Fire-Sale Channel of Industry Contagion: Evidence from the Pricing of Industry Recovery Rate

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Abstract

How does bankruptcy contagion propagate among industry peers? We study the fire-sale channel of industry contagion by examining whether the cost of a company's debt is affected by the observed recovery rates of its bankrupt industry peers. Our results show that lower industry recovery rates are associated with higher loan spreads but only when the contracts are originated during industry bankruptcy waves. Confirming the fire-sale channel of industry contagion, we find that the negative effect of industry recovery rate is significantly stronger under conditions where fire-sale discount is expected to be more salient. We also find that information asymmetry is an important determinant of the significance of the fire-sale effect, which manifests itself in both the pricing and non-pricing terms of newly negotiated bank loans.

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1. Introduction

Extant research finds that a bankruptcy contagion effect is prevalent among firms operating in the same industry. When a company files for bankruptcy, there are different kinds of valuation and financial implications on its industry peers (Lang and Stulz, 1992; Jorion and Zhang, 2007; Hertzel and Officer, 2012). There are different channels through which bankruptcy contagion propagates within the industry, three of which are extensively studied in the literature. First, industry contagion could be the result of a change in the competitive environment when one or more significant players in the marketplace are in distress. Second, as much as business linkages (e.g., in the form of customer-supplier relation or counterparty relation) exist among industry peers, the failure of one of the parties results in a ripple effect among its business partners. Finally, industry contagion could simply be an information effect. Subsequent to the bankruptcy announcement of a company, market participants update their beliefs on the operational and financial conditions of its peers with the expectation that they share the same challenges that have caused the downfall of the defaulted company.

The nature and consequences of industry contagion are commonly viewed through the lens of event studies. For example, Lang and Stulz (1992) examine how bankruptcy announcements may affect the value of industry peers. Hertzel and Officer (2012) study the effects of bankruptcy filings on the cost of debt of industry peers. The focus of these event studies is on the implications given the *occurrence* of a single or cluster of default events, while the potentially crucial information carried by the actual outcomes characterizing the default process are mostly ignored. For instance, the implication of a swift default resolution outcome of a peer that involves minimal write-down of its asset value could be very different from the implication of a default resolution that fundamentally alters the viability of the peer's business model and thus results in a significant destruction of its asset value. In the present study, we enrich the exposition of the industry contagion effect by examining the information conveyed by one of the crucial outcomes of the peer's bankruptcy process—the ultimate recovery value of its creditors. Specifically, we use the recovery value as an instrument to examine the *fire-sale* channel of industry contagion, which is relatively under-explored in the literature.[5]

The fire-sale notion of Shleifer and Vishny (1992) suggests that, in the event of financial distress, industry-specific assets that are not readily re-deployable in other industries are likely to be subject to a larger discount in their liquidation value when potential industry buyers (i.e., its peers) themselves are financially constrained and/or forbidden by government regulations (e.g., antitrust regulation) to acquire the assets. How much the creditors of a defaulted company can recover in the bankruptcy process (i.e., their recovery value) is therefore dictated by the financial condition of its industry peers (Acharya et al., 2007). Since the debtholder of a company is subject to both *default risk* (i.e., the risk of default of the debtor) and *recovery risk* (i.e., the risk of recovering less than the amount owed in a default event), the market price of a corporate debt instrument is dictated by not only the probability of default of the company but also by the expected recovery rate in a possible default event (Hull, 2012). Therefore, any fire-sale discount as reflected in the observed recovery values of defaulted companies within the industry should translate into an indirect (ex-ante) cost of debt for all industry peers. This results in a specific channel of industry contagion that manifests itself in the form of an externality on the cost of

[5] In the literature of bankruptcy contagion, most of the studies of the fire-sale channel are on the contagion effect among financial companies (e.g., Brunnermeier, 2009; Helwege and Zhang, 2016).

debt for non-bankrupt competitors. In particular, this externality is expected to be more salient when the industry faces a wave of bankruptcies. To verify the fire-sale channel, we adopt a novel approach by examining if and to what extent creditors' recovery values of default events are incorporated in the pricing of debts issued by industry peers.[6] To that end, we conduct an empirical study with an extensive dataset of newly negotiated or renegotiated loan contracts from 1987 to 2010, studying the informativeness of industry-wide recovery value in the loan spreads and non-price contractual terms.

This study makes several contributions to the existing literature. First, we confirm the role played by industry-wide recovery risk in defining the contagion effect on the costs of debt of industry peers. Consistent with the fire-sale channel of industry contagion, we find that realized industry-wide recovery rate is reflected in the loan spreads of contracts originated at the time when there is a cluster of bankruptcy filings by industry rivals. The effect is both statistically and economically significant. A one-standard deviation increase in the industry-wide recovery rate is associated with an average decrease in loan spreads of about 28 basis points in the middle of the industry bankruptcy wave.

Second, by repeating our analysis under situations where we expect the significance of the fire-sale channel effect to differ, we confirm it is indeed the fire-sale channel that governs the informativeness of industry recovery rate in loan spreads. Specifically, we find that the negative externality on the cost of debt is stronger: (a) for industries with a higher degree of asset specificity, with a lower asset growth rate, with more debt overhang, that are less liquid, that are more financially constrained, that are bounded by anti-trust law, or that are more concentrated; (b) for non-investment grade peer companies; (c) for loan contracts that are secured; and (d)

[6] We are not the first to consider creditors' recovery values in the examination of fire-sale discount. In their study of the effect of fire-sale discount on loan pricing, James and Kizilaslan (2014) find that their industry risk measures are associated with the observed creditors' recovery rates.

when the general market condition is considered to be less liquid. Our empirical results therefore suggest that the fire-sale channel seems to dominate in terms of its influence on peers' cost of debt, though we cannot dismiss the possibility of other effects in play at the same time.

Third, we confirm the role played by information asymmetry in governing the significance of the fire-sale effect. Consistent with our hypothesis, we find that the ex-ante effect of fire-sale discount on loan spreads is stronger during periods when the market is generally considered to be less informationally efficient and for peers that are more prone to information asymmetry. This finding therefore supports the information channel of bankruptcy contagion, which points to a stronger industry contagion effect under circumstances of higher information asymmetry. It also highlights the interaction between the fire-sale channel and the information channel in governing the extent of industry contagion on the cost of debt.

Finally, we demonstrate that the effect of industry contagion is not limited to loan spreads, but also extends to non-price contractual terms. Consistent with the notion that lenders are concerned about the implications of the fire-sale discount when formulating and negotiating loan contracts, we find that a lower industry-wide recovery rate is associated with a higher chance that the loan is being secured and with more covenant restrictions being in place. For example, a one-standard deviation drop in the industry-wide recovery rate is associated with a 19-percentage point increase in the chance of the loan being secured and an increase in our covenant intensity index of about 0.05.

One possible concern of our empirical design is that industry recovery rate may not be exogenous in explaining loan spread. There is always the chance that loan spread and industry recovery rate are jointly governed by unknown factors for which we have not controlled in our regression analysis. As a robustness test, we address this endogeneity problem by conducting a two-stage regression using bankruptcy venue and time spent in bankruptcy process as instrumental variables for recovery rate. Our main conclusion is still valid based on the two-stage regression results, thus confirming the significance of the fire-sale channel of industry contagion.

The findings from this study can enhance the pricing and risk management of the corporate debt market, which has experienced rapid growth in the last decade. Spurred by the low interest rate environment since the 2008 global financial crisis, US corporate bond and loan issuance topped $1 trillion in 2015, which is close to four times of that in 2005 (Platt, 2015).[7,8] As corporate debt becomes a critical source of external financing for corporations and an indispensable investment vehicle for investors in pursuit of yield, the importance of its pricing and risk management increases to ensure market efficiency and stability. Our findings benefit market participants in their understanding of how price is formulated for debt issued by companies vulnerable to fire-sale discount. For policymakers and market regulators, our findings support the argument that one way to promote financial stability is to institute provisions in the bankruptcy code that enhance the liquidity in the trading of distressed assets so as to inhibit the propagation of industry contagion via the fire-sale channel.

The rest of our paper is organized as follows. In Section 2, we review the relevant literature and develop our main hypotheses. In Section 3, we describe the data and methodology employed in our empirical analysis. The main empirical results are presented and discussed in Section 4. We then report the results of our robustness test (Section 5) and finally conclude with a few remarks (Section 6).

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[7] Recently, the proceeds from debt issuance have been commonly used to finance share repurchase programs and merger and acquisition activities.

[8] The growing appetite for corporate debt issuance is in fact a global phenomenon. Global corporate bond issuance reached $3.2 trillion in 2013, compared to only $0.9 trillion at the beginning of the last decade (Tendulkar and Hancock, 2014).

2. Related Literature and Hypotheses Development

Lang and Stulz (1992) first document intra-industry bankruptcy contagion effect. They find that the equity values of companies are affected by the bankruptcy announcements of their industry peers. On average, the bankruptcy announcement of a company leads to decreases in its peers' equity values. However, it tends to benefit those peers with lower leverage and in concentrated industries resulting in higher stock prices.[9] Using a different sample of bankruptcy companies, Ferris et al. (1997) confirm the findings of Lang and Stulz by showing that bankruptcy filings of both large and small companies tend to exert a negative effect on their peers' equity values. Akhigbe et al. (2005) find that stock prices of large and key (but not small) competitors are adversely affected by the bankruptcy of WorldCom, which they attribute to the scrutiny of rivals perceived to be facing similar problems. Industry contagion is not limited to stock valuation effect. For example, by examining the spread of industry peers' credit default swap (CDS), Jorion and Zhang (2007) find evidence of intra-industry credit contagion. In particular, they find that Chapter 11 reorganization in general leads to wider credit spreads (i.e., increase in credit risks) for industry peers, whereas Chapter 7 liquidation results in narrower credit spreads (i.e., decrease in credit risks).[10] Hertzel and Officer (2012) expand the investigation by examining the effect on industry peers' costs of debt. They find that loan spreads are significantly higher in the years surrounding industry-specific bankruptcy waves.

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[9] Industry contagion effect is not limited to bankruptcy events. Researchers have identified intra-industry effects when industry peers are subject to different kinds of adverse conditions. For example, Hadlock and Sonti (2012) show that the increase in a company's liabilities as a result of asbestos litigation exerts a negative impact on its close competitors. Gleason et al. (2008) find that accounting restatements that adversely affect equity value of the restating company also result in stock price declines among non-restating industry peers. Slovin et al. (1999) document different kinds of intra-industry effect among commercial banks when their peers reduce dividends.

[10] Jorion and Zhang attribute the negative influence of Chapter 11 bankruptcies on industry peers to the strengthening of the competitive position of the reorganized company as it enjoys different kinds of subsidy under the protection of Chapter 11. On the other hand, Chapter 7 forces the liquidation of the distressed company, thus benefiting its peers.

Although bankruptcy events generally exert a negative influence on its peers in terms of higher costs of debt, consistent with the results of Lang and Stulz, companies in concentrated industries tend to benefit from their peers' bankruptcies in the form of a lower cost of debt.[11]

There could be different channels through which the contagion effect takes shape within an industry. First, it may be the result of a fundamental change in the competition environment of the industry. For instance, bankruptcy protection from creditors may in fact strengthen the competitive position of the distressed company at the expense of its peers (Jorion and Zhang, 2007). The change in the competition environment may be the result of a change in product market behavior (e.g., product pricing, advertising, product entry/exit decisions, etc.). For example, the findings of Taillard (2008) and Hadlock and Sonti (2012) suggest that financial distress induced by asbestos liabilities could make a company more aggressive and efficient, thus hurting its peers. On the other hand, the change in competitive position may also result in a positive rather than negative impact on its peers (in the literature, this is sometimes referred to as a competitive effect rather than a contagion effect). For example, peers may benefit from growth opportunity as the bankrupted company exits from a certain product market. Moreover, the burden of both the direct and indirect bankruptcy costs may weaken the competitiveness of the distressed company.

Second, industry contagion may be the result of fundamental business linkages among companies within the same industry. For example, collusion among peers may break down when one of the colluding parties files for bankruptcy, thus jeopardizing the product market equilibrium and hurting other colluding parties. Another common form of intra-industry business

[11] The impact of a bankruptcy event is not limited to peers of the defaulted company in the same industry, but also extends to its other stakeholders and business partners. For example, the contagion effect can propagate itself through the supply chain. Hertzel et al. (2008) document a significantly negative stock price effect on suppliers of bankrupted companies.

relation particularly susceptible to bankruptcy contagion is the extension of credits (e.g., trade credits) among peers. Jorion and Zhang (2009) document the contagion effect on the creditors of the defaulted companies as a result of this kind of counterparty exposure (e.g., Battiston et al., 2007; Giesecke and Weber, 2004, for the theoretical framework underlying this kind of credit contagion). The financial industry is particularly susceptible to credit contagion as financial institutions are constantly subject to counterparty credit risk as a result of their contractual relations with their peers (e.g., via inter-bank lending and derivative contracts). The collapse of *Lehman Brothers* and the fall of *American International Group* (AIG) offer researchers an opportunity to examine this specific kind of industry contagion among financial institutions (e.g., Chakrabarty and Zhang, 2012; Helwege and Zhang, 2016).

Third, industry contagion could simply be an information effect, where the bankruptcy announcement of a company reveals negative information about the operations and prospect of their peers in the same industry (Lang and Stulz, 1992; Akhigbe et al., 2005; Chakrabarty and Zhang, 2012; Helwege and Zhang, 2016). It therefore leads to a downward revision of the market's expectation of the profitability of peer companies. Thus, under the information channel, the contagion effect could extend to peers that have no direct competition or business relations with the bankrupted company. It is however difficult to empirically disentangle the information effect from other fundamental channels of industry contagion (e.g., the counterparty channel). The empirical results are mixed. Based on a large sample of financial company bankruptcies, Helwege and Zhang (2016) document a significant information effect for peers of close geographic proximity and in the same line of business. However, in focusing on the peer effect as a result of the bankruptcy of *Lehman Brothers*, Chakrabarty and Zhang (2012) find that a substantial amount of the information-based contagion could in fact be attributed to counterparty relations.

In the present study, we focus on the industry contagion effect as a result of the fire-sale discount. Shleifer and Vishny (1992) demonstrate how, when a distressed company needs to dispose its assets (e.g., to satisfy financial obligations under a debt contract) under an industry- or economy-wide shock, the lack of potential buyers among its industry peers may lead to liquidation values that are far below values in best use (i.e., at *fire-sale* prices). The argument is based on the idea that industry-specific assets that are not readily redeployable outside of the industry have limited utility values to industry outsiders. The effect is expected to be particularly salient if the peers themselves are financially constrained or there exists government regulations (e.g., antitrust regulation) that prohibit or hinder asset sales. Shleifer and Vishny postulate that the prospect of such an ex-post fire-sale discount should translate into an ex-ante private cost of leverage as companies attempt to mitigate the possibility of forced asset sales. Empirical research lends support to the liquidation valuation model of Shleifer and Vishny. For example, Acharya et al. (2007) find that creditors' recovery rates are significantly lower when the industry is in distress and when non-defaulted companies in the industry are illiquid. More importantly, they find that such negative effects are particularly salient in industries of which assets are specific and thus not easily redeployed by other industries.[12] Fire sale may lead to bankruptcy contagion as the drop in the liquidation prices of a bankrupted company's assets results in a decline in value of similar assets held by its peers, thus bringing the peers financial distress. A number of studies examine the role played by this fire-sale channel of bankruptcy contagion in the recent global financial crisis (e.g., Allen et al., 2009; Brunnermeier, 2009; Shleifer and Vishny, 2011; Helwege and Zhang, 2016).

[12] Shleifer and Vishny (2011) conduct a systematic review of the literature on fire sales.

We examine the fire-sale channel of the contagion effect manifested as an ex-ante indirect cost of debt for industry peers. Fire-sale discount should not only result in a lower asset liquidation value for the defaulted company; as creditors of its (non-defaulting) industry peers become aware of the prospect of a fire-sale discount of assets underlying their debt contracts, they will lower their expectation of the asset value that can be recovered in a possible future default event. To the extent that debt pricing involves an assessment of the likelihood of default as well as the expected recovery rate upon a default event, we expect the fire-sale effect to result in a higher cost of debt financing for industry peers when they negotiate debt contracts with corporate lenders. We dissect this negative externality by using the realized recovery values of defaulted debt contracts as our instrument to gauge the degree of fire-sale discount as reflected in the bankruptcy resolution outcomes of defaulted companies within a certain industry.[13] To the extent that the fire-sale effect is transmitted via the expected recovery values, we anticipate the currently observed industry-wide recovery rate to be reflected in the ex-ante cost of debt. In addition, we expect a clustering of default events within the same industry to heighten the concerns for the fire-sale discount, thus leading to a stronger influence of industry-wide recovery rate on peers' costs of debt. We therefore formulate our first testable hypothesis as follows:

H1: The lower the industry-wide recovery rate, the higher are the all-in spreads of loan contracts originated during industry-specific *bankruptcy wave*.

Along the same argument, in a recent empirical study, James and Kizilaslan (2014) also examine the effect of fire-sale discount on loan pricing. They find that corporate loan spreads

[13] The realized recovery value of a defaulted debt instrument could be dictated by a number of factors other than the liquidation value of the assets of the defaulting company. In Chapter 11, the ultimate recovery value of a creditor is the outcome of a negotiation process involving different stakeholders that could be influenced by all kinds of firm-level characteristics. For instance, given the more involving negotiation process, we would expect in general a lower recovery value if the debt structure is more complicated with creditors of different seniority and rights than if there is only a single class of creditors. In this study, we use the industry average realized recovery rate as our (inverse) proxy for fire-sale discount at the industry level. We expect any firm-specific effects captured in the realized recovery rates would have subsided when we take the average value across the whole industry.

are positively related to their industry (tail) risk measures constructed based on the relationship between the borrower's stock returns and its industry returns conditional on an industry downturn. They further show that their risk measures can predict observed recovery rates and thus conclude that at least part of a company's cost of debt may be attributed to the susceptibility of its assets to fire-sale discount during adverse industry conditions. Unlike James and Kizilaslan, we address the research question by using actual industry-wide recovery rate observed when a debt contract is negotiated. By using this direct measure of liquidation value, we can more readily gauge the economic significance of the effect of fire-sale discount.[14]

With the objective of distinguishing the fire-sale channel of industry contagion from that resulting from a fundamental change in the competitive environment within the industry (e.g., change in market shares among industry rivals), we formulate a second set of hypotheses. We examine the conditions in which we expect the implications of the various channels to be different. Specifically, fire-sale discount is expected to be more salient for industries with a higher degree of asset specificity, with a lower asset growth rate, with more debt overhand, that are less liquid, that are more financially constrained, that are bounded by anti-trust law, and/or that are more concentrated (Shleifer and Vishny, 1992; Acharya et al., 2007). Moreover, given the higher probability of default, any variation of the liquidation value as a result of fire-sale discount will exert a stronger influence on the costs of debts of non-investment grade companies than those that are investment-grade. Furthermore, as the expected payoffs of secured debts are more directly related to the liquidation values of specific assets of the borrower than those that are otherwise unsecured, we expect the former rather than the latter to be more susceptible to

[14] Using US airlines data, Benmelech and Bergman (2011) investigate a collateral channel of industry contagion through which the bankruptcy of a company reduces the collateral values of its industry peers. They find that industry bankruptcies have a sizeable impact on the cost of debt financing of their peers. In the present study, rather than focusing on a particular industry, we examine the industry contagion effect on the cost of debt across a variety of industries altogether representing the US corporate universe.

fire-sale discount. Finally, we anticipate the imbalance in the supply and demand of distressed assets as a result of bankruptcy-induced forced sale to become more acute during time periods when the general market is illiquid. If the fire-sale channel indeed dominates, the negative externalities of bankruptcy on peers' costs of debt should be stronger under the above mentioned conditions. We therefore hypothesize:

H2: The negative effect of industry-wide recovery rate on loan spread is stronger and more significant: (a) for industries with a higher degree of asset specificity, with a lower asset growth rate, with more debt overhang, that are less liquid, that are more financially constrained, that are bounded by anti-trust law, or that are more concentrated; (b) for non-investment grade peer companies; (c) for loan contracts that are secured; and (d) when the general market condition is considered to be less liquid.

To examine the interaction of the fire-sale channel and the information channel of industry contagion, we devise our third hypothesis based on various information asymmetry measures. According to the information channel, the bankruptcy of a company in an industry reveals negative information on the financial health of all industry peers. To compensate for the higher risks, creditors therefore naturally demand a higher spread in negotiating loan contracts with these companies. However, if information is efficient, we expect market participants to be able to accurately assess the financial health of the non-defaulting peers even prior to the bankruptcy announcement. Any operational or financial problems encountered by the bankrupted company that are also challenging the peers should have already been reflected in the company-specific information (e.g., market prices, annual/quarterly reports, financial statements, corporate announcements, etc.) that is readily accessible by all market participants in an informationally efficient environment. Under such an ideal information environment, we also expect any fire-sale discount to have already incorporated in company-specific information, thus leaving no room for industry-wide recovery rate to explain loan spread. The strength of the information channel of industry contagion is therefore dictated by the extent of information asymmetry that may exist between corporate insider and market participants. We expect that the higher the information asymmetry, the more informative the industry-wide recovery rate is in explaining the loan spreads of industry peers. We thus hypothesize:

H3: The negative effect of industry-wide recovery rate on loan spread is stronger and more significant during time periods when the market is less informationally efficient and for companies that are more prone to information asymmetry.

Finally, we expect negative externality as a result of the fire-sale discount will emerge not only in the pricing of loan contracts but also in non-price contractual terms. Concerned about the possibility of realizing a low liquidation value as a result of a forced asset sale in the event that the borrower files for bankruptcy, creditors should rationally demand security to pledge against the loan and impose more constraints in governing the actions of the borrower before he or she is comfortable executing the loan contract. We therefore hypothesize:

H4: The lower the realized industry-wide recovery rate, the higher is the chance of the loan being secured and/or more covenants being in place.

3. Data and Methodology

3.1 Data

We obtain our loan contract information from Thomson-Reuters' LPC DealScan. It is one of the most extensive sources of information on large bank loans. The database contains historical information on loan pricing and contract details, terms, and conditions. The version of the database used consists of origination information of loan facilities from 1987 to 2010. Our main variable of interest is the all-in spread on the drawn portion of loan facility.

We use the average creditors' recovery rate from bankruptcy resolution processes of defaulted companies in the industry as our (inverse) measure of fire-sale discount for that industry. To compute the industry-average recovery rates, we obtain the recovery rates of individual defaulted debt instruments from Standard & Poor's (S&P's) CreditPro Recovery Database (or *LossStats* Database), which is one of the most comprehensive sources of commercially assembled credit loss information on defaulted loans and bonds. Public and private US companies, both rated and non-rated, that have bank loans and/or bonds of more than fifty million dollars are analyzed and included in the database. The companies must have fully completed their restructuring, and all recovery information must be available in order to be included. Recovery rate is expressed as a fraction of notional value of the defaulted debt instrument and is computed by discounting the ultimate recovery values back to the time of default. Ultimate recovery value is the value pre-petition creditors would have received had they held onto their position from the point of default through the emergence date of the restructuring event.[15,16] To calculate the industry-average recovery rate for each four-digit SIC code industry, we use the recovery information on debt instruments issued by companies within that industry that filed for bankruptcy during each year from 1987 to 2010. There are a total of 4,289 defaulted debt instruments from 940 separate company default events in a variety of industries.

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[15] Pre-petition creditors are creditors that were in place prior to filing a petition for bankruptcy.

[16] Ultimate recovery values of the defaulted debts are calculated in the CreditPro Recovery Database by one of three methods: (1) *emergence pricing* - trading price of the defaulted instrument at the point of emergence from default; (2) *settlement pricing* - trading price at emergence of those instruments received in the workout process in exchange for the defaulted instrument; and/or (3) *liquidity event pricing* - values of those instruments received in settlement at their respective liquidity events (e.g., suppose creditors receive newly issued bonds during the settlement process; liquidation event prices are the liquidation values of these bonds at their respective maturity dates). When possible, all three methods are considered in the calculation of the recovery value of each instrument. Then, based on additional information, the method expected to be most representative of the recovery experience of the pre-petition creditors was used to arrive at the recovery value.

Not all defaulted cases are covered by the S&P's CreditPro Recovery Database. In order to accurately measure the intensity of industry-specific bankruptcy events at the time when a loan is originated, we calculate default rates for each industry defined by its four-digit SIC code (from CRSP) using bankruptcy statistics obtained from BankruptcyData.com.[17] BankruptcyData.com is one of the most comprehensive collections of US corporate bankruptcy information on both public and private defaulted companies. The database includes over 3,000 bankruptcy filings dating back to 1986. For each loan facility in our sample from DealScan, we identify where the timing of its origination is located in the bankruptcy waves specific to the industry to which it belongs. Specifically, we identify them as belonging to one of four different distinct phases of a bankruptcy wave based on the industry-specific default rates observed in the 12 months before and after the respective loan origination dates. The four phases are: (1) *Beginning*: industry default rate is below (above) 1% in the 12 months before (after) the loan origination date; (2) *Middle*: industry default rate is above 1% in both the 12-month periods before and after the loan origination date; (3) *Ending*: industry default rate is above (below) 1% in the 12 months before (after) the loan origination date; and (4) *Outside*: the loan origination date is not located in an industry-specific bankruptcy wave (i.e., not belonging to *Beginning*, *Middle*, or *Ending*).[18] As an example, we present the bankruptcy waves of the Wholesale and Retail industry in Figure 1. Based on our definition, two bankruptcy waves are identified for this

[17] Industry-specific default rate is defined as the number of bankruptcy filings in the industry according to BankruptcyData.com divided by the average number of companies within that industry in a 12-month period according to CRSP.

[18] Our definitions of the different phases of the industry bankruptcy wave are different from those in Hertzel and Officer (2012). In particular, Hertzel and Officer use the *absolute number* of the bankruptcy filings rather than the *proportion* of bankruptcy filings (i.e., default rate) within each industry to define the bankruptcy wave. We choose to use the latter since it facilitates the comparison of bankruptcy intensities among industry sectors of different sizes. We assume the effect of one bankruptcy filing in an industry of 100 companies is comparable to that of two bankruptcy filings in another industry of 200 companies. Our main conclusions essentially remain unchanged when we use the former definition of bankruptcy wave. The results based on this alternative definition are available upon request.

industry sector. The first wave, covering the period of 1998-2002, more or less coincided with the collapse of the dot-com bubble. The second wave, which is less severe than the first one based on the default rate, occurred a couple of years after the 2008-2009 global financial crisis.

INSERT FIGURE 1 ABOUT HERE

We perform several screenings on the DealScan dataset before we arrive at our final sample of loan contract data. We only include those loans of which the corporate borrowers can be identified as US companies with valid stock price information from CRSP and financial statement information from Compustat over our sample period from 1987 to 2010. We exclude loans originated in those calendar years where the industries to which their borrowers belong do not have valid industry-average recovery rate values (based on the CreditPro Recovery Database) and/or valid bankruptcy wave phase identifications (based on BankruptcyData.com). After these screenings, we have a sample of 5,463 loan facilities issued by a total of 2,681 companies, representing a wide variety of industries. In Table 1, we present the distributions of: (1) the number of loan facilities (obtained from DealScan); (2) the number of defaulted instruments and companies (obtained from CreditPro) with which we calculate the industry-specific recovery rates; and (3) the number of bankruptcy events (obtained from BankruptcyData.com) with which we define the different phases of the industry-specific bankruptcy waves. In the same table, we also report the average values of our main variables of interest, namely the all-in spreads (in basis points) on the drawn portion of loan facilities and the industry-specific recovery rates expressed as percentages of notional values of the defaulted instruments. Detailed definitions of all the variables used in this study are provided in the Appendix.

INSERT TABLE 1 ABOUT HERE

In Panel A of Table 1, we present the distributions of the variables over time. As a result of bankruptcy contagion, defaults tend to cluster over time. Tracking the annual number of bankruptcy events (last column of Table 1), we notice three distinct episodes of high bankruptcy counts. Number of bankruptcies peaks in early 1990s in the midst of the recession and the credit crunch in the banking sector. The second peak occurs in early 2000s when the dot-com bubble burst and the number of bankruptcies increases rapidly. After subsiding for a few years, bankruptcy count peaks again during the 2008-2009 global financial crisis. There are substantial time series variations in both the average all-in spread and the average industry-specific recovery rate around their respective means of 247 basis points (bps) and 58%. Consistent with the generally expected negative relation between aggregated default rate and aggregated recovery rate (Altman et al., 2005), average industry-specific recovery rate tends to be lower as bankruptcy count peaks. Not surprisingly, loan contracts originated during the three episodes of market downturn tend to command higher all-in spreads. For example, the average all-in spread of loan contracts originated in 2009—which include some of the darkest days of the recent financial crisis—was approximately 425 bps. This is almost twice that of the long-term average spread of 247 bps.

In Panel B of Table 1, we report the distributions of the variables across the 12 industries according to the Fama-French classification. Except for the Chemicals industry where we have only 33 loan contract observations, all industries are well represented in our sample. Wholesale and Retail, Business Equipment, and Manufacturing industries have the highest numbers of bankruptcy counts. This is not surprising given that they are also among the most populated industries. The variations of both average spread and average recovery rate across the industries are found to be less than their variations over time as reported in Panel A. Based on Scheffé's

(1999) tests on differences in industry averages, only the Utilities industry stands out among the 12 industries with significantly lower all-in spread (132 bps) and significantly higher recovery rate (78%).[19]

As a preliminary analysis on the industry effect, we calculate the average industry recovery rates and the average spreads of loans originated at different phases of the bankruptcy wave specific to the four-digit SIC code industry to which they belong (see Table 2). The average industry recovery rates in different phases of the wave are presented in the last column of Table 2. Recovery rate is the lowest in the middle of industry bankruptcy wave, which is consistent with the notion that there exists fire-sale discount in the liquidation value of industry-specific assets when industry peers themselves are in distress. On the other hand, the average all-in spread tends to be higher when the industry is in a bankruptcy wave. The highest average spread of 262 bps is witnessed in the middle of a bankruptcy wave. This is more than 61 bps higher than the case when the loan is originated outside the wave. This difference is also highly statistically significant. In Table 2, we also report the statistics for two non-pricing characteristics of loan contracts. It seems that lenders tend to demand more stringent requirements if the loan originates when the industry is subject to a bankruptcy wave. Specifically, the loan is more likely to be secured and subject to more covenants (according to the covenant intensity index defined as the sum of six covenant indicators; see the Appendix for details). The above univariate results suggest that both the pricing and non-pricing terms of a newly negotiated loan contract are negatively associated with the prevailing default incidence of industry peers. How much can we attribute this to the fire-sale channel of industry contagion? We address this research question by conducting a number of regression analyses as described below.

[19] Acharya et al. (2007) also document the highest recovery rate for the Utilities sector.

INSERT TABLE 2 ABOUT HERE

3.2 Empirical Design

To test our hypotheses on the fire-sale channel of industry contagion, we consider the following benchmark model where we regress the natural log of the all-in-drawn spread of each loan facility (*Loan Spread*) against the average recovery rate of the company's industry (*Industry Recovery Rate*) that is observed in the year of loan origination and other control variables that have been shown to dictate loan spreads. That is,

$$\begin{aligned} \textit{Loan Spread} = \delta_0 + \delta_1 \cdot \textit{Industry Recovery Rate} + \beta' \cdot \textit{Risk} + \gamma' \cdot \textit{Borrower Characteristics} \\ + \eta' \cdot \textit{Deal Characteristics} + \lambda' \cdot \textit{Macroeconomics} + \varepsilon \end{aligned} \tag{1}$$

A negative and significant coefficient δ_1 will lend support to our hypothesis *H1*. To ensure we can dissect the potential confounding effects, we control for four different risk factors (*Risk*). The first risk factor is the marginal distress estimate (*MDE*) of the borrower of the loan facility. Following James and Kizilaslan (2014), MDE is defined as the average monthly stock return of the borrower of the loan facility over those months where the value-weighted portfolio return of all the companies in the same four-digit SIC code is among the worst 5%. James and Kizilaslan show that this industry tail risk measure is significantly related to the recovery rates and all-in-drawn spreads on bank loans. We also control for the systematic market risk by calculating the annual *Market Beta* of the borrower's asset using market and industry returns in the trailing 60 months. To rule out the possibility that we are in fact capturing a default risk effect rather than a recovery risk effect in our hypothesis tests, we also control for default risk of both the borrower (*Firm Default Risk*) and its industry (*Industry Default Risk*). Here, we follow the methodology of Bharath and Shumway (2008) to estimate the expected default frequency for each borrower in our sample at the time when the respective loan is originated, which serves as our default risk measure for individual company. To construct *Industry Default Risk*, we calculate the average expected default frequency of all the companies that share the same four-digit SIC code as the borrower again at the time when the loan is originated.

We also control for a number of borrower characteristics, deal characteristics, and macroeconomic conditions that may also affect loan pricing. A list of these control variables together with their detailed definitions are in the Appendix. Finally, to account for any unobserved industry factors, we control for the borrower's industry fixed effect in our regressions. Summary statistics of all the variables used in the regressions are reported in Table 3.

INSERT TABLE 3 ABOUT HERE

As a further test on hypothesis *H1*, we compare the informativeness of industry-wide recovery rate in loan pricing at different phases of the industry-specific bankruptcy wave by adding three interaction terms, namely $Beginning \times Industry\ Recovery\ Rate$, $Middle \times Industry\ Recovery\ Rate$, and $Ending \times Industry\ Recovery\ Rate$, to our benchmark regression model. Specifically, we run the following regression.

$$\begin{aligned} Loan\ Spread = {} & \delta_0 + \delta_1 \cdot Industry\ Recovery\ Rate + \theta_1 \cdot Beginning + \theta_2 \cdot Middle + \theta_3 \cdot Ending \\ & + \varphi_1 \cdot Beginning \times Industry\ Recovery\ Rate + \varphi_2 \cdot Middle \times Industry\ Recovery\ Rate \\ & + \varphi_3 \cdot Ending \times Industry\ Recovery\ Rate + \beta' \cdot Risk + \gamma' \cdot Borrower\ Characteristics \\ & + \eta' \cdot Deal\ Characteristics + \lambda' \cdot Macroeconomics + \varepsilon \end{aligned} \tag{2}$$

We expect that the more default incidences there are within the same industry, the more concern the creditors have about the fire-sale discount; as a result, a more important role is played by the industry-wide recovery rate in explaining the cost of debt. Among the coefficients of the three interaction terms, we therefore expect φ_2 to be the most negative and statistically significant followed by φ_1 and φ_3. Such an empirical outcome will therefore lend support to our hypothesis *H1*.

To test hypothesis *H2*, we run our benchmark regression model (i.e., Equation (1)) on pairs of subsamples that we expect will differ in terms of their susceptibility to fire-sale discount. The objective is to verify that the negative effect of industry recovery rate may indeed be attributable to the fire-sale channel. If the coefficient δ_1 is negative and statistically significant only in the subsample where the fire-sale channel of industry contagion is expected to be more prevalent but not so in the one that should be less affected by fire-sale discount, we will have support for hypothesis *H2*.

To investigate the information channel of industry contagion and how it may interact with the fire-sale channel, we split our overall sample into pairs of subsamples based on commonly used indicators of high versus low information asymmetry and conduct our benchmark regression model of Equation (1) separately on the subsamples. If the coefficient δ_1 is negative and statistically significant only in the subsample of high information asymmetry but not so in the one of low information asymmetry, we will have support for hypothesis *H3*, thus confirming the importance of the information channel.

Finally, we examine the fire-sale effect on non-pricing terms of loan contracts by testing hypothesis *H4*. To study the effects on the choice between secured versus unsecured loans, we run the following probit regression with the dependent variable $Secured$ equals to unity if the loan is secured and zero otherwise.

$$\textit{Secured} = \delta_0 + \delta_1 \cdot \textit{Industry Recovery Rate} + \beta' \cdot \textit{Risk}$$

$$+\gamma' \cdot \textit{Borrower Characteristics} + \eta' \cdot \textit{Deal Characteristics} + \lambda' \cdot \textit{Macroeconomics} + \varepsilon \tag{3}$$

To test the significance of the fire-sale effect on the extent of covenant restrictions being imposed on the contracts, we follow Bradley and Roberts (2004) in constructing a covenant intensity index based on the sum of six covenant indicators: (i) whether the loan is secured, (ii) whether there are restrictions on the dividend, (iii) whether there are more than two financial covenants, (iv) whether there are asset sale sweeps, (v) whether there are debt issuance sweeps, and (vi) whether there are equity issuance sweeps. The index value therefore lies between 0 and 6, with 0 (6) being least (most) restrictive.[20] We then conduct the following regression analysis with the dependent variable equal to the covenant intensity index value of each of the loans.

$$\textit{Covenant Intensity Index} = \delta_0 + \delta_1 \cdot \textit{Industry Recovery Rate} + \beta' \cdot \textit{Risk}$$

$$+\gamma' \cdot \textit{Borrower Characteristics} + \eta' \cdot \textit{Deal Characteristics} + \lambda' \cdot \textit{Macroeconomics} + \varepsilon \tag{4}$$

A negative and statistically significant coefficient δ_1 in both Equations (3) and (4) will confirm the fire-sale effect on non-pricing terms of loan contracts.

4. Empirical Results

4.1 Benchmark model

We report the full sample regression results of our benchmark model of Equation (1) in Columns (1) to (4) of Table 4. Our dependent variable is the natural log of loan spread (*Loan Spread*) of each individual facility and our key independent variable is the average

[20] Summary statistics of the covenant intensity index can be found in Table 3.

industry recovery rate (*Industry Recovery Rate*) realized when the loan is originated. The four regressions differ in the risk factors (*Risk*) being considered. In the first regression (Column (1)), none of the risk factors are considered. In the second regression (Column (2)), we include only *MDE* and *Market Beta*, which capture the exposures of the borrower to industry-level tail risk and market-wide systematic risk, respectively. In the third regression (Column (3)), we include only the firm-level and industry-level default risk measures (*Firm Default Risk* and *Industry Default Risk*). Finally, in Column (4), we consider a specification where all four risk factors are controlled for. In all four regressions, we control for all the borrower's characteristics, loan's characteristics, and macroeconomic variables that may also influence loan pricing. We assess the statistical significance of the estimated coefficients using robust standard errors adjusted for clustering at the borrower level to account for multiple observations of the same company.

INSERT TABLE 4 ABOUT HERE

Consistent with hypothesis *H1*, we find a negative and significant relationship between industry recovery rate and loan spreads regardless of whether we control for the four risk factors. Based on the estimated regression coefficient of Column (4), a one-standard deviation increase in the industry-wide recovery rate is associated with an average decrease in loan spreads of about 5.5 bps. Not surprisingly, we also find that higher industry tail risk, higher default risk, higher financial leverage, lower growth potential, and lower long-term debt credit rating tend to be associated with significantly higher loan spreads. In addition, loan pricing is found to be governed by the prevailing macroeconomic conditions under which the contract is originated. Since the governing factors of the price of debt issued by companies in the Utilities and Financial Services industries may differ from those of other industries, we repeat our benchmark regression while excluding the loans of these two industries (see Column (5)). The effect of industry recovery rate on loan spread is even stronger when these two sectors are excluded.

4.2 The significance of industry recovery rate in different phases of industry bankruptcy wave

To test if a clustering of default events within the same industry will heighten the concerns for the fire-sale discount thus leading to a stronger influence of industry-wide recovery rate on peers' costs of debt, we conduct the regression of Equation (2) by including the interaction terms of industry recovery rate and indicator variables identifying the different phases of industry bankruptcy wave. The full sample results are reported in Columns (6) and (7) of Table 4.

In Column (6), we report the regression results with only the wave indicator variables ($Beginning$, $Middle$, and $Ending$). Hertzel and Officer (2012) show that industry contagion is particularly severe in industry bankruptcy waves. Consistent with their findings, the estimated coefficients of the wave indicator dummy variables in Column (6) are positive and statistically significant, indicating that the loan contracts that originated within industry bankruptcy wave tend to have higher spreads than those originated outside of the wave. More importantly, when we include the interaction terms with industry recovery rate (see results reported under Column (7)), we find that the negative externality of the fire-sale discount on the cost of debt as manifested in the informativeness of industry recovery rate is indeed more significant in the middle of the wave. A one-standard deviation increase in the industry-wide recovery rate is associated with an average decrease in loan spreads of about 28 bps. We obtain essentially the same (if not more significant) results when we exclude loan contracts in the Utilities and Financial Services industries (see Columns (8) and (9)). These interaction regression results further confirm our hypothesis *H1* and lend support to the fire-sale channel of industry contagion.[21]

4.3 Verification of the fire-sale channel of industry contagion

To verify that it is indeed the fire-sale channel at play, we test the significance of the negative influence exerted by industry recovery rate on loan spread on subsamples that we expect are different in their susceptibility to fire-sale discount. We essentially repeat our benchmark regression analysis (i.e., Equation (1)) on loan spreads using only facilities within each subsample under consideration. The regression results are reported in Table 5. Similar to the regressions conducted above, we control for four different risk factors (*Risk*) together with a number of borrower/deal characteristics and macroeconomic factors. To conserve space, we only present the estimated coefficients (and their significance) for industry recovery rate and the four control risk factors.

INSERT TABLE 5 ABOUT HERE

In total, we consider 10 pairs of subsamples of which the regression results are reported in Panels A and B. In Panel A, Columns (1) and (2), we have the results for loan contracts of companies belonging to industries with a low versus high degree of asset specificity respectively. We follow Acharya et al. (2007) in defining asset specificity as the ratio of the book value of machinery and equipment to total assets. We calculate the average value of this ratio of all companies in each four-digit SIC code industry in each year. We then partition our loan contract

[21] To confirm the robustness of our results, we repeat our regression analysis by directly using the continuous variable of annual industry-level default rate at the time the loan is originated as opposed to using the discrete wave indicator variables ($Beginning$, $Middle$, and $Ending$) to identify the different phases of industry bankruptcy wave. In explaining the loan spread, the coefficient of the interaction term of industry recovery rate with industry-level default rate is found to be negative and statistically significant, thus confirming our conclusion that the negative externality of the fire-sale discount on the cost of debt tends to be more severe the higher the default intensity within the industry. To conserve space, the regression results are available upon request.

sample according to whether the issuing company belongs to an industry with asset specificity that is below or above the industry median value in the year the loan is originated. Based on the fire-sale model of Shleifer and Vishny (1992), the more specific and thus the less re-deployable the assets of an industry, the stronger will be the fire-sale discount. Consistent with this prediction, we find that, as in inverse proxy for fire-sale discount, industry recovery rate only exerts a negative influence on loan spread that is statistically significant in industries with a high degree of asset specificity.

In Columns (3) and (4), we report the results for industries with low versus high asset growth rate. We partition our loan sample into two subsamples based on whether the borrower belongs to a four-digit SIC code industry with an average annual total asset growth rate that is below or above the industry median value in the year the loan originated. We expect fire-sale discount to be less significant for industry with high asset growth rate as companies are more willing to purchase any assets offered for sale by their distressed peers so as to benefit from the growth opportunity within the industry, which is consistent with our findings. The negative externality on the cost of debt disappears in industries of high asset growth rate whereas the negative effect remains significant for those with low growth rate. The effect of the amount of debt overhang can be found in Columns (5) and (6). Following Hennessy et al. (2007), we define debt overhang as the expected proportion of assets claimed by debtholders in the case of default. We calculate the average amount of debt overhang at the four-digit SIC code industry level for each year, so we can categorize our loan contracts into those where the borrower belongs to an industry with a low versus high amount of debt overhang in the year the loan originated. Since distressed companies with less debt overhang can more readily refinance and avoid the force-sale of their assets, we expect the fire-sale channel of industry contagion to be less significant in industries with a lower amount of debt overhang. This prediction is indeed supported by our regression results. The negative effect of industry recovery rate mostly subsides in the subsample of low debt overhang, while remaining strong and statistically significant in that of high debt overhang.

Liquidity of industry peers plays an essential role in governing the extent of fire-sale discount. A lack of liquidity will deter industry buyers from bidding on the distressed assets, resulting in lower liquidation values and thus more fire-sale discount. We verify this liquidity effect of fire-sale discount using two different industry-level liquidity measures (see the last two pairs of subsample regressions in Panel A). We first construct subsamples based on industry average quick ratio defined as current assets less inventory divided by current liabilities. Those loan contracts, of which the borrowers belong to industries with average quick ratios that are below (above) the industry median, are expected to be subject to stronger (weaker) fire-sale discount. As an alternative liquidity measure, we estimate the degree of financial constraint of each industry. We follow Rajan and Zingales (1998) by calculating the intrinsic demand for external finance in the absence of financial constraints and partition the loan contracts based on whether the industries of the borrowers have a financial constraint measure that is below or above the industry median value. The regression results in Columns (7) to (10) confirm the liquidity effect. Only in the subsamples of low industry's quick ratio and high industry's financial constraint do we observe a statistically significant industry contagion effect.

In Panel B, we have two more pairs of industry-level subsamples. We classify industries into those that are and those that are not subject to anti-trust law according to the US Department of Justice. The regression results of the loan contracts in these two subsamples are reported in Columns (11) and (12) of Panel B. Given the regulatory barrier that deters the acquisitions of peers' assets, borrowers in industries that are subject to anti-trust law are more affected by the fire-sale effect. This is confirmed by the regression results where industry recovery rate is significantly associated with loan spread only in the anti-trust law subsample. We then examine if the significance of the fire-sale channel is affected by the market concentration of the industry. We calculate the Herfindahl-Hirschman index (HHI) for each four-digit SIC code industry and divide the industries into two groups based on whether their HHI are below or above the industry median HHI. If industry contagion indeed propagates via the fire-sale channel, we will expect lenders to be more concerned about the possibility of fire-sale discount in industries of higher market concentration, since there will be fewer potential bidders of distressed assets from inside the industries. Thus, industry recovery rate should exert a stronger influence on the costs of debt in more concentrated industries. On the other hand, if the effect is mainly dictated by a fundamental change in the competitive environment, we will expect the negative externalities to in fact be weaker for industries that are more concentrated, as rivals in such industries are better able to benefit from taking over the market share vacated by the defaulted company (Lang and Stulz, 1992). The regression results reported under Columns (13) and (14) point to a dominating fire-sale channel, with industry recovery rate being negatively significant only in high concentration industries.

In examining borrower-specific characteristic, we expect that, given the higher probability of default, any variation of the liquidation value as a result of fire-sale discount will exert a stronger influence on the costs of debts of non-investment grade companies than those that are investment-grade. This is verified by running our benchmark regression for investment grade and non-investment grade borrowers separately. A borrower is defined as investment grade if its Standard & Poor's long-term debt rating is BBB or higher, otherwise it is classified as non-investment grade. Consistent with our expectation, the negative effect of industry recovery rate on loan spread is statistically significant (though weakly) for only non-investment grade borrowers (see Columns (15) and (16) of Panel B). Next, we test the effect separately for secured and unsecured loans. As the expected payoffs of secured debts are more directly related to the liquidation values of specific assets of the borrower than those that are otherwise unsecured, we expect the former to be more susceptible to fire-sale discount than the latter, which is consistent with the findings in our regression analysis. The negative externality is significant for secured loans but not for those that are unsecured (Columns (17) and (18)).

Finally, we examine how the fire-sale effect may vary with the liquidity of the general market. We expect an imbalance in the supply and demand of distressed assets as a result of a bankruptcy-induced forced sale becoming more severe as the market becomes more illiquid. Thus, lenders should be more concerned about any fire-sale discount when they negotiate loan contracts during such market conditions, resulting in a stronger negative association between industry recovery rate and loan spread. Using the monthly liquidity index constructed by Pastor-Stambaugh (2003), we partition our sample based on whether the loan contract originates in a year where the average liquidity index is below or above the median value over our sample period. Consistent with our expectation regarding the behavior of the fire-sale channel, the negative effect of industry recovery rate is found to be stronger when market-wide liquidity is low (Columns (19) and (20)).

In summary, for all 10 pairs of subsamples, the negative effect of industry recovery rate on loan spread is statistically significant only in the subsamples where we expect the fire-sale channel of industry contagion to be stronger. Taken together, these consistent results therefore provide strong support for hypothesis *H2*.

4.4 The role of the information channel of industry contagion

If the information channel of industry contagion is also at play as the fire-sale discount is reflected in the loan spread, we will expect the explanatory power of industry recovery rate to vary with the informational characteristics of the borrower and the informational efficiency of the market. Specifically, the higher the information asymmetry between corporate insider and market participants, the more significant should be the industry recovery rate in explaining the loan spreads of industry peers. To study this interaction of the information and fire-sale channels of industry contagion, we repeat our benchmark regression analysis on a number of subsamples that are different in terms of information asymmetry. The results are reported in Table 6. Similar to the regressions conducted above, we control for four different risk factors (*Risk*) together with a number of borrower/deal characteristics and macroeconomic factors. To conserve space, we do not present the estimated coefficients for the borrower/deal characteristics and macroeconomic factors.

INSERT TABLE 6 ABOUT HERE

Firm size is commonly used as an information asymmetry indicator in the literature (e.g., Gilchrist and Himmelberg, 1995; Almeida, Campello, and Weisbach, 2004; Faulkender and Wang, 2006). In general, the smaller a company in terms of its total assets, the higher is the information asymmetry. We construct two subsamples. The large-size firm subsample is comprised of borrowers belonging to the top 30% of their respective four-digit SIC code in terms of their asset values, whereas the small-size firm subsample is made up of those in the bottom 30%. Consistent with our hypothesis, industry recovery rate is significant in explaining the spread of loans to small-size borrowers, but not loans to large-size borrowers (Columns (1) and

(2) of Table 6). To ensure the robustness of our conclusion, we repeat the analysis based on an alternative firm-level measure of information asymmetry. We use the probability of information-based trading (PIN) measure developed by Easley at al. (2002) to partition our loan sample into two groups with borrowers that are subject to low versus high information asymmetry. Specifically, borrowers are considered to be subject to low (high) information asymmetry if their PIN is in the bottom (top) 30% among their peers in the same industry. The regressions results reported under Columns (3) and (4) confirm the previous finding based on firm size. We detect a statistically significant effect of industry recovery rate among borrowers with high PIN, but not for those with low PIN.

We also examine the effect under different informational conditions of the general market. Here we use the volatility index (VIX) of the Chicago Board Options Exchange (CBOE) as our indicator of market-wide informational efficiency. It is generally believed that, the higher the VIX, the less informationally efficient is the market. We construct two subsamples based on the time a loan is originated. The low-VIX (high-VIX) subsample consists of loans that are originated in those years where the VIX are in the bottom (top) 30% among the annual average VIX values realized over our sample period. Confirming our expectation, industry recovery rate is statistically significant in explaining the spreads of loans that are originated when VIX is high, but not so when VIX is low.

In summary, we find empirical evidence supporting our hypothesis *H3*. Specifically, we find that the information characteristics of the borrower and the state of the informational environment can dictate the significance of the fire-sale channel of industry contagion.

4.5 Effects on non-pricing contractual terms

We expect the negative externality as a result of the fire-sale discount will appear not only in the pricing of loan contracts but also in non-price contractual terms. To test this hypothesis, we conduct a couple of regressions with the secured debt indicator variable and the covenant intensity index as our dependent variables, respectively (i.e., Equations (3) and (4)). To rule out any confounding effects, we control for the four risk factors (*Risk*) together with the same set of borrower/deal characteristics and macroeconomic factors considered in previous regressions. More importantly, we also control for the all-in spread of the loan, which may also influence the non-price terms of the contract. The full sample results are reported under Columns (1) and (2) of Table 7. To conserve space, we do not present the estimated coefficients for the borrower/deal characteristics and macroeconomic factors.

INSERT TABLE 7 ABOUT HERE

Supporting our hypothesis *H4*, as an inverse proxy for fire-sale discount, the lower the industry recovery rate, the higher the chance that the loan is secured and the more covenant restrictions are imposed. A one-standard deviation drop in the industry-wide recovery rate is associated with a 19-percentage point increase in the chance of the loan being secured and an increase in the covenant intensity index by about 0.05. These findings are consistent with the notion that, given their concerns about fire-sale discount, lenders tend to demand collateral and/or impose more constraints on borrowers' actions when formulating their loan contracts. To ensure the robustness of our conclusion, we repeat the regression analysis after excluding loans made to utilities companies and financial institutions from our sample. The results, reported under Columns (3) and (4), are qualitatively the same as (if not stronger than) the full sample results.

5. Robustness Tests

One possible concern of our research design is that industry recovery rate may be endogenously determined in loan pricing. There is always the possibility that industry recovery rate and loan spread are jointly determined by some unobserved variables that we have not controlled for in our regression analysis. This could potentially result in biased estimation results in our ordinary least square regressions. We address this endogeneity issue by conducting a two-stage regression. In the first stage, we obtain a *fitted value* of industry recovery rate with exogenous instrumental variables. We then use this fitted value of industry recovery rate together with other control variables as independent variables to explain loan spread in the second-stage regression. We use two kinds of instrumental variables that are expected to be highly correlated with recovery rate, but are unrelated to loan pricing. The first kind of instrumental variable is based on bankruptcy venue. Chen (2013) shows that, controlling for other factors, recovery rate tends to be lower if the bankruptcy is filed in the courts belonging to the District of Delaware or the Southern District of New York. The other instrumental variable is the length of the time spent in bankruptcy process, which is considered a key measure of bankruptcy costs (Hotchkiss et al., 2008) and thus should be negatively associated with recovery rate. At the same time, these instrumental variables of the defaulted companies are unlikely to be related to the loan pricing process of their industry peers.

To obtain the fitted value of industry recovery rate, we conduct our first-stage regression by regressing the observed company-level recovery rate from S&P's CreditPro against: (i) a dummy variable indicating whether the bankruptcy is filed in Delaware; (ii) a dummy variable indicating whether the bankruptcy is filed in New York; and (iii) the time between the bankruptcy date and the emergence date of the bankruptcy process. We also control for the same set of company-level variables and macroeconomic factors that we considered in our previous regressions. We then calculate the fitted value of industry recovery rate by taking the average of the fitted recovery rates of individual defaulted companies within each four-digit SIC code industry.

The estimation results of the second stage of our two-stage regression are reported in Table 8.[22] Instead of using the observed industry recovery rate, here we use the fitted value of industry recovery rate obtained from the first-stage regression as our main explanatory variable. We control for the same set of borrower/deal characteristics and macroeconomic conditions considered in our previous regressions. The regression results based on our full sample can be found under Columns (1) to (4). Regardless of whether the other four risk factors are controlled for or not, the negative coefficient of the fitted industry recovery rate is found to be statistically significant. The result remains robust when we exclude those loans made to utilities companies and financial institutions (see Column (5)). Our previous conclusions regarding the fire-sale channel of industry contagion are therefore robust to any potential endogeneity issue.

INSERT TABLE 8 ABOUT HERE

6. Conclusion

Previous literature on industry contagion effects of financial distress have mainly focused on short-run stock price reactions or CDS spread changes of industry peers. Whether such effects can be observed in other markets, and through which channel these contagion effects take shape, is not well understood. This paper provides insight on these questions by examining the

[22] To conserve space, the estimation results of the first-stage regression are available upon request.

recovery rates of defaulted companies and the price of loans of their industry peers negotiated around bankruptcy waves. We find that the cost of debt of a company is affected by the observed recovery rates of its bankrupt industry peers, particularly in the middle of industry bankruptcy waves. The empirical evidence we document in this study supports the hypothesis that industry contagion of financial distress affects industry competitors via a fire-sale channel. We argue that when creditors of non-defaulting industry peers become aware of the prospect of a fire-sale discount of assets underlying their debt contracts, they will lower their expectation of the asset value that can be recovered in a possible future default event. Based on this argument, we therefore expect the fire-sale concern to result in a higher cost of debt financing for industry peers when they negotiate debt contracts with corporate lenders. Consistent with this argument, we find that higher loan spreads are indeed associated with lower realized recovery values of industry peers, which measure the extent of fire-sale discount.

We also verify that fire-sale discount is more salient for industries with a higher degree of asset specificity, with a lower asset growth rate, with more debt overhang, and that are more concentrated. Furthermore, the negative effect of industry-wide recovery rate on loan spread is stronger and more significant during time periods when market is less informationally efficient and for companies that are more prone to information asymmetry. These results suggest that information asymmetry is an important determinant of the significance of the fire-sale effect in debt pricing.

References

Acharya, V.V., Bharath, S.T., Srinivasan, A., 2007. Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries. *Journal of Financial Economics* 85(3), 787-821.

Akhigbe, A., Martin, A.D., Whyte, A.M., 2005. Contagion effects of the world's largest bankruptcy: The case of WorldCom. *Quarterly Review of Economics and Finance* 45, 48-64.

Almeida, H., M. Campello, and Weisbach, M.S., 2004. The cash flow sensitivity of cash, *Journal of Finance* 59, 1777-1804.

Allen, F., Babus, A., Carletti, E., 2009. Financial crisis: Theory and evidence. *Annual Review of Financial Economics* 1, 97-116.

Altman, E.I., Brady, B., Resti, A., Sironi, A., 2005. The link between default and recovery rates: Theory, empirical evidence, and implications. *Journal of Business* 78 (6), 2203-2227.

Battiston, S., Gatti, D.D., Gallegati, M., Greenwald, B., Stiglitz, J.E., 2007. Credit chains and bankruptcy propagation in production networks. *Journal of Economic Dynamics & Control* 31, 2061-2084.

Benmelech, E., Bergman, N.K., 2011. Bankruptcy and the collateral channel. *Journal of Finance* 66(2), 337-378.

Bharath, S.T., Shumway, T., 2008. Forecasting default with the Merton distance to default model. *Review of Financial Studies* 21(3), 1339-1369.

Bradley, M., Roberts, M.R., 2004. The structure and pricing of corporate debt covenants. The 6th Annual Texas Finance Festival.

Brunnermeier, M.K., 2009. Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives* 23 (1), 77-100.

Chakrabarty, B., Zhang, G., 2012. Credit contagion channels: market microstructure evidence from Lehman Brothers' bankruptcy. *Financial Management* 41(2), 320-343.

Chen, D., 2013. Bankruptcy venue choice and creditor recovery. Available at SSRN 2209607.

Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns? *Journal of Finance* 57(5), 2185-2221.

Faulkender, M., and Wang, R., 2006. Corporate financial policy and value of firm, *Journal of Finance* 61, 1957–1990.

Ferris, S.P., Jayaraman, N., Makhija, A.K., 1997. The response of competitors to announcements of bankruptcy: An empirical examination of contagion and competitive effects. *Journal of Corporate Finance* 3, 367-395.

Giesecke, K., Weber, S., 2004. Cyclical correlations, credit contagion, and portfolio losses. *Journal of Banking and Finance* 28, 3009-3036.

Gilchrist, Simon, and Himmelberg, C., 1995. Evidence on the role of cash flow for investment, *Journal of Monetary Economics* 36, 541–572.

Gleason, C.A., Jenkins, N.T., Johnson, W.B., 2008. The contagion effects of accounting restatements. *The Accounting Review* 83(1), 83-110.

Hadlock, C.J., Sonti, R., 2012. Financial strength and product market competition: Evidence from asbestos litigation. *Journal of Financial and Quantitative Analysis* 47(1), 179-211.

Helwege, J., Zhang, G. 2016. Financial Firm Bankruptcy and Contagion. *Review of Finance* 20(4), 1321-1362.

Hennessy, C.A., Levy, A., Whited, T.M., 2007. Testing Q theory with financing frictions. *Journal of Financial Economics* 83, 691-717.

Hertzel, M.G., Li, Z., Officer, M.S., Rodgers, K.J., 2008. Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics* 87, 374-387.

Hertzel, M.G., Officer, M.S., 2012. Industry contagion in loan spreads. *Journal of Financial Economics* 103(3), 493-506.

Hotchkiss, E.S., John, K., Mooradian, R.M., Thorburn, K.S., 2008. Bankruptcy and the resolution of financial distress, in B. Espen Eckbo, ed. *Handbook of Empirical Corporate Finance* 2.

Hull, J.C., 2012. *Options, Futures, and Other Derivatives*, 8th edition. Prentice Hall.

James, C., Kizilaslan, A., 2014. Asset specificity, industry-driven recovery risk, and loan pricing. *Journal of Financial and Quantitative Analysis* 49(3), 599-631.

Jorion, P., Zhang, G., 2007. Good and bad credit contagion: Evidence from credit default swaps. *Journal of Financial Economics* 84(3), 860-883.

Jorion, P., Zhang, G., 2009. Credit contagion from counterparty risk. *Journal of Finance* 64(5), 2053-2087.

Lang, L.H., Stulz, R., 1992. Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of Financial Economics* 32(1), 45-60.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642-685.

Platt, E., 2015. Boom times for US corporate bond sales. *Financial Times* (November 12, 2015).

Rajan, R.G., Zingales, L., 1998. Which capitalism? Lessons from the East Asian crisis. *Journal of Applied Corporate Finance* 11, 40-48.

Scheffé, H., 1999. *The Analysis of Variance* (Vol. 72). John Wiley & Sons.

Shleifer, A., Vishny, R.W., 1992. Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance* 47(4), 1343-1366.

Shleifer, A., Vishny, R., 2011. Fire sales in finance and macroeconomics. *Journal of Economic Perspectives* 25(1), 29-48.

Slovin, M.B., Sushka, M.E., Polonchek, J.A., 1999. An analysis of contagion and competitive effects at commercial banks. *Journal of Financial Economics* 54, 197-225.

Tendulkar, R., Hancock, G., 2014. Corporate bond markets: A global perspective (volume 1). Working paper, International Organization of Securities Commissions (IOSCO).

Appendix. Definitions of variables

This table provides detailed definitions for the variables considered in the study.

Variable name	Variable definition
Main Variables:	
Loan Spread	Natural log of the all-in-drawn spread of the loan. It is the interest the borrower pays in basis points over LIBOR (or LIBOR equivalent) plus any annual fee payable on the drawn portion of the loan facility at initiation.
Covenant Intensity	The covenant intensity index is defined as the sum of six covenant indicators: (i) whether the loan is secured, (ii) whether there are restrictions on dividend, (iii) whether there are more than two financial covenants, (iv) whether there are asset sale sweeps, (v) whether there are debt issuance sweeps, and (vi) whether there are equity issuance sweeps. The index value therefore lies between 0 and 6, with 0 (6) being least (most) restrictive. The index is set to missing if one of the six indicators is missing.
Industry Recovery Rate	Industry recovery rate is defined as the average recovery rate of the creditors of companies in the industry the borrowers belong to that have defaulted in the year the loan was originated. The industry classification is based on the four-digit SIC code and the creditors' recovery rates are obtained from S&P's CreditPro database.
Risk Variables:	
MDE	Marginal distress estimate (MDE) is defined as the average monthly stock return of the borrower of the loan facility over those months where the value-weighted portfolio return of all the companies in the same four-digit SIC code is among the worst 5% (see James and Kizilaslan, 2014).
Market Beta	Market beta is defined as the asset market beta, calculated from the equity market beta. Equity market beta is obtained from a two-factor model where firm return is regressed on the market return and industry return over the trailing 60 months. We ignore the industry return factor if the industry portfolio is made up of fewer than five companies.
Firm Default Risk	Firm default risk is defined as the expected default frequency of the borrower calculated based on distance-to-default measure of Bharath and Shumway (2008) and evaluated at the issuance date of the loan.
Industry Default Risk	Industry default risk is defined as the average default risk of all the companies in the four-digit SIC code industry the borrower belongs to. It is also evaluated at the issuance date of the loan.
Bankruptcy Wave Indicators:	
Four phases of bankruptcy wave:	
Beginning	An indicator variable that equals one if the default rate of the four-digit SIC code industry the borrower belongs to is below (above) 1% in the 12 months before (after) the loan origination date.
Middle	An indicator variable that equals one if the default rate of the four-digit SIC code industry the borrower belongs to is above 1% in both the 12-month periods before and after the loan origination date.
Ending	An indicator variable that equals one if the default rate of the four-digit SIC code industry the borrower belongs to is above (below) 1% in the 12 months before (after) the loan origination date.
Outside	An indicator variable that equals one if the loan origination date is not located in an industry-specific bankruptcy wave (i.e., not belonging to *Beginning*, *Middle*, or *Ending*)
Borrower Characteristics:	
Log (assets)	Natural log of the total assets.
Leverage	Sum of long-term debt and current liabilities divided by total assets.

Tobin q	Sum of market value of equity and book value of debt divided by total assets. Market value of equity is defined as the price per share multiplied by the total number of shares outstanding. Book value of debt equals to total assets minus book value of equity.
Tangibility	Net property, plant, and equipment divided by total assets.
Investment	Capital investment divided by total assets.
Profitability	Net income divided by total assets.
Rating Dummy A	A dummy variable equals to one if the borrower's S&P long-term debt rating is A- or higher and zero otherwise.
Rating Dummy BBB	A dummy variable equals to one if the borrower's S&P long-term debt rating is BBB- to BBB+ and zero otherwise.
Rating Dummy BBC	A dummy variable equals to one if the borrower's S&P long-term debt rating is BB+ or lower and zero otherwise.
Deal Characteristics:	
Log (amount)	Natural log of the loan facility amount.
Log (maturity)	Natural log of the loan maturity.
Performance pricing	A dummy variable equals to one if the loan uses performance pricing and zero otherwise.
Financial covenant	A dummy variable equals to one if the loan is subject to financial covenant constraint.
Secured	A dummy variable equals to one if the loan is secured by collateral and zero otherwise.
Senior	A dummy variable equals to one if the loan is senior and zero otherwise.
Loan purposes:	
Corporate	A dummy variable equals to one if the loan is for corporate purposes and zero otherwise.
Work capital	A dummy variable equals to one if the loan is for working capital purposes and zero otherwise.
Takeover	A dummy variable equals to one if the loan is for takeover purpose and zero otherwise.
Loan types:	
Term loan	A dummy variable equals to one if the loan is a term loan and zero otherwise.
Credit line	A dummy variable equals to one if the loan is a credit line and zero otherwise.
Bridge loan	A dummy variable equals to one if the loan is a bridge loan and zero otherwise.
Refinancing	A dummy variable equals to one if the loan is to refinance existing debt and zero otherwise.
Guarantor	A dummy variable equals to one if the loan has a guarantor and zero otherwise.
Sponsor	A dummy variable equals to one if the loan has a sponsor and zero otherwise.
Syndicated	A dummy variable equals to one if the loan is a syndicated loan and zero otherwise.
Relationship	A dummy variable equals to one if the company has borrowed from the same lead arranger(s) of the loan syndicate at least once in the year prior to the origination of the loan contract.
Macroeconomics factors:	
BBB spread	BBB spread is defined as the average month-end difference between Moody's Seasoned Baa Corporate Bond Yield and Moody's Seasoned Aaa Corporate Bond Yield in the year the loan is originated.
TED spread	TED spread is defined as the average month-end difference between the three-month LIBOR and three-month T-Bill rate in the year the loan is originated.
GDP growth rate	GDP growth rate is the annual GDP growth rate in the year the loan is originated.

Table 1 Distributions of loan facilities, defaulted instruments/companies, and bankruptcy events by year and industry.

This table presents the distributions of: (1) the number of loan facilities (obtained from DealScan); (2) the number of defaulted instruments and companies (obtained from CreditPro) with which we calculate the industry-specific recovery rates; (3) the number of bankruptcy events (obtained from BankruptcyData.com) with which we define the different phases of the industry-specific bankruptcy waves. We also report the average values of our main variables of interest, namely the all-in spreads (in basis points) on the drawn portion of loan facilities and the industry-specific recovery rates expressed as percentages of notional values of the defaulted instruments. Panel A shows the time-series distribution by year from 1987 to 2010. For loan facility, it is the year in which the loan contract is originated. For defaulted instrument and bankruptcy event, it is the year in which the company files for bankruptcy. Panel B shows the distributions across industries as defined using the Fama and French 12-industry categorization.

Panel A. Time-series distribution

Year	From DealScan		From CreditPro			From BankruptcyData.com
	Number of loan facilities	Average all-in spread (bps)	Number of defaulted instruments	Number of defaulted companies	Ave. industry recovery rate (%)	Number of bankruptcy events
1987	7	246.43	32	6	47.41	21
1988	106	225.69	78	14	57.39	35
1989	178	267.44	109	25	40.30	67
1990	255	252.19	173	38	52.18	84
1991	200	258.56	241	64	54.51	110
1992	197	246.84	203	45	57.92	78
1993	264	256.15	160	41	59.47	69
1994	208	196.90	67	27	65.26	55
1995	194	204.38	83	28	62.50	68
1996	216	210.71	80	24	63.27	64
1997	288	189.09	69	19	61.64	63
1998	181	242.31	71	20	36.99	108
1999	352	240.79	179	55	55.21	150
2000	488	233.36	286	66	47.05	230
2001	484	257.50	527	96	46.57	382
2002	586	224.15	632	116	50.52	291
2003	471	244.91	347	70	70.14	209
2004	175	278.57	150	35	70.90	110
2005	235	176.75	129	17	72.65	99
2006	57	279.08	65	16	70.05	77
2007	14	162.50	33	6	78.14	99
2008	80	292.21	122	23	47.89	237
2009	159	425.49	401	73	64.24	253
2010	68	308.46	52	16	59.38	110
Total (**Mean**)	5,463	**246.69**	4,289	940	**57.98**	3,069

Panel B. Industry distribution

Industry	From DealScan		From CreditPro			From BankruptcyData .com
	Number of loan facilities	Average all-in spread (bps)	Number of defaulted instruments	Number of defaulted companies	Ave. industry recovery rate (%)	Number of bankruptcy events
Consumer Non-durables	180	235.83	334	95	56.77	221
Consumer Durables	290	305.16	199	42	61.98	115
Manufacturing	323	260.17	512	128	58.65	331
Energy	719	240.15	172	47	64.22	123
Chemicals	33	221.71	72	18	58.22	59
Business Equipment	475	264.72	276	68	51.98	380
Telecom	697	279.68	735	111	57.05	204
Utilities	722	132.03**	263	24	77.82**	39
Wholesale and Retail	957	251.16	690	172	55.69	526
Healthcare	147	256.89	149	38	48.86	195
Finance	180	231.63	186	37	52.66	285
Other	740	281.16	701	160	51.86	591
Total (**Mean**)	5,463	**246.69**	4,289	940	**57.98**	3,069

**indicates significantly different from other group means at the 5% level using Scheffé's (1999) test.

Table 2 Distribution of loan contract terms over industry bankruptcy wave

This table documents the distribution of loan contract terms over industry bankruptcy wave. Loan contract terms (i.e., all-in spread, secured or not, and covenant intensity) are obtained from DealScan. Industry recovery rate is from S&P's CreditPro. Please refer to the Appendix for their detailed definitions. The four different phases of the industry bankruptcy wave are defined based on average industry default rates calculated according to the default events obtained from BankruptcyData.com. Specifically, the four phases are: (1) *Beginning*: industry default rate is below (above) 1% in the 12 months before (after) the loan origination date; (2) *Middle*: industry default rate is above 1% in both the 12-month periods before and after the loan origination date; (3) *Ending*: industry default rate is above (below) 1% in the 12 months before (after) the loan origination date; (4) *Outside*: the loan origination date is not located in an industry-specific bankruptcy wave (i.e., not belonging to *Beginning*, *Middle*, or *Ending*).

Industry bankruptcy wave	Number of loan facilities	Average all-in spread (bps)	Secured	Covenant intensity	Industry recovery rate %
Beginning of bankruptcy wave	857	220.11	0.455	1.455	63.63
Middle of bankruptcy wave	2,126	261.84	0.510	1.636	55.43
Ending of bankruptcy wave	1,061	253.35	0.506	1.511	72.09
Outside bankruptcy wave	932	200.06	0.441	0.896	66.88
t-test					
Differences (Middle- Outside wave)		61.780***	0.069***	0.740***	-11.450***

*** represents significance at the 1% level.

Table 3 Summary statistics

Variable	N	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
Main Variables:						
Loan Spread	5,463	241.699	215.376	87.500	200.000	325.000
Covenant Intensity	5,463	1.452	1.728	0.000	1.000	2.000
Industry Recovery Rate	5,463	0.617	0.271	0.461	0.626	0.832
Risk Variables:						
MDE	5,038	0.098	0.052	0.065	0.084	0.120
Market Beta	4,799	-2.124	34.787	0.079	0.334	0.680
Firm Default Risk	3,787	0.027	0.121	<0.0001	<0.0001	<0.0001
Industry Default Risk	5,119	0.005	0.018	0.000	0.001	0.003
Borrower Characteristics:						
Log (assets)	4,967	6.794	2.178	5.255	6.739	8.387
Leverage	4,965	1.150	41.504	0.397	0.528	0.677
Tobin’s q	4,314	1.304	22.165	0.324	0.651	1.187
Tangibility	4,897	0.454	0.268	0.225	0.445	0.681
Investment	4,789	0.230	0.297	0.092	0.168	0.291
Profitability	4,868	0.200	68.016	0.061	0.137	0.282
Rating Dummy A	5,463	0.087	0.282	0.000	0.000	0.000
Rating Dummy BBB	5,463	0.135	0.342	0.000	0.000	0.000
Rating Dummy BBC	5,463	0.732	0.443	0.000	1.000	1.000
Deal Characteristics:						
Log (amount)	5,463	18.189	1.826	17.034	18.421	19.501
Log (maturity)	5,170	3.445	0.837	2.565	3.584	4.094
Performance pricing	5,463	0.284	0.451	0.000	0.000	1.000
Financial covenant	5,463	0.413	0.492	0.000	0.000	1.000
Secured	5,463	0.492	0.500	0.000	0.000	1.000
Senior	5,463	0.793	0.084	0.000	1.000	1.000
Loan purposes						
Corporate purpose	5,463	0.323	0.467	0.000	0.000	1.000
Work capital purpose	5,463	0.173	0.378	0.000	0.000	0.000
Takeover purpose	5,463	0.064	0.244	0.000	0.000	0.000
Loan types						
Term loan	5,463	0.296	0.456	0.000	0.000	1.000
Credit line	5,463	0.504	0.500	0.000	1.000	1.000
Bridge loan	5,463	0.019	0.138	0.000	0.000	0.000
Refinancing	5,463	0.012	0.109	0.000	0.000	0.000
Guarantor	5,463	0.057	0.233	0.000	0.000	0.000
Sponsor	5,463	0.062	0.241	0.000	0.000	0.000
Syndicated	5,463	0.793	0.405	0.000	0.000	1.000
Relationship	5,463	0.324	0.468	0.000	0.000	1.000
Macroeconomics factors:						
BBB spread	5,463	0.935	0.296	0.750	0.840	1.100
TED spread	5,463	0.424	0.246	0.235	0.364	0.536
GDP growth rate	5,463	2.775	1.643	1.776	2.791	4.091

Table 4. The effect of industry recovery rate on loan spread

We conduct the regression based on Equation (1) with the loan spread of individual facility at origination as our dependent variable and industry recovery rate together with four different risk factors (*MDE*, *Market Beta*, *Firm Default Risk*, and *Industry Default Risk*) as our main independent variables. In the regression, we control for a number borrower characteristics, deal characteristics, and macroeconomic factors that may also affect loan pricing. We also control for the industry fixed effect, where industry is defined based on the Fama-French 12-industry classification. Detailed definitions of the variables can be found in the Appendix. The regression results on our full sample are reported under Columns (1) to (4) with different combinations of the four risk factors. We also conduct a regression by excluding those loans in the Utilities and Financial Services industries (Column (5)). We then examine the role played by the industry-specific bankruptcy wave by including the dummy variables representing different phases of the wave and the interaction variables of these dummies with industry recovery rate in our regression (i.e., Equation (2)). The full sample results are reported under Columns (6) and (7). The subsample results after excluding loans in the Utilities and Financial Services industry are reported under Columns (8) and (9). All the t-statistics (in parentheses) are based on robust standard errors that are adjusted for heteroskedasticity. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Independent variables	Dependent variable: Loan spread								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry Recovery Rate	-0.104**	-0.121***	-0.126***	-0.163***	-0.315***	-0.196***	-0.116*	-0.332***	-0.150*
	(-2.57)	(-2.85)	(-2.94)	(-3.87)	(-6.24)	(-4.57)	(-1.70)	(-6.60)	(-1.89)
MDE		1.929***		2.003***	2.394***	2.606***	2.913***	2.698***	2.926***
		(7.93)		(6.60)	(7.26)	(8.36)	(9.00)	(8.17)	(8.88)
Market Beta		0.001		0.000	0.000	0.000	0.000	0.001	0.000
		(0.82)		(0.29)	(0.88)	(0.39)	(0.22)	(0.90)	(0.32)
Firm Default Risk			0.296*	0.356**	0.473**	0.357**	0.637***	0.467***	0.641***
			(1.72)	(1.99)	(2.50)	(2.08)	(4.82)	(2.61)	(4.85)
Industry Default Risk			2.230***	2.228***	2.064**	1.694*	2.586***	1.758**	2.587***
			(2.72)	(2.61)	(2.53)	(1.91)	(4.50)	(2.16)	(4.50)
Beginning						0.284***	0.305***	0.304***	0.578***
						(8.81)	(2.68)	(5.97)	(4.19)
Middle						0.228***	0.343***	0.222***	0.417***
						(6.78)	(2.70)	(4.56)	(3.15)
Ending						0.273***	0.356**	0.245***	0.426***
						(9.56)	(2.53)	(4.97)	(2.94)
Beginning ×Industry Recovery Rate							-0.319*		-0.334*
							(-1.77)		(-1.83)
Middle ×Industry Recovery Rate							-0.329**		-0.371**
							(-2.35)		(-2.49)
Ending ×Industry Recovery Rate							-0.146		-0.217
							(-0.77)		(-1.10)
Log (assets)	0.004	0.005	-0.008	-0.006	0.018	-0.007	-0.015	0.014	-0.016
	(0.38)	(0.58)	(-0.83)	(-0.57)	(1.44)	(-0.75)	(-1.31)	(1.10)	(-1.39)
Leverage	0.243***	0.269***	0.268***	0.252***	0.284***	0.213***	0.300***	0.296***	0.297***

	(5.03)	(5.19)	(4.58)	(4.13)	(4.46)	(3.56)	(4.71)	(4.67)	(4.64)
Tobin's q	-0.112***	-0.097***	-0.087***	-0.084***	-0.094***	-0.077***	-0.068***	-0.088***	-0.067***
	(-6.67)	(-5.67)	(-4.74)	(-4.55)	(-4.83)	(-4.43)	(-3.78)	(-4.74)	(-3.77)
Tangibility	0.052	0.125**	0.172***	0.178***	0.285***	0.171***	0.273***	0.265***	0.267***
	(0.92)	(2.10)	(2.67)	(2.70)	(3.77)	(2.62)	(3.64)	(3.52)	(3.56)
Investment	-0.315***	-0.248**	-0.158	-0.063	-0.264**	-0.121	0.095	-0.225*	0.084
	(-3.40)	(-2.47)	(-1.45)	(-0.56)	(-2.17)	(-1.07)	(0.88)	(-1.83)	(0.78)
Profitability	-0.022	-0.022	-0.036	-0.021	-0.028	-0.003	0.040	0.001	0.050
	(-0.62)	(-0.57)	(-0.64)	(-0.37)	(-0.45)	(-0.05)	(0.69)	(0.01)	(0.85)
Rating Dummy A	-0.751***	-0.675***	-0.672***	-0.682***	-0.877***	-0.685***	-0.613***	-0.869***	-0.613***
	(-15.34)	(-13.61)	(-13.46)	(-13.64)	(-13.83)	(-13.38)	(-10.94)	(-13.91)	(-10.95)
Rating Dummy BBB	-0.179***	-0.164***	-0.121**	-0.138***	-0.324***	-0.115**	-0.057	-0.330***	-0.060
	(-3.72)	(-3.35)	(-2.46)	(-2.81)	(-5.06)	(-2.25)	(-1.03)	(-5.13)	(-1.07)
Rating Dummy BBC	0.323***	0.348***	0.348***	0.327***	0.327***	0.339***	0.479***	0.315***	0.482***
	(6.62)	(6.83)	(6.64)	(6.15)	(5.75)	(6.30)	(8.58)	(5.60)	(8.64)
Log(amount)	-0.147***	-0.149***	-0.142***	-0.141***	-0.161***	-0.136***	-0.130***	-0.161***	-0.131***
	(-15.23)	(-14.98)	(-14.28)	(-13.85)	(-10.82)	(-13.17)	(-9.55)	(-11.05)	(-9.63)
Log(maturity)	-0.056***	-0.049***	-0.056***	-0.064***	-0.059*	-0.050***	-0.072***	-0.065**	-0.073***
	(-3.47)	(-2.90)	(-3.21)	(-3.51)	(-1.84)	(-2.73)	(-3.36)	(-2.09)	(-3.37)
Performance pricing	-0.121***	-0.119***	-0.123***	-0.118***	-0.111***	-0.122***	-0.122***	-0.106***	-0.123***
	(-5.30)	(-4.91)	(-4.98)	(-4.65)	(-3.41)	(-4.91)	(-4.32)	(-3.26)	(-4.33)
Financial covenant	0.239***	0.232***	0.229***	0.230***	0.238***	0.227***	0.246***	0.238***	0.249***
	(9.49)	(8.44)	(8.31)	(7.96)	(6.14)	(7.98)	(7.63)	(6.20)	(7.72)
Secured	0.363***	0.358***	0.356***	0.365***	0.312***	0.362***	0.227***	0.327***	0.223***
	(12.39)	(11.37)	(10.88)	(10.51)	(8.15)	(10.67)	(6.31)	(8.63)	(6.25)
Senior	-0.283	-0.286	-0.193	-0.143	-0.060	-0.217	-0.005	-0.130	0.012
	(-0.84)	(-0.85)	(-0.56)	(-0.41)	(-0.16)	(-0.64)	(-0.02)	(-0.36)	(0.04)
Corporate purpose	0.010	-0.007	-0.007	-0.007	0.031	0.018	-0.028	0.042	-0.024
	(0.51)	(-0.35)	(-0.32)	(-0.34)	(0.93)	(0.93)	(-1.11)	(1.26)	(-0.97)
Work capital purpose	0.116***	0.086***	0.089***	0.086***	0.093***	0.091***	0.092***	0.095***	0.100***
	(5.24)	(3.82)	(3.73)	(3.66)	(2.58)	(3.88)	(3.27)	(2.65)	(3.60)
Takeover purpose	0.045	0.073	0.095*	0.120**	0.224***	0.093*	0.153***	0.211***	0.144***
	(0.95)	(1.49)	(1.88)	(2.30)	(4.20)	(1.83)	(2.83)	(4.01)	(2.70)
Term loan	0.412***	0.401***	0.424***	0.416***	0.295***	0.454***	0.482***	0.327***	0.486***
	(9.73)	(9.15)	(9.12)	(8.79)	(4.39)	(9.66)	(9.24)	(4.92)	(9.30)
Credit line	0.114***	0.098***	0.131***	0.117***	0.184***	0.151***	0.263***	0.195***	0.268***
	(4.12)	(3.52)	(4.43)	(3.92)	(3.86)	(5.11)	(7.56)	(4.16)	(7.68)
Bridge loan	0.540***	0.557***	0.600***	0.593***	0.864***	0.634***	0.785***	0.912***	0.822***
	(5.77)	(5.91)	(6.41)	(6.36)	(5.26)	(6.54)	(7.49)	(5.87)	(8.18)
Refinancing	0.046	0.053	0.060	0.065	0.147	-0.007	0.086	0.091	0.088

	(0.16)	(0.20)	(0.22)	(0.25)	(1.07)	(-0.03)	(0.28)	(0.57)	(0.29)
Guarantor	0.134***	0.086**	0.144***	0.089**	0.007	0.110**	-0.117**	-0.022	-0.113**
	(3.27)	(2.20)	(3.21)	(2.17)	(0.14)	(2.57)	(-2.57)	(-0.43)	(-2.50)
Sponsor	0.163***	0.193***	0.166***	0.201***	0.180***	0.171***	0.111*	0.157**	0.105*
	(4.16)	(3.86)	(3.59)	(3.26)	(2.83)	(2.65)	(1.76)	(2.36)	(1.65)
Syndicated	-0.162**	-0.215**	-0.104	-0.164*	-0.037	-0.196**	-0.135*	-0.049	-0.136*
	(-2.08)	(-2.57)	(-1.14)	(-1.70)	(-0.35)	(-2.05)	(-1.65)	(-0.48)	(-1.66)
Relationship	0.053***	0.064***	0.071***	0.077***	0.071***	0.068***	0.101***	0.070***	0.104***
	(3.28)	(3.91)	(4.16)	(4.58)	(2.99)	(4.12)	(5.03)	(2.95)	(5.10)
BBB spread	0.498***	0.500***	0.541***	0.421***	0.289***	0.247***	0.361***	0.283***	0.346***
	(9.52)	(9.39)	(8.81)	(7.20)	(4.13)	(3.98)	(5.52)	(3.98)	(5.28)
TED spread	-0.442***	-0.586***	-0.705***	-0.816***	-0.639***	-0.709***	-0.724***	-0.650***	-0.677***
	(-5.27)	(-7.45)	(-7.77)	(-11.07)	(-7.76)	(-9.68)	(-9.29)	(-8.24)	(-9.22)
GDP growth rate	-0.046***	-0.037***	-0.034***	-0.034***	-0.022**	-0.040***	-0.024**	-0.022**	-0.027**
	(-5.20)	(-4.03)	(-3.42)	(-3.44)	(-1.99)	(-3.91)	(-2.15)	(-1.97)	(-2.43)
Intercept	7.802***	7.669***	7.537***	7.493***	7.563***	7.298***	6.536***	7.434***	6.481***
	(21.27)	(21.12)	(19.46)	(19.40)	(17.42)	(19.21)	(16.40)	(17.77)	(16.32)
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,945	4,579	4,443	4,298	2,528	4,298	4,298	2,528	2,528
adj. R^2	0.732	0.739	0.718	0.727	0.770	0.735	0.701	0.774	0.703

Table 5. Significance of fire-sale channel given different industry, company, and market characteristics

We further verify the fire-sale channel of industry contagion by repeating our benchmark regression on different subsamples that we expect are different in their susceptibility to fire-sale discount. For each subsample, we conduct the regression based on Equation (1) with the loan spread of individual facility at origination as our dependent variable and industry recovery rate together with four different risk factors (*MDE*, *Market Beta*, *Firm Default Risk*, and *Industry Default Risk*) as our main independent variables. In each regression, we control for a number borrower characteristics, deal characteristics, and macroeconomic factors that may also affect loan pricing. Detailed definitions of these variables can be found in the Appendix. We also control for the industry fixed effect, where industry is defined based on the Fama-French 12-industry classification. All the t-statistics (in parentheses) are based on robust standard errors that are adjusted for heteroscedasticity. To conserve space, we only present the estimated coefficients (and their significance) for industry recovery rate and the four risk factors. We consider altogether 10 pairs of subsamples, of which the regression results are reported in Panels A and B. The 10 pairs of subsamples are constructed based on various characteristics of the industry the borrower belongs to, the characteristics of the borrower and the loan facility, and market characteristic. Specifically, they are partitioned based on: (i) low vs. high degree of industry's asset specificity (Columns (1) and (2)), (ii) low vs. high industry's asset growth rate (Columns (3) and (4)), (iii) low vs. high amount of industry's debt overhang (Columns (5) and (6)), (iv) low vs. high industry's quick ratio (Columns (7) and (8)), (v) low vs. high degree of industry's financial constraint (Columns (9) and (10)), (vi) whether the industry is governed by any anti-trust law (Columns (11) and (12)), (vii) low vs. high degree of industry's market concentration (Columns (13) and (14)), (viii) investment vs. non-investment grade borrowers (Columns (15) and (16)), (ix) whether the loan facility is secured or not (Columns (17) and (18)), and (x) low vs. high degree of market liquidity (Columns (19) and (20)). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A.

Independent variables	Dependent variable: Loan Spread									
	Degree of industry's asset specificity		Industry's asset growth rate		Amount of industry's debt overhang		Industry's quick ratio		Degree of industry's financial constraint	
	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Industry Recovery Rate	-0.138	-0.250***	-0.379***	0.017	-0.090	-0.410***	-0.171***	-0.089	-0.097	-0.189***
	(-0.50)	(-3.37)	(-4.23)	(0.23)	(-0.56)	(-4.97)	(-2.67)	(-0.80)	(-1.05)	(-2.77)
MDE	0.242	3.092***	1.711***	3.259***	1.655***	2.519***	1.338***	4.416***	3.970*	2.643***
	(0.26)	(6.14)	(3.97)	(5.99)	(3.11)	(6.06)	(3.10)	(5.81)	(1.71)	(7.56)
Market Beta	0.126**	0.001	0.000	0.077**	1.122***	0.001***	0.000	0.003	0.044	0.000
	(1.99)	(1.46)	(0.58)	(2.13)	(13.38)	(2.75)	(0.08)	(0.46)	(0.29)	(0.34)
Firm Default Risk	0.174	1.094***	0.413***	0.360	0.302	0.461***	0.767***	0.065	0.056	0.951***
	(0.67)	(4.27)	(2.79)	(0.87)	(0.88)	(3.07)	(4.07)	(0.32)	(0.14)	(5.71)
Industry Default Risk	4.487	2.911***	0.369	4.547**	2.100*	4.048***	3.272***	2.141**	11.795***	5.642***
	(1.07)	(3.87)	(0.56)	(1.96)	(1.73)	(5.13)	(3.31)	(2.27)	(5.23)	(3.89)
Borrower Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomics Factors Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,151	2,147	2,130	2,168	2,685	1,613	1,963	2,335	2,278	2,020
adj. R^2	0.825	0.691	0.740	0.697	0.691	0.705	0.701	0.704	0.659	0.684

Panel B:

	Dependent variable: Loan Spread									
	Industry governed by anti-trust law		Degree of industry's market concentration		Borrower's credit rating		Loan contracts that are secured		Degree of market liquidity	
Independent variables	No	Yes	Low	High	Investment grade	Non-investment grade	No	Yes	Low	High
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Industry Recovery Rate	-0.109	-0.177***	-0.007	-0.266***	-0.015	-0.126*	-0.064	-0.247***	-0.176***	-0.106
	(-0.94)	(-2.97)	(-0.05)	(-4.66)	(-0.17)	(-1.85)	(-0.66)	(-3.39)	(-2.67)	(-1.13)
MDE	26.168***	3.097***	3.919***	0.991***	2.437***	1.626***	4.368***	0.336	0.732*	2.539***
	(6.15)	(9.08)	(4.90)	(2.66)	(4.56)	(4.17)	(6.34)	(0.84)	(1.74)	(4.22)
Market Beta	0.337***	0.000	0.002***	0.061***	0.029	0.001*	0.075*	0.000	0.025***	0.001
	(5.00)	(0.94)	(3.34)	(2.79)	(0.93)	(1.68)	(1.74)	(0.45)	(5.42)	(1.56)
Firm Default Risk	1.414**	0.363***	1.214***	0.386***	4.167	0.439***	0.739**	0.562***	0.846***	0.462**
	(2.60)	(2.71)	(3.28)	(2.83)	(1.31)	(3.59)	(2.56)	(3.46)	(5.11)	(2.22)
Industry Default Risk	24.265	2.077***	-1.019	1.514**	1.465	2.067***	4.017**	0.059	7.930***	4.062***
	(0.84)	(3.24)	(-0.10)	(2.58)	(1.19)	(2.71)	(2.14)	(0.08)	(8.90)	(3.48)
Borrower Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomics Factors Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,781	2,517	1,375	2,923	2,870	1,428	1,779	2,519	2,448	1,810
adj. R^2	0.669	0.662	0.977	0.690	0.690	0.571	0.722	0.603	0.738	0.677

Table 6. The role of information asymmetry

To examine the role played by the information channel of industry contagion, we repeat our benchmark regression on different subsamples that are different in terms of their information efficiency. For each subsample, we conduct the regression based on Equation (1) with the loan spread of individual facility at origination as our dependent variable and industry recovery rate together with four different risk factors (*MDE*, *Market Beta*, *Firm Default Risk*, and *Industry Default Risk*) as our main independent variables. In each regression, we control for a number borrower characteristics, deal characteristics, and macroeconomic factors that may also affect loan pricing. Detailed definitions of these variables can be found in the Appendix. We also control for the industry fixed effect, where industry is defined based on the Fama-French 12-industry classification. All the t-statistics (in parentheses) are based on robust standard errors that are adjusted for heteroscedasticity. To conserve space, we only present the estimated coefficients (and their significance) for industry recovery rate and the four risk factors. The first pair of subsamples are constructed according to the firm size of the borrower. The large-size firm subsample is made up of borrowers belonging to the top 30% of their respective four-digit SIC code based on their asset values; whereas the small-size firm subsample is made up of those in the bottom 30%. The regressions results are reported under Columns (1) and (2). The second pair is based on the probability of information-based trading (PIN) measure developed by Easley at al. (2002). Borrowers are considered to be subject to low (high) information asymmetry if their PIN is in the bottom (top) 30% among their peers in the same industry. The regression results of these two subsamples are reported under Columns (3) and (4). Finally, we construct two subsamples based on the informational environment of the general market as proxied by the volatility index (VIX) of the Chicago Board Options Exchange (CBOE). We construct two subsamples based on the time a loan is originated. The low-VIX (high-VIX) subsample consists of loans that are originated in those years where the VIX are in the bottom (top) 30% among the annual average VIX values realized over our sample period. The regression results are reported in Columns (5) and (6). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Loan Spread					
Independent variables	Low asym. information	High asym. information	Low asym. information	High asym. information	Low asym. information	High asym. information
	Large Size firms in each industry	Small Size firms in each industry	Low PIN firms in each industry	High PIN firms in each industry	Low CBOE VIX	High CBOE VIX
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Recovery Rate	-0.078	-0.309***	-0.025	-0.317***	-0.089	-0.164**
	(-0.73)	(-4.57)	(-0.21)	(-5.12)	(-0.41)	(-2.32)
MDE	1.386**	3.409***	0.158	2.580***	3.601**	3.377***
	(2.26)	(7.00)	(0.22)	(5.91)	(2.13)	(6.58)
Market Beta	0.017***	0.035	0.001**	0.061**	0.001**	0.122***
	(5.18)	(1.33)	(2.34)	(2.46)	(2.34)	(3.61)
Firm Default Risk	0.459***	0.674***	0.173	0.584***	0.428*	1.225***
	(3.12)	(3.18)	(0.91)	(3.64)	(1.91)	(6.75)
Industry Default Risk	2.105***	5.362***	2.036	5.484***	2.699	4.523***
	(2.80)	(7.11)	(1.46)	(9.56)	(1.58)	(7.05)
Borrower Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes
Deal Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomics Factors Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	814	1,823	845	1,838	585	1,417
adj. R^2	0.697	0.739	0.615	0.758	0.655	0.758

Table 7. The effect of industry recovery rate on non-pricing terms of loans

To examine the effect of industry recovery rate on the non-pricing terms of loans, we conduct the regressions based on Equations (3) and (4) with the secured loan indicator variable and the covenant intensity index of the loan facility as our dependent variables and industry recovery rate together with the four different risk factors (*MDE*, *Market Beta*, *Firm Default Risk*, and *Industry Default Risk*) as our main independent variables. We control for a number borrower characteristics, deal characteristics, macroeconomic factors, and the all-in spread of the loan that may also influence the non-pricing terms of the contract. Detailed definitions of these variables can be found in the Appendix. We also control for the industry fixed effect, where industry is defined based on the Fama-French 12-industry classification. All the t-statistics (in parentheses) are based on robust standard errors that are adjusted for heteroscedasticity. To conserve space, we only present the estimated coefficients (and their significance) for our main variables of interest. We follow Bradley and Roberts (2004) in constructing the covenant intensity index based on the sum of six covenant indicators: (i) whether the loan is secured, (ii) whether there are restrictions on dividend, (iii) whether there are more than two financial covenants, (iv) whether there are asset sale sweeps, (v) whether there are debt issuance sweeps, and (vi) whether there are equity issuance sweeps. The index value therefore lies between 0 and 6, with 0 (6) being least (most) restrictive. The full sample regression results are reported under Columns (1) and (2). The results after excluding loans in the Utilities and Financial Services industries are presented under Columns (3) and (4). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	Whole sample		Excluding Utilities and Financial Services industries	
	Loan is secured (Y/N)	Covenant Intensity	Loan is secured (Y/N)	Covenant Intensity
	(1)	(2)	(3)	(4)
Industry Recovery Rate	-0.166***	-0.186*	-0.170***	-0.310***
	(-4.80)	(-1.80)	(-3.60)	(-2.58)
MDE	-0.626**	-2.291***	-0.746**	-1.547*
	(-2.47)	(-2.82)	(-2.11)	(-1.81)
Market Beta	-0.014	0.001	-0.013**	0.000
	(-1.51)	(0.69)	(-2.38)	(0.30)
Firm Default Risk	0.208***	-1.696***	0.253**	-1.874***
	(2.86)	(-6.11)	(2.56)	(-6.31)
Industry Default Risk	-1.390***	4.380***	-1.588***	5.820***
	(-3.99)	(3.86)	(-3.49)	(4.92)
Loan Spread	0.104***	0.516***	0.172***	0.489***
	(6.64)	(10.46)	(7.97)	(8.13)
Borrower Characteristics Control	Yes	Yes	Yes	Yes
Deal Characteristics Control	Yes	Yes	Yes	Yes
Macroeconomics Factors Control	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes
N	3,421	3,421	2,401	2,401
adj. R^2		0.587		0.587
(Pseudo) R^2	0.519		0.499	

Table 8. Robustness Test – Two-stage regression

To address the potential endogeneity issue regarding industry recovery rate, we conduct a two-stage regression. In the first-stage regression, the dependent variable is the observed company-level recovery rate from S&P's CreditPro database. We use three instrumental variables: (i) a dummy variable indicating whether the bankruptcy is filed in Delaware or not; (ii) a dummy variable indicating whether the bankruptcy is filed in New York or not; and (iii) the time between the bankruptcy date and the emergence date of the bankruptcy process. We control for the same set of company-level variables and macroeconomic factors that we considered in our previous regressions. To conserve space, we do not report the results of the first-stage regression. We then calculate the *fitted* value of industry recovery rate by taking the average of the *fitted* recovery rates of individual defaulted companies (obtained from the first-stage regression) within each four-digit SIC code industry. This *fitted* industry recovery rate is then used to replace the *observed* industry recovery rate in the second-stage regression, where the dependent variable is the loan spread at origination. We control for the four different risk factors (*MDE*, *Market Beta*, *Firm Default Risk*, and *Industry Default Risk*) together with a number borrower characteristics, deal characteristics, and macroeconomic factors that may also affect loan pricing. We also control for the industry fixed effect, where industry is defined based on the Fama-French 12-industry classification. Detailed definitions of the variables can be found in the Appendix. The results of the second-stage regression are reported in this table. All the t-statistics (in parentheses) are based on robust standard errors that are adjusted for heteroscedasticity. To conserve space, we only present the estimated coefficients (and their significance) for our main variables of interest. The regression results based on our full sample can be found under Columns (1) to (4) with different combinations of the four risk factors. We also repeat the regression after excluding the loans in the Utilities and Financial Services industries (Column (5)). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Independent variables	Dependent Variable: Loan Spread				
	(1)	(2)	(3)	(4)	(5)
Industry Recovery Rate (*fitted*)	-1.759***	-1.633***	-1.672***	-1.814***	-1.836***
	(-7.10)	(-6.67)	(-8.00)	(-7.26)	(-7.27)
MDE		2.401***		2.484***	2.572***
		(7.05)		(5.73)	(5.84)
Market Beta		0.000		0.000	0.000
		(0.78)		(0.35)	(0.33)
Firm Default Risk			0.747***	0.849***	0.855***
			(4.35)	(4.54)	(4.55)
Industry Default Risk			2.100***	2.979***	2.998***
			(3.64)	(5.17)	(5.19)
Borrower Characteristics Control	Yes	Yes	Yes	Yes	Yes
Deal Characteristics Control	Yes	Yes	Yes	Yes	Yes
Macroeconomics Factors Control	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
N	4,945	4,579	4,443	4,294	2,528
adj. R^2	0.561	0.597	0.567	0.569	0.568

Figure 1: Bankruptcy waves of the Wholesale and Retail industry