Asset Specificity, Industry Driven Recovery Risk and Loan Pricing

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Abstract

We provide evidence that a firm's exposure to industry downturns, what we refer to as *industry risk*, is a significant factor affecting ex post recovery rates and ex ante bank loan pricing. The basic idea is that if it is costly to redeploy industry assets, then the liquidity of a firm's assets will vary with the industry as well as macroeconomic conditions. Since the cost of bank financing depends in part on the bank's assessment of loss given default (LGD), firms with greater exposure to industry downturns (and hence higher expected LGD) will find bank loans a more expensive and conditional source of liquidity. We measure industry risk based on the relationship between a firm's stock returns and industry returns conditional on an industry downturn. We find that, controlling for firm financial characteristics and market risk, industry risk is significantly related to the likelihood of the firm experiencing financial distress when its peers are also in distress and recovery rates in bankruptcy. More importantly, we find that the spreads on unsecured bank loans are significantly related to our industry risk measures. We find that these relationships are stronger for firms with industry specific assets. We also find that cash reserves and the reliance on cash relative to lines of credit are significantly related to our measures of industry risk exposure. Overall, our results suggest that the liquidity of a firm's operating assets affects recovery rates, loan pricing and reliance on cash as a source of liquidity.

1. Introduction

A potentially important factor affecting the current liquidity of a firm's assets is the expected financial condition of the firm's industry peers when the firm (or its creditors) is looking to sell assets. As Shleifer and Vishny (1992) and Williamson (1988) point out, many assets are specialized and thus cannot be readily redeployed to industry outsiders without considerable loss in value. This in turn implies that, for many assets, the asset's highest valued user is another firm within the same industry. As a result, asset illiquidity, or the spread between the best valued use of an asset and the price the asset can draw in liquidation, is likely to vary with the liquidity and performance of the selling firm's industry peers. This is because when a distressed firm is trying to sell assets, industry peers may be facing liquidity problems of their own and therefore may be unable to bid aggressively for the selling firm's assets or may also be trying to sell their own assets. The combination of lower demand and higher supply can lead to fire sale prices for industry specific assets during an industry downturn.[1] Consistent with this phenomenon, commercial lending manuals and bank regulations caution loan officers to take discounts on collateral with limited marketability.[2]

Several recent studies examine the importance of fire sale discounts by examining the relationship between liquidation or recovery values and industry conditions. For example, Pulvino (1998) examines the prices at which commercial airline assets are liquidated and finds evidence of a fire sale discount for financially constrained sellers only when the seller's industry is distressed. Benmelech and Bergman (2010) also use the airline industry to investigate the importance of a collateral channel through which bankrupt firms impose negative externalities on

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[1] See Shleifer and Vishny (2010) for a recent review of the literature on fire sale discounts.
[2] See for example Ruth (1999) or the Federal Reserve Commercial Bank Examination Manual available at http://www.federalreserve.gov/boarddocs/supmanual/cbem/cbem.pdf.

their non-distressed competitors. Using data on the pricing of tranches of debt secured by commercial aircraft, the authors find that the bankruptcy of an airline is associated with significant declines in the value of tranches whose underlying collateral is secured by aircraft that are similar to aircraft in the fleet of the bankrupt airline. Acharya, Bharath and Srinivasan (2007) examine a broad cross section of industries and find that recoveries are significantly lower when the industry of the defaulted firm is also in distress. More importantly, consistent with the fire sale hypothesis, Acharya et al. (2007) find that the effect of industry distress on recovery values is greatest for industries that rely heavily on assets that are not easily redeployed. Overall they find that "The indirect costs of corporate defaults arising from industry equilibrium effects are substantial…" (p 819).

The primary focus of the existing empirical work has been on the relationship between recovery values and contemporaneous industry conditions. Empirical evidence of the significance of potential fire sale discounts on loan pricing and firm liquidity choice is limited. However, as Shleifer and Vishny (1992) point out, the potential for fire sale discounts may affect ex ante capital structure and liquidity choices. For example, most models of corporate cash and other liquid assets are based on the notion that external financing frictions give rise to a demand for liquidity reserves as a form of insurance against operating cash flow shocks (e.g., Almeida, Campello and Weisbach (2004) and Faulkender and Wang (2006)).[3] Since financing frictions are greatest when industry assets are more illiquid, firms with greater exposure to industry downturns and firms in industries with specialized assets may offset greater potential operating asset illiquidity by holding more cash reserves.

[3] See Bates, Kahle and Stulz (2009) for a survey of the literature on the precautionary demand for cash and recent trends in corporate cash holdings.

A firm's exposure to industry downturns, what we will refer to as *industry risk*, may also affect the pricing and structure of bank loans and a firm's reliance on bank lines of credit as a source of liquidity. The simplest channel is through credit risk spreads. Specifically, loan pricing and the evaluation of credit risk involve both an assessment of the likelihood of default as well as the loss given default (LGD) (Saunders and Allen (2010)). Ceteris paribus, the higher the expected LGD, the higher the credit spread and thus the higher the expected cost of borrowing under lines of credit. As a result, if industry recovery risk is a substantial cost of financial distress, then firms with greater industry risk exposure will face higher credit risk spreads (and perhaps more onerous contract terms in terms of lower advance rates or higher collateral requirements) and therefore rely more heavily on cash as a source of liquidity.

In this paper, we develop measures of industry risk and empirically examine the importance of industry risk in bank loan pricing and liquidity management. We begin by examining several potential measures of industry risk based on the relationship between a firm's stock returns and the stock returns of its industry peers. Our objective is to come up with ex ante predictors of how a firm's value is related to changes in the value of its industry peers conditional on an industry downturn. Our industry risk measures are similar in spirit to systemic risk measures used in the banking literature (which focus on an individual bank's exposure to financial sector shocks) . We evaluate potential industry risk measures based on their ability to predict recovery rates (or LGD) and financial distress. A good industry risk measure should have predictive power both in terms of the likelihood of firm distress, conditional on industry distress, and in terms of recovery rates in bankruptcy. Following Opler and Titman (1994) and others we define firm and industry distress using stock return measures as well as sales growth and interest coverage measures (see Acharya et al. (2007) and Asquith, Gertner and Scharfstein (1994)). We focus on the latter measures to alleviate concerns about a mechanical relationship between distress and our industry risk measures. We examine whether our industry risk measures are related to bank loan pricing, line of credit usage and cash holdings. If industry risk affects expected LGD we would expect the cost of borrowing to be positively related to a firm's industry risk exposure. For this analysis we use Dealscan data on loan pricing and hand collect data on bank credit line usage and cash holdings for a panel of 348 publicly traded companies over the 1999 to 2009 time period.

The first challenge in analyzing the importance of industry risk is to come up with a measure of industry risk exposure and to distinguish between industry effects and a firm's aggregate risk exposure. Both industry and aggregate risk are likely to affect loan pricing for at least two reasons. First, previous empirical studies have found that recovery rates are related to the aggregate number of defaults (e.g., Altman, Brady, Resti and Sironi (2005)) and are significantly lower during recessions (e.g., Schuermann (2004)). Lower expected recovery rates due to a firm's aggregate risk exposure should be reflected in credit spreads and therefore may affect the choice between cash and lines of credit. Second, and perhaps more important, Acharya, Almedia and Campello (2010) argue that a firm's aggregate risk exposure (measured by the firm's asset beta) affects the banking sector's cost of providing liquidity insurance through lines of credit. The basic idea behind their model is that banks are able to create liquidity by pooling idiosyncratic risks. Firms with higher aggregate risk exposure are more likely to demand liquidity when liquidity is scarce and thus are charged more for insurance. Consistent with this argument, Acharya et al. (2010) find that firms with high asset betas rely more heavily on cash as a precautionary hedge against liquidity shocks and pay higher spreads on their bank borrowing.

We examine the importance of industry risk and try to disentangle the effects of aggregate and industry risk using several measures of industry risk. Our first approach is to estimate a two factor model by regressing the firm's stock returns on market returns and industry returns to obtain estimates of (leverage adjusted) asset betas and industry betas. While providing potentially useful information concerning how a firm's value fluctuates with its industry peers, industry betas do not isolate the relationship between the firm's return and the value of its industry peers conditional on an industry downturn. Moreover, industry driven recovery risk is about how a firm's value changes during an industry downturn.

Our second approach is to estimate "tail risk" measures (i.e. the extent to which a firm is likely to be in distress when its industry peers are also in financial distress). Our first measure of tail risk is the correlation between firm and industry returns conditional on downside movements of industry returns. We use this measure because empirical evidence suggests that downside measures of correlations are much higher than upside correlations, and beta may therefore underestimate the correlations in the tail (e.g., Longin and Solnik (2001) and Ang and Chen (2002)). Moreover, what should matter in terms of industry risk is whether the firm is likely to be distressed when its peers are in distress, so downside risk should be more important. Our second tail risk measure is based on a recent paper by Acharya, Pedersen, Philippon and Richardson (2010) on systemic risk. They focus on bank systemic risk exposure but their approach is applicable to our analysis because bank systemic risk is really just a special (but perhaps more important) case of industry risk. They measure a firm's exposure to large negative shocks by the average of the firm's daily returns on the 5% of days with the worst market returns. The idea is that information contained in moderately bad days can be used to estimate what would happen during extreme events. We calculate a similar measure using monthly returns and compute the average of the firm's monthly returns in the worst 5% of industry return months. We call this measure marginal distress estimate (MDE).

To isolate the effect of industry risk we examine the relationship between both recovery rates and the likelihood of financial distress and our tail risk measures controlling for a firm's market or aggregate risk exposure. We also compute a market or aggregate tail risk measure and examine the relationship between aggregate tail risk and recovery rates. The aggregate tail risk measures is computed the same way as industry tail risk except that we use the return on the market portfolio to calculate marginal distress estimates.

Overall, we find that controlling for firm characteristics and macroeconomic factors, our industry tail risk measures are negatively related to recovery rates. To illustrate the importance of industry risk, Figure 1 provides a comparison of recovery rates on unsecured claims in bankruptcy for firms in the highest and lowest industry tail risk (MDE) quartiles. As shown we find recovery rates average 75.6% on unsecured loans for firms with the least industry risk exposure compared to the recovery rate of only 49.3% for the loans in the top industry risk quartile.[4] In contrast, we find no statistically significant relationship between recovery rates and aggregate risk measures.

We also examine the likelihood of firm distress conditional on industry distress. We find that, controlling for aggregate risk, our industry risk measures are positively related to the likelihood that a firm will become distressed during times of industry-wide distress. Overall, the

[4] We test the null hypothesis that the recovery rates are equal for the unsecured loans that are in the top and bottom quartile using a t-test. We reject the null hypothesis that the recovery rates are equal between two groups (t-stat: 4.72).

recovery rate findings and the distress analysis indicate that our tail risk measures capture industry recovery risk.

Finally, controlling for aggregate risk, all of our industry risk measures are significantly and positively related to the all in drawn spreads or cost of borrowing associated with lines of credit. We also find that the ratio of a firm's cash to lines of credit is positively related to our industry risk measures.

If industry risk matters because asset specificity affects expected recovery rates, then industry risk should have a greater effect on loan spreads in industries characterized by greater asset specificity.[5] Following Berger, Ofek and Swary (1996), we measure asset specificity as the ratio of plant and equipment to total assets in an industry. Consistent with industry risk affecting expected recovery values, we find that industry risk has the greatest effect on loan spreads for industries characterized by high asset specificity.

As Acharaya et al. (2007) and Benmelech and Bergman (2010) point out, the effect of asset specificity on loan pricing is expected to be greatest for unsecured loans because asset specificity should matter most for creditors whose priority make them most vulnerable to fluctuations in the value of collateral. Since secured creditors have the highest priority claim and can impose lower advance rates (i.e. require more collateral per dollar lent) when collateral values are more uncertain, we would expect industry risk to have the greatest effect on unsecured

[5] Leary and Roberts (2010) and Frank and Goyal (2009) find that firm leverage is significantly related to the leverage of the firm's industry peers. This relationship may arise for a variety of reasons; because the firms employ similar assets, use similar production technology, have similar cash flows, for strategic reasons or simply because firms within an industry benchmark against one another. For similar reasons, firms within the same industry may make similar liquidity choices and our industry risk measure may simply reflect how closely related a firm is to its industry peers.

loan spreads. Consistent with this argument we find that industry risk has the greatest impact on unsecured loan spreads in industries with greater asset specificity.

Our analysis contributes to the literature in several ways. First, we develop ex ante measures of industry risk and show how these measures are related to distress likelihood and recovery rates. Since our industry risk measures are computed before the onset of financial distress they provide a measure of the effect of fire sale externalities on recovery values that is independent of contemporaneous industry conditions. Second, since our industry risk measures are computed in manor similar to systemic the systemic risk measures proposed by Acharya et al (2010) our findings provide additional evidence of the ability of these measures to predict firm performance conditional on an industry downturn. Third, we provide evidence that the potential for fire sale discounts is reflected in borrowing costs. In particular, we show that borrowing costs are significantly related to our industry risk measures, especially for firms operating in industries with high asset specificity. These results extend recent empirical findings concerning the influence of asset redepolyability on borrowing costs and capital structure decisions by examining a broad cross section of industries (e.g., Benmelech and Bergman (2009) and Campello and Giambona (2010)). Third, we add to the literature on liquidity management by showing that the liquidity of operating assets affects cash holdings and reliance on bank debt. Firms whose asset values are closely linked to the value of their industry peers face potentially limited access to bank lending during an industry downturn and thus appear to rely more heavily on cash as a source of liquidity. This finding provides additional support for the Sufi (2009) argument that cash and lines of credit are imperfect corporate liquidity substitutes. Finally, we document that both aggregate risk and industry risk impact loan pricing and liquidity choice. Our findings indicate that industry risk effects loan pricing and liquidity choice through its effect on the quality of collateral and the liquidity of the borrower's assets.

The remainder of the paper is organized as follows. Section 2 discusses the data. Section 3 presents summary statistics. In section 4 we begin by examining the relationship between industry and market risk and recovery rates. We next examine the relationship between the likelihood of firm distress during industry-wide distress and our various risk measures. Next, in section 5 we examine the relationship between loan pricing, loan contract terms and the various risk measures. In section 6, we present the results of our analysis of the relationship between cash reserves, lines of credit usage and the various risk measures. Section 7 provides a summary of our findings and concludes.

2. Sample

To examine the relationship between industry risk, the likelihood of distress, loan pricing and liquidity management we use data collected from several sources. The sample we use in our various analyses depends on the availability of data.

2.1. Recovery Sample

To investigate whether creditor losses during financial distress are related to our risk measures (estimated before the firm enters into financial distress) we use data on recovery rates from Bankruptcydata.com. We first identify a list of firms that filed for bankruptcy during the January 1998 to February 2010 time period using Bankruptcydata.com. Bankruptcydata.com provides information on the bankruptcies of public firms as well as selected private companies that have public debt or are deemed significant or newsworthy (Ayotte and Morrison (2009)).

Bankruptcydata.com provides data for 1,396 bankruptcies during the 1998 to 2010 time period. We hand match this list to Compustat by firm name and require that the bankrupt firm file at least one annual financial statement with the Securities and Exchange Commission during the two fiscal years preceding the bankruptcy filing. Overall, 781 firms satisfy this condition.

Next, we search Banktrupctydata.com for the reorganization plans of these firms. We found reorganization plans for 309 of the public firms meeting our selection criteria.[6] We eliminate all non-debt related claims (i.e. equity, fee, administrative and compensation related claims). This process yields 2,371 debt claims issued by 309 firms.

2.2. Compustat Sample

In order to examine whether our industry risk measures predict firm/industry distress, we construct a sample of firm-year observations from Compustat during the period 1999 to 2009. We exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999). We also exclude any observations with missing data on total assets. Stock return data for our sample of Compustat firms are obtained from the CRSP monthly stock price database. We merge the CRSP and Compustat data using the historical file from CRSP. Our final sample consists of firm-year observations in the intersection of our Compustat sample and CRSP.

2.3. Dealscan sample

[6] Reorganization plans (that include debt recovery rates) are available from Bankruptcydata.com for less than 50% of the bankruptcies. Reorganization plans are missing for (1) firms that were acquired or liquidated while in bankruptcy, (2) firms whose bankruptcies are still in progress, and (3) some firms that successfully exited bankruptcy. Using the universe of firms that successfully exited bankruptcy, we examine whether there are any differences between firms with and without reorganization plans in Bankruptcydata.com (not tabulated for brevity). Relative to firms whose reorganization plans are missing, firms with reorganization plans are larger, have higher cash flows, hold more tangible assets, and have higher leverage. Also, reorganization plans are more likely to be available for firms that operate in more asset specific industries. However, there is no significant difference in the industry distress exposure measures of the two groups.

For our loan pricing analysis we use data from Dealscan. In particular, we obtained from Dealscan a list of US dollar denominated lines of credit taken out by all industrial US firms during the 1987 through 2009 time period.[7] From that list, we selected loans to firms with non-missing financial information in Compustat at the end of the fiscal year preceding the loan date. For these loans, we obtained information on the amount, pricing and maturity of the credit facility. Our Dealscan sample consists of 26,378 loans taken out by 6,232 unique firms.

2.4 Lines of credit sample

To examine the relationship between cash holdings, line of credit usage and industry risk, we hand collected information on line of credit use for a random sample of firms.[8] We start by randomly selecting 500 US industrial firms[9] from Compustat with non-missing information on cash flows, cash holdings, and with stock price information available for fiscal years 2005, 2006 and 2007. We apply these screens to ensure that firms are public and report the key financials that we need for our analysis. Then, we search the SEC's Electronic Data Gathering and Retrieval (EDGAR) system for the annual reports (10-Ks) of the firms in this sample for the period 1999 to 2009. Following Sufi (2009), we define the bank loan as a line of credit if it is described as a "credit line", "credit facility", "revolving credit agreement", "bank credit line", "working capital facility", "lines of credit" or "line of credit" in the 10-Ks. We obtain information on the size as well as drawn and undrawn portions of the firms' credit lines from the 10-Ks. We eliminate firms that do not provide sufficiently detailed information on the presence,

[7] Given our focus on liquidity management, we examine the relationship between the pricing of lines of credit and industry risk. However, we obtain qualitatively similar results if we include all short term bank loan agreements in our sample.

[8] Information on line of credit use is not available from Compustat or other machine readable sources.

[9] We restrict our sample to industrial firms in order to avoid capital structures governed by regulatory environments, such as financial and utility firms.

size, and utilization of their lines of credit. This procedure yields a sample of 348 firms that we follow from 1999 to 2009.

2.5. Potential Industry Distress Exposure Measures (IDEMs)

We examine three potential industry distress exposure measures (IDEMs). Following other studies that examine the effect of industry conditions and peer group effects, we define a firm's industry by its 3-digit SIC Code (Acharya et al. (2007) and Leary and Roberts (2010)). We also replicate our analysis using 2-digit SIC Code classifications and Fama-French (48) industry classifications and find qualitatively similar results.[10]

Our first IDEM is a firm's industry asset (unlevered) beta. It is straightforward to calculate equity betas using stock price data, but there is a mechanical relationship between beta and leverage. All else equal, higher leverage implies a higher beta. As high leverage firms rely more on credit lines in their liquidity management, this can introduce a bias in our results. To mitigate this potential bias, we deleverage industry betas. In particular, we obtain stock return data for our sample firms from the Center for Research in Security Prices (CRSP) monthly stock price database. Next, we calculate yearly industry betas using the following two factor model:

$$R_{i,t} = \propto \ + \beta_m R_{m,t} + \beta_I R_{I,t} \ . \tag{1}$$

where $R_{i,t}$ is return on stock *i* in month *t*, $R_{m,t}$ is the market return in month *t*, and $R_{I,t}$ is the industry return in month *t*. We obtain the market return from CRSP index files and calculate the

[10] A recent study by Hoberg and Phillips (2010) finds that more refined industry definitions based on detailed information (i.e. SEC filings) do not explain financial and investment choices better than SIC codes.

value-weighted return on the industry portfolio excluding firm *i*'s return. We set industry returns to missing if the industry portfolio has less than 5 firms. We estimate the model above using the monthly stock return over the prior 60 months for each firm-fiscal year observation. Then, we unlever both betas using the ratio of market value of equity to face value of debt plus market value of equity. We calculate the face value of debt for each firm by summing the total book value of short-term debt and one-half of the book value of long-term debt (Acharya et al. (2010)). To eliminate the impact of outliers, we winsorize market and industry asset betas at the bottom and top 2.5%.

Although adjusting betas for leverage should eliminate the mechanical relationship between leverage and beta, our estimated betas may still suffer from measurement error. In order to mitigate this problem, we employ the approach suggested by Grilishes and Hausman (1986) and Acharya et al. (2010) and instrument the endogenous variable (asset betas) using a linear combination of the prior two year lags.

We disentangle the effects of aggregate and industry risk by controlling for aggregate risk in our analysis. We control for aggregate risk using a market beta that is based on the two factor model described above in equation (1). Similar to industry beta, market beta is unlevered and we instrument for it using its own lags in order to mitigate the impact of measurement error.

Industry beta measures how a firm's asset value is correlated with its industry peers both in industry upturns and downturns. However, Longin and Solnik (2001) find that downside correlations are much higher than upside correlations. In addition, Ang and Chen (2002) show that conditional correlations on the downside are approximately 12% higher than correlations implied by a normal distribution. Thus, industry beta may underestimate exposure to industry distress in the tail. Moreover the relationship between a firm's return and the return of its industry peers in down markets may be a better measure of industry risk because we expect that a firm's assets are more likely to be illiquid, and thus likely to have lower recovery rates, when both the firm and its peers are performing poorly.

In order to address the problems related to betas, we use two alternative measures of "tail risk" industry distress exposure. The first measure is the correlation between the firm's return and its industry return when normalized industry returns are below zero. We calculate conditional correlations using up to 120 monthly returns for each firm-fiscal year observation. Next, since we are interested in down side risk, we eliminate observations in which the industry return is greater than or equal to zero.[11] Then, we calculate the correlations between the firm's stock return and its industry return for each firm-fiscal year observation.

Acharya, Pedersen, Philippon and Richardson (2010) present a systemic risk model for financial institutions and propose a systemic risk measure based on how much a particular bank is expected to lose at times when the entire financial system is undercapitalized. This measure captures the contribution of each bank to systemic risk. Empirically, the likelihood of experiencing banking crises is relatively low. Therefore, they suggest using information contained in moderately bad days (i.e. the worst 5% of market outcomes) to estimate what would happen during extreme events. We adopt this method in our empirical analysis, and we refer to this measure as the marginal distress estimate (MDE). Using up to 120 monthly returns, we take the worst 5% of months for the industry return for each firm-fiscal year observation and compute

[11] Since we examine the impact of conditional correlations using both cross-sectional and panel data, we standardize returns using the mean values and standard deviations before we calculate conditional correlations.

the average return of those months for each firm-fiscal year observation.[12] We assume that a firm's return in moderately bad months is informative of the relationship in the extreme tail of the industry return distribution.

As discussed earlier, we also compute aggregate tail risk measures; these are computed in the same way as our industry tail risk measures except that we use the CRSP market return instead of the industry return when computing aggregate tail risk measures. Since our findings are similar whether we measure aggregate risk by conditional correlation or market MDE we focus on Market MDE.

In our analysis we focus on how recovery values and liquidity choices vary with asset specificity. Following the literature (see Berger, Ofek and Swary (1996), Stromberg (2001) and Acharya et al. (2007)), we measure asset specificity as the ratio of the book value of machinery and equipment relative to book value of total assets. We measure industry asset specificity as the median of specific assets of all firms in that industry over the entire sample period.[13]

We also examine how the cost of bank credit varies with bank lending standards. In particular, we want to examine the relationship between loan pricing and industry risk controlling for credit market and macroeconomic conditions. We measure lending standards as the ratio of large banks that tightened lending standards (according to the Federal Reserve

[12] We expand the calculation period because we calculate both conditional correlations and MDE conditional on downturns and thus number of observations per year are smaller than the number of observations used to compute unconditional measures. However, we obtain similar results if compute tail risk measures using up to 60 months of returns.

[13] Previous studies use the net value of machinery and equipment (ppenme), but this variable is missing after 1999. We use the net value for the years it is available and use gross value of machinery and equipment (fate) for the rest. In unreported results, we use net value and calculate the asset specificity over different time horizons. We also use only gross values of machinery and equipment. Results are qualitatively and quantitatively similar if we use those alternative definitions.

Bank's Loan Officer Survey) in the last quarter of the fiscal year.[14] Lown and Morgan (2006) find that net percentage of banks tightening standards is more informative of changes in bank lending than are changes in Fed Funds rates or changes in loan rates.

3. Summary Statistics

In Table I we provide summary statistics for the recovery sample (Panel A), the Dealscan sample (Panel B), and the lines of credit sample (Panel C). As shown in Panel A, the average claim size in bankruptcy is $369.5 million and the average recovery rate is 74.1%. The recovery rate is higher than 51.1% reported by Acharya et al. (2007). Their sample ends in 1999 and includes many high yield debt restructurings during the early 1990's. In addition, recent work by Bharath, Panchapegesan and Werner (2007) finds a significant decline in the duration of bankruptcy during the last two decades. Quicker exits from bankruptcy are likely to be associated with lower bankruptcy costs and thus higher recovery values.[15]

We find that the recovery rate is 53% for unsecured claims and 97.3% for secured ones. These results are similar to the findings of Baird, Bris and Zhu (2007) concerning recovery rates for secured and unsecured creditors. Note that a relatively few (16%) secured claims recover less than 100% of face value. This is consistent with lenders setting advance rates and collateral coverage requirements so that conditional on distress, secured creditors are unimpaired. If advance rates and collateral coverage requirements are set based on expected loss severity, then for secured claims, credit risk spreads may not vary much with industry risk. In other words, for

[14] In the Dealscan sample, we measure lending standards in the quarter of the initiation date of credit lines.
[15] In our sample, the average (median) number of months spent in Chapter 11 is 12.55 (9) months. Consistent with the notion that quicker exits from bankruptcy are positively associated with higher recovery rates, the average recovery rate on debt claims is 76% for firms who spend less than a year in Chapter 11, whereas the average recovery rate on debt claims drops to 70% for firms who spend more than a year in Chapter 11.

secured claims, industry risk is likely to affect lending terms primarily through advance rates rather than loan spreads. We investigate this issue later in the paper.

Finally, notice that while the average tail risk measures for the recovery sample are similar for the Dealscan and credit line samples, the average industry and market betas are substantially lower for the recovery sample. One potential concern is that betas are estimated over a 5 year period prior to the bankruptcy filing (when the firm's equity returns are likely to be negative) whereas, out of necessity, tail risk measures must be estimated over a longer time horizon (up to 10 years). However, when we estimate market and industry betas over the same time period as the tail risk measures, we still find betas are lower for the recovery sample. For example, the industry and market betas are .20 and .34 respectively when estimated over the longer time interval. The results reported later in the paper are qualitatively similar if we use betas estimated over a longer time horizon.

As shown in Panel B, the median price on credit lines is 150 bps (over LIBOR) and the median line of credit is 16% of firm's assets. This result is similar to the median line of credit size reported by Sufi (2009) and Lins et al. (2010). In addition, 72.1% of these credit lines are secured.

As explained in Sufi (2009) firms determine their cash holding and credit line usage jointly. This joint determination creates a mechanical negative relation between any measure scaled by total assets and the availability and use of credit lines. Thus, we scale cash flows, tangible assets, net worth, and market value of assets by book value of non-cash assets. We provide a detailed description of each of the variables in the Appendix.[16] As shown in Panel C,

[16] To reduce the impact of outliers, we winsorize all financial ratios at the 2.5st and 97.5th percentile.

consistent with the notion that lines of credit are an important source of liquidity, we find that 67.2% of firm-years have lines of credit. In addition, we find that 44% (38%) of total firm liquidity comes from total (unused) lines of credit. By comparison, Sufi (2009) reports that 74.8% of firm-years have lines of credit and 51.2% of total firm liquidity comes from total lines in his random sample.[17] Note that firms in our sample are older and have larger non-cash assets and lower cash flows than the firms in his sample. Therefore, they may rely less on their credit lines for liquidity management since they can easily raise external capital.[18]

In Panel D of Table I, we examine the correlation among the various IDEMs, as well as aggregate risk measures. Since the correlation matrices are similar across all samples, we report the correlations for the Compustat sample (the broadest of the samples that we use). All the IDEMs are positively correlated with one another. However, conditional correlations and MDE measure are more highly correlated with each other and both are not highly correlated with industry beta. The high correlation between tail measures is not surprising since both the conditional correlations and marginal distress are computed conditional on an industry downturn. Moreover, as discussed earlier, beta may underestimate correlations in the tail. Finally, the correlations between the market beta and industry tail risk measures are quite low suggesting the industry tail risk is not simply measuring market risk. Note however that the correlation between

[17] Sufi (2009) collects detailed data on used and unused lines of credit for a random sample of 300 public firms from 10-K SEC filings between 1996 and 2003.

[18] The Sufi sample ends in 2003 and thus does not include data on liquidly choices leading up to and during the credit crisis that began in 2007. Our sample goes through 2009 and includes information on lines of credit usage and cash holdings during the recent financial crisis. To shed some light on the influences of the financial crisis of 2008 on lines of credit usage, we examine univariate differences in line usage and firm characteristics based on whether the firm-year observation is 2008 and after. Consistent with the survey findings of Campello, Graham, Giambona and Harvey (2009), we find no significant difference in line utilization between the pre- and post- financial crisis periods.

MDE and market MDE is higher (.61) than the correlation with market beta. This is perhaps not surprising given that low industry returns are likely to occur when the overall market is down.[19]

4. Industry Risk, Recovery Rates and the Likelihood of Distress

If industry risk is related to the quality of collateral then we would expect that a good industry risk measure would predict loss given default and the likelihood of firm distress given industry distress. In this section, we examine whether potential industry risk measures are related to loss given default and the likelihood of distress controlling for aggregate risk as well as firm and industry characteristics. We employ univariate and multivariate tests to address these questions.

4.1. Industry risk and recovery rates

As discussed earlier, the argument that borrowing costs are related to industry risk is based on the idea that greater industry distress exposure is related to lower expected recovery rates when a firm defaults on its debt obligations. If this argument is correct, we would expect a negative relationship between recovery rates for creditors and industry risk prior to becoming

[19] We also compute but not report CoVAR measures of industry risk. In particular, Adrian and Brunnermeier (2010) propose a financial sector systemic risk measure which they refer to as CoVAR. CoVAR is intended to capture the marginal contribution of a particular financial institution to the overall systemic risk of the financial sector (i.e the likelihood that the capital of the industry falls below some critical value). They define institution i's CoVAR as the Value at Risk (VAR) of the whole financial sector conditional on institution i being in distress. They take the difference between the CoVAR conditional on the distress of an institution and the CoVAR conditional on the normal state of the institution. Note that the direction of conditioning in CoVAR is the value at risk of the system conditional on institution i being in distress ($\Delta Covar^{system|i}$). However, for industry risk, we are interested in an individual firm's exposure to industry wide distress. Adrian and Brunnermeier (2010) define this opposite conditioning as "exposure CoVAR" which measures an individual institution's exposure to system wide risk($\Delta Covar^{i|system}$). Using the same methodology as Adrian and Brunnermeier (2010), we calculate industry exposure CoVAR measures for the firms in our sample. We find a significant relationship between the likelihood of firm distress when its industry is in distress and our exposure CoVAR measure. However, we find no significant relation between recovery rates and exposure CoVAR.

financially distressed. To investigate this issue, we examine the relationship between recovery rates for creditors in bankruptcy (a measure of LGD) and the potential measures of industry risk.

We model recovery rates as a function of firm financials prior to the bankruptcy filing, industry risk and market risk. We also control for claim size because larger claims may have higher recovery rates since a larger stakeholder may have greater bargaining power in bankruptcy. In addition, we control for growth in GDP because recovery rates are lower during recessions (see Scheurmann (2004) and Chen (2010)).

Our findings are presented in Table II. As shown in regressions (1) through (3), neither industry nor market beta are significantly related to recovery values. Indeed, both industry and market beta are *positivel*y related to recovery rates. We also test whether industry betas and market betas are jointly significant using an F test. We can’t reject the hypothesis that the two betas are different from zero (the F statistic is 0.63). These results indicate that there is no relationship between unconditional industry or aggregate risk measures and LGD. In contrast, as shown in columns (4) and (5), our industry tail risk IDEMs (conditional correlations and MDE) are negative and significantly related to recovery rates. The relationships are economically significant as well. For example, a one standard deviation increase in the conditional correlation is associated with a 3.5 % decrease in recovery rates. We also calculated conditional correlations and MDE using market returns instead of industry returns. If we observe the impact of industry distress exposure only at the tail, then we might also observe the impact of market risk exposure only at the tail. However, as shown in columns (6), we find no significant relationship between recovery rates and market MDE.

As shown in Table II recovery rates are significantly lower for unsecured and subordinate claims relative to senior claims (the omitted category) and secured claims. Recall that for secured claims recovery rates are generally 100%. If lenders adjust collateral coverage ex ante to account for industry risk then recovery rates on secured claims would not be expected to vary with industry risk. This argument suggests that industry driven recovery risk is likely to have the greatest impact of unsecured claims. Consistent with this argument the estimated coefficient on the conditional correlation and MDE are higher for the unsecured sample (.25 and .40 respectively and coefficients are significant at the .05 level or higher).

Overall, these results indicate that our industry tail risk measures provide a better measure of the quality of collateral (in terms of recovery rates) than unconditional risk measures or market-based risk measures. Given these findings, we focus primarily on our industry tail risk measures in the remainder of the paper.

4.1. Industry risk and financial distress: Univariate tests

Following the literature on financial distress, we employ four different distress definitions (Gilson, John and Lang (1990), Opler and Titman (1994), Asquisth et al. (1994) and Acharya et al. (2007)). Our first measure of industry distress is based on the median annual stock return for the industry. In particular, an industry is defined as being in distress if the median stock returns of all the firms in the same three-digit SIC code are less than -30% in a given year. Similarly, the firm is defined as distressed if the stock return of the firm is less than -30% in a given year.

A potential concern with using stock returns as a measure of distress is that stock returns reflect both economic as well as financial distress and thus are likely to be systematically related to leverage. More important, since our industry risk measures are based on stock returns, there may be a mechanical relationship between our industry risk measures and the likelihood of distress when distress is defined by stock returns. To address these concerns, we also define distress in terms of sales growth (see Acharya et al. (2007)). An industry is defined to be distressed if the median sales growth of all of the firms in the same three-digit SIC code is negative in either of the two previous years. Similarly, a firm is defined as distressed if the sales growth of the firm is negative in either of the two previous years. Our third measure of distress is based on stock returns and sales growth. An industry is defined to be distressed if the median stock return of all the firms in the three-digit SIC code is less than -30% in a given year and if the median sales growth of all the firms in the same three-digit SIC code is negative in either of the two previous years. A firm is defined as distressed if the stock return of the firms is less than -30% in a given year and if the sales growth of the firm is negative in either of the two previous years. The fourth definition is an interest coverage based measure. An industry is defined to be distressed if the median EBITDA over interest expense ratio of all the firms in the same three-digit SIC code is less than 0.8 in a given year. A firm is defined as distressed if its EBITDA over interest expense ratio is less than 0.8 in a given year.

We sort firms based on each of our potential IDEMs (computed using stock returns data up to the fiscal year before the onset of distress) and compare firms in the top and bottom quartiles of the distribution. As shown in Table III, firms with a high industry risk exposure measure are significantly more likely to be in distress when their industry is also in distress. The difference in likelihood of firm distress during industry-wide distress between firms in the top and bottom quartiles of the distress exposure measure ranges from 2.4 % to 9.4%. In only one instance, when we use conditional correlations as an IDEM and define distress by interest coverage, do we find that firms in the lowest IDEM quartile are more likely to be distressed during an industry downturn.[20]

We also sort firms based market MDE and group firms in the top (bottom) quartile of market MDE distributions. Not surprisingly, the likelihood of firm distress during industry-wide distress is greater in down markets. However, when we group firms by market beta we find that market beta has little ability to predict firm distress conditional on industry distress. For example, we find no significant difference in the incidence of firm distress conditional on industry distress between the top and bottom beta rank quartiles. Moreover, we find that the likelihood of distress based on sales growth is lower for the high beta quartile.

Since the likelihood of financial distress is likely to be related to firm characteristics (see for example Altman (1968) and Shumway (2001) on predictors of individual firm distress), we turn next to an examination of whether our industry risk measures have predictive power after controlling for firm and macroeconomic factors.

4.2. Multivariate Tests

We investigate whether our industry tail risk measures are related to the likelihood that a firm will be in distress during an industry downturn using multivariate probit regressions. We measure firm characteristics in the fiscal year prior to the distress year. As in section 4.1, our industry and market risk measures are computed using stock return data ending one year prior to the distress date. Since our empirical findings are not sensitive to the distress measure we use, we report results using the stock return based distress measure.

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[20] This result is mainly driven by firms in the chemicals and allied products industry (2-digit SIC code: 28). When we exclude those firms, we find that firms with high industry risk exposure are more likely to be in distress during industry-wide distress.

We analyze the likelihood that a firm is in distress conditional on industry distress using a sample of distressed industries. This enables us to examine firm distress conditional on industry distress. However, we obtain similar results if we use the entire Compustat panel data set and examine the likelihood of a firm being in distress at the same time its industry peers are distressed. Table IV provides estimates of a multivariate probit model in which the dependent variable is an indicator variable equal to one if the firm is in distress and zero otherwise. The sample is limited to industries that are also in distress in the same calendar year. In all of the regressions, we include both year and industry fixed effects. As shown in regressions (1) and (2), controlling for firm financial characteristics and GDP growth, firms with high conditional correlations and MDEs are significantly more likely to be in distress during industry-wide distress. The results are economically significant as well. For example, holding everything else in the model constant, a one standard deviation increase in the conditional correlation (marginal distress estimate) is associated with a 3.3% (3.8%) increase in the likelihood of firm distress when its industry is in distress

In regressions (3) and (4) of Table IV we examine the relationship between firm distress and MDE controlling for market beta and market MDE (the results are similar if we use conditional correlation as our industry risk measure). As shown we find a positive and statistically significant relationship between the likelihood of firm distress and MDE controlling for market beta and market MDE. As shown, we find a positive and significant relationship between firm distress only in for market MDE. We find no significant relationship between firm distress and market beta (with or without controlling for MDE). [21] These findings are consistent

[21] In contrast, we find a positive and significant relationship (not reported) between the likelihood of financial conditional on industry distress and industry beta (the coefficient estimate is .05 significant at the .01 level)

with industry risk being different from aggregate risk and an important predictor of firm distress during industry-wide distress.

The relationship between the likelihood of firm distress conditional on industry distress and firm financial characteristics are consistent with finds of prior studies of financial distress. For example, consistent with Shumway (2001) we find a negative relationship between the likelihood of distress and cash flows. In addition, consistent with Zmijewski (1984) we find that leverage is a strong predictor of distress.[22]

5. Industry risk and bank loan pricing

5.1. Industry risk and loan pricing

In the previous section we documented a significant relationship between our tail risk measures and both the likelihood of firm distress in an industry downturn and recovery rates. These findings suggest that higher industry risk, if economically important to lenders, should be associated with ex ante higher interest rates on bank loans. Moreover, industry risk should be a more important component for firms in industry that employ specific or difficult to redeploy assets.

We investigate these issues using loan pricing information from Dealscan. The dependent variable in our loan pricing regression analysis is the all in drawn spread. Dealscan defines all in drawn spread as the amount the borrower pays in basis points over LIBOR for each dollar drawn down. The All in Drawn Spread thus includes the interest cost of borrowing plus any fees

[22] In untabulated results, we repeat analysis using Altman (1968) control variables including retained earnings over assets, market equity of total liabilities and sales of assets. Using Altman's control variables we find qualitatively and quantitatively similar results to those reported in Table IV.

associated with the line of credit and line usage. We model this spread as a function of lending standards, firm financial characteristics including size, cash flow, net worth, market to book, tangible assets and industry cash flow volatility. These controls are motivated by previous empirical work by Strahan (1999) and others who find that large, profitable and high market-to-book firms, along with firms with more tangible assets, pay less on their bank loans. We also control for other loan characteristics including the size of the credit line scaled by total assets, the natural logarithm of loan maturity and dummy variables for deal purpose. More creditworthy firms are more likely to obtain larger loans with longer maturity. However, credit risk may also be increasing in the maturity of the loan. Thus the impact of maturity is ambiguous.[23]

Our loan pricing results are presented in Table V. As in the previous section, we focus on industry tail risk measure and, for brevity, we present results for MDE (our findings are similar if we use measure industry risk by industry beta or conditional correlations). Regression results in column (1) indicate that firms with greater industry tail risk pay more for their credit lines. For example, a one standard deviation increase in marginal distress exposure is associated with a 7.5 bps increase in loan price. As shown these results are robust to including market based risk measures. For example, as shown in column (2), when we include the firm's market beta we continue to find a positive and statistically significant relationship between all in drawn spreads and our industry risk measures. Interestingly controlling for industry risk we find no statistically significant relations between borrowing costs and market beta (indeed the point estimate is negative). Finally, in column (3) we report the results of the credit spread regression including

[23] Loan maturity and deal size are almost certainly endogenous. However, our primary interest is in whether industry risk is related to loan pricing. Since industry risk is measured prior to the deal, it is exogenous to loan pricing. We obtain similar results when we exclude maturity and deal size from the pricing regressions.

both industry and market MDE as explanatory variables. As shown both tail risk measures are significantly related to credit spreads.

Table V also provides some insights into the relationship between all in drawn spreads and firm financials and other loan characteristics. Borrowers pay less for larger and longer term loans. In terms of firm characteristics, not surprisingly, we find that larger, more profitable and less levered firms borrow at lower rates. Finally, greater industry cash flow volatility is associated with significantly higher spreads.

5.2. Does the importance of industry risk vary with loan security?

Acharya et al. (2007) argue that industry driven recovery risk should matter most in the loan pricing of unsecured claims. The basic idea is that, because of the priority of their claim, unsecured creditors have a greater exposure to variations in asset values than secured creditors. Consistent with this argument, Acharya et al. (2007) find that the recovery rates on unsecured claims (particularly senior unsecured) are significantly more sensitive to industry distress than the recovery rates on secured claims. Benmelech and Berman (2009) also examine this issue and find that the redeployability of airlines' assets matters most for the junior tranches of airline CDOs. To investigate this issue, we obtained information from Dealscan on the whether a loan in our Dealscan sample was secured or unsecured. Using this information, we test whether the importance of industry risk varies with whether a loan is secured or unsecured.

As shown in columns (1) and (2) of Table VI, industry risk matters the most for unsecured loans. Indeed, as shown in columns (1) and (2), industry risk exposure is significantly related to loan spreads only for unsecured loans. The economic impact of industry risk also differs significantly between the secured and unsecured samples. For example, a one standard deviation increase in marginal distress estimate corresponds to a 5.7 bps increase in the all in drawn spread for unsecured loans. On the other hand, a one standard deviation increase in marginal distress estimate implies only a 1.9 bps increase for secured loans (which is not statistically different from zero). In contrast, we find no significant relationship between the spreads on unsecured loans and market MDE (or market beta not shown).

5.3. Does the importance of industry risk vary with credit market conditions?

Arguably, creditors should be more concerned with industry risk during tight credit market conditions and during economic downturns because the overall likelihood of distress is higher. We measure lending standards by the net percentage of banks reporting an increase in lending standards on Commercial and Industrial loans in the Federal Reserve Board's Senior Loan Officer Survey. We define economic downturns as recessions based on the NBER . We investigate the relationships between loan rates, industry risk and lending standards by dividing the sample into two groups using the sample median of tightness of lending standards. As shown in Table VI in columns (3) and (4), industry distress exposure has a significantly greater impact on loan pricing during tight credit markets. For example, the coefficient on marginal distress estimate almost doubles in tight market conditions. In terms of economic significance, a one standard deviation increase in MDE implies a 9.8 bps increase in borrowing costs during tight credit markets, while it is only 5.3 bps during loose credit markets.

Tight credit market conditions occur primarily during economic downturns. There are 47 tight credit market quarters in our sample (out of 92). Fifteen of these quarters are also recession quarters as defined by the NBER. When we divide our sample into recession and non-recession quarters (not tabulated), we also find that the effect of industry distress exposure is significantly greater in recession quarters than in expansion quarters.

Since our sample extends through the financial crisis, it is interesting to examine how the financial crisis affected loan pricing. During the financial crisis, an average of 55.4 percent of lenders indicated that they tightened lending standards.[24] The average all in drawn spread increased to 238 bps from an average of 136.5 bps during the pre-crisis period. In untabulated results, we examine whether the financial crisis that began in late 2007 had a differential impact on the cost of borrowing based on the size, profitability and industry risk exposure of the firm prior to the crisis. Greater loss aversion among lenders, supply constraints or errors in measurement may result in higher observed risk premia for observably similar firms during a financial crisis. Consistent with this argument, the size of the coefficients on our industry risk measures increase significantly. For example, in the pre-crisis period, a one standard deviation increase in our marginal distress estimate increases loan spread by 7.5 bps, whereas one standard deviation increase in our marginal distress estimate increases loan spread by 15.4 bps during the crisis. On the other hand, the impact of firm financial characteristics decreases significantly during the crisis. For example, in the pre-crisis period, a one standard deviation increase in firm size (profitability) leads to a 77 (24) bps decrease in spread, whereas the same amount of change decrease loan spread only by 37 (18) bps during the recent financial crisis.

5.2. Does the importance of industry risk vary with asset specificity?

Previous empirical studies find that LGD is lower for firms operating in industries with more readily deployable assets. Ex ante, lower expected LGD should be reflected in lower loan

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[24] See Federal Reserve Board's Loan Officer Opinion Survey on Bank Lending Practices available at Federal Reserve Board's website at http://www.federalreserve.gov/econresdata/releases/surveysreports.htm.

rates. Consistent with this argument, Benmelech and Bergman (2010) find that credit spreads are lower on debt tranches that are secured with more deployable collateral. We investigate this issue by sorting firms based on their industry asset specificity and then examining whether the effect of industry risk on loan pricing varies with asset specificity. We also examine whether the importance of industry level asset specificity varies with whether or not the loan is secured. Acharya et al (2007) find that industry level asset specificity matters most for in terms of recovery rates for unsecured claims. The idea is ex ante secured lenders adjust collateral coverage requirements based on quality of collateral with coverage requirements set higher for collateral that is more difficult to redeploy. If collateral coverage is adjusted based on quality of collateral then industry risk may have a greater impact on the pricing of *unsecured* loans to firms operating in industries with high levels of asset specificity.

Table VII provides estimates of the loan spread regression for subsamples of loans grouped by whether or not the loan is secured and whether the firm operates in an industry with high (above the median) or low (below the median) asset specificity. As shown, we find a significant relationship between loan spreads and MDE only for unsecured loans to firms operating in industries with high asset specificity. The impact of industry risk is economically significant as well. For example, a one standard deviation increase in marginal distress estimate increases the cost of unsecured loans by 8.2 bps for firms in the high asset specificity sample, whereas the same impact increases the loan price by only 0.8 bps for firms in the low asset specificity sample. These finding is consistent with argument that our industry risk measures reflect expected loss given default since as unsecured creditors are most likely to bear the brunt of the cost associated with variability in asset values in financial distress. These findings add to those of Acharya et al. (2007) and Benmelech and Berman (2009) who find that industry distress affects recovery rates more for firms with difficult to redeploy assets.

6. Industry risk and liquidity choice

6.1. Industry risk and liquidity management

The evidence in the previous sections suggests that greater industry exposure is associated with lower debt recovery rates during industry downturns and that creditors build this into the price of credit (*pricing channel*). The pricing of credit lines, in turn, should determine how much the firm relies on cash versus lines of credit for liquidity management purposes.

Creditors may also respond to industry downturns by denying the firm credit or restricting the use of a firm's lines of credit. Firms may take into account the more contingent access to bank credit during downturns by increasing their cash holding (*availability channel*). In particular, Sufi (2009) finds that the use of cash flow based covenants by bank lenders leads to lines of credit being a close substitute for cash only for firms with high expected future cash flows. Moreover, Chava and Roberts (2008) and Nini, Smith and Sufi (2009) find that technical covenant violations lead to tighter lending terms and less availability. As a result, cash flow covenants together with net worth and borrowing base covenants that tie credit availability to firm cash flows and the value of collateral may make lines of credit a poor substitute for cash reserves for firms with significant industry risk exposure.

Finally, cash holdings may be related to industry risk because firms with greater industry risk exposure hold more precautionary cash balances. In particular, firms with greater industry risk exposure have less liquid operating assets and thus may choose to hold more cash as a hedge against operating cash flow shocks (see Shleifer and Vishny (2010) for a discussion of the impact of potential fire sale discounts on cash holdings).

In this section, we address these questions by examining whether the proportion of bank-provided liquidity to total liquidity and the ratio of cash to assets are related to the degree of firms' industry distress exposure. Since our findings are similar whether we measure industry risk by MDE or conditional correlation, for brevity we report our results only using MDE.

6.1.1. Cash vs. lines of credit

We measure bank-provided liquidity as the sum of the firm's lines of credit and define total liquidity as the sum of cash and bank liquidity. The bank liquidity ratio equals zero for firms with no lines of credit. Since the bank liquidity variable is left truncated, we examine the determinants of the bank liquidity ratio using a one-sided Tobit regression. We estimate the regressions using control variables including lending standards, firm size, cash flow, net worth, market to book, tangible assets, industry cash flow volatility, age and year and industry fixed effects. These control variables are motivated by the fact that firm and industry characteristics are likely to explain why firms choose cash over bank lines. For example, the cost of external financing is a function of firm characteristics such as size, cash flow volatility and industry conditions (see Sufi (2009)). Credit market conditions may also affect the access to and utilization of credit lines, especially for smaller firms (Demiroglu, James and Kizilaslan (2011)).

Our findings are presented in Table VIII. Since we are using panel data, we cluster standard errors by firm in all of the regressions to account for within-firm correlation of regression residuals. As shown in column (1), controlling for firm financials and credit market conditions, firms rely more on cash and less on credit lines as MDE increases. Since Acharya et al. (2010), find that firms with higher market betas hold more cash relative to bank credit we include the firm's market beta in column (2). Consistent with Acharya et al., we find a positive relationship between cash holdings and market beta. However, controlling for aggregate risk exposure, we continue to find a positive and significant relationship between cash holdings and our industry tail risk measures.

The findings reported in Table VIII also provide some insights into the relationship between liquidity choice and firm financial characteristics. Consistent with the findings of previous empirical studies, we find older firms and firms with fewer growth opportunities rely more heavily on credit lines as a source of liquidity (Sufi (2009)). Note that the coefficient on cash flow has the expected sign but is not statistically significant when we use total lines of credit to define bank liquidity. The lack of a significant relationship between line usage and cash flows appears to because our sample period is different from Sufi's and, more importantly, it includes data from the recent financial crisis. In untabulated analysis, when we exclude observations for fiscal years 2008 and 2009, we find that cash flows are significantly and positively associated with line usage.[25]

6.2. Industry risk and cash holdings

In the previous section we showed that firms with greater industry risk exposure rely more heavily on cash relative to lines of credit for their liquidity needs. We next examine whether these firms also hold higher cash reserves as a form of protection from liquidity shocks. Following the literature on cash holdings, we measure cash reserves as the ratio of cash to the book value of assets (see for example Almeida et al. (2004) and Bates, Kahle and Stulz (2009)).

[25] Industry distress exposure measures continue to be negative and statistically significant in the pre-crisis period.

If firms with potentially less liquid operating assets face potentially greater external financing frictions, we would expect these firms to hold more precautionary cash balances.

Our regression model assumes that cash holdings are a function of firm characteristics, credit market conditions and industry distress exposure measures. As shown in column (3) of Table VIII, firms with high MDE hold significantly more cash relative to total assets. In column (4), we include both MDE and market risk together and continue to find a negative and statistically significant relationship between cash holdings and both the industry MDE and market beta.[26]

One potential concern with the analysis thus far is that our IDEMs, as well as our aggregate risk measures, may simply be proxies for the overall volatility of a firm's cash flows or operating performance. This is plausible since overall volatility in returns may affect the likelihood of distress and the external financing costs that a firm may face. Moreover, Bates et al. (2009) find that the increase in cash holdings since 2000 is related to an increase in the volatility of cash flows and an increase in idiosyncratic risk. To address this issue, in the regressions reported in Table VIII, we control for industry cash flow volatility, which should be related to the volatility of an individual firm's cash flows and is a standard control variable used in the literature on cash holdings. As a further robustness check, we compute the volatility of individual firm monthly returns over the prior 60 months as well as the volatility of cash flows (using yearly data for the prior 10 years). After controlling for the volatility of individual firm returns and cash flows, we continue to find a negative and significant relationship between both industry as well as aggregate risk measures.

[26] In untabulated results, we control for the Bank MDE. Bank MDE is equal to the average of the firm's monthly returns in the worst 5% of bank return months. After controlling for Bank MDE, we continue to find a negative and significant relationship between MDE and bank liquidity ratio.

7. Conclusion

In this paper, we calculate several potential industry risk measures and examine their relationship to recovery rates in financial distress and the likelihood of financial distress. We find that industry tail risk measures are significantly related to both the likelihood that a firm becomes distressed during an industry downturn and what creditors are able to recover in bankruptcy. We also find that loan rates and firms' reliance on bank lines of credit as a source of liquidity are significantly related to these industry risk measures. Our results are robust to including aggregate risk measures and other controls. These findings are consistent with the argument that greater industry risk is associated with higher LGD which, in turn, leads to higher credit spreads on bank loans. Moreover, higher industry risk may affect the conditionality of lines of credit because, conditional on distress, high industry risk borrowers may be forced to renegotiate their lines when industry conditions are unfavorable and collateral values are low. Consistent with this argument, we find that firms with greater industry risk exposure rely more heavily on cash and less on bank lines of credit as a source of liquidity.

Overall, these results suggest that the potential for fire sale discounts affects that ex ante pricing and structure of bank loans. To the best of our knowledge, ours is the first study to show that the liquidity of a firm's operating assets is an important factor affecting loan pricing and firm liquidity choices.

Appendix: Variable Definitions

Industry Beta = the asset (unlevered) industry beta, calculated from the equity (levered) industry beta. Equity industry beta is obtained from a two-factor model in which firm return is regressed on market return (value weighted return of CRSP universe - vwretd) and industry return (value weighted return of all the firms in the three-digit SIC code of the firm). The asset industry beta is obtained by multiplying equity industry beta with equity / (debt + equity) where equity is the market capitalization of the firm and debt is equal to the sum of short term debt and long term debt multiplied by 0.5.

Conditional Correlation = correlation between the normalized stock return of the firm and the normalized return on the value weighted portfolio of all the firms in the same 3-digit SIC code of the firm given the normalized return on the value weighted portfolio of all the firms in the same 3-digit SIC is less than zero.

Marginal Distress Estimate (MDE) = average stock return of the firm given that the return on the value weighted portfolio of all the firms in the same 3-digit SIC code of the firm is below its 5^{th} percentile.

Market Beta = the asset (unlevered) market beta, calculated from the equity (levered) market beta. Equity market beta is obtained from a two-factor model where firm return is regressed on market return (value weighted return of CRSP universe - vwretd) and industry return (value weighted return of all the firms in the three-digit SIC code of the firm). The asset market beta is obtained by multiplying equity market beta with equity / (debt + equity) where equity is the market capitalization of the firm and debt is equal to the sum of short term debt and long term debt multiplied by 0.5.

Market Marginal Distress Estimate (MDE) = average stock return of the firm given that market return (value weighted return of CRSP universe- vwretd) is below its 5^{th} percentile.

Total Line / (Total Line + Cash) = total amount of lines of credit / total amount of lines of credit +cash (che)

Unused / (Unused Line + Cash) = unused amount of lines of credit / unused amount of lines of credit + cash (che)

Cash / Assets = che / at

Debt /Assets = (dlc + dltt) / at

Net Debt /Assets = (dlc + dltt - che) / at

LN (Assets – Cash) = ln(at – che)

Net Worth/(Assets – Cash)= ceq /(at-che)

Market to book = (at – ceq + prcc_f*csho) / at

Tangible/(Assets – Cash) = ppent/(at-che)

ROA, Cash Adjusted = oibdp / (at-che)

Industry Cash Flow Volatility = the median 10 year moving standard deviation of cash flow over lagged assets (oibdp(t) / at(t-1)) of all the firms in the 3-digit SIC of the firm.

LN (age) = Log (current fiscal year (fyear) – first fiscal year of available accounting data (year1))

Asset Specificity = the median ratio of machinery and equipment (net = ppenme, gross = fate) to total assets, using one-digit SIC code over sample period.

Lending Standards = the percentage of (large) banks tightening lending standards in the loan quarter (based on Federal Reserve Bank's Survey of Business Lending).

All in drawn = spread paid by firms over LIBOR for each dollar drawn down from the loan.

Deal Amount / Assets = ratio of loan amount to total assets.

LN (Deal Maturity) = natural logarithm of the loan maturity reported in Dealscan.

Recovery Rate = the estimated recovery rate on the claim.

LN (Claim) = the natural logarithm of the amount of the claim.

LN (Assets) = ln(at)

EBITDA / Assets = oibdp/at

Tangible / Assets = ppent/at

Long-Term Debt / Assets = dltt /at

Industry MTB = the median of the ratio of market value of the firm (book value of assets (at) – book value of equity (ceq) + market value of equity (prcc_f*csho)) to book value of assets of all the firms in the 3-digit SIC.

Change in GDP = annual GDP percent change based on 2005 dollars, obtained from Bureau of Economic Analysis' webpage (www.bea.gov).

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Figure 1

Recovery Rates of Unsecured Loans

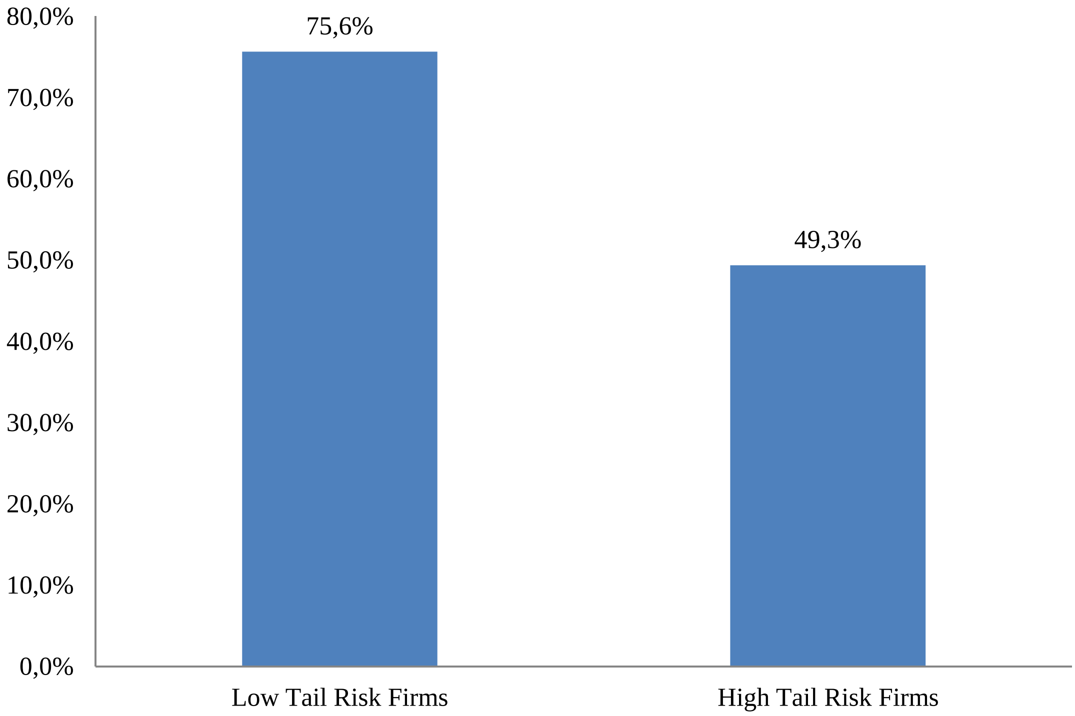

Table I. Summary statistics

This table presents summary statistics for some of the key variables used in the empirical analysis. Panel A presents summaries for public firms that filed bankruptcy between 1998 and 2010. Information on third party claims are obtained from reorganization plans that are reported at bankruptcydata.com. All firm financials are measured at the last fiscal year available before the bankruptcy filing date and are obtained from Compustat. All industry variables are measured in the year of bankruptcy. Panel B provides summary statistics for the Dealscan sample which includes lines of credit that are completed between 1987 and 2009. Information on lines of credit and firm financials are obtained from LPC's Dealscan database and Compustat, respectively. All firm financials and industry variables are measured at the last fiscal year available before the loan completion date. Panel C provides summary statistics for the lines of credit sample (panel data set of 348 public firms). In Panel D, we present correlations among distress exposure measures in the Compustat sample. Variable definitions are provided in the Appendix.

Panel A: Recovery sample

Summary Statistics	N	Mean	1st Quartile	Median	3rd Quartile	Standard Deviation
Recovery Rate (%)	1958	74.1	39.1	100	100	39.87
Dummy: Unsecured Claim	2371	21.00%	--	--	--	--
Dummy: Secured Claim	2371	23.50%	--	--	--	--
Dummy: Subordinated Claim	2371	7.30%	--	--	--	--
Recovery Rate on Unsecured Claims (%)	383	53.11	10	47.5	100	42.5
Recovery Rate on Secured Claims (%)	465	97.3	100	100	100	13.74
Recovery Rate on Subordinated Claims (%)	134	20.19	0	0	33.65	34.49
Claim Amount	1482	369.5	1.1	25.95	214.1	1517.75
Assets –Cash	301	2319.72	275.82	687.66	2043	4420.55
Cash/Assets	300	0.07	0.01	0.03	0.09	0.10
Market Beta	176	0.16	0.00	0.08	0.23	0.34
Industry Beta	176	0.18	0.10	0.16	0.26	0.19
Conditional Correlation	207	0.38	0.21	0.37	0.53	0.21
Marginal Distress Estimate (MDE)	184	15.00%	6.60%	13.50%	20.80%	14.00%

Panel B: Dealscan sample

Summary Statistics	N	Mean	1st Quartile	Median	3rd Quartile	Standard Deviation
All in drawn (bps)	23717	179.49	75	150	255	129.26
Secured	16936	72.10%	--	--	--	--
Assets – Cash	26342	2842.58	101.29	458.66	2083.44	5909
Cash/Assets	26345	0.08	0.01	0.04	0.10	0.11
Deal Amount / Assets	26378	0.24	0.07	0.16	0.32	0.24
Deal Maturity	24349	37.9	13	36	60	22.3
Market Beta	17599	0.39	0.12	0.32	0.62	0.45
Industry Beta	17599	0.44	0.18	0.42	0.67	0.39
Conditional Correlation	19258	0.4	0.24	0.39	0.54	0.21
Marginal Distress Estimate (MDE)	18546	10.70%	5.40%	9.90%	15.50%	9.90%

Panel C: Lines of credit sample

Summary Statistics	N	Mean	1st Quartile	Median	3rd Quartile	Standard Deviation
Dummy: Lines of Credit	3828	67.20%	--	--	--	--
Total Line / (Total Line + Cash)	3713	0.44	0	0.41	0.84	0.39
Unused Line / (Unused Line + Cash)	3712	0.38	0	0.31	0.75	0.37
Cash / Assets	3713	0.24	0.04	0.13	0.37	0.26
Assets – Cash	3714	2219.12	39.73	184.86	947.34	5713.65
Market Beta	3055	0.57	0.19	0.47	0.90	0.67
Industry Beta	3055	0.48	0.17	0.43	0.74	0.48
Conditional Correlation	3127	0.31	0.17	0.29	0.44	0.19
Marginal Distress Estimate (MDE)	3238	12.20%	5.10%	11.00%	18.40%	13.10%

Panel D: Correlations

	Industry Beta	Conditional Correlation	Marginal Distress Estimate	Market Beta	Market Marginal Distress Estimate	Stock Return Volatility
Industry Beta	1.00	--	--	--	--	--
Conditional Correlation	0.26	1.00	--	--	--	--
Marginal Distress Estimate	0.30	0.52	1.00	--	--	--
Market Beta	-0.55	-0.06	0.04	1.00	--	--
Market Marginal Distress Estimate	0.14	0.28	0.61	0.23	1.00	--
Stock Return Volatility	0.18	-0.01	0.32	0.11	0.44	1.00

Table II. Recovery rates and industry distress exposure measures (IDEM)

This table presents regressions that examine how market and industry distress exposure affect the recovery of claims in bankruptcy. The period of analysis is from 1998 to 2010. Information on bankruptcies and firm financials are obtained from bankruptcydata.com and Compustat, respectively. We report the coefficient estimates and t-statistics (based on standard errors clustered by firm). We use ***, **, and * to denote that the coefficient estimate is different from zero at the 1%, 5% and 10% levels (two-tailed), respectively. Variable definitions appear in the Appendix.

Dependent Variable:	Recovery Rate					
Estimation Method:	OLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Beta	0.05	--	0.11	--	--	--
	(0.53)	--	(0.93)	--	--	--
Market Beta	--	0.05	0.10	--	--	--
	--	(0.75)	(1.11)	--	--	--
Conditional Correlation	--	--	--	-0.16**	--	--
	--	--	--	(-1.99)	--	--
MDE	--	--	--	--	-0.27**	--
	--	--	--	--	(-2.01)	--
Market MDE	--	--	--	--	--	-0.11
	--	--	--	--	--	(-1.01)
Change in GDP	0.06*	0.06*	0.06**	0.02	0.01	0.04
	(1.94)	(1.91)	(2.03)	(0.55)	(0.25)	(1.07)
Log (Assets)	0.03	0.03*	0.03*	0.02	0.03*	0.02
	(1.56)	(1.66)	(1.65)	(1.30)	(1.69)	(1.31)
Log (Claim)	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
	(-8.53)	(-8.47)	(-8.15)	(-9.00)	(-7.75)	(-7.93)
EBITDA / Assets	0.24	0.20	0.25	0.20	0.06	0.17
	(1.31)	(1.13)	(1.38)	(1.16)	(0.30)	(0.91)
Tangible / Assets	0.10	0.09	0.10	0.16*	0.08	0.11
	(1.04)	(0.99)	(1.05)	(1.84)	(1.03)	(1.28)
Long-Term Debt / Assets	-0.05	-0.05	-0.04	-0.14**	-0.06	-0.08
	(-0.74)	(-0.80)	(-0.63)	(-2.20)	(-1.00)	(-1.24)
Dummy: Unsecured Claim	-0.22***	-0.22***	-0.22***	-0.23***	-0.22***	-0.23***
	(-6.06)	(-6.00)	(-5.96)	(-6.14)	(-6.02)	(-6.16)
Dummy: Secured Claim	0.15***	0.15***	0.15***	0.16***	0.15***	0.16***
	(5.04)	(5.05)	(5.06)	(5.31)	(5.19)	(5.36)
Dummy: Subordinated Claim	-0.42***	-0.42***	-0.42***	-0.40***	-0.40***	-0.41***
	(-6.52)	(-6.49)	(-6.48)	(-5.96)	(-6.10)	(-6.66)
Number of observations	701	701	701	807	737	781
Adjusted R^2	34.7%	34.7%	34.8%	36.3%	34.0%	34.4%
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table III. Likelihood of firm distress during industry distress

This table examines the likelihood of firm distress when its industry is also in distress. Distress is calculated at the firm and industry level using four different definitions. For the stock return based distress measure, the industry is defined to be distressed if the median stock return of all the firms in the three-digit SIC code of the firm is less than -30% in a given year. Similarly, the firm is defined as distressed if the stock return of the firm is less than -30% in a given year. For the sales growth based distress measure, the industry is defined to be distressed if the median sales growth of all the firms in the three-digit SIC code of the firm is negative in either of the two previous years. Similarly, the firm is defined as distressed if the sales growth of the firm is negative in either of the two previous years. For the stock return and sales growth based distress measure, the industry is defined to be distressed if the median stock return of all the firms in the three-digit SIC code of the firm is less than -30% in a given year and if the median sales growth of all the firms in the three-digit SIC code of the firm is negative in either of the two previous years. Similarly, the firm is defined as distressed if the stock return of the firms is less than -30% in a given year and if the sales growth of the firm is negative in either of the two previous years. For the interest coverage based measure, the industry is defined to be distressed if the median EBITDA over interest expense ratio of all the firms in the three-digit SIC code of the firm is less than 0.8 in a given year. Similarly, the firm is defined as distressed if the EBITDA over interest expense ratio of the firm is less than 0.8 in a given year. The sample is the Compustat universe excluding financial and utility firms. The sample period is from 1999 to 2009. We present univariate analysis where we compare the frequency of both firm and industry distress categorized by high and low values of the industry distress exposure measure. We test the null that the probability that both the firm and its industry are in distress are equal for the firms whose risk proxy is in the top and bottom quartiles of the sample distribution using t-tests. We assume unequal variances for t-tests. We use ***, **, and * to denote that the null is rejected at the 1%, 5%, and 10% level, respectively.

	Industry beta				
	Top Quartile			Bottom Quartile	
Both the firm and its industry are in distress based on…	N	Mean		N	Mean
Stock Return	10514	13.3%	**	10179	12.3%
Sales Growth	10507	16.4%	***	10360	11.5%
Stock Return and Sales Growth	10112	3.5%	***	9703	1.8%
Interest Coverage	8189	19.9%	***	8835	14.2%

	Conditional Correlation				
	Top Quartile			Bottom Quartile	
Both the firm and its industry are in distress based on…	N	Mean		N	Mean
Stock Return	9476	13.5%	***	9009	10.8%
Sales Growth	9604	19.8%	***	9365	12.7%
Stock Return and Sales Growth	9056	4.1%	***	8623	1.7%
Interest Coverage	8334	11.1%	***	7903	14.3%

	MDE				
	Top Quartile			Bottom Quartile	
Both the firm and its industry are in distress based on…	N	Mean		N	Mean
Stock Return	9738	14.2%	***	8811	9.2%
Sales Growth	9865	21.0%	***	9221	11.8%
Stock Return and Sales Growth	9438	4.5%	***	8413	1.2%
Interest Coverage	7754	18.3%	***	7963	8.9%

	Market beta				
	Top Quartile			Bottom Quartile	
Both the firm and its industry are in distress based on…	N	Mean		N	Mean
Stock Return	10414	13.9%		10227	14.1%
Sales Growth	10206	10.8%	***	10192	16.7%
Stock Return and Sales Growth	9946	2.2%	***	9831	3.7%
Interest Coverage	7789	24.0%	***	8572	14.5%

	Market MDE				
	Top Quartile			Bottom Quartile	
Both the firm and its industry are in distress based on…	N	Mean		N	Mean
Stock Return	9986	15.8%	***	9188	8.1%
Sales Growth	10056	18.7%	***	9771	13.4%
Stock Return and Sales Growth	9618	4.6%	***	8915	1.5%
Interest Coverage	7763	23.0%	***	8659	5.3%

Table IV. Likelihood of firm distress during industry distress: Multivariate

This table reports the regressions that examine the likelihood of firm distress when its industry is also in distress. The industry is defined as distressed if the median stock returns of all the firms in the three-digit SIC code of the firm is less than -30% in a given year. Similarly, the firm is defined as distressed if the stock return of the firm is less than -30% in a given year. The dependent variable is an indicator variable that is equal to one if the firm is in distress, and we estimate the model using firm-year observations in which the industry is in distress. The sample period is from 1999 to 2009. We report marginal effects of the coefficient estimates, as well as t-statistics based on robust standard errors. We use ***, **, and * to denote that the coefficient estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Dummy: Firm is in distress (Ri < -0.30)			
Sample:	only distressed industries			
Estimation Method	Probit			
	(1)	(2)	(3)	(4)
Conditional Correlation	0.16***	--	--	--
	(4.79)	--	--	--
MDE	--	0.28***	0.29***	0.14***
	--	(5.91)	(5.58)	(2.62)
Market Beta	--	--	0.00	--
	--	--	(0.32)	--
Market MDE	--	--	--	0.24***
	--	--	--	(3.49)
Change in GDP	-0.01	-0.01	-0.01	-0.01
	(-0.90)	(-0.79)	(-1.04)	(-0.74)
LN (Assets)	0.01**	0.01***	0.01***	0.01***
	(2.39)	(2.82)	(2.96)	(3.20)
EBITDA / Assets	-0.59***	-0.56***	-0.58***	-0.55***
	(-15.22)	(-14.16)	(-13.90)	(-13.77)
Debt / Assets	0.25***	0.25***	0.25***	0.25***
	(4.90)	(4.66)	(4.56)	(4.71)
Net Worth /Assets	0.12***	0.09**	0.10**	0.09**
	(3.02)	(2.21)	(2.32)	(2.27)
Market to Book	0.02***	0.01***	0.01***	0.01***
	(4.30)	(3.41)	(3.23)	(3.37)
Number of observations	6,242	6,010	6,285	5,991
Pseudo R^2	8.4%	8.2%	8.2%	8.3%
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

Table V. Loan pricing and IDEM

This table presents regressions that examine how industry distress exposure affects the spreads of lines of credit. Information on lines of credit and firm financials are obtained from LPC's Dealscan database and Compustat, respectively. We report the coefficient estimates and t-statistics (based on standard errors clustered by firm). The period of analysis is from 1987 to 2009. We use ***, **, and * to denote that the coefficient estimate is different from zero at the 1%, 5% and 10% levels (two-tailed), respectively. Variable definitions appear in the Appendix.

Dependent Variable:		All in Drawn	
Estimation Method:		OLS	
	(1)	(2)	(3)
MDE	76.44***	84.62***	47.85***
	(6.50)	(7.01)	(3.72)
Market Beta	--	-3.62	--
	--	(-1.49)	--
Market MDE	--	--	69.55***
	--	--	(4.77)
Log (Deal Maturity)	-5.08***	-4.69***	-5.00***
	(-3.48)	(-3.08)	(-3.43)
Deal Amount / Assets	-67.85***	-67.45***	-66.76***
	(-13.47)	(-12.53)	(-13.22)
Lending Standards	33.37***	33.73***	32.68***
	(3.75)	(3.65)	(3.68)
Ln (Assets - Cash)	-37.11***	-37.02***	-36.59***
	(-48.09)	(-46.26)	(-46.64)
Net Worth/(Assets - Cash)	-105.23***	-104.72***	-104.65***
	(-22.96)	(-21.80)	(-22.94)
Market to Book	-9.91***	-9.08***	-9.79***
	(-6.79)	(-6.33)	(-6.69)
Tangible /(Assets - Cash)	6.46	7.73	7.37
	(1.25)	(1.45)	(1.42)
ROA, Cash Adjusted	-227.35***	-232.46***	-225.53***
	(-17.88)	(-18.74)	(-17.67)
Industry CF Volatility	2.18***	2.25***	2.07***
	(9.02)	(9.02)	(8.58)
Number of observations	15,119	13,800	15,051
Adjusted R^2	54.8%	55.2%	55.0%
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Deal Purpose Dummies	Yes	Yes	Yes

Table VI. Loan pricing and IDEM: Subsample analysis

This table presents regressions that examine how the impact of industry distress exposure on the spreads of lines of credit varies for different subsamples. In order to examine how impact of industry distress exposure on the spreads of lines of credit vary with the existence of collateral, we divide the sample into two based on the existence of loan security and we divide the sample into two (high and low) using the sample median of lending standards to examine how impact of industry distress exposure on spreads of lines of credit vary across credit market conditions. Information on lines of credit and firm financials are obtained from LPC's Dealscan database and Compustat, respectively. We report the coefficient estimates and t-statistics (based on standard errors clustered by firm). The period of analysis is from 1987 to 2009. We use ***, **, and * to denote that the coefficient estimate is different from zero at the 1%, 5% and 10% levels (two-tailed), respectively. Variable definitions appear in the Appendix.

Dependent Variable:	All in Drawn			
Estimation Method:	OLS			
Sample:	Collateral		Lending Standards	
	No	Yes	Loose	Tight
MDE	78.20***	15.67	53.87***	99.43***
	(5.19)	(1.33)	(3.38)	(6.93)
Log (Deal Maturity)	-7.41***	-12.01***	-12.78***	0.35
	(-4.16)	(-4.42)	(-6.17)	(0.19)
Deal Amount / Assets	-14.68**	-80.76***	-59.99***	-72.01***
	(-2.22)	(-12.80)	(-9.46)	(-10.22)
Lending Standards	33.99***	34.27**	--	--
	(2.69)	(2.43)	--	--
Ln (Assets - Cash)	-18.24***	-28.59***	-39.19***	-34.73***
	(-17.14)	(-22.02)	(-41.52)	(-35.28)
Net Worth/(Assets - Cash)	-19.26***	-98.46***	-98.34***	-111.09***
	(-2.98)	(-17.02)	(-17.11)	(-18.59)
Market to Book	-10.64***	-8.24***	-8.54***	-11.33***
	(-6.05)	(-4.41)	(-3.89)	(-6.36)
Tangible /(Assets - Cash)	-14.09***	14.08**	9.14	4.44
	(-2.58)	(2.01)	(1.33)	(0.73)
ROA, Cash Adjusted	-60.37***	-218.26***	-231.17***	-225.66***
	(-3.07)	(-15.36)	(-11.92)	(-14.15)
Industry CF Volatility	0.58**	1.28***	2.20***	2.26***
	(2.37)	(3.77)	(7.38)	(7.55)
Number of observations	3,603	6,614	6,767	8,352
Adjusted R^2	40.4%	37.1%	54.6%	54.4%
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Deal Purpose Dummies	Yes	Yes	Yes	Yes

Table VII. Loan pricing and IDEM: Subsample analysis

This table presents regressions that examine how the impact of industry distress exposure on the spreads of lines of credit varies with the asset specificity of the industry for secured and unsecured loans. We divide the sample into two based on the existence of loan security and then we split sample into two (high and low) using the sample median of industry asset specificity. . Information on lines of credit and firm financials are obtained from LPC's Dealscan database and Compustat, respectively. We report the coefficient estimates and t-statistics (based on standard errors clustered by firm). The period of analysis is from 1987 to 2009. We use ***, **, and * to denote that the coefficient estimate is different from zero at the 1%, 5% and 10% levels (two-tailed), respectively. Variable definitions appear in the Appendix.

Dependent Variable:	All in Drawn			
Estimation Method:	OLS			
Sample:	Unsecured Loans		Secured Loans	
	Asset Specificity		Asset Specificity	
	Low	High	Low	High
MDE	8.90	121.41***	16.16	14.05
	(0.38)	(6.53)	(1.00)	(0.82)
Log (Deal Maturity)	-8.68***	-6.84***	-6.01	-15.67***
	(-2.85)	(-3.18)	(-1.54)	(-4.10)
Deal Amount / Assets	-32.76***	-3.85	-92.30***	-70.24***
	(-2.90)	(-0.48)	(-10.09)	(-8.19)
Lending Standards	81.82***	17.13	32.71	37.98**
	(3.89)	(1.13)	(1.47)	(2.15)
Ln (Assets - Cash)	-20.99***	-17.42***	-33.77***	-25.16***
	(-13.27)	(-13.03)	(-16.24)	(-15.63)
Net Worth/(Assets - Cash)	-3.63	-36.00***	-91.48***	-102.43***
	(-0.39)	(-4.43)	(-10.27)	(-13.60)
Market to Book	-7.88***	-11.81***	-8.34***	-7.85***
	(-2.80)	(-5.35)	(-3.06)	(-3.16)
Tangible /(Assets - Cash)	14.66	-21.03***	27.10***	7.24
	(1.30)	(-3.49)	(2.67)	(0.78)
ROA, Cash Adjusted	-78.28**	-69.86***	-221.66***	-219.28***
	(-2.54)	(-2.73)	(-10.01)	(-12.05)
Industry CF Volatility	0.41	0.97***	0.98*	1.60***
	(0.94)	(3.46)	(1.80)	(3.61)
Number of observations	1,078	2,525	2,771	3,843
Adjusted R^2	42.4%	41.7%	38.0%	36.1%
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Deal Purpose Dummies	Yes	Yes	Yes	Yes

Table VIII. Liquidity management and IDEM

This table reports regressions that examine the impact of industry distress exposure measures on the liquidity management of the firms. Information on debt structure of public firms is hand collected from 10-Ks. The period of analysis is from 1999 to 2009. The financials of the firms are obtained from Compustat. We report the coefficient estimates and t-statistics (based on standard errors clustered by firm). We use ***, **, and * to denote that the coefficient estimate is different from zero at the 1%, 5% and 10% levels (two-tailed), respectively. Variable definitions appear in the Appendix.

Dependent Variable:	Total Line / (Total Line + Cash)		Cash / Assets	
Estimation Method:	Tobit		OLS	
MDE	-0.37***	-0.39***	0.17***	0.19***
	(-3.99)	(-3.27)	(4.63)	(4.56)
Market Beta	--	-0.07***	--	0.03***
	--	(-3.01)	--	(3.97)
Lending Standards	-1.26	-1.79**	0.13	0.16
	(-1.60)	(-2.36)	(0.63)	(0.63)
Ln (Assets - Cash)	-0.00	-0.00	-0.02***	-0.02***
	(-0.47)	(-0.42)	(-5.63)	(-5.33)
Net Worth/(Assets - Cash)	-0.21***	-0.19***	0.10***	0.10***
	(-4.22)	(-4.01)	(11.89)	(11.64)
Market to Book	-0.05***	-0.05***	0.02***	0.02***
	(-5.27)	(-4.70)	(7.54)	(6.94)
Tangible /(Assets - Cash)	-8.29***	-8.11***	-0.97	-0.85
	(-3.76)	(-3.65)	(-1.34)	(-1.16)
ROA, Cash Adjusted	0.07	0.05	-0.01	-0.01
	(1.49)	(1.22)	(-1.17)	(-0.87)
Industry CF Volatility	-0.02***	-0.02***	0.01***	0.01***
	(-6.24)	(-5.87)	(6.60)	(6.15)
Log (Age)	0.05*	0.05	-0.02**	-0.02
	(1.86)	(1.54)	(-2.01)	(-1.63)
Number of observations	3,227	2,988	3,227	2,988
Pseudo R^2/ Adjusted R^2	37.9%	37.7%	69.6%	70.4%
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes