxy for issue cost. Row (1) reports the summary statistics for the yield spread of bonds issued by firms entering the public debt market, and the row (2) reports the statistics for yield spread of bonds issued by rated firms. The number of observations for group (1) is smaller than actual number of firms being rated because the SDC data does not cover other sources of public or semi-public debt types such as syndicated loans.

The results from the mean comparison test and the Wilcoxon rank sum test on the two groups show that the debt issue cost is higher for newly rated firms than that for rated firms. Panel C further divides the firms issuing public bonds around rating years into four groups by firm size and analyst coverage. Comparison among the groups reveals that firm size and analyst coverage are inversely correlated with the cost of debt issuance, and this is consistent with the earlier assumption that third-party information production and firm size are negatively correlated with the cost of borrowing.

Panels in Figure 2 illustrate the changes the firms entering the public debt market undergo in their capital structure and asset size. Panel A in Figure 2 presents the firm-year average book leverage of the sample firms during [-6 +6] panel years surrounding the rating years (year 0). I only include observations of firms having no missing year observations for the panel period. There is a substantial upward shift in leverage in the rating year, consistent with the summary statistics in Table 12. Panel B shows average asset size of firms around the rating years. The asset growth rate appears to increase in the rating years, consistent with the findings from the Table 12.

P2 and P3 predict that firms that had greater financing frictions are more financially constrained in terms of both capital structure and growth, and so they would increase leverage more and grow faster as they gain access to the new and cheaper financing source. Figure 3 highlights this positive relation between the extent of *ex ante* financing frictions and changes in leverage as well as financing frictions and firm growth in the rating years. The first column reports annual changes in leverage and growth rate during the years surrounding the rating years for small and large firm groups. Propositions P2 and P3 predict a higher rating-year (year 0) increase for the small firm group in each category than for the large firm group, and that is precisely what the graphs show.

The graphs in the second column report average annual changes in each category for the less analyst coverage group as well as for the more coverage group. As in column 1, the pattern in column 2 is consistent with P2 and P3 in that a higher rating-year (year 0) increase for the less covered firm group in every category compared to the more covered group, but the effect in column 2 is smaller than that in column 1.

2.4 Empirical Results

2.4.1 Public debt access and leverage change

In this section, I report the empirical results examining the relation between financing frictions and the likelihood of unrated firms' entering the public debt market. There are two main explanatory variables in the regression. The first one is Asset Size < median dummy, a binary variable that takes the value 1 if book asset size of a firm is smaller than the median asset size of firms securing a debt rating for the first time and 0 if the book asset size of the firm is greater than the median. The second key variable is Number of analyst forecasts < median dummy, a binary variable that takes the value 1 if the annual average number of analyst forecasts of a firm is fewer than the median count of analyst forecasts of firms securing a debt rating for the first time and 0 if the forecast count of the firm is greater than the median.

Proposition P1-1 states that small firm size and weak third-party information production negatively affects firms' likelihood of accessing public debt. The empirical prediction is that there is a negative relation between the likelihood of accessing public debt and the two key explanatory variables, small firm size and weak analyst coverage.

Table 13 reports the regression results on all unrated firm observations with non-missing data during the sample period. The first three columns are estimated using probit models with year fixed effects, and the latter three columns are estimated using linear probability models with firm and year fixed effects. The dependent variable for the models is a binary variable that takes the value 1 if a firm secures a debt rating for the first time in the observed year and

0 otherwise, and all explanatory variables are lagged by one year.

Consistent with the predictions, all columns report negative and statistically significant coefficients on the two key explanatory variables. Coefficients on other variables are also consistent with the findings in the literature (Datta, Iskandar-Datta, Patel (2000) and Faulkender and Petersen (2006)). In untabulated logit estimation, the coefficients for the two explanatory variables expressed in odds ratios are 0.186 and 0.716 respectively, indicating a significant reduction in the probability of securing a debt rating for small firms and firms with low analyst coverage.

Proposition P1-2 states that poor financial market conditions make the negative relation between the two friction variables and the likelihood of securing a debt rating shown in P1-1 more pronounced. In order to test this prediction, I estimate the following regression model for a sample of firms entering the public debt market:

$$Friction\ variable_{yr-1} = \alpha + Proxies\ for\ Economic\ Conditions_{yr-1} \times \mathrm{B} + X_{yr-1} \times \beta + e_t$$

Friction variable is either the firm size or the number of analyst following on the firms receiving a debt rating in the following year. *Proxies for economic conditions* are variables that are correlated with the overall conditions in the financial market and the economy. Following Harford (2005), I use the C&I loan spread, which is the spread between the average interest rate on commercial and industrial loans and the Federal Funds rate, as a proxy for credit tightening in the economy.[25] Another proxy used for the economic conditions is the industry-year median cash flow compiled at the three-digit SIC code level. The prediction is that there is a positive relation between the overall credit tightness in the financial market and the firm size and information production (thus low information asymmetry) required for accessing public debt.

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[25] The data is available in the Federal reserve's Survey of Terms of Business Lending at http://www.federalreserve.gov/releases/e2/e2chart.htm.

Table 14 presents the estimation results. The dependent variable for the first column is the analyst coverage variable in raw number. Because the dependent variable's discreteness violates OLS assumptions, I estimate a negative binomial model instead of an OLS model for the test. The model setting is similar to that of the empirical setting used in Chang et. al. The result shown in the first column is consistent with the prediction in that the coefficient on the C&I loan spread, 1.52, expressed in the incidence rate ratio, indicates a positive correlation between the spread and the number of analyst following. The coefficient on the industry median cash flow variable is less than 1 and indicates that the level of industry cash flows, which is correlated with easing of liquidity in the economy, is negatively related with the number of analyst following of firms entering the public debt market.

The second column presents results from OLS regression estimation. In order to achieve normality of the residuals, I log-transform the dependent variable, which is the book asset size of firms entering the public debt market. Again, the positive and statistically significant coefficient on the C&I spread and the negative coefficient on the industry median cash flow are consistent with the prediction. In both models the substantial statistical significance of the coefficient on the C&I spread and relatively weak coefficient on the industry cash flow may suggest that the C&I spread is strongly associated with the financing frictions in the credit market.

Proposition P2-1 and P2-2 state that the effect of *ex ante* small firm size and weak information production on leverage after securing access to public debt is positive. I test this prediction on the firms receiving a debt rating in the following year, using OLS regressions. Table 15 reports the results from the following model:

$$\Delta Book\ Leverage_{yr0} = \alpha + \gamma_1 \times Small\ size_{yr-1} + \gamma_2 \times Low\, analyst\, coverage_{yr-1} + X_{yr-1} \times \beta + e_t$$

The firm characteristics variables in the lagged X_{yr-1} are from the reduced form leverage models in the capital structure literature.[26] The dependent variable for the first three columns is annual changes in book leverage and constructed as $Book\ lverage_{year0} - book\ leverage_{year-1}$. Column (1) shows that the coefficient on *Small size* is positive and statistically significant, consistent with P2-1. Column (2) reports that the coefficient on the *Low analyst following* is also positive and statistically significant, consistent with P2-2. Column (3) reports results having both variables in the regression, displaying little changes in the coefficients compared to the previous models. The models in the latter three columns use *Net debt issued,* the net debt issues amount deflated by firm asset size with a one year lag, as an alternative dependent variable. Following Chang et. al. I define net debt issues amount as long term debt issuance – long term debt reduction + current portion of long term debt. The empirical models in columns (4), (5) and (6) estimated using this dependent variable are all consistent with the predictions in P2-1 and P2-2 with the strong positive coefficients.

The economic magnitude of ex ante frictions on the rating-year changes in leverage is substantial. Considering the mean leverage for the firms acquiring a debt rating in the years leading to the rating year is 0.34, the small and less covered firms increase leverage by more than 40% in their rating years ((0.09 + 0.04) / 0.34) and raise net debt by 49% of their book asset value one year before the rating years.

Individual firms' entering the public debt market and thus into the sample is not a random event. To mitigate the potential self-selection problem, I use the Heckman two-step selection method to control for unobservable factors that may simultaneously affect the sample selection process and the outcome variable. The censored group consists of the firms being rated from column (3) and (6) in Table 15, and the uncensored group consists of firm year observations of unrated firms from column (3) in Table 14. Column (1) and (3) report the

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[26] Frank and Goyal (2009) provide a good review of the empirical models.

outcome model estimates and column (2) and (4) report the selection model estimates.[27] The coefficients on the inverse Mills ratios are statistically insignificant and the coefficients on small size and weak analyst coverage continue to be statistically and economically significant.

Overall, test results presented in this section provide evidence consistent with the prediction that segmented financial markets and financing frictions are important factors that influence corporate capital structure decisions.

2.4.2 Public debt access and firm growth

This section focuses on the relation between firms' growth and the changes in leverage in the rating year. Proposition P3-1 and P3-2 state that the marginal effect of an increased borrowing in the rating year on firm growth is positive and the effect is more pronounced with *ex ante* small firm size and weak information production.

The main empirical model is similar to the constrained investment models in the literature:

$$\begin{aligned} \Delta\ \text{Assets}_t = {} & \alpha + \beta_1 \times \left(CF_t / asset_{t-1} \right) + \beta_2 \times Q_{t-1} \\ & + \gamma_1 \times \boldsymbol{\Delta\ Leverage_t * Rating\ year\ dummy} \\ & + \gamma_2 \times \Delta\ Leverage_t + \gamma_3 \times Rating\ year\ dummy + u + v + \varepsilon_t \end{aligned}$$

I use the panel data of firms that are being rated for the first time during the sample period. In the model, *Rating year* is a dummy variable that takes the value 1 if an observation is from the rating years and 0 otherwise. As in the previous section, I use changes in book leverage and net debt issued as two proxies for changes in debt financing. The dependent variable *ΔAssets* is compiled as the changes in book asset from the previous year to the concurrent year deflated by book asset in the previous year. All estimation includes year and firm fixed

[27] The Heckman model does not include an industry fixed effect to avoid the well-documented incidental parameter problem associated with maximum likelihood estimation and fixed length of a panel. The model uses firm age as the exclusion restriction, following the implication from the literature that firm age is one of the determinants of firms' having a debt rating (Faulkender and Peterson (2006)).

effects. I divide the sample observations into four subgroups by firm size and the number of analyst following measured in the year preceding the rating years. Namely, the four groups are (1) small size and less analyst coverage group, (2) small size and more coverage group, (3) large size and less coverage group, and (4) large size and more coverage group. I then estimate the regression model on each of the four subgroups separately.

The coefficient of interest is γ_1, which captures the sensitivity of asset growth to the leverage change in the rating year. The testable implication drawn from Propositions P3-1 and P3-2 is that the sensitivity is more pronounced for firm groups with more severe frictions because *ex ante* financially constrained firms would use the proceeds from debt issuance to finance their asset growth that were previously constrained. Specifically, the hypothesis is that γ_1 from the financially constrained firms, e.g. firms in group (1), is different from zero and also greater than γ_1 of the financially unconstrained firms, e.g. firms in group (4).

Panel A and Panel B in Table 17 report the test results, with the changes in book leverage and net debt issued as the main explanatory variable of Panel A and Panel B, respectively. The key coefficient estimates γ_1 are positive and statistically different from 0 in both Panel A and Panel B, consistent with P3-1 and P3-2 that the sensitivity of firm growth to the rating year debt financing is more pronounced for firms with severe financing frictions. In both tables the coefficient γ_1 in the unconstrained firm group, e.g. group (4), is negative, indicating that the speed of asset growth in unconstrained firms may actually slow down during their rating years. Another result worth noting is that γ_2, the coefficient of the stand-alone changes in leverage variable, is economically smaller in the most constrained group than γ_2 in the unconstrained firm group. Finally, the cash flow sensitivity coefficient β_1 is larger in the most constrained group than β_1 in the unconstrained group in both tables. These observations imply that, compared to unconstrained firms, firms constrained due to financing frictions use internal financing more and rely relatively less on external financing to fund their growth during normal times, but as they become mature enough to gain access to new and cheaper means of financing in public debt, the firms issue debt for growth that was previously constrained due to costly financing.

2.4.3 Public debt access and payout

A result in the previous section indicates that the asset growth rate of unconstrained firms may actually slow down as the firms raise debt in the rating years. There could be other reasons for the observed pattern, but one possible explanation that fits nicely with the predictions from the earlier model is that the unconstrained firms, having little unresolved growth opportunity, enter and raise public debt to distribute some of the proceeds to shareholders instead of financing growth.

To test this prediction, I compile a measure for annual total cash payout, which is equal to annual cash dividends plus repurchase of common stock. Following Grullon and Michaely (2002), I define common stock repurchase as total expenditure on the purchase of common and preferred stocks minus any reduction in the value of preferred stocks outstanding. To observe the relation between cash inflow from debt issuance and cash outflow through payout more directly, I only use *Net debt issued* for the regression model, which is as follows:

$$\begin{aligned}\Delta Payout_t = \alpha &+ \gamma_1 \times \boldsymbol{Net\ debt\ issued_t * Rating\ year\ dummy} \\ &+ \gamma_2 \times Net\ debt\ issued_t + \gamma_3 \times Rating\ year\ dummy \\ &+ \gamma_4 \times Payout_{t-1} + X_{t-1}\mathrm{B} + u + \nu + \varepsilon_t\end{aligned}$$

where $\Delta Payout_t = Payout_t - Payout_{t-1}$. The empirical prediction is that the key coefficient γ_1 is positive and statistically significant for the unconstrained firm group while it shows no significant sensitivity in the constrained group.

The results in Table 18 present evidence that is consistent with this prediction. The estimate for γ_1 in column (4) is significant at the 10% level and the size of the coefficient, 0.051, is greater than that of the coefficient on the stand-alone net debt issue, which as 0.016.

This implies that an average unconstrained firm may enter and raise public debt to pay out a substantial portion of the proceeds to shareholders, and this distribution of firm assets along with other reasons may contribute to the slow down of the asset growth rate seen in the previous section. As expected, γ_1 in the constrained group shows no sensitivity.

Overall, this result combined with the findings in the previous section provide support for the prediction that financial market frictions negatively affect firms' growth and that when a new and cheap financing source becomes available to the previously constrained firms, they allocate the funds raised from the new financing source heavily on growth.

2.5 Conclusion

The goal of this paper is to study the sources of financial market frictions and investigate how the financial market segmentation due to such frictions affects firms' capital structure and growth. The findings from this study are as follows. First, small firms with weak third-party information production have a low likelihood of entering the public debt market, and more so when the overall economic condition is poor. Next, firms that enter the public debt market increase their leverage proportional to the extent of financing constraints they experience prior to gaining access to it. For instance, a small firm with low information production would increase leverage in the rating year by 39% relative to its pre-rating level. Then, the previously constrained firms use the proceeds acquired from the new and cheaper funding source to finance growth that was previously more costly, accelerating the speed of growth.

Together, the findings in this paper highlight the importance of financial market segmentation due to financing frictions in shaping corporate capital structure as well as investment.

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Appendix A: Variable descriptions

Paid in cash is a dummy variable that takes the value 1 if the SDC indicates that only cash is used for the acquisition and takes 0 otherwise.

Toehold is a dummy variable that takes the value 1 if the SDC indicates that the acquirer holds shares of the target firm prior to the merger announcement and takes 0 otherwise.

LN(Mkt equity) is the natural log of the inflation-adjusted share price times the number of shares outstanding at the beginning of the fiscal year in which the merger announcements are made.

Tender offer is a dummy variable that takes the value 1 if the SDC indicates that the deal is a tender offer.

Focused is a dummy variable that takes the value 1 if the two-digit SIC code of the target firm and that of the acquiring firm is the same and takes 0 otherwise.

Q is the ratio of book liability plus the market value of common stock to book assets.

Competed is a dummy variable that takes the value 1 if the SDC indicates more than one bidder for the target and takes 0 otherwise.

Relative size is the ratio of the total transaction value to the market value of the acquirer at the beginning of the fiscal year.

Target termination fee is a dummy variable that takes the value 1 if the SDC indicates that a merger contract includes a target termination fee agreement.

R&D/assets is the ratio of research and development expense to book assets of an acquirer.

Tangible assets is the ratio of net property, plant and equipment to book assets.

Industry concentration is the eight-firm concentration ratio provided by the US Census Bureau for the 1997 report.

Book leverage is the ratio of short term debt plus long term debt to book assets.

Profitability is the ratio of operating income before depreciation to book assets.

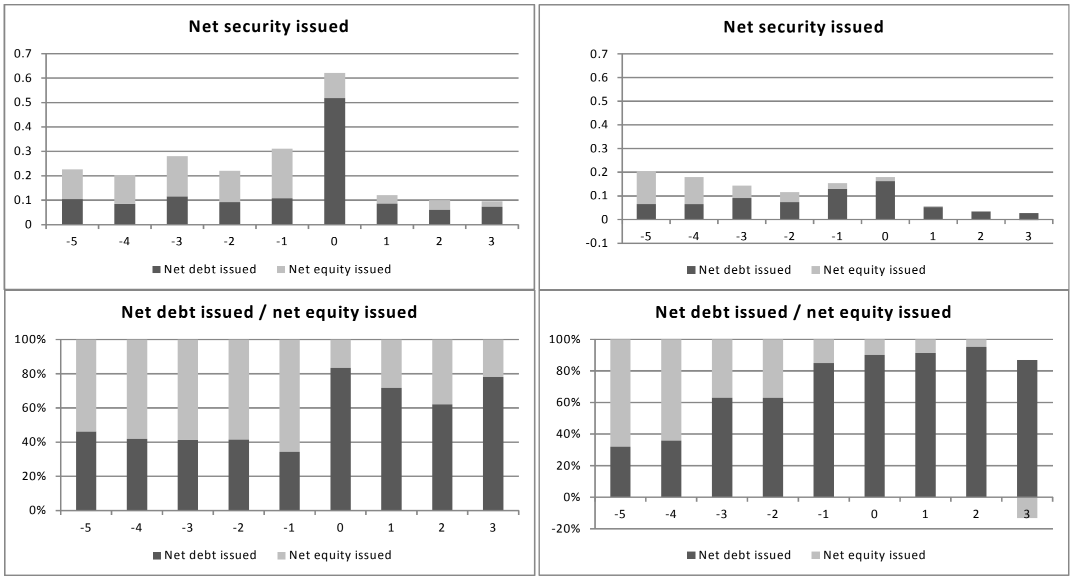
Advert./assets is the ratio of advertising expenses to book assets.

Appendix B: Changing firms' security issuance choice between debt and equity

The sample consists of firms that are rated for the first time during the 1987-2011 period. Each bar in its entirety represents the average total net security issued for the year. Average net debt issued is in black and the average net equity issued is in gray. The top row in each panel shows the actual issue amount deflated by the book asset size with a one year lag, and the bottom row shows the ratio of each security type within each given total security issued. I only include observations of firms with complete panel year observations for these graphs.

Panel A.

Small firm group | Large firm group



Panel B.

Less analyst coverage group | More analyst coverage group

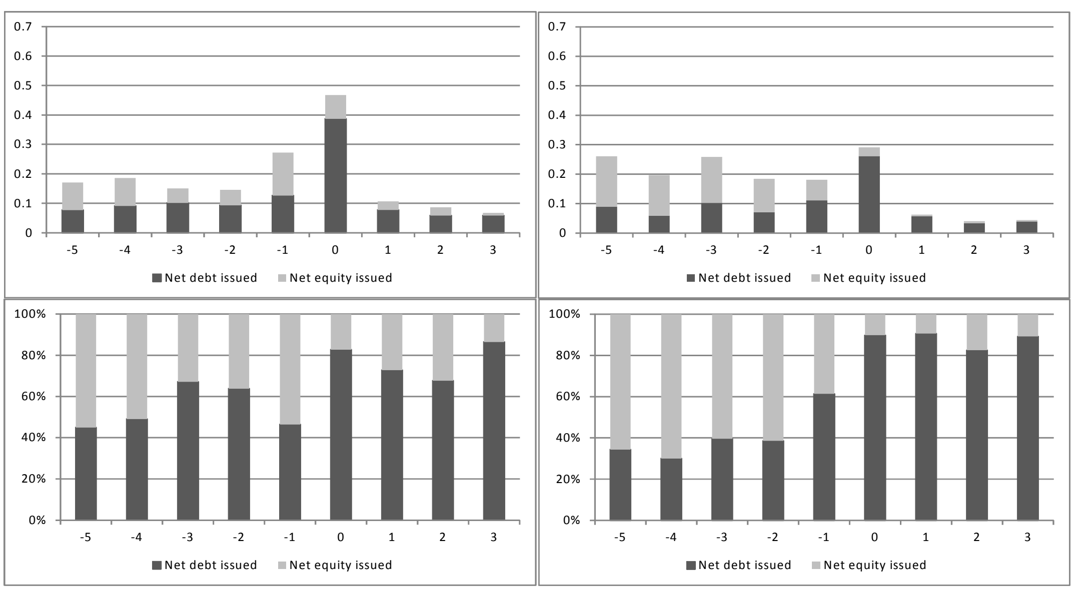


Table 12: Sample Group Comparison

This table reports the summary statistics for different firm groups during the 1987-2011 sample period. *Book asset* is adjusted for inflation. *Asset growth* is book assets of the current year minus book asset from the previous year divided by book asset from the previous year. *Book leverage* is the ratio of short term debt plus long term debt to book asset. *ΔBLev* is book leverage in the current period minus book leverage in the previous period. *Net debt issued* is long term debt issuance minus long term debt reduction plus current portion of long term debt deflated by book asset with a one year lag. *Net equity issued* is sale of common stock minus stock repurchases. *Number of analyst following* is a fiscal-year average of the monthly count of analyst forecasts reported by I/B/E/S. *C&I loan spread* is the spread between the average interest rate on commercial and industrial loans and the Federal Funds, reported in the Federal reserve's Survey of Terms of Business Lending. *Firm age* is the difference between a firm's year of equity IPO and the year of observation. *Q* is the ratio of book liability plus the market value of common stocks to book assets. *PPE/asset* is net total property, plant and equipment to book assets. *Profitability* is operating income before depreciation to book assets. *R&D/asset* is research and development expense to book assets. In Panel A, *Unrated firms* in Column (1) consist of firms that are never rated before and during the sample period. *Firms being rated first time* in Column (2) consist of firms that are rated for the first time during the sample period. *Rated firms* in Column (3) consist of firms rated before the beginning of the sample period. Panel B compares the cost of public debt issuance of firms being rated first time to that of rated firms. Panel C compares the cost of public debt issuance among the four subgroups of the firms being rated. The stars, ***, **, *, indicate statistical significance at the 1%, 5% and 10% levels.

Panel A.

	(1) Unrated firm group				(2) Firms being rated (2yr avg.)				(3) Rated firm group				Mean difference test		Wilcoxon rank sum test	
Variables	**N**	**Mean**	**Median**	**St. Dev.**	**N**	**Mean**	**Median**	**St. Dev.**	**N**	**Mean**	**Median**	**St. Dev.**	**(2)-(1)**	**(2)-(3)**	**(2)-(1)**	**(2)-(3)**
Book asset	81,969	284.4	76.3	1443.6	1,797	1336.8	469.4	3520.3	31,267	5467.3	1316.5	20385.6	***	***	***	***
Asset growth[t, t-1]	76,880	0.32	0.05	1.03	1,595	0.53	0.13	1.16	30,846	0.10	0.01	0.49	***	***	***	***
Asset growth[t+1, t]	73,379	0.17	0.03	0.7	**1,793**	**0.59**	**0.18**	**1.14**	28,047	0.06	0.01	0.36	***	***	***	***
Book leverage t	81,577	0.21	0.14	0.23	1,790	0.34	0.31	0.27	31,148	0.39	0.34	0.24	***	***	***	***
Δ BLev[t, t-1]	76,392	-0.01	0	0.15	1,585	0.01	0	0.18	30,687	0	0	0.13	***		**	
Δ BLev[t+1, t]	72,896	0	0	0.14	**1,784**	**0.07**	**0.02**	**0.2**	27,903	0	0	0.12	***	***	***	***
Net debt issued t	71,110	0.06	0	0.21	1,646	0.13	0.01	0.33	28,007	0.07	0.01	0.21	***	***	***	***
Net debt issue amt t+1	67,839	0.05	0	0.18	**1,423**	**0.25**	**0.08**	**0.41**	25,500	0.05	0.01	0.16	***	***	***	***
Net equity issued t	69,117	0.20	0	0.76	1,601	0.19	0	0.69	28,277	0.01	0	0.17		***		***
Net equity issued t+1	66,000	0.12	0	0.53	**1,444**	**0.13**	**0**	**0.53**	25,774	0	0	0.1		***		***
Asset Size < median dummy	81,969	0.89	1	0.31	1,797	0.52	1	0.5	31,267	0.26	0	0.44	***	***	***	***
Number of analyst forecasts	92,630	1.83	0	3.57	1,797	2.66	0	5.07	31,528	6.27	2.7	8.15	***	***	**	***
C&I loan spread	92,630	2.16	2.05	0.46	1,988	2.06	1.97	0.4	31,528	2.24	2.12	0.5	***	***	***	***
Firm age	92,630	11.09	8	9.45	1,797	8.26	5	8.49	31,528	20.75	20	12.18	***	***	***	***
Q	72,665	1.87	1.24	2.12	1,271	2	1.42	2.26	26,629	1.38	1.11	1.06	***	***	***	***
Profitability	81,400	0.04	0.1	0.25	1,779	0.12	0.13	0.13	31,082	0.13	0.13	0.1	***		***	
PPE/TA	81,969	0.25	0.18	0.23	1,797	0.35	0.29	0.26	31,267	0.35	0.29	0.24	***		***	
R&D/TA	77,272	0.08	0	0.15	1,595	0.03	0	0.1	30,961	0.02	0	0.05	***	***	***	***
Stock volatility	67,011	0.04	0.04	0.02	1,146	0.03	0.03	0.02	24,395	0.03	0.03	0.02	***	***	***	***
Dividend & repurchase	69,418	0.02	0	0.05	1,446	0.03	0	0.06	15,366	0.03	0.01	0.05	***		***	***

Panel B.

			Bond yield spread over treasury	Bond issue size ($ mil, annual)	Bond issue size / asset
(1)	**Firms issuing bonds in [-2, +2] yrs**	Mean	286	733.3	0.37
		Median	255.5	221.4	0.36
		St. Dev.	189.5	1937.3	0.23
		Obs.	338	366	365
(2)	**Rated firms issuing bonds**	Mean	188	1286.5	0.13
		Median	134	394.4	0.18
		St. Dev.	151.3	3183.2	0.07
		Obs.	2,111	2,247	2,245
	Mean diff. test	(1)-(2)	***	***	***
	Rank sum test	(1)-(2)	***	***	***

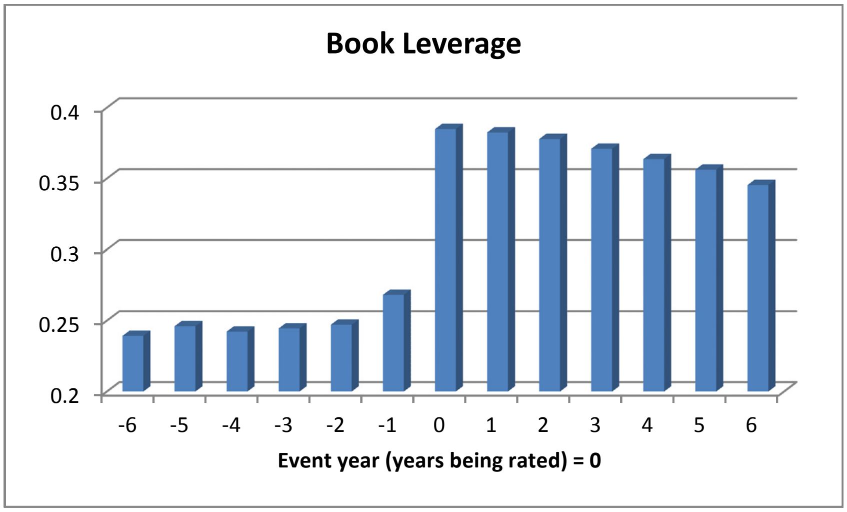
Panel C.

			Yield spread	Firm size ($ mil)	Analyst coverage
(1)	**Small & less covered group**	Mean	431.5	529.9	1.4
		Median	407	362.8	0
		St. Dev.	138.5	765.7	2.7
		Obs.	71	75	79
(2)	**Small & more covered group**	Mean	372.7	389.0	5.4
		Median	401	328	4.0
		St. Dev.	147.8	325.3	4.1
		Obs.	26	27	27
(3)	**Large & less covered group**	Mean	241.3	6168.9	4.7
		Median	183	2515	0
		St. Dev.	179.0	9129.1	7.4
		Obs.	119	122	126
(4)	**Large & more covered group**	Mean	203.0	4198.4	12.8
		Median	144.0	1937.0	10.8
		St. Dev.	160.1	7237.1	8.1
		Obs.	180	193	193

Figure 2: Capital structure and firm growth around rating years

The sample consists of firms that are rated for the first time during the 1987-2011 sample period. The figures in Panel A and Panel B report the firm-year average book leverage and book asset size of the sample firms in event time relative to the rating year (year 0). I only include observations of firms with complete panel year observations for these graphs.

Panel A.



Panel B.

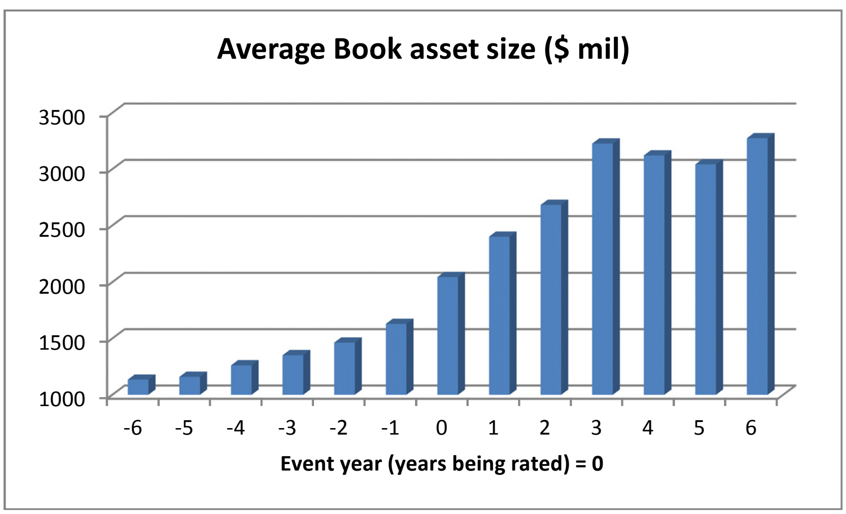


Figure 3: Changes in capital structure and firm growth in relation to *ex ante* frictions

The sample consists of firms that are rated for the first time during the 1987-2011 period. The three figures on the left compare changes in book leverage, changes in net debt issued and the asset growth rate of the firms in the small size group (black) to those of the firms in the large size group (gray) in event time relative to the rating year (year 0). The three figures on the right compare the firms in the less analyst coverage group (black) to the firms in the more analyst coverage group (gray). I only include observations of firms with complete panel year observations for these graphs.

Small and large group — Less covered and more covered group

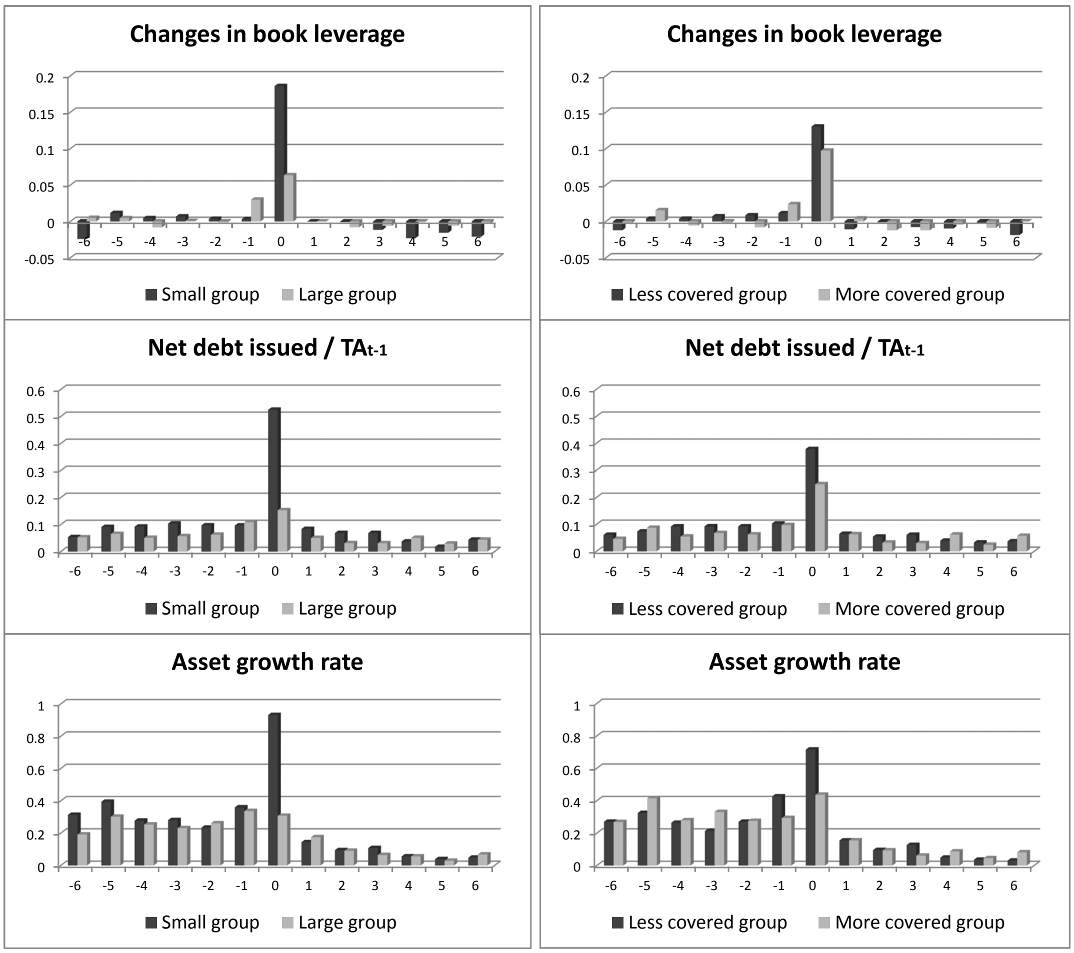


Table 13: Likelihood of entering the public debt market

This table reports the coefficient estimates of probability models on the sample firms. The sample consists of firm observations of unrated and to be rated firms during the 1987-2011 period. The dependent variable is a binary variable that takes the value 1 if a firm is rated in the observation year and 0 otherwise. The first three columns display estimates from probit models with year fixed effects, and the latter three columns display estimates from linear probability models with both firm and year fixed effects. All explanatory variables are lagged by one year. *Asset size < median dummy* takes the value 1 if the book asset of a firm is smaller than the median book asset size of firms being rated for the first time, and 0 otherwise. *# of Analyst forecasts < median dummy* takes the value 1 if the number of analyst following of a firm is smaller than the median number of analyst following of firms being rated for the first time. z-statistics appear in the parenthesis in column (1), (2) and (3). Student's t-statistics appear in the parentheses in column (4), (5) and (6). Standard error is adjusted for clustering at the firm level. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	Probit			Linear probability		
Dependent variable:	Being rated 0/1	Being rated 0/1	Being rated 0/1	Being rated 0/1	Being rated 0/1	Being rated 0/1
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.350***	-2.605***	-2.343***	-0.231**	-0.338***	-0.172*
	(-9.469)	(-10.952)	(-9.436)	(-2.496)	(-3.340)	(-1.821)
Asset Size < median dummy	**-0.775*****		**-0.733*****	**-0.043*****		**-0.042*****
	(-22.532)		**(-20.384)**	**(-6.942)**		**(-6.794)**
# of Analyst forecast < mean dummy		**-0.292*****	**-0.154*****		**-0.013*****	**-0.011*****
		(-10.048)	**(-4.912)**		**(-6.890)**	**(-6.144)**
Firm age *t-1*	-0.020***	-0.017***	-0.020***	0.010***	0.013***	0.008**
	(-11.591)	(-9.754)	(-11.263)	(2.964)	(3.469)	(2.339)
Book asset *t-1*	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
	(5.037)	(5.498)	(5.007)	(2.627)	(2.799)	(2.629)
Profitability *t-1*	0.246***	0.218***	0.186**	0.007***	0.006***	0.005***
	(3.045)	(2.778)	(2.306)	(3.189)	(2.873)	(2.652)
PPE/TA *t-1*	0.418***	0.444***	0.416***	0.005	0.002	0.004
	(6.973)	(7.724)	(6.900)	(0.739)	(0.347)	(0.626)
R&D/TA *t-1*	-0.845***	-1.034***	-0.939***	-0.007	-0.006	-0.006
	(-4.785)	(-5.467)	(-5.116)	(-1.591)	(-1.211)	(-1.202)
Q *t-1*	0.045***	0.040***	0.043***	0.001***	0.001***	0.001***
	(7.847)	(6.320)	(7.200)	(4.079)	(3.358)	(3.848)
Δ BLev [*t-1, t-2*]	0.125	0.112	0.096	0.019***	0.017***	0.017***
	(1.071)	(0.985)	(0.814)	(4.249)	(3.864)	(3.877)
Ind. adjusted BLev *t-1*	0.613***	0.767***	0.637***	0.011**	0.014***	0.012***
	(8.486)	(11.054)	(8.762)	(2.489)	(3.201)	(2.712)
Stock volatility *t-1*	-8.840***	-11.890***	-8.189***	-0.090***	-0.084***	-0.075***
	(-9.625)	(-11.754)	(-8.808)	(-4.300)	(-3.977)	(-3.675)
Dividend dummy *t-1*	0.057*	0.124***	0.060*	-0.001	>-0.000	-0.001
	(1.802)	(4.102)	(1.902)	(-0.557)	(-0.081)	(-0.458)
Firm fixed effects	No	No	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,358	67,358	67,358	67,533	67,533	67,533
Pseudo R^2 or R^2	0.168	0.130	0.171	0.029	0.025	0.030

Table 14: Accessing public debt and the overall credit market condition

This table reports the coefficient estimates of a negative binomial model on the left column and an OLS model on the right. The sample consists of firm observations of firms being rated during the 1987-2011 sample period. The dependent variable for the model on the left is the number of analyst following for firms entering the public debt market, which is a raw count variable. The dependent variable on the right is log-transformed book asset size. *C&I loan spread* is the spread between the average interest rate on commercial and industrial loans and the Federal Funds, reported in the Federal reserve's Survey of Terms of Business Lending. *Ind. median cash flow* is the industry-year median cash flow compiled at the three-digit SIC industry level. *Ind. median analyst following* is the industry-year median number of analyst following compiled at the three-digit SIC industry level. Ind. concentration is generated by summing squared market shares at the three-digit SIC industry level. *# of industry segments* is the annual count of industry segments of a firm reported in the COMPUSTAT. *Stock volatility* is the standard deviation of daily stock returns during the 250 trading days period ending on fiscal end dates. *Annual stock return* is the abnormal buy-and-hold return over the equal weighted market return during the 250 trading days period ending on fiscal end dates. *Share turnover* is the average daily trading volume divided by total common shares outstanding. *NYSE dummy* and *AMEX dummy* take the value 1 if a firm is included in the respective exchanges and 0 otherwise. *S&P500 dummy* takes the value 1 if it is included in the index in that year and 0 otherwise. z-statistics appear in the parenthesis in the negative binomial model. Student's t-statistics appear in the parentheses in the OLS model. Standard error is adjusted for clustering at the three-digit industry level. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	Negative binomial		OLS	
Dependent variable:	Number of analyst following		*Log* (Book asset)	
	Coef. (Incid. ratio)	z-Stat.	Coef.	t-Stat
Constant	0.353***	(4.317)	5.017***	(16.455)
C&I rate spread	**1.520*** **	**(4.896)**	**0.552*** **	**(4.765)**
Ind. median cash flow	**0.524* **	**(-1.651)**	**-0.203**	**(-0.473)**
Book asset	1.000*	(1.704)		
Number of analyst following			0.047***	(9.064)
Ind. median analyst following	1.033	(1.385)	-0.005	(-0.228)
Q	1.097***	(2.736)	-0.018	(-0.878)
Ln(Firm age)	1.131*	(1.951)	-0.053	(-0.809)
Ind. concentration	0.568*	(-1.879)	-0.371	(-1.397)
Profitability	1.647	(1.440)	-0.045	(-0.078)
# of industrial segments	0.906***	(-3.687)	0.128***	(5.072)
Stock volatility	0.003	(-1.623)	-11.982***	(-4.203)
Annual stock return	0.910	(-1.506)	0.077	(1.068)
Expected sales growth	0.831**	(-2.246)	-0.229***	(-3.318)
Share turnover	1.000***	(-4.133)	0.000***	(3.820)
NYSE dummy	1.215**	(2.241)	0.396***	(5.715)
AMEX dummy	0.706	(-1.325)	-0.504*	(-1.689)
S&P 500 dummy	2.197***	(7.642)	0.999***	(5.430)
Observations	990		990	
Pseudo R^2 or R^2	0.031		0.430	

Table 15: Sensitivity of rating-year changes in leverage to *ex ante* frictions

This table reports the coefficient estimates of the following linear regression model on the sample firms. The sample consists of firms that are rated for the first time during the 1987-2011 sample period. The dependent variable in the first three models is changes in book leverage from one year prior to the rating year to the rating year. The dependent variable in the latter three models is net debt issued divided by book asset one year before the rating year. All models are estimated with year fixed effects. All explanatory variables are lagged by one year. *Asset size < median dummy* takes the value 1 if the book asset of a firm is smaller than the median book asset size of firms being rated for the first time, and 0 otherwise. *# of Analyst forecasts < median dummy* takes the value 1 if the number of analyst following of a firm is smaller than the median number of analyst following of firms being rated for the first time. Student's t-statistics appear in the parentheses. Standard error is adjusted for clustering at the three-digit industry level. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Dependent variable:	Δ BLev [*t, t-1*]	Δ BLev [*t, t-1*]	Δ BLev [*t, t-1*]	Net debt issued *t*	Net debt issued *t*	Net debt issued *t*
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.088*	0.112**	0.071	0.165*	0.041	0.079
	(1.699)	(2.033)	(1.361)	(1.784)	(0.665)	(1.367)
Asset Size < median dummy	**0.102***** **(9.426)**		**0.099***** **(9.234)**	**0.276***** **(7.850)**		**0.258***** **(7.801)**
# of Analyst forecast < mean dummy		**0.050***** **(4.579)**	**0.040***** **(3.803)**		**0.161***** **(4.750)**	**0.137***** **(4.407)**
Book asset *t-1*	-0.000**	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(-2.564)	(-3.688)	(-2.594)	(-2.813)	(-4.427)	(-3.687)
Profitability *t-1*	0.093	0.105	0.109	0.184	0.184	0.170
	(1.202)	(1.225)	(1.348)	(0.898)	(0.813)	(0.809)
PPE/TA *t-1*	-0.014	-0.016	-0.015	-0.026	-0.023	-0.024
	(-0.694)	(-0.786)	(-0.768)	(-0.551)	(-0.474)	(-0.513)
R&D/TA *t-1*	0.229***	0.234***	0.254***	0.183	0.064	0.151
	(2.859)	(2.782)	(3.062)	(0.694)	(0.298)	(0.660)
Q *t-1*	0.004	0.005*	0.004	0.016	0.023*	0.019
	(1.263)	(1.686)	(1.223)	(1.209)	(1.677)	(1.357)
Ind. adjusted BLev *t-1*	-0.392***	-0.413***	-0.405***	-0.326***	-0.421***	-0.394***
	(-18.412)	(-19.450)	(-18.978)	(-3.947)	(-4.896)	(-4.707)
Δ BLev [*t-1, t-2*]	-0.126***	-0.116***	-0.103***			
	(-4.392)	(-3.701)	(-3.350)			
Net debt issued *t-1*				-0.040	-0.026	-0.013
				(-0.807)	(-0.486)	(-0.247)
Net equity issue *t*				0.296***	0.320***	0.282***
				(5.457)	(5.469)	(5.199)
Net equity issue *t-1*				0.052**	0.051*	0.041
				(1.982)	(1.737)	(1.475)
Stock volatility *t-1*	0.799**	1.552***	0.677**	1.009	2.793**	0.450
	(2.496)	(4.483)	(2.089)	(0.827)	(2.235)	(0.368)
Dividend dummy *t-1*	-0.003	-0.013	-0.002	0.011	-0.030	0.013
	(-0.334)	(-1.409)	(-0.204)	(0.386)	(-1.013)	(0.452)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,207	1,123	1,123	1,033	965	965
R^2	0.373	0.342	0.388	0.268	0.203	0.290

Table 16: Heckman selection model

This table reports the coefficient estimates of the Heckman two step selection model. The sample consists of firms that are unrated firms as well as to be rated firms during the 1987-2011 sample period. The dependent variable of the outcome model in the first Heckman estimation is changes in the book leverage from one year prior to the rating year to the rating year. The dependent variable of the outcome model in the second Heckman estimation is net debt issued divided by book asset with a one year lag. The dependent variable of selection model in each set of Heckman estimation is a binary variable that takes the value 1 if a firm is rated for the first time in the following year and 0 otherwise. All models are estimated with year fixed effects. All explanatory variables are lagged by one year. Asset size < median dummy takes the value 1 if the book asset of a firm is smaller than the median book asset size of firms being rated for the first time, and 0 otherwise. # of Analyst forecasts < median dummy takes the value 1 if the number of analyst following of a firm is smaller than the median number of analyst following of firms being rated for the first time. *lambda* is the Inverse Mill's ratio. Dividend dummy takes the value 1 if a firm pays dividends that year and 0 otherwise. Standard error is adjusted using two-step variance estimator derived by Heckman. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	Outcome	Selection	Outcome	Selection
Dependent variable:	Δ BLev [*t*, *t-1*]	Being rated 0/1	Net debt issued *t*	Being rated 0/1
Constant	0.092 (1.230)	-1.350*** (-13.913)	0.404* (1.680)	-1.431*** (-12.585)
Asset Size < median dummy	**0.095***** **(4.215)**	**-0.733***** **(-21.713)**	**0.347***** **(4.973)**	**-0.721***** **(-17.882)**
# of Analyst forecast < mean dummy	**0.039***** **(3.698)**	**-0.154***** **(-5.160)**	**0.158***** **(5.133)**	**-0.178***** **(-5.026)**
Firm age *t-1*		-0.020*** (-11.697)		-0.017*** (-8.740)
Book asset *t-1*	>-0.001 (-1.491)	<0.001*** (7.606)	>-0.001*** (-2.676)	<0.001*** (7.081)
Profitability *t-1*	0.110** (2.540)	0.186* (1.952)	0.124 (0.897)	0.332*** (2.701)
PPE/TA *t-1*	-0.013 (-0.579)	0.416*** (7.355)	-0.090 (-1.324)	0.478*** (7.304)
R&D/TA *t-1*	0.247*** (3.570)	-0.939*** (-5.523)	0.313 (1.475)	-1.138*** (-5.614)
Q *t-1*	0.004 (1.508)	0.043*** (6.944)	0.015** (2.016)	0.028*** (3.396)
Ind. adjusted BLev *t-1*	-0.401*** (-12.976)	0.637*** (8.980)	-0.477*** (-5.284)	0.599*** (6.873)
Δ BLev [*t-1*, *t-2*]	-0.103*** (-3.508)	0.096 (0.961)		
Net debt issued *t-1*			-0.066 (-1.123)	0.420*** (6.448)
Net equity issued *t*			0.252*** (5.021)	0.215*** (4.294)
Net equity issued *t-1*			0.022 (0.931)	0.118*** (5.064)
Stock volatility *t-1*	0.639 (1.536)	-8.189*** (-8.601)	1.172 (0.987)	-7.759*** (-6.828)
Dividend dummy *t-1*	-0.002 (-0.212)	0.060** (1.975)	0.020 (0.721)	0.018 (0.503)
lambda	0.007 (0.218)		-0.149 (-1.410)	
Year fixed effects	Yes	Yes	Yes	Yes
Observations	67,358		62,909	

Table 17: Sensitivity of the rating-year firm growth rate to *ex ante* financing frictions

Panel A and Panel B in this table report the coefficient estimates of a panel regression model on the sample firms. The sample consists of the panel data of firms that are being rated during the 1987-2011 sample period. The models in both Panel A and Panel B use *Asset growth* as the dependent variable. Panel A and Panel B use changes in book leverage and net debt issued as the key explanatory variables, respectively. Each column reports model estimates for one of the four subgroups: (1) small & less covered group, (2) small & more covered group, (3) large & less covered group, and (4) large & more covered group. *Rating year dummy* is a dummy variable that takes the value 1 if a firm observation is from the firms' rating year and 0 otherwise. All columns include year and firm-level fixed effects. Student's t-statistics appear in the parentheses. Standard error is adjusted for clustering at the firm level. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A.

	(1) Small & less coverage group	(2) Small & more coverage group	(3) Large & less coverage group	(4) Large & more coverage group
Dependent variable:	Asset growth [*t, t-1*]	Asset growth [*t, t-1*]	Asset growth [*t, t-1*]	Asset growth [*t, t-1*]
Constant	0.103	0.078	0.003	0.022
	(0.783)	(1.141)	(0.036)	(0.542)
Rating year dummy ×	**2.022***	**1.789***	**-0.183**	**-0.303**
Δ BLev [*t, t-1*]	**(3.222)**	**(3.993)**	**(-0.292)**	**(-0.941)**
Rating year dummy	0.497***	0.274***	0.204***	0.022
	(3.603)	(3.629)	(3.224)	(0.700)
Δ BLev [*t, t-1*]	0.031	0.196	0.582**	1.069***
	(0.238)	(1.231)	(2.473)	(6.216)
CF/TA *t-1*	0.304***	-0.162	0.369***	-0.041
	(2.670)	(-0.662)	(2.840)	(-0.250)
Q *t-1*	0.169***	0.080***	0.119***	0.065***
	(8.450)	(3.356)	(3.708)	(3.841)
Stock return *t-1*	0.060***	0.124***	0.074***	0.094***
	(3.586)	(5.048)	(3.177)	(5.309)
Profitability *t-1*	-0.112	0.286	-0.202	0.430**
	(-0.633)	(1.391)	(-0.398)	(2.121)
Book asset *t-1*	>-0.001***	>-0.001	>-0.001	>-0.001**
	(-3.006)	(-1.446)	(-1.582)	(-2.286)
Asset growth [*t-1, t-2*]	-0.055***	-0.036	-0.054**	-0.038
	(-3.373)	(-1.494)	(-2.243)	(-1.106)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	4,182	2,644	3,706	5,486
R^2	0.298	0.278	0.176	0.174

Panel B.

	(1)	(2)	(3)	(4)
	Small & less coverage group	Small & more coverage group	Large & less coverage group	Large & more coverage group
Dependent variable:	Asset growth [*t*, *t*-*1*]	Asset growth [*t*, *t*-*1*]	Asset growth [*t*, *t*-*1*]	Asset growth [*t*, *t*-*1*]
Constant	0.032	-0.098**	0.001	-0.107***
	(0.201)	(-2.424)	(0.014)	(-4.026)
Rating year dummy × Net debt issue *t*	**0.654******	**0.650******	**0.072**	**-0.659******
	(3.210)	**(3.170)**	**(0.199)**	**(-3.940)**
Rating year dummy × Net equity issue *t*	-0.289	0.278	-0.723	-0.136
	(-1.568)	(0.793)	(-1.361)	(-0.848)
Net debt issue *t*	**1.063******	**1.132******	**1.232******	**1.644******
	(11.972)	**(12.424)**	**(10.091)**	**(14.232)**
Net equity issue *t*	1.003***	1.135***	1.001***	1.268***
	(15.137)	(20.967)	(7.194)	(10.528)
Rating year dummy	-0.054	-0.127*	0.019	0.012
	(-0.694)	(-1.844)	(0.401)	(0.537)
CF/TA *t-1*	0.236***	0.234*	0.172	0.059
	(2.825)	(1.933)	(1.391)	(0.425)
Q *t-1*	0.108***	0.017	0.084**	0.035***
	(3.953)	(1.438)	(2.535)	(5.564)
Stock return *t-1*	0.022	0.048***	0.055**	0.043***
	(1.533)	(3.086)	(2.189)	(3.648)
Profitability *t-1*	0.045	0.402***	-0.300	0.630***
	(0.305)	(3.170)	(-0.547)	(4.476)
Book asset *t-1*	>-0.001**	>-0.001	>-0.001	>-0.001**
	(-2.186)	(-1.180)	(-1.349)	(-2.428)
Asset growth [*t-1*, *t-2*]	-0.029*	-0.030*	-0.030	-0.026
	(-1.703)	(-1.804)	(-1.462)	(-0.934)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	3,477	2,173	3,005	4,496
R^2	0.595	0.708	0.420	0.577

Table 18: Sensitivity of the rating-year payout to *ex ante* financing frictions

This table reports the coefficient estimates of a panel regression model on the sample firms. The sample consists of the panel data of firms that are being rated during the 1987-2011 sample period. The model uses *Total payout,* which is a sum of cash dividend and repurchase of common stock, as the dependent variable. Each column reports model estimates for one of the four subgroups: (1) small & less covered group, (2) small & more covered group, (3) large & less covered group, and (4) large & more covered group. *Rating year dummy* is a dummy variable that takes the value 1 if a firm observation is from the firms' rating year and 0 otherwise. All columns include year and firm-level fixed effects. Student's t-statistics appear in the parentheses. Standard error is adjusted for clustering at the firm level. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

	(1) Small & less coverage group	(2) Small & more coverage group	(3) Large & less coverage group	(4) Large & more coverage group
Dependent variable:	Δ Dividend & repurchase [*t,t-1]*	Δ Dividend & repurchase [*t,t-1]*	Δ Dividend & repurchase [*t,t-1]*	Δ Dividend & repurchase [*t,t-1]*
Constant	-0.001	-0.020	0.013*	0.011***
	(-0.208)	(-1.546)	(1.719)	(2.798)
Rating year dummy × Net debt issue *t*	**0.012**	**0.002**	**0.039**	**0.053***
	(0.882)	**(0.165)**	**(1.271)**	**(1.846)**
Rating year dummy × Net equity issue *t*	-0.024	-0.018	-0.024	-0.017
	(-1.440)	(-0.850)	(-0.275)	(-0.343)
Net debt issue *t*	0.018***	0.001	0.018*	0.006
	(2.855)	(0.233)	(1.880)	(1.103)
Net equity issue *t*	-0.011	-0.020***	-0.132***	-0.100***
	(-1.035)	(-3.208)	(-2.822)	(-5.460)
Rating year dummy	-0.002	-0.011*	0.001	-0.004
	(-0.437)	(-1.783)	(0.208)	(-0.971)
CF/TA *t-1*	0.004	-0.006	0.003	-0.005
	(0.549)	(-0.975)	(0.248)	(-0.296)
Stock return *t-1*	0.002	0.003*	0.006***	0.007***
	(1.531)	(1.813)	(3.761)	(4.531)
Q *t-1*	>-0.001	0.001*	0.002	-0.001
	(-0.183)	(1.818)	(1.004)	(-0.560)
Profitability *t-1*	0.001	-0.001	-0.038*	-0.018
	(0.159)	(-0.104)	(-1.685)	(-0.986)
Book asset *t-1*	>-0.001	<0.001	>-0.001	>-0.001
	(-0.736)	(1.024)	(-1.218)	(-1.319)
Δ Dividend & repurchase [*t-1,t-2]*	-0.450***	-0.319***	-0.371***	-0.364***
	(-12.709)	(-9.034)	(-13.876)	(-17.702)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	3,227	1,987	2,778	4,212
R^2	0.237	0.174	0.247	0.220

VITA

Joon Ho Kim was born in Seoul, South Korea and lived there before coming to the U.S. He obtained his bachelor’s degree in Economics and a GEMBA degree from the University of Washington. He had industry experience as a product market researcher in Korea. In 2007, he joined the finance doctoral program of the Foster School of Business at the University of Washington, where he earned a Doctor of Philosophy in 2013.