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Asset Specificity, Industry-Driven Recovery Risk, and Loan Pricing

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Abstract

This paper examines the relationship between a firm's exposure to industry downturns that we call industry risk and bank loan pricing. We measure industry risk based on the relationship between a firm's stock returns and industry returns conditional on an industry downturn. We find industry risk is significantly related to the recovery rates in bankruptcy and the likelihood of the firm experiencing financial distress when its peers are also in distress. More importantly, we find that the spreads on unsecured bank loans are positively related to industry risk measures. These relationships are stronger for firms with more industry-specific assets.

I. Introduction

A potentially important factor affecting the liquidity of a firm's assets is the financial condition of the firm's industry peers when the firm (or its creditors) is looking to sell assets. If assets are specialized and thus cannot be readily redeployed to industry outsiders without considerable loss in value, then the asset's highest-valued user is likely to be another firm within the same industry.[1] As a result, asset illiquidity is likely to vary with the liquidity and performance of the selling firm's industry peers, because when a distressed firm is trying to sell assets, industry peers may also be facing liquidity problems of their own and may be unable to bid aggressively for the selling firm's assets, resulting in fire sale discounts.

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[1] See Shleifer and Vishny (1992) and Williamson (1988). Also see Shleifer and Vishny (2011) for a recent review of the literature on fire sale discounts.

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Shleifer and Vishny (1992) argue that the potential for fire sale discounts may affect ex ante capital structure and liquidity choices. Two recent papers empirically examine these issues. Specifically, Campello and Giambona (2013) examine the relationship between leverage and asset redeployability. They find that redeployability of tangible assets is an important driver of leverage for financially constrained firms. They also find that asset redeployability affects corporate borrowing more during tight credit market conditions. Related work by Acharya, Almeida, and Campello (2013) examines the relationship between a firm's aggregate risk exposure (measured by the firm's asset beta) and the firm's liquidity choice. They argue that a firm's aggregate risk exposure affects the banking sector's cost of providing liquidity insurance through lines of credit. The basic idea 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, they 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 loans.

We add to this literature by examining the relationship of a firm's exposure to industry downturns, which we will refer to as *industry risk*, and the pricing and structure of bank loans and reliance on bank lines of credit as a source of liquidity. The basic idea is that 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 component of distress costs, then firms with greater industry risk exposure will face higher credit risk spreads (and perhaps more onerous contract terms, such as lower advance rates or higher collateral requirements) and therefore rely more heavily on cash as a source of liquidity. Since liquidity risk may affect the costs of raising cash (and the willingness of banks to lend) in adverse markets, firms with significant industry risk exposure may hold more precautionary cash balance and rely less on bank lines of credit as a source of liquidity.

We begin our analysis 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. 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.

We next examine the relationship between various industry risk measures and 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.

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One challenge in analyzing the importance of industry risk is to distinguish between industry effects and a firm's aggregate risk exposure. Both industry and aggregate risks 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 et al. (2013) argue that a firm's aggregate risk exposure (measured by the firm's asset beta) affects the banking sector's cost of providing liquidity through lines of credit. Consistent with this argument, Acharya et al. (2013) 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 using several measures. Our first industry risk measure is a firm's industry beta. We calculate industry betas by estimating a 2-factor model relating a firm's stock returns on market returns and industry returns and adjusting these estimates for leverage. While providing potentially useful information concerning how a firm's value fluctuates with that of 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. 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 tail 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). In particular, our first tail risk measure is based on works by Acharya, Pedersen, Philippon, and Richardson (2010) on systemic 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. 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 the marginal distress estimate (MDE). Our second tail risk measure is the correlation between firm and industry returns conditional on negative industry returns.

Overall, we find a negative and significant relationship between recovery rates and our industry tail risk measures. We find no significant relationship between recovery rates and aggregate risk measures. We also find that, controlling for aggregate risk, industry risk is positively related to the likelihood that a firm will become distressed during times of industry-wide distress. The recovery rate findings and the distress analysis indicate that our tail risk measures are better proxies of industry recovery risk than industry beta.

We find that all industry risk measures are significantly and positively related to the all-in-drawn spreads charged on bank loans. Consistent with industry risk reflecting higher expected LGD, we find greater effect of industry risk on loan rates for firms in industries with greater asset specificity and during tight credit market conditions. We also find that the ratio of a firm's cash to lines of credit is positively related to our industry risk measures.

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Our study contributes to the literature in several ways. First, we show that ex ante measures of industry risk 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, we provide evidence that the potential for fire sale discounts is reflected in loan pricing. 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 and for firms with a shorter distance to default. These findings are consistent with empirical work concerning the influence of asset redeployability capital structure decisions (e.g., Benmelech and Bergman (2009), Rauh and Sufi (2012), and Campello and Giambona (2013)). We extend the results of these papers by showing how asset specificity affects the cost (as opposed to the quantity) of borrowing. Third, we extend recent empirical works by Acharya et al. (2013) on liquidity management to show that industry risk in addition to aggregate risk affects loan pricing and the reliance on bank lines of credit as a source of liquidity. This last finding provides additional support for the Sufi (2009) argument that cash and lines of credit are imperfect substitutes for corporate liquidity.

The remainder of the paper is organized as follows: Section II discusses the data. Section III presents summary statistics. In Section IV, 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 V, we examine the relationship between loan pricing, loan contract terms, and the various risk measures. In Section VI, we present the results of our analysis of the relationship between cash reserves, lines of credit usage, and the various risk measures. Section VII provides a summary of our findings and concludes.

II. Sample

We collected data on recovery rates, industry risk, loan pricing, and line of credit usage from several sources. The sample we use in our various analyses depends on the availability of data.[2]

A. 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 Jan. 1998–Feb. 2010 time period using BankruptcyData.com, which 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 1998–2010 time period. We hand-match this list to Compustat by firm name and require that the bankrupt firm file

[2]Please see Appendix B for a more detailed description of data formation for each sample we use.

at least one annual financial statement with the Securities and Exchange Commission (SEC) during the two fiscal years preceding the bankruptcy filing. Overall, 781 firms satisfy this condition.

Next, we search BankruptcyData.com for the reorganization plans of these firms. We found reorganization plans for 309 of the public firms meeting our selection criteria.[3] 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.

B. Compustat Sample

To examine whether our industry risk measures predict firm/industry distress, we construct a sample of firm-year observations from Compustat during the period 1999–2009. We exclude financial firms and utilities (Standard Industrial Classification (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 Center for Research in Security Prices (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.

C. DealScan Sample

For our loan pricing analysis, we use data from DealScan. In particular, we obtain from DealScan a list of U.S. dollar-denominated lines of credit taken out by all industrial U.S. firms during the 1987–2009 time period.[4] From that list, we select loans to firms with nonmissing financial information in Compustat at the end of the fiscal year preceding the loan date. For these loans, we obtain information on the amount, pricing, and maturity of the credit facility. We also obtain information from DealScan on the number of financial covenants associated with the loan facilities.[5] Our DealScan sample consists of 26,378 loans taken out by 6,232 unique firms.

[3]Reorganization plans (that include debt recovery rates) are available from BankruptcyData.com for less than 50% of the bankruptcies. Reorganization plans are missing for i) firms that were acquired or liquidated while in bankruptcy, ii) firms whose bankruptcies are still in progress, and iii) 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.

[4]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.

[5]As Chava and Roberts (2008) and Demiroglu and James (2010) discuss, DealScan data on loan covenants are often missing. Following previous studies, we exclude from our analysis of covenant structure observations with missing data and specifically do not assume that when covenant information is missing, a specific covenant was not imposed.

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D. Lines of Credit Sample

To examine the relationship between cash holdings, line of credit usage, and industry risk, we hand-collect information on line of credit use for a random sample of firms.[6] We start by randomly selecting 500 U.S. industrial firms[7] from Compustat with nonmissing information on cash flows and 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, Analysis, 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, size, and utilization of their lines of credit. This procedure yields a sample of 348 firms that we follow from 1999 to 2009.

E. Industry Distress Exposure Measures

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, Bharath, and Srinivasan (2007), Leary and Roberts (2014)). We also replicate our analysis using 2-digit SIC code classifications and Fama-French (48) industry classifications and find qualitatively similar results.[8]

We examine three industry distress exposure measures (IDEMs). Our first IDEM is a firm's industry asset (unlevered) beta. It is straightforward to calculate equity betas using stock price data, but since there is a mechanical relationship between beta and leverage, we use de-levered industry betas. We estimate industry betas using stock return data for our sample obtained from the CRSP monthly stock price database. Next, we calculate yearly industry betas using the following 2-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 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 five firms. We estimate the model above using the

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

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

[8] A recent study by Hoberg and Phillips (2013) 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.

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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. (2013)). 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 Griliches and Hausman (1986) and Acharya et al. (2013) and instrument the endogenous variable (asset betas) using a linear combination of the prior 2-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 2-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 that of its industry peers both in industry upturns and downturns. However, Longin and Solnik (2001) find that downside correlations are much higher than upside correlations.[9] Thus, industry beta may underestimate exposure to industry distress in the tail. In order to address the problems related to betas, we use two alternative measures of "tail risk" industry distress exposure.

Our first measure of tail risk is the firm's average stock return on worse industry return months. This measure is based on work by Acharya et al. (2010) on systemic risk in the banking industry. Specifically, they propose measuring a bank's systemic risk exposure (i.e., a bank's exposure to a collapse of the financial sector) by the bank stock returns on the worst 5% of market outcomes. The idea is that returns on moderately bad days are informative of what would happen during extreme events. We adopt this method in our empirical analysis, and define MDE as minus one times the firm's return on the worst industry return months. Specifically, 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 the average return of those months for each firm-fiscal year observation.[10]

The second measure is the correlation between the firm's return and its industry return when industry returns are less than 0. We calculate conditional correlations using up to 120 monthly returns for each firm-fiscal year observation.[11]

[9] Ang and Chen (2002) show that conditional correlations on the downside are approximately 12% higher than correlations implied by a normal distribution.

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

[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.

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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.

III. Summary Statistics

In Table 1 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 the 51.1% reported by Acharya et al. (2007). Their sample ends in 1999 and includes many high-yield debt restructurings during the early 1990s. In addition, work by Bharath, Panchapegesan, and Werner (2010) 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.[12]

We find that the recovery rate is 53.1% for unsecured claims and 97.3% for secured claims. These results are similar to the findings of Baird, Bris, and Zhu (2007) concerning recovery rates for secured and unsecured creditors. Note that relatively few (6.3%) 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 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.

As shown in Panel B of Table 1, the median price on credit lines is 150 basis points (bps) (over the London Interbank Offered Rate (LIBOR)) and average maturity of loans in the DealScan just over 3 years (37.9 months). On average, loans in the DealScan sample have 2.7 financial covenants. In addition, 72.1% of these credit lines are secured. Later in the paper we examine the relationship between industry risk and the covenant and collateral of the loans in our sample. The median loan in our sample is 16% of the firm's assets. This result is similar to the median line of credit size reported by Sufi (2009) and Lins, Servaes, and Tufano (2010).

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

[12]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 that spend less than a year in Chapter 11, whereas the average recovery rate on debt claims drops to 70% for firms that spend more than a year in Chapter 11.

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TABLE 1
Summary Statistics

Table 1 presents summary statistics for the 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 tabulates summaries 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 Loan Pricing Corporation's (LPC) 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 presents summaries for the lines of credit sample (panel data set of 348 public firms). Information on the debt structure of public firms is hand-collected from 10-Ks, and firm financials are obtained from Compustat. In Panel D, we present correlations among distress exposure measures in the Compustat sample. Variable definitions appear in Appendix A.

Variables	*N*	Mean	1st Quartile	Median	3rd Quartile	Std. Dev.
Panel A. Recovery Sample						
Recovery rate (%)	1,958	74.10	39.10	100.00	100.00	39.87
Dummy: Unsecured claim	2,371	21.00%	—	—	—	—
Dummy: Secured claim	2,371	23.50%	—	—	—	—
Dummy: Subordinated claim	2,371	7.30%	—	—	—	—
Recovery rate on unsecured claims (%)	383	53.11	10.00	47.50	100.00	42.50
Recovery rate on secured claims (%)	465	97.30	100.00	100.00	100.00	13.74
Recovery rate on subordinated claims (%)	134	20.19	0.00	0.00	33.65	34.49
Claim amount (in $million)	1,482	369.50	1.10	25.95	214.10	1,517.75
Assets − Cash (in $million)	300	2,366.87	258.70	653.28	1,925.16	5,202.49
Cash/Assets	300	0.07	0.01	0.03	0.09	0.09
Market beta	176	0.17	0.03	0.10	0.23	0.30
Industry beta	176	0.18	0.07	0.14	0.26	0.21
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						
All-in-drawn spreads (bps)	23,717	179.49	75.00	150.00	255.00	129.26
Dummy: Secured loan	16,936	72.10%	—	—	—	—
Assets − Cash (in $million)	26,346	2,842.58	101.29	458.66	2,083.44	5,909.00
Cash/Assets	26,345	0.08	0.01	0.04	0.10	0.11
Deal amount/Assets	26,367	0.24	0.07	0.16	0.32	0.24
Deal maturity	24,349	37.90	13.00	36.00	60.00	22.30
Market beta	17,599	0.39	0.12	0.32	0.62	0.45
Industry beta	17,599	0.44	0.18	0.42	0.67	0.39
Conditional correlation	19,258	0.40	0.24	0.39	0.54	0.21
Marginal distress estimate (MDE)	18,546	10.70%	5.40%	9.90%	15.50%	9.90%
Number of financial covenants	13,253	2.67	2.00	3.00	3.00	1.16
Covenant intensity	26,378	1.54	0.00	1.00	2.00	1.75
Panel C. Line of Credit Sample						
Dummy: Lines of credit	3,828	67.20%	—	—	—	—
Total line/(Total line + Cash)	3,713	0.44	0.00	0.41	0.84	0.39
Unused line/(Unused line + Cash)	3,712	0.38	0.00	0.31	0.75	0.37
Cash/Assets	3,713	0.24	0.04	0.13	0.37	0.26
Assets − Cash (in $million)	3,714	2,219.12	39.73	184.86	947.34	5,713.65
Market beta	3,055	0.57	0.19	0.47	0.90	0.67
Industry beta	3,055	0.48	0.17	0.43	0.74	0.48
Conditional correlation	3,127	0.31	0.17	0.29	0.44	0.19
Marginal distress estimate (MDE)	3,238	12.20%	5.10%	11.00%	18.40%	13.10%

	Industry Beta	Conditional Correlation	MDE	Market Beta	Market Conditional Correlation	Market MDE	Stock Return Volatility	Distance to Default
Panel D. Correlations								
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 conditional correlation	0.04	0.48	0.39	0.16	1.00	—	—	—
Market marginal distress estimate	0.14	0.28	0.61	0.23	0.54	1.00	—	—
Stock return volatility	0.18	−0.01	0.32	0.14	0.05	0.46	1.00	—
Distance to default	0.09	−0.01	−0.09	0.00	−0.07	−0.14	−0.21	1.00

assets by book value of noncash assets. We provide a detailed description of each of the variables in Appendix A.[13]

As shown in Panel C of Table 1, 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.

In Panel D of Table 1, 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 measures 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. 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 MDE and market MDE is much higher (0.61) 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.

Finally, we investigate the relationship between our industry risk measures and default risk. For each firm in the sample, we calculate Merton's "distance to default" measure. We compute the distance to default using the methodology described in Bharath and Shumway (2008). Higher values of the distance to default imply the firm is less likely to default. Intuitively, the distance to default provides a measure of the number of standard deviations in asset returns the firm is from default. As shown in Panel D of Table 1, the correlations between our industry risk measures and the distance to default are generally quite low.

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

We hypothesize that if industry risk is related to the quality of collateral, then we would expect industry risk to be negatively related to recovery rates. We also investigate the extent to which industry risk measures are related and the likelihood of distress controlling for aggregate risk as well as firm and industry characteristics. We employ multivariate tests to address these questions.

A. Industry Risk and Recovery Rates

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

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

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may have greater bargaining power in bankruptcy. In addition, we control for growth in gross domestic product (GDP) because recovery rates are lower during recessions (see Schuermann (2004), Chen (2010)).

Our recovery rate analysis is presented in Table 2. As shown in regressions (1) through (3), neither industry nor market beta is significantly related to recovery values. Indeed, both industry and market betas are *positively* related to recovery rates. We also test whether industry betas and market betas are jointly significant using an F-test. We cannot reject the hypothesis that the two betas are equal to 0 (the F-statistic is 0.64). To the extent that these risk measures are related to loan pricing and liquidity choice, the evidence in Table 2 suggests it is not through a relationship with LGD. In contrast, as shown in columns (4) and (5), our industry tail risk measures (conditional correlations and MDE) are negative and

TABLE 2

Recovery Rates and Industry Distress Exposure Measures (IDEMs)

Table 2 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: Recovery Rate					
	Estimation Method: Ordinary Least Squares (OLS)					
Variables	(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*	—	—
	—	—	—	(−1.80)	—	—
MDE	—	—	—	—	−0.27**	—
	—	—	—	—	(−2.02)	—
Market MDE	—	—	—	—	—	−0.21
	—	—	—	—	—	(−1.23)
Change in GDP	0.06*	0.06*	0.06**	0.02	0.01	0.03
	(1.92)	(1.90)	(2.01)	(0.52)	(0.24)	(1.04)
ln(Assets)	0.03	0.03*	0.03*	0.02	0.03*	0.02
	(1.60)	(1.70)	(1.69)	(1.34)	(1.71)	(1.34)
ln(Claim)	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***	−0.04***
	(−8.53)	(−8.47)	(−8.15)	(−9.01)	(−7.75)	(−7.94)
EBITDA/Assets	0.23	0.20	0.25	0.19	0.06	0.15
	(1.32)	(1.14)	(1.40)	(1.14)	(0.32)	(0.87)
Tangible/Assets	0.10	0.09	0.10	0.17*	0.08	0.11
	(1.04)	(0.99)	(1.05)	(1.84)	(1.03)	(1.29)
Long-term debt/Assets	−0.05	−0.05	−0.04	−0.14**	−0.06	−0.08
	(−0.74)	(−0.80)	(−0.63)	(−2.20)	(−1.01)	(−1.24)
Dummy: Unsecured claim	−0.22***	−0.22***	−0.22***	−0.23***	−0.22***	−0.23***
	(−6.06)	(−5.99)	(−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)	(5.35)
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)
No. of obs.	701	701	701	807	737	781
Adj. R^2	34.7%	34.7%	34.8%	36.2%	34.0%	34.4%
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

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significantly related to recovery rates. The relationships are economically significant as well. For example, a 1-standard-deviation increase in the conditional correlation is associated with a 3.5% decrease in recovery rates.

We also calculate 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 statistically significant relationship between recovery rates and market MDE. 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.

As shown in Table 2, 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 on unsecured claims. Consistent with this argument, in untabulated results, we find that the estimated coefficients on the conditional correlation and MDE are higher for the unsecured sample (0.25 and 0.40, respectively, and coefficients are significant at the 0.05 level or higher).

B. Industry Risk and Financial Distress

Following the literature on financial distress, we employ a stock-return-based distress measure (Gilson, John, and Lang (1990), Opler and Titman (1994), and Acharya et al. (2007)). In particular, an industry is defined as being in distress if the median stock returns of all the firms in the same 3-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. We investigate whether our industry risk measures are related to the likelihood that a firm will be in distress during an industry downturn using multivariate probit regressions. A potential concern with using stock returns as a measure of distress is that stock returns reflect 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 alternative distress measures based on sales growth (Acharya et al. (2007)) and coverage ratio (Asquith, Gertner, and Scharfstein (1994)). Since our empirical findings are not sensitive to these alternative distress measures we use, we report results using the stock-return-based distress measure.[14]

Table 3 provides estimates of probit models in which the dependent variable is an indicator variable equal to 1 if the firm is in distress and its industry is in

[14]The results using these alternative measures are available from the authors.

TABLE 3

Likelihood of Firm Distress during Industry Distress

Table 3 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 return of all the firms in the 3-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 1 if both the firm and industry are 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 0 at the 1%, 5%, and 10% levels, respectively. Variable definitions appear in Appendix A.

	Dependent Variable: Dummy (both firm and industry are in distress)						
	Estimation Method: Probit						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry beta	0.03***	—	0.05***	—	—	—	—
	(6.68)	—	(8.70)	—	—	—	—
Market beta	—	−0.00	0.02***	—	—	−0.00	—
	—	(−0.17)	(5.34)	—	—	(−1.05)	—
Conditional correlation	—	—	—	0.05***	—	—	—
	—	—	—	(6.13)	—	—	—
MDE	—	—	—	—	0.11***	0.18***	0.04***
	—	—	—	—	(8.54)	(9.53)	(2.82)
Market MDE	—	—	—	—	—	—	0.12***
	—	—	—	—	—	—	(6.79)
Change in GDP	−0.10***	−0.10***	−0.10***	−0.07***	−0.06***	−0.10***	−0.06***
	(−40.96)	(−40.95)	(−40.43)	(−14.95)	(−14.17)	(−40.19)	(−14.18)
ln(Assets)	0.01***	0.01***	0.01***	0.00***	0.00***	0.01***	0.01***
	(5.05)	(6.09)	(4.69)	(4.81)	(5.14)	(5.37)	(5.88)
EBITDA/Assets	−0.21***	−0.22***	−0.21***	−0.15***	−0.13***	−0.21***	−0.12***
	(−19.11)	(−19.51)	(−18.37)	(−12.88)	(−11.87)	(−18.00)	(−11.58)
Net worth/Assets	0.02**	0.03***	0.01	0.02***	0.01*	0.02**	0.01*
	(2.10)	(2.93)	(1.16)	(3.32)	(1.89)	(2.22)	(1.86)
Market-to-book ratio	0.01***	0.01***	0.01***	0.01***	0.00***	0.01***	0.00***
	(4.98)	(5.60)	(3.94)	(6.49)	(5.56)	(5.66)	(5.60)
No. of obs.	20,028	20,028	20,028	24,335	23,919	19,448	23,793
Pseudo R^2	38.2%	38.0%	38.3%	42.1%	41.7%	38.4%	41.9%
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

distress, and 0 otherwise. As shown, controlling for firm financial characteristics and GDP growth, the likelihood of firm distress conditional on industry distress is positively and significantly related to all industry risk. Each measure is economically significant as well. For example, holding everything else in the model constant, a 1-standard-deviation increase in the MDE (conditional correlation) is associated with a 13.1% (8.4%) increase in the likelihood of firm distress when its industry is in distress.

In regressions (6) and (7) of Table 3, 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. These findings are consistent 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 is consistent with the findings of

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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.[15]

V. Industry Risk and Bank Loan Pricing

A. 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 industries 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 associated with the line of credit and line usage. We model this spread as a function of lending standards and firm financial characteristics including size, cash flow, net worth, market-to-book ratio, 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 firms with a high market-to-book ratio, 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.[16]

Our loan pricing results are presented in Table 4. As shown in column (1), higher industry beta is associated with significantly higher all-in-drawn spreads. In terms of economic significance, a 1-standard-deviation increase in industry beta is associated with a 3.5-bp increase in loan price. As shown in column (2), we find no statistically significant relationship between loan rates and market beta. Indeed, the coefficient estimate is negative. In addition, as shown in column (3), the statistically significant relationship between industry beta and all-in-drawn spreads is robust to including market beta.

[15]In untabulated results, we repeat the 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 3.

[16]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.

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TABLE 4

Loan Pricing and IDEM

Table 4 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: All-in-Drawn Spreads						
	Estimation Method: OLS						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry beta	8.93***	—	9.74***	—	—	—	—
	(3.27)	—	(3.04)	—	—	—	—
Market beta	—	−3.38	1.22	—	—	−3.62	—
	—	(−1.44)	(0.44)	—	—	(−1.49)	—
Conditional correlation	—	—	—	9.44*	—	—	—
	—	—	—	(1.75)	—	—	—
MDE	—	—	—	—	76.44***	84.62***	47.85***
	—	—	—	—	(6.50)	(7.01)	(3.72)
Market MDE	—	—	—	—	—	—	69.55***
	—	—	—	—	—	—	(4.77)
ln(Deal maturity)	−4.27***	−4.34***	−4.28***	−5.13***	−5.08***	−4.69***	−5.00***
	(−2.83)	(−2.87)	(−2.84)	(−3.52)	(−3.48)	(−3.08)	(−3.43)
Deal amount/Assets	−70.22***	−70.26***	−70.17***	−69.46***	−67.85***	−67.45***	−66.76***
	(−13.20)	(−13.19)	(−13.19)	(−14.33)	(−13.47)	(−12.53)	(−13.22)
Lending standards	33.77***	33.71***	33.78***	30.76***	33.37***	33.73***	32.68***
	(3.69)	(3.67)	(3.69)	(3.44)	(3.75)	(3.65)	(3.68)
ln(Assets − Cash)	−37.56***	−37.06***	−37.60***	−37.23***	−37.11***	−37.02***	−36.59***
	(−46.25)	(−46.70)	(−46.27)	(−48.22)	(−48.09)	(−46.26)	(−46.64)
Net worth/ (Assets − Cash)	−107.49***	−104.85***	−107.80***	−101.67***	−105.23***	−104.72***	−104.65***
	(−22.08)	(−21.71)	(−21.72)	(−22.85)	(−22.96)	(−21.80)	(−22.94)
Market-to-book ratio	−9.74***	−9.15***	−9.83***	−9.41***	−9.91***	−9.08***	−9.79***
	(−6.83)	(−6.43)	(−6.90)	(−6.73)	(−6.79)	(−6.33)	(−6.69)
Tangible/ (Assets − Cash)	7.25	8.28	7.33	5.38	6.46	7.73	7.37
	(1.35)	(1.54)	(1.36)	(1.05)	(1.25)	(1.45)	(1.42)
Return on assets, cash adjusted	−233.16***	−235.24***	−232.72***	−223.28***	−227.35***	−232.46***	−225.53***
	(−19.03)	(−19.22)	(−18.96)	(−18.54)	(−17.88)	(−18.74)	(−17.67)
Industry cash flow volatility	2.27***	2.30***	2.27***	2.14***	2.18***	2.25***	2.07***
	(9.10)	(9.21)	(9.11)	(8.97)	(9.02)	(9.02)	(8.58)
No. of obs.	14,274	14,274	14,274	15,474	15,119	13,800	15,051
Adj. R^2	54.7%	54.6%	54.7%	53.9%	54.8%	55.2%	55.0%
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal purpose dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

As shown in regressions (4) and (5) of Table 4, firms with greater industry tail risk pay more for their credit lines. For example, a 1-standard-deviation increase in marginal distress exposure is associated with a 7.5-bp increase in loan price. The statistically significant relationship between the industry tail risk and loan pricing is robust to including market-based risk measures. For example, as shown in column (6), when we include the firm's market beta, we continue to find a positive and statistically significant relationship between all-in-drawn spreads and marginal distress exposure.

Finally, in column (7) we report the results of the credit spread regression, including both industry and market MDE as explanatory variables. As shown, both tail risk measures are significantly related to credit spreads. This result is perhaps not surprising, given (as shown in Table 1) that industry and market MDE are

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positively correlated. More important, finding that loan rates are increasing in both aggregate and industry tail risk is consistent with the Acharya et. al. (2013) argument that lenders price liquidity risk (arising from an increase in the demand for bank-provided liquidity during macro downturns) and in banks pricing industry risk, recovery risk, because LGD increases during industry downturns. Specifically these results, together with our findings concerning industry tail risk and recovery rates, are consistent with loan rates reflecting industry recovery risk.

Table 4 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.

B. 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. Moreover, since secured creditors can impose lower advance rates (i.e., require more collateral per dollar loaned) when collateral values are more uncertain, we would expect industry risk to have the greater effect on unsecured loan spreads. 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 Bergman (2009) also examine this issue and find that the redeployability of airlines' assets matters most for the junior tranches of airline collateralized debt obligations (CDOs).

To investigate the relationship between loan pricing, collateral, asset specificity, and industry risk, we obtain information from DealScan on whether or not a loan in our sample was secured. Using this information, we test whether the importance of industry risk varies with whether a loan is secured or unsecured. For brevity, we report the results using MDE as a measure of industry risk and note where these results are sensitive to the industry risk measures used.

As shown in Table 5, industry risk matters the most for unsecured loans. The effect of industry risk is almost five times as large for the unsecured as for secured lending. Indeed, we find no statistically significant relationship between loan rates and industry risk for secured loans in our sample. The economic impact of industry risk differs significantly between the secured and unsecured samples. For example, a 1-standard-deviation increase in MDE corresponds to a 5.7-bp increase in the all-in-drawn spread for unsecured loans. On the other hand, a 1-standard-deviation increase in the MDE implies only a 1.9-bp increase for secured loans. This is consistent with the recovery risk being more important for unsecured loans, because secured lenders can vary advance rates to account for differences in recovery rates. In addition, we find no statistically significant relationship between the spreads on unsecured loans and market risk.

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TABLE 5

Loan Pricing and IDEM: Subsample Analysis

Table 5 presents regressions that examine how the impact of industry distress exposure on the spreads of lines of credit varies with the existence of collateral. 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. 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: All-in-Drawn Spreads	
	Estimation Method: OLS	
	Sample: Collateral	
Variables	No	Yes
MDE	78.20***	15.67
	(5.19)	(1.33)
ln(Deal maturity)	−7.41***	−12.01***
	(−4.16)	(−4.42)
Deal amount/Assets	−14.68**	−80.76***
	(−2.22)	(−12.80)
Lending standards	33.99***	34.27**
	(2.69)	(2.43)
ln(Assets − Cash)	−18.24***	−28.59***
	(−17.14)	(−22.02)
Net worth/(Assets − Cash)	−19.26***	−98.46***
	(−2.98)	(−17.02)
Market-to-book ratio	−10.64***	−8.24***
	(−6.05)	(−4.41)
Tangible/(Assets − Cash)	−14.09***	14.08**
	(−2.58)	(2.01)
Return on assets, cash adjusted	−60.37***	−218.26***
	(−3.07)	(−15.36)
Industry cash flow volatility	0.58**	1.28***
	(2.37)	(3.77)
No. of obs.	3,603	6,614
Adj. R^2	40.4%	37.1%
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Deal purpose dummies	Yes	Yes

C. 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 rates. 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.[17] 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.[18]

[17]Consistent with this argument, Benmelech and Bergman (2011) find that credit spreads are lower on debt tranches that are secured with more redeployable collateral.

[18]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

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Table 6 provides estimates of the loan spread regression for subsamples of unsecured loans grouped by whether the firm operates in an industry with high (above the median) or low (below the median) asset specificity. As shown, we find a statistically significant relationship between loan spreads and MDE only for unsecured loans of firms operating in industries with high asset specificity. The impact of industry risk is economically significant as well. For example, a 1-standard-deviation increase in the MDE 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 0.7 bps for firms in the low asset-specificity

TABLE 6

Loan Pricing and IDEM: Subsample Analysis

Table 6 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 unsecured loans. In order to examine how the impact of industry distress exposure on spreads of line of credits varies with the asset specificity of the industry, we divide the unsecured loan 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: All-in-Drawn Spreads	
	Estimation Method: OLS	
	Sample: Unsecured Loans	
	Asset Specificity	
Variables	Low	High
MDE	8.90	121.41***
	(0.38)	(6.53)
ln(Deal maturity)	−8.68***	−6.84***
	(−2.85)	(−3.18)
Deal amount/Assets	−32.76***	−3.85
	(−2.90)	(−0.48)
Lending standards	81.82***	17.13
	(3.89)	(1.13)
ln(Assets − Cash)	−20.99***	−17.42***
	(−13.27)	(−13.03)
Net worth/(Assets − Cash)	−3.63	−36.00***
	(−0.39)	(−4.43)
Market-to-book ratio	−7.88***	−11.81***
	(−2.80)	(−5.35)
Tangible/(Assets − Cash)	14.66	−21.03***
	(1.30)	(−3.49)
Return on assets, cash adjusted	−78.28**	−69.86***
	(−2.54)	(−2.73)
Industry cash flow volatility	0.41	0.97***
	(0.94)	(3.46)
No. of obs.	1,078	2,525
Adj. R^2	42.4%	41.7%
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Deal purpose dummies	Yes	Yes

and equipment (FATE) for the rest. In unreported results, we use only gross value of machinery and equipment when it is available. Results are qualitatively and quantitatively similar if we use this alternative definition.

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sample.[19] This finding is consistent with the argument that our industry risk measures reflect expected LGD since 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 Bergman (2009), who find that industry distress affects recovery rates more for firms with difficult-to-redeploy assets.

D. 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. For example, Bernanke and Gertler (1995) argue that during tight credit market conditions, agency problems become more acute and thus lenders are likely to place greater emphasis on the quality of collateral when making loan decisions. Consistent with this argument, Campello and Giambona (2013) find that asset redeployability has a greater impact on the amount of borrowing during tight credit market conditions.

We examine whether the importance of industry risk for loan pricing varies during tight credit market conditions. 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.[20] Lown and Morgan (2006) find that the 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. We define economic downturns as recessions based on the National Bureau of Economic Research (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 7, industry distress exposure has a significantly greater impact on loan pricing during tight credit markets. For example, the coefficient on MDE almost doubles in tight market conditions. In terms of economic significance, a 1-standard-deviation increase in MDE implies a 9.8-bp 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 nonrecession 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 2008 financial crisis, we are able to examine the extent to which the financial crisis affected loan pricing. Specifically,

[19] We test the equality of the average industry distress exposure measure between high and low asset-specificity samples using an F-test. We reject the null hypothesis that asset specificity has no impact on average industry distress exposure measures at the 0.01 level.

[20] We measure lending standards in the quarter of the initiation date of credit lines.

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TABLE 7

Loan Pricing and IDEM: Subsample Analysis

Table 7 presents regressions that examine how the impact of industry distress exposure on the spreads of lines of credit varies with credit market conditions. In order to examine how the impact of industry of distress exposure on spreads of line of credits varies across credit market conditions, we divide the loan sample into two (high and low) using the sample median of lending standards. 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: All-in-Drawn Spreads	
	Estimation Method: OLS	
	Lending Standards	
Variables	Loose	Tight
MDE	53.87***	99.43***
	(3.38)	(6.93)
ln(Deal maturity)	−12.78***	0.35
	(−6.17)	(0.19)
Deal amount/Assets	−59.99***	−72.01***
	(−9.46)	(−10.22)
ln(Assets − Cash)	−39.19***	−34.73***
	(−41.52)	(−35.28)
Net worth/(Assets − Cash)	−98.34***	−111.09***
	(−17.11)	(−18.59)
Market-to-book ratio	−8.54***	−11.33***
	(−3.89)	(−6.36)
Tangible/(Assets − Cash)	9.14	4.44
	(1.33)	(0.73)
Return on assets, cash adjusted	−231.17***	−225.66***
	(−11.92)	(−14.15)
Industry cash flow volatility	2.20***	2.26***
	(7.38)	(7.55)
No. of obs.	6,767	8,352
Adj. R^2	54.6%	54.4%
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Deal purpose dummies	Yes	Yes

a potential concern is that given the importance of industry risk during tight credit market conditions and given the extraordinary credit conditions that prevailed during the crisis, the relationship between loan pricing and tail risk is driven primarily by observations from the 2008–2009 time period. In Panel A of Table 8, we examine univariate differences in loan pricing for loans originated in 2008 and after, and line usage based on whether the firm-year observation is 2008 or after. The average all-in-drawn spread increased to 238 bps from an average of 178 bps during the precrisis period. In terms of line of credit access, we find no significant difference in the proportion of firms with lines of credit pre- and post-financial crisis. We also find no significant difference in the proportion of bank-provided liquidity to total liquidity pre and post the financial crisis. One potential explanation for this finding is that our sample consists primarily of large, relatively profitable, publicly traded firms. Survey evidence from Campello, Giambona, Graham, and Harvey (2011) suggests that declines in access to credit lines during the financial crisis were limited to smaller private firms. They also find that only unprofitable firms and firms with limited access to credit markets drew more on their credit lines during the crisis. Consistent with this evidence, we find that for unprofitable

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TABLE 8

Loan Pricing and IDEM: Financial Crisis of 2008

Table 8 presents the analysis of how the impact of industry distress exposure on terms and usage of lines of credit varies during the financial crisis of 2008. Panel A presents how terms and usage of lines of credit vary in the periods before and during the financial crisis of 2008. In order to examine how the impact of industry distress exposure on terms and usage of lines of credit varies during the financial crisis of 2008, we divide DealScan sample into two based on whether loans are originated in 2008 or after, and we divide the line of credit sample into two based on whether the firm-year observations are in 2008 or after. Information on lines of credit and firm financials are obtained from LPC's DealScan database and Compustat, respectively. Information on debt structure of public firms is hand-collected from 10-Ks. The period of analysis is from 1987 to 2009 for the DealScan sample, and the period analysis is from 1999 to 2009 for the line of credit sample. We test the null that the means (medians) during and before the financial crisis are equal using *t*-tests (Wilcoxon rank-sum tests). We assume unequal variances for *t*-tests. We use ***, **, and * to denote that the null is rejected at the 1%, 5%, and 10% levels, respectively. Panel B presents the regression analysis. We divide the DealScan sample into two based on whether loans are originated in 2008 or after. 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

Panel A. Univariate Analysis

	Financial Crisis of 2008			Before Crisis		
DealScan Sample	*N*	Mean	Median	*N*	Mean	Median
All-in-drawn spreads	694	237.5***	225***	23,023	177.7	150
Deal amount/Assets	750	0.19***	0.13***	25,617	0.24	0.16
Deal maturity	741	37	36	23,608	37.98	36
Dummy: Secured loan	562	74.20%		16,374	72.00%	
Assets − Cash	750	4,302.5***	1,078.49***	25,596	2,799.8	445.8
Return on assets, cash adjusted	750	0.13	0.13	25,416	0.13	0.13
Line of credit sample						
Dummy: Lines of credit	696	65.90%	—	3,132	67.50%	—
Total line/(Total line + Cash)	620	0.43	0.43	3,093	0.44	0.41

Panel B. Multivariate Analysis

	Dependent Variable: All-in-Drawn Spreads	
	Estimation Method: OLS	
	Loans Originated	
Variables	2008–2009	1987–2007
MDE	178.93***	71.76***
	(3.18)	(6.08)
ln(Deal maturity)	6.22	−5.20***
	(0.76)	(−3.55)
Deal amount/Assets	−42.87*	−68.20***
	(−1.74)	(−13.44)
Lending standards	86.75***	23.53**
	(3.25)	(2.48)
ln(Assets − Cash)	−18.78***	−37.60***
	(−5.67)	(−47.87)
Net worth/(Assets − Cash)	−102.22***	−104.56***
	(−4.54)	(−22.56)
Market-to-book ratio	−23.68***	−9.35***
	(−3.31)	(−6.36)
Tangible/(Assets − Cash)	36.14*	5.23
	(1.65)	(1.00)
Return on assets, cash adjusted	−194.53***	−232.01***
	(−3.03)	(−18.15)
Industry cash flow volatility	1.50	2.18***
	(1.29)	(8.97)
No. of obs.	591	14,528
Adj. R^2	52.6%	54.7%
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Deal purpose dummies	Yes	Yes

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firms in our sample (i.e., firms with return on assets (ROA) < 0), the reliance on bank-provided liquidity increased during the 2008–2009 time period.[21]

In Panel B of Table 8, 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 or supply constraints may result in higher risk premia for observably similar firms during a financial crisis. Consistent with this argument, as shown in Panel B of Table 8, the size of the coefficients on our industry risk measures increase significantly for crisis years. For example, in the precrisis period, a 1-standard-deviation increase in our MDE increases loan spread by 7.1 bps, whereas a 1-standard-deviation increase in our MDE increases loan spread by 16.0 bps during the crisis. However, during the precrisis period we find a positive and significant relationship between all-in-drawn spreads and our industry risk measures.

E. Industry Risk and Terms of Loan Contract

Previous research on the terms of loan contracts finds collateral is more likely to be required by lenders on loans with higher default risk (see Berger and Udell (1995), Jimenez, Salas, and Saurina (2006), and Booth and Booth (2006)). If firms with greater industry risk are perceived by lenders as being riskier borrowers (because the LGD is higher), we would expect that loans to these borrowers are more likely to require collateral. Moreover, in the previous section we found that higher industry risk is associated with higher credit spreads only in the unsecured loan sample. This finding suggests that high industry risk borrowers may attempt to mitigate the higher cost of unsecured borrowing by borrowing on secured terms.

To investigate whether the likelihood of loan security increases with the industry distress exposure risk, we estimate probit regressions in which the dependent variable is an indicator variable that is equal to 1 if the line of credit is secured, and 0 otherwise. We model this variable as a function of industry tail risk as well as firm financials and credit market conditions.

We also examine the relationship between industry risk and the restrictiveness of financial covenants associated with bank loan contracts. Alternatively, lenders can use financial covenants. Financial covenants enable lenders to set operational or balance sheet benchmarks that borrowers must comply with. Covenants provide lenders with state contingent control rights in that, conditional on default, they enable lenders to modify the loan contract in ways that mitigate lenders' loss exposure (see, e.g., Chava and Roberts (2008)). Demiroglu and James (2010) show that the number of financial covenants and the tightness of financial covenants depend on contracting parties' expectation of future changes in the borrowers' financials as well as the borrowers' risk characteristics. These

[21] In untabulated results, we find that proportion of bank-provided liquidity to total liquidity is higher for unprofitable firms during the financial crisis. Specifically, we find a statistically significant (1%) difference in the proportion of bank-provided liquidity to total liquidity between the pre- and post-financial crisis (pre-financial crisis: 12% vs. post-financial crisis: 24%).

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arguments suggest that the restrictiveness of financial covenants may vary with the industry risk exposure of the borrowing firm.

We examine the relationship between the covenant structure associated with the loan and the industry risk using an index of covenant intensity developed by Bradley and Roberts (2004). Specifically, Bradley and Roberts construct a covenant intensity index that is defined as the sum of the following six covenant indicators: collateral, dividend restriction, having more than two financial covenants, asset sales, debt issuance, and equity issuance sweeps. Since the index takes on integer values between 0 and 6, we examine the relationship between covenant intensity and industry risk using a Poisson model.

Table 9 presents coefficient estimates for probit and Poisson models. As shown in regression (1), MDE has a statistically significant impact on the likelihood of loan security. For example, holding everything else constant, a 1-standard-deviation increase in MDE implies an 11.8% increase in the likelihood of loan security. As shown in regression (2), MDE also has a statistically significant impact on the covenant intensity index.

TABLE 9

Terms of Loan Contract and IDEM

Table 9 presents regressions that examine how industry distress exposure affects the collateral and covenant structure in lines of credit. Information on lines of credit and firm financials are obtained from LPC's DealScan database and Compustat, respectively. For the probit estimation, we report marginal effects of the coefficient estimates, as well as *t*-statistics based on robust standard errors. For the Poisson estimation, we report the coefficient estimates, as well as *t*-statistics based on robust standard errors. The period of analysis is from 1987 to 2009. We use ***, **, and * to denote that the coefficient estimate is different from 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable	
	Dummy: Loan is Secured	Covenant Intensity
	Estimation Method	
Variables	Probit	Poisson
MDE	0.38***	0.24**
	(4.79)	(2.33)
ln(Deal maturity)	0.06***	0.26***
	(5.79)	(16.33)
Deal amount/Assets	−0.11***	−0.03
	(−3.06)	(−0.69)
Lending standards	0.08	0.14
	(1.23)	(1.61)
ln(Assets − Cash)	−0.17***	−0.16***
	(−24.80)	(−22.17)
Net worth/(Assets − Cash)	−0.43***	−0.42***
	(−14.48)	(−12.59)
Market-to-book ratio	−0.05***	−0.12***
	(−4.74)	(−9.42)
Tangible/(Assets − Cash)	0.04	−0.13***
	(1.06)	(−2.81)
Return on assets, cash adjusted	−0.84***	0.08
	(−9.14)	(0.96)
Industry cash flow volatility	0.01***	0.01***
	(6.42)	(3.19)
No. of obs.	10,562	16,137
Adj. R^2	35.3%	20.2%
Year fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Deal purpose dummies	Yes	Yes

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F. Industry Risk and Distance to Default

If industry risk provides an ex ante measure of the severity of LGD, then we would expect the effect of industry risk on loan spreads to decrease as the distance to default increases (since the more remote the possibility of default, the less important LGD is in the loan pricing decision). While our previous analysis of loan spreads contains controls for credit risk, our focus here is on the interaction effect of industry risk and the likelihood of default on loan rates. To examine this issue, we calculated the Merton distance to default measure following the methodology outlined in Bharath and Shumway (2008).[22]

As shown in Table 10, we find a negative and statistically significant relationship between loan spreads and the interaction of industry risk with distance

TABLE 10

Loan Pricing, IDEM, and Distance to Default

Table 10 presents regressions that examine how industry distress exposure and its interaction with distance to default affect the spreads of lines of credit. We measure the likelihood of distress using a distance to default measure. Distance to default is calculated based on the methodology described in Bharath and Shumway (2008). 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variable: All-in-Drawn Spreads		
	Estimation Method: OLS		
Variables	(1)	(2)	(3)
MDE	129.69***	144.35***	95.91***
	(5.49)	(6.18)	(5.40)
MDE × Distance to default	−3.83***	−3.92***	−1.32**
	(−4.74)	(−4.86)	(−2.19)
Distance to default	−2.26***	−2.20***	−0.91***
	(−19.65)	(−19.01)	(−10.11)
ln(Deal maturity)	—	−5.29***	−3.71**
	—	(−2.94)	(−2.50)
Deal amount/Assets	—	72.89***	−67.23***
	—	(11.46)	(−13.68)
Lending standards	—	—	35.30***
	—	—	(3.90)
ln(Assets − Cash)	—	—	−34.79***
	—	—	(−43.60)
Net worth/(Assets − Cash)	—	—	−80.73***
	—	—	(−15.47)
Market-to-book ratio	—	—	−1.82
	—	—	(−1.13)
Tangible/(Assets − Cash)	—	—	4.45
	—	—	(0.98)
Return on assets, cash adjusted	—	—	−211.34***
	—	—	(−15.05)
Industry cash flow volatility	—	—	1.98***
	—	—	(8.90)
No. of obs.	14,768	14,222	14,107
Adj. R^2	25.6%	26.9%	56.2%
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Deal purpose dummies	No	No	Yes

[22]We also use Altman's Z as a measure of the likelihood of default and obtain results similar to those described in the text.

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to default. This result indicates that the importance of industry risk in loan pricing decreases as the likelihood of default declines. This finding is consistent with the interpretation of our industry risk measures as proxies for the loss severity.

VI. Industry Risk and Liquidity Choice

A. 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 lines (*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. Given our findings that covenant intensity is increasing with a firm's industry risk exposure, we expect lines of credit to be a poorer substitute for cash for firms with higher industry risk.

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 (2011) 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 using only MDE.

B. Cash versus 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 0 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 ratio, tangible assets, industry cash flow volatility, age, and year and industry

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fixed effects. Credit market conditions may also affect the access to and utilization of credit lines, especially for smaller firms (Demiroglu, James, and Kizilaslan (2012)).

Our findings are presented in Table 11. Since we are using panel data, we cluster standard errors by firm in all regressions to account for within-firm

TABLE 11

Liquidity Management and IDEM

Table 11 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variables			
	Total Line/(Total Line + Cash)		Cash/Assets	
	Estimation Method			
Variables	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 ratio	−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)
Return on assets, cash adjusted	0.07	0.05	−0.01	−0.01
	(1.49)	(1.22)	(−1.17)	(−0.87)
Industry cash flow volatility	−0.02***	−0.02***	0.01***	0.01***
	(−6.24)	(−5.87)	(6.60)	(6.15)
ln(Age)	0.05*	0.05	−0.02**	−0.02
	(1.86)	(1.54)	(−2.01)	(−1.63)
No. of obs.	3,227	2,988	3,227	2,988
Pseudo R^2/Adj. R^2	37.9%	37.7%	69.6%	70.4%
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

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. (2013) 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. (2013), 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.[23]

[23]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 the bank liquidity ratio.

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The findings reported in Table 11 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 be because our sample period is different from Sufi's and, more importantly, it includes data from the 2008 financial crisis.

In Table 12, we divide our sample into two based on whether the firm-year observation is before or after 2008. As shown in regressions (1) and (2), the industry distress exposure measure is negative and statistically significant in both the precrisis period and during the crisis. While the absolute value of the point estimate on MDE is higher during the crisis period, the coefficient estimates for the pre- and postcrisis periods are not significantly different from one another.

TABLE 12

Liquidity Management and IDEM: Financial Crisis of 2008

Table 12 reports regressions that show how the impact of industry distress exposure measures on the liquidity management of the firms varies during the financial crisis of 2008. We divide the line of credit sample into two based on whether firm-year observations are in 2008 or after. 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 0 at the 1%, 5%, and 10% levels (two-tailed), respectively. Variable definitions appear in Appendix A.

	Dependent Variables			
	Total Line/(Total Line + Cash)		Cash/Assets	
	Estimation Method			
	Tobit		OLS	
	Sample			
Variables	2008–2009	1999–2007	2008–2009	1999–2007
MDE	−0.40**	−0.37***	0.20***	0.16***
	(−2.10)	(−4.07)	(3.59)	(4.25)
Lending standards	0.05*	0.21***	0.01	−0.06***
	(1.73)	(6.25)	(0.69)	(−4.54)
ln(Assets − Cash)	−0.00	−0.00	−0.02***	−0.02***
	(−0.30)	(−0.42)	(−5.26)	(−4.79)
Net worth/(Assets − Cash)	−0.22***	−0.21***	0.10***	0.10***
	(−4.17)	(−3.94)	(8.43)	(10.56)
Market-to-book ratio	−0.05**	−0.05***	0.02***	0.02***
	(−2.48)	(−5.26)	(4.56)	(6.54)
Tangible/(Assets − Cash)	−6.77**	−7.95***	−1.13	−1.01
	(−2.08)	(−3.49)	(−0.94)	(−1.44)
Return on assets, cash adjusted	0.01	0.09*	0.00	−0.02*
	(0.11)	(1.96)	(0.24)	(−1.68)
Industry cash flow volatility	−0.02***	−0.02***	0.01***	0.01***
	(−5.72)	(−5.96)	(5.32)	(6.82)
ln(Age)	0.09**	0.03	−0.02	−0.02*
	(2.03)	(1.28)	(−1.23)	(−1.81)
No. of obs.	600	2,627	934	2,293
Pseudo R^2/Adj. R^2	36.7%	37.0%	68.2%	70.1%
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes

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C. 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, e.g., Almeida, Campello, and Weisbach (2004), Bates, Kahle, and Stulz (2009)). 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 11, 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 positive and statistically significant relationship between cash holdings and both the industry MDE and market beta.

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 11, 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 and aggregate risk measures.

VII. 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 our industry risk measures. Our results are robust to including aggregate risk measures and other controls. Our 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

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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 the 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 A. Variable Definitions

All-in-Drawn Spread: The spread paid by firms over LIBOR for each dollar drawn down from the loan.

Asset Specificity: The median ratio of machinery and equipment (net: PPENME, gross: FATE) to total assets, using 1-digit SIC code over the sample period.

Cash/Assets: CHE/AT

Change in GDP: Annual GDP percent change based on 2005 dollars, obtained from the Bureau of Economic Analysis Web page (www.bea.gov).

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 0.

Covenant Intensity Index: Sum of the following six covenant indicators: collateral, dividend restriction, having more than two financial covenants, asset sales, debt issuance, and equity issuance sweeps.

Deal Amount/Assets: Ratio of loan amount to total assets.

Deal Maturity: Maturity of a loan reported in DealScan.

Debt/Assets: (DLC + DLTT)/AT

Distance to Default: We calculate distance to default following the methodology described in Bharath and Shumway (2008). For each firm, they define distance to default as

$$\text{Distance to Default} = \frac{\ln\left[\frac{(E+F)}{F}\right] + \left(r_{i,t-1} - 0.5\sigma_V^2\right)T}{\sigma_V^2\sqrt{T}}, \tag{A-1}$$

where

$$\sigma_V^2 = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25\sigma_E). \tag{A-2}$$

Dummy: Lines of Credit: A dummy variable that is equal to 1 if a bank loan 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 10Ks, and 0 otherwise.

Dummy: Secured Claim: An indicator variable that is equal to 1 if a claim is reported as secured in BankruptcyData.com, and 0 otherwise.

Dummy: Secured Loan: An indicator variable that is equal to 1 if a line of credit is reported as secured in DealScan, and 0 otherwise.

Dummy: Subordinate Claim: An indicator variable that is equal to 1 if a claim is reported as subordinated in BankruptcyData.com, and 0 otherwise.

Dummy: Unsecured Claim: An indicator variable that is equal to 1 if a claim is reported as unsecured in BankruptcyData.com, and 0 otherwise.

E: Equal to market value of the firm's equity, F is the face value of the debt, and T refers to time to maturity. Here, $r_{i,t-1}$ is the firm's stock return over the previous year and σ_E is the stock return volatility.

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We calculate distance to default for each firm as of the fiscal year end date. Similar to Bharath and Shumway (2008), we choose time to maturity as 1 year. We calculate market value of equity for each firm-fiscal year observation by multiplying the number of shares outstanding and share price. The face value of debt for each firm is equal to the sum of debt in current liabilities (DLC) and one-half of the long-term debt (DLTT). We calculate the firm's yearly stock return using the prior 12 months for each firm-fiscal year observation. Similarly, we calculate the firm's stock return volatility using the prior 12 months for each firm-fiscal year observation.

EBITDA/Assets: OIBDP/AT

Industry Beta: The asset (unlevered) industry beta, calculated from the equity (levered) industry beta. Equity industry beta is obtained from a 2-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 3-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.

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 code of the firm.

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

ln(Age): The natural log of (current fiscal year (FYEAR) – first fiscal year of available accounting data (YEAR1))

ln(Assets): ln(AT)

ln(Assets – Cash): ln(AT – CHE)

ln(Claim): The natural logarithm of the amount of the claim.

ln(Deal Maturity): The natural logarithm of the loan maturity reported in DealScan.

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

Long-Term Debt/Assets: DLTT/AT

Marginal Distress Estimate (MDE): The 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 5th percentile.

Market Beta: The asset (unlevered) market beta, calculated from the equity (levered) market beta. Equity market beta is obtained from a 2-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 3-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): The average stock return of the firm given that market return (value-weighted return of CRSP universe (VWRETD)) is below its 5th percentile.

Market-to-Book Ratio: (AT − CEQ + PRCC_F × CSHO)/AT

Net Debt/Assets: (DLC + DLTT − CHE)/AT

Net Worth/(Assets – Cash): CEQ/(AT − CHE)

Return on Assets, Cash Adjusted: OIBDP/(AT − CHE)

Recovery Rate: The estimated recovery rate on the claim.

Recovery Rate on Secured Claims (%): The estimated recovery rate of secured claims.

Recovery Rate on Subordinate Claims (%): The estimated recovery rate of subordinate claims.

Recovery Rate on Unsecured Claims (%): The estimated recovery rate of unsecured claims.

Tangible/Assets: PPENT/AT

Tangible/(Assets – Cash): PPENT/(AT − CHE)

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Total Line/(Total Line + Cash): The total amount of lines of credit/total amount of lines of credit + cash (CHE).

Unused/(Unused Line + Cash): The unused amount of lines of credit/unused amount of lines of credit + cash (CHE).

Appendix B. Sample Formation

Bankruptcy Sample

- Number of bankruptcy filings between 1998 and 2010: 1,396.[24]
- Match with Compustat: 826 firms.
- File at least one annual financial statement with SEC during two fiscal periods before the bankruptcy filing: 781 firms.
- Reorganization plans are available on BankruptcyData.com: 309 firms.

Compustat Sample

- Number of firms[25] in Compustat between 1999 and 2009: 19,325 firms.
- Exclude firms with no stock price data available in CRSP: 12,510 firms.
- Exclude nonindustrial firms: 10,961 firms.
- Exclude firms with no data on total assets: 9,174 firms.

DealScan Sample

- Loans originated between 1987 and 2009 in DealScan:[26] 202,694 loans.
- Exclude loans originated outside of United States: 106,377 loans.
- Exclude loans taken out by nonindustrial firms: 86,667 loans.
- Keep "line of credit"[27] loans: 48,187 loans.
- Exclude loans for which financial information in Compustat is missing at the end of the fiscal year preceding the loan date: 26,378 loans.

Line of Credit Sample

- Number of firms[28] in Compustat between 1999 and 2009: 19,325 firms.
- Exclude nonindustrial firms: 17,517 firms.
- Exclude firms with no data on total assets: 15,056 firms.
- Exclude firms with missing information on cash flow, cash holdings, and without stock price information for fiscal years 2005, 2006, and 2007: 4,473 firms.
- Randomly select 500 firms out of 4,473.
- Exclude firms without detailed information on presence, size, and utilization of lines of credit: 348 firms.

[24]There are 1,306 unique firms based on company name.

[25]Count based on unique Global Company Keys (GVKEYs).

[26]We only include loans if their loan status is reported as "Completed" in DealScan.

[27]The loan is evaluated as line of credit if the loan type is "Revolver/Line $\geq$ 1 year," "364-day facility," or "Revolver/Line $<$ 1 year."

[28]Count based on unique GVKEYs.

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