Mind the Cost of Disturbance:

Firm-Level Supply Chain Risk and the Bank Loan Cost

Daxuan Cheng [a] Lei Gao [b] Yin Liao [a] Zheyao Pan [a*]

Abstract

We investigate how the credit market evaluates firm-level supply chain risk. We document that supply chain risk is associated with unfavorable loan condition changes, which leads to extra loan costs including a significant increase in the loan interest spread and collateralization requirement. The response of bank loan cost is exceptionally pronounced when the information asymmetry between borrower firms and their bank lenders is exaggerated, including weaker prior lending relationships, smaller-size banks, or less accumulated knowledge of the borrower's industry. In addition, we also provide evidence that bank creditors learn information about supply chain risk from borrowers' earnings calls. Overall, we show that the bank market treats the supply chain risk as an unfavourable factor and has incorporated it into the loan contracts. This emphasizes the importance of supply chain risk management in firm operations.

Keywords: Supply chain risk, Bank loan, Loan interest spread, Earnings conference call

---

We are grateful for constructive comments and suggestions from Charlene Chen, Yi Chen, Mingze Gao, Tom Smith, Gary Tian, Clara Zhou, and seminar participants at Macquarie University. All errors remain our own.

[a] Macquarie Business School, Macquarie University, Australia. Emails: daxuan.cheng@mq.edu.au; yin.liao@mq.eu.au; terry.pan@mq.edu.au.

[b] School of Business, George Mason University, United States. Email: lgao9@gmu.edu.

1. Introduction

The importance of supply chains to firm operations cannot be overstated. Modern corporate production and operation heavily rely on global supply chains that have been meticulously optimized and connected to improve efficiency and minimize costs. However, the complexity and interdependence characteristics are associated with the fragility of the supply chain network and make firms vulnerable to the disruptions caused by unexpected events such as the COVID-19 pandemic, the China-America trade war, the Russia-Ukraine conflict, and natural disasters like earthquakes and hurricanes. Even minor shocks can propagate and be exaggerated throughout the supply chain, reverberating far beyond manufacturing firms. According to industrial research by JP Morgan [May 2022]:

> "*Supply chain problems were prominent during the COVID-19 lockdown amid a 'perfect storm' of causes, including shifts in demand, labour shortages, and structural factors. The Russia-Ukraine conflict and COVID-19 lockdowns in China have recently exacerbated issues, affecting supply in certain sectors including consumer goods, metals, food, chemicals and commodities*"[1].

They find that supply chain distress problems widely disrupted various industries, including metals and mining, chemical supply, the automotive sector, semiconductor, and technology industries. At the same time, supply chain risk exposure varies significantly at the firm level. For example, product manufacturing is subject to the supply of different materials, while different logistics and climate risks can be related to the choice of plant or head office locations (Ersahin et al., 2024b). Thus, even similar firms within the same industry may have distinct risk exposures due to differentiated positioning in the supply chain and corporate strategy. Yet little is known of such differences currently because research has only begun to explore firms' exposure to supply chain risk (Singhal & Singhal, 2012; Sodhi et al., 2012). In this study, we join the recent literature estimating the supply chain risk and its economic implications (Ersahin et al., 2024a; Wu, 2024) by studying how firm-level supply chain risk exposure affects corporate financing through the lens of bank loans.

Bank credit constitutes a significant source of corporate financing. Almost all major banks and lending institutions are paying close attention to the supply chain conditions of borrower firms. Many of them

[1] https://www.jpmorgan.com/insights/global-research/supply-chain/global-supply-chain-issues. Another anecdotic evidence is the report from Commonwealth Bank of Australia in August 2022, "*The sectors most affected by supply chain issues were production (58%), retail and hospitality (53%), distribution (52%), and construction (48%).*" https://www.commbank.com.au/articles/business/foresight/rising-costs-and-supply-chain-issues-stimulate-innovation.html.

have launched specialized supply chain financing (SCF) programs in recent years. In addition to providing liquidity to firms from both upstream and downstream of the supply chain, these bank programs assist their firm clients in supporting supplier-customer relationships and maintaining production and operation continuity. Theoretically, bank creditors are expected to assess and price the supply chain risk for three main reasons: first, supply chain disruption shock may lead to unexpected financial losses for banks through borrowers' potential default or delay; second, the supply chain network volatility of the borrower firms could raise agency costs for banks, as they cannot share the equivalent return while risk exposure increases, and third, the high complexity of supply chain risk raises the information asymmetry and friction cost for banks. However, the literature remains unclear on how lenders in the banking credit market assess the supply chain risks that borrower firms perceive. This study examines how the bank credit market evaluates the supply chain health of borrower firms, showing the negative influence of supply chain risk exposure on a firm's creditworthiness and loan lending conditions. Detailed loan-level data allows us to investigate how the supply chain risk information disclosed from earnings conference calls influences loan negotiations between firms and their bank lenders. We demonstrate the impact of supply chain risk on bank loan costs. Our results are novel in revealing extra loan costs associated with firms' exposure to supply chain risk.

To perform our tests, we utilize the SCRisk dataset developed by Ersahin et al. (2024a). Based on a natural language process algorithm, this firm-year level dataset captures stakeholders' risk concerns about supply chain issues through earnings conference call transcripts. Our bank loan variables are sourced from the DealScan database. A comprehensive test sample is formed with 9,879 loan tranche observations of 2,065 borrower firms from 2003 to 2020. We add information on firm-level characteristics and macroeconomic factor data to further sharpen our inferences.

Our baseline results in brief are as follows. Higher supply chain risk disclosed through earnings calls generally increases both the interest rate spreads and the likelihood of collateral requirement featured in bank loans. These effects are statistically and economically significant. Controlling for three levels of characteristics as well as industry and lender fixed effects, a one-standard-deviation increase in supply chain risk leads to 5.04 basis points higher interest spreads on bank loans, or a 2.38% higher loan markup compared to an average spread of 212.64 basis points. Economically, this represents more than 200,000 dollars of extra loan costs for a firm annually on average. We also show that the total cost of borrowing (Berg et al., 2016), a more comprehensive loan cost measurement that takes into account various fee types in loan contracts, is 4.54 basis points higher associated with a one-standard-deviation increase of firm-level supply chain risk. Additionally, the same increase also significantly leads to an 8.3% higher likelihood of collateral requirement in the loan contracts.

We perform a battery of robustness checks to deepen our baseline results. First, we add customer concentration indicators as extra controls to establish the unique role of supply chain risk in loan contracts beyond customer relationships (Cai & Zhu, 2020; Campello & Gao, 2017). Second, we switch to two different sets of control variables and time-period matching procedures (Bharath et al., 2011; Campello & Gao, 2017) to confirm that the specific estimation model does not drive our results. To address endogeneity concerns, we further use the maximum risk value of supply chain stakeholders as the instrument variable and estimate a two-stage least-squares regression (2SLS) following the approach in Ersahin et al. (2024a). Consistent with the baseline results, the test results above indicate a robust association between the supply chain risk and the loan interest spread of borrower firms.

Next, we conduct two extended analyses to further explore how banks perceive the firm-level supply chain risk. First, we conduct a series of sub-sample tests and find that the influence of supply chain risk on loan cost is only pronounced when the borrower firms have weaker or no prior relationship with their bank lenders. In addition, the influence is also exceptionally significant when the lenders are small-size banks or when they have accumulated less industry knowledge of the borrower firms. The cross-sectional variability can be mainly attributed to incremental information asymmetry as well as the extra costs that bank lenders pay to investigate the supply chain element during the ex-ante assessment and the ex-post monitoring procedures. Therefore, the results further support our view that bank lenders treat the supply chain risk of borrower firms as unfavourable and have incorporated it into bank loan contract pricing adaptively.

Second, we provide pieces of evidence that banks use borrower firms' earnings calls to supplement their assessment of firms' supply chain risk. By showing that the positive impact of supply chain risk on bank loan costs increases with the number of analysts following the firm, we provide further evidence that beyond private information accumulation, banks also benefit from earnings conference calls indirectly by acquiring information via analyst research. This enables them to form a more comprehensive knowledge of the borrowers' operational status and price their loan contracts with the supply chain risk information more effectively.

Our study contributes to the existing literature in the following ways. First, it extends the literature on supply chain risk and supply chain management (Chopra & Sodhi, 2014; Hendricks & Singhal, 2005a; Singhal & Singhal, 2012). To the best of our knowledge, it is the first study to investigate the impact of supply chain risk on firm loan financing. In response to calls for research by Kouvelis et al. (2006) and Sodhi et al. (2012), our findings help to narrow the gap between theoretical and empirical understanding of supply chain risk. By demonstrating that this risk increases loan interest spread, we point out a previously undocumented reason firms should enhance their supply chain management (Choi et al., 2023; Kleindorfer & Saad, 2005; Tomlin, 2006). The connection between supply chain risk and the overall firm financing cost should be paid more attention considering that the risk is not only conditional on market exogenous shock such as geopolitical and natural disaster factors (Ersahin et al., 2024b; Y. Huang et al., 2023; Jacobs et al., 2022), but also varies at the firm level due to product characteristics, commercial strategies, and distribution channels (Baldwin & Freeman, 2022; Choi et al., 2023; Wu, 2024).

Second, this study also enriches the literature on the determinants of bank loan financing. Given the vital role of loan lending in corporate financing, various unique determinants of bank loan terms have been studied, such as lending relationship (Bharath et al., 2011), bank private knowledge (Carvalho et al., 2023; M. Gao et al., 2024; Herpfer, 2021), climate risk management (H. Huang et al., 2022), corporate social responsibility (H. Gao et al., 2021), bank loan syndicate structure (Lin et al., 2012), and political uncertainty (Gad et al., 2024). Complementing the prior literature, we identify supply chain risk as a distinct determinant in loan contract negotiation. The linkage between supply chain risk and incremental loan cost also helps to establish the role of supply chain and operational management in the entrepreneurial value chain (Joglekar & Lévesque, 2013). Our paper is closely related to the work of Campello and Gao (2017) which also investigates the impact of supply chain conditions on loan borrowing by examining firm-level customer concentration. However, customer concentration captures only one limited aspect of the supply chain status. More importantly, lenders and other stakeholders do not necessarily perceive it as a risk signal[2] for firm operations (Croci et al., 2021; Dhaliwal et al., 2016; Ma et al., 2020). In contrast, by employing an overall risk measurement, our study finds that bank

[2] For example, literature also presents evidence that stronger and persistent customer-supplier link benefits suppliers' loan lending conditions due to supply chain stability (Cen et al., 2016). Yet Croci et al. (2021) found customer concentration has complicated and non-linear impacts on loan risk-taking and syndicate loan structure. Additionally, Cai and Zhu (2020) find that enhanced relationship with principal customers provides extra certification to suppliers in bond issuance, as customers help screen and monitor the quality of supplier firms, which reduces information asymmetry between the firms and their bond-holders.

creditors treat supply chain risk as a significant signal and it affects their loan decisions.

Finally, using a supply chain risk measure based on earnings conference calls, our study adds to the emerging literature that applies textual data in the financial business area. It also answers calls to assess operational risk (Graves et al., 2022; Sanders & Ganeshan, 2015) and enhance supply chain transparency (Sodhi & Tang, 2019) by taking advantage of alternative data available to stakeholders and the public. A stream of studies on earnings conference calls as well as newspapers, 10-K files, and other sources provides novel evidence on how soft communication disclosures help firm stakeholders identify non-traditional corporate risks (Florackis et al., 2023; Hassan et al., 2019; Sautner et al., 2023) and eliminate information asymmetry. It has shown that the earnings call is highly informative as it captures various topics that may be non-financial but still impactful for firm operations. A recent work by Cao et al. (2023) found that insurance companies adjust their corporate bond investment based on earnings call information, as it helps predict the default risk of bond issuers. Similarly, Gad et al. (2024) examined the effect of political risk discussion on bank loans. In this study, we highlight that earning calls also benefit bank creditors' loan lending decisions by delivering information about supply chain risk beyond existing information channels, so that the banks can adjust loan spread effectively in response to the disclosed risk of borrower firms.

The remainder of this paper is organized as follows: Section 2 introduces a literature review as well as develops the central hypotheses of this study. Section 3 describes our data and sample. Section 4 presents the applied methodology and main empirical results about both pricing and non-pricing terms. Section 5 presents several robustness checks. Section 6 discusses the additional results. Section 7 concludes.

2. Theoretical Framework and Hypotheses Development

2.1 Supply Chain Risk and Bank Loan Contracting

Supply chain risk exposure of borrower firms could be incorporated into loan contracting in various ways. First, transaction procedures and the hold-up problem can be considerably severe when supply chain coordination is disturbed (Chopra & Sodhi, 2014), leading to the inefficiency of firm production. Such complexity of the supply chain network exacerbates information asymmetries between borrowers and lenders, which increases banks' ex-ante investigation costs and the ex-post supervisory and monitory costs (Bharath et al., 2011; Lin et al., 2012). Second, banks might suffer from unexpected losses for sharing the tail risk of their borrower firms triggered by extreme events from the supply chain network. A loan credited to a limited liability corporation could be seen as an implicit put option written by banks (H. Huang et al., 2022; Merton, 1974). When borrowers supply chain glitches that disrupt firm operations and cause significant losses (Hendricks & Singhal, 2003, 2005b), they may leave this put option in the money, which leaves banks' payoff at risk in case of delinquency and default.

Third, supply chain risk may cause higher agency costs for banks (Jensen & Meckling, 1976; Leland, 1998). Such costs would arise from the potential impairment of existing debt claims, which would further decrease the stability of repayment including both loan interest and principal. For example, if supply chain risk negatively affects the financial performance of borrowers, managers will be either forced to delay the loan repayment due to more restricted cash flow liquidity or motivated to take more exaggerated operational strategies with more risks. Thus, higher supply chain risk from the firm borrowers could induce larger cash flow volatility and default risk to bank creditors.

In addition, The negative influence of the supply chain is hard to quantify not only because of its complex sources (Ho et al., 2015; Sodhi et al., 2012) but also because of the transmission and spillover mechanisms in the supply chain network (Kolay et al., 2016; Qiu et al., 2024). This may prevent stakeholders from identifying and quantifying its negative impact comprehensively and accurately; thus it is hard for banks to assess the credit quality of firms in screening and monitoring. As a result, supply chain risk induces more uncertainty and information friction costs for banks in the form of more frequent information tracking and monitoring and, due to limited access to information, a more arduous appraisal process.

2.2 Loan Spread

Given the impact of supply chain risk, it is likely to disadvantage borrower firms in loan contract negotiation, which may manifest in both pricing and non-pricing terms in loan contracting. This would include loan spread which is the main pricing tool bank creditors use to incorporate the distress status of borrowers as well as the default risk that status brings into loan contracts. In other words, banks would expect to offset the potential losses caused by the higher supply chain risk via the incremental part of interest spread, in case the borrower cannot fulfill future loan payments. For instance, Hendricks and Singhal (2005b) record the wide negative influence of supply chain glitches on firm operational performance, including revenues, costs, and asset utilization. This negative shock usually results in financial loss to firm stakeholders (Hendricks & Singhal, 2003). As well, lenders could increase the spread as compensation for the higher cost of ex-ante information collection and ex-post monitoring because of supply chain risk. Therefore, we propose our first hypothesis as below:

Hypothesis 1 (H1): Higher supply chain risk of a borrower firm is associated with higher loan spread in its loan contract with bank creditors.

2.3 Collateral Requirement

Besides pricing terms, lenders may also manage risk through non-pricing terms. In the presence of great uncertainty about the supply chain conditions, it is difficult for bank creditors to collect comprehensive information and monitor the financial and operational status changes of borrowers, which may lead to post-contractual opportunism and cause damage to lenders' welfare (Chava & Roberts, 2008; Demerjian & Owens, 2016). Therefore, after the loan contract is granted, banks are motivated to require asset control rights via non-pricing terms in extreme cases. This mechanism is an efficient complement to pricing mechanisms and beneficial for coordinating loan transactions and maintaining the survival of loan contracts, which reflects the flexibility of the loan contracting dynamic. Related literature documents that banks can implement constraints on borrowers through stricter covenant design (Cen et al., 2016; Chava & Roberts, 2008), shorter loan maturity (Campello & Gao, 2017), smaller loan size (Bharath et al., 2011), and collateral warranty (H. Huang et al., 2022).

However, it remains unclear whether the risk affects other non-pricing terms, such as loan size, loan maturity, and the number of covenants, in a similar way. The effects of supply chain risk on these contract terms could be less predictable, given the complex negotiation strategies that balance pricing and non-pricing terms, which vary based on individual firm circumstances and lender preferences (Bharath et al., 2011; Chava & Roberts, 2008). For example, Ersahin et al. (2024b) found that operating shocks prompt firms to delay their payment and demand higher trade credit from their supply chain network. Therefore, firms may seek greater flexibility to manage their capital structures and operations when experiencing distress, which may be reflected in less-constrained contract terms, such as longer loan maturity or larger loan size. Given this and the fact that firms seek to obtain financial liquidity through loan lending and improve operational performance ultimately, it is hard to predict a monotonous relationship between supply chain risk and non-pricing terms like loan size and loan maturity.

Therefore, our second hypothesis about non-pricing terms focuses on the collateral requirement change in dealing with supply chain risk, as collateral provides a straightforward solution to risk mitigation. The potential impairment of property from supply chain shocks justifies banks' requirement for a larger package of collateral pledged in exchange for loans. It also prevents opportunistic divestiture of pledged assets during high-risk periods, which would endanger enterprises' productive capacity and repayment ability (H. Huang et al., 2022). Therefore, collateralization serves as a more viable option for both lenders and borrowers to manage increased supply chain risks without compromising operational flexibility. Given these dynamics, we propose the following hypothesis:

Hypothesis 2 (H2): A firm's supply chain risk will positively correlate with the likelihood that its loans will be collateralized.

3. Sample Construction and Summary Statistics

3.1 Data Sources

We combine a variety of data sources to construct our sample, primarily firm-level supply chain risk data, loan tranche data, and a range of control variables.

We use the novel SCRisk score dataset developed by Ersahin et al. (2024a) as a proxy for firm-level supply chain risk. Applying textual analysis technology[3], the data is generated by utilizing transcripts of earnings conference calls from listed firms and is defined as the proportion of the conversations focusing on supply chain risk during the conference calls. Although earnings conference calls are usually held quarterly responding to the earnings announcement schedule in the U.S. market, the SCRisk dataset is constructed annually to avoid disruption through seasonal factors and short-term noise (Ersahin et al., 2024a). The $SCRisk$ score quantifies the perception of changes in the sources of supply chain risk from information provided by listed firms and captures the impact of motivating supplier-customer corporations and vertical integration during high-risk periods in their study. Thus, it is a measure of uncertainty and fear of future supply chain shocks.

The SCRisk dataset is available for 2002 to 2022. To ensure that only publicly available information from earnings conference calls is used at the time of a loan, we lag them for one year. Thus our final sample starts from January 2003. It ends in June 2020 to align with the availability of the linking table provided by Chava and Roberts (2008), which we use to match the loan data with Compustat and

[3] Recent literature that adopts similar approach to establish firm-level topic indices includes studies of cybersecurity risk (Florackis et al., 2023), political uncertainty (Hassan et al., 2019), corporate culture (Li et al., 2021), and climate change risk (Sautner et al., 2023), among others.

SCRisk data at the firm-year level.

Our bank loan data is obtained from the DealScan database. We focus on individual loan tranches (facilities) and use the all-in-spread-drawn (AISD) variable to measure the loan spread, the additional basis points required in loan contracts over the London Interbank Offered Rate (LIBOR). The financial information of matched borrower firms is collected from the Compustat database. The firm-level credit ratings data is sourced from the S&P Credit Ratings database. All necessary data for macroeconomic status are obtained from the Board of Governors of the Federal Reserve System.

Our sample keeps the loan tranche observations only if they have no missing values on the all-in-drawn spread, loan maturity, loan amount, and other necessary loan information. Also, we require the loan to be non-amended and delivered in USD currency. Because term and revolver loans have more detailed information in the database and to avoid the potential interference of various fee structures and restrictive pricing policies, we only include these two loan types (Berg et al., 2016; Campello & Gao, 2017). In line with past research, we exclude financial service firms (SIC codes 6000 to 6999) from the sample because they have greater than average access to financing resources (e.g., Berg et al., 2016; Chava & Roberts 2008).

3.2 Summary Statistics

Besides our main dependent variable, the SCRisk score[4], we also include three aspects of control variables that may affect the loan spread determination: borrower firm characteristics, loan characteristics, and macroeconomic factors. Those controls are motivated by a group of prior literature on bank loans (e.g., Bharath et al., 2011; Campello & Gao, 2017; Chava & Roberts, 2008; Gao et al., 2024). Specifically, for borrower characteristics, we include firm size, profitability, tangibility, leverage, market-to-book ratio, modified Altman's Z-score (without leverage), cash holding ratio, and a dummy indicator of whether the firm has a credit rating (Bharath et al., 2011). We also add SCSentiment to control for the recently realized shock in the supply chain. Regarding loan-level controls, we employ characteristics including loan maturity in months, loan size, and a dummy indicator to distinguish the loan type. Macroeconomic conditions are controlled by two variables: credit spread and term spread. Credit spread is calculated as the average yield spread between AAA-rated and BBB-rated corporate

[4] Following the method of Ersahin et al. (2024a), we scale the SCRisk and SCSentiment value with a constant factor of 0.01 in the empirical tests and analysis discussions. However, the baseline results stay robust with similar significance levels when standardized or natural logarithm form of SCRisk and SCSentiment score data is applied.

bonds. Term spread is the difference in yields between the U.S. 10-year treasury bond and 3-month T-bills.

To eliminate the potential effect of inflation, we adjust price terms (firm size and loan size) in the year 2005 dollars (H. Gao et al., 2021). Similarly, we lag all dependent variables for one period to ensure economic and accounting information is publicly available before each loan is activated. To minimize the effect of outliers, we winsorize all continuous variables at the 1st and 99th percentiles, except that the leverage ratio of borrower firms is restricted to the (0, 1) range. Detailed variable definitions are provided in Appendix I.

[Insert Table 1 about here]

Table 1 reports the summary statistics of our sample. The baseline test sample covers 9,879 loan tranches from 2,065 firms. The earliest (latest) loan tranche in our sample was activated on January 10, 2003 (June 30, 2020). The median loan tranche in our sample has a loan spread of 176 basis points over the LIBOR, a maturity of 60 months, and a loan size of $223.85 million (deflated in 2005 USD currency). In the sample, about 49% of loan tranches require collateral, while 36% of loan tranches are term loans. Regarding firm-level characteristics, the median (mean) book value of total assets deflated in 2005 USD currency is $2.05 (2.24) billion, and the median book leverage ratio is 27%. In terms of performance, the median profitability measured as the ratio of earnings before interest, taxes, depreciation, and amortization (*EBITDA*) to total assets is 13%, and the median modified Z-score is 1.56. About 55% of observations have a credit rating (when the loan is activated) in the S&P crediting rating database. SCRisk score ranges from 0.00 to 82.79. In terms of macroeconomic factors, the median credit spread is 100.18 basis points, while the median term spread is 187.55 basis points.

4. Empirical Analysis

In this section, we conduct a series of empirical tests to examine the influence of borrower firm-level supply chain risk on their loan contracts. A brief description is provided before the test demonstrations. First, we analyze the relationship between the change in loan spread and supply chain risk by running loan-level panel regressions with a set of control variables and fixed effects. We then analyze how the supply chain risk influences the likelihood of collateral requirement in the contract, as well as borrowers' future relationship with their lead lender banks after renewing the supply chain risk information.

4.1 Supply Chain Risk and Loan Interest Spread

To empirically test whether borrowers' supply chain risk increases loan cost, we start by estimating the baseline model with equation (2) and the following regression specifications:

$$\begin{aligned} \ln\,(Loan\_Spread_{l,i,t}) &= \beta_1 SCRisk_{i,t-1} + \beta_2 Firm\_controls_{i,t-1} + \beta_3 Loan\_controls_{i,l,t-1} \\ &+ \beta_4 Macro\_factors_{t-1} + Fixed\ Effects + \varepsilon_{l,i,t} \end{aligned} \quad (1)$$

where $Loan\_Spread_{l,i,t}$ is the AISD spread of loan l for borrower firm i in year t. $SCRisk_{i,t-1}$ is our proxy for supply chain risk for firm i in the year before the loan activation ($t-1$). $Firm\_controls_{i,t}$ and $Loan\_controls_{i,l,t}$ represent the vector of firm-level control variables and loan-level control variables separately as discussed in section 3. $Macro\_factors_t$ represents the vector of macroeconomic control variables. We include industry-fixed effects[5] because the variation of supply chain risk is highly heterogeneous across industries (Ersahin et al., 2024a). Loan contract terms may be different due to the differentiated screening and negotiating procedures of banks, so we also include bank (lender) fixed effects[6]. Following the discussion of Campello and Gao (2017), we choose to not include firm-fixed effect given that our basic unit of observation is individual loan tranche. We report heteroskedasticity-robust standard errors clustered by borrower firm and year.

[Insert Table 2 about here]

Table 2 presents the baseline model results for regressions of loan spreads on supply chain risk. Consistent with our prediction in Hypothesis 1, we find that loans require significantly higher interest spreads when firms have a larger SCRisk value in the previous year. Specifically, the β_1 is equal to about 0.005 with all three levels of characteristics as well as industry and lender fixed effects in column (4). Thus the loan spreads are positively associated with supply chain risk, and this relationship stays statistically significant at the 1% level after employing various settings of controls. Holding all else conditions constant, a one-standard-deviation increase in the SCRisk value increases the loan spread by 5.04 basis points[7]. Economically, it represents a sizable incremental loan cost of 213,233 USD dollars

[5] We mainly report the empirical results using a four-digit SIC code as industry classification method, although our baseline results stay robust with similar significance levels when other industry classifications methods are applied, including the two-digit SIC and NAICS codes.

[6] We mainly report the empirical results using direct lender as lender fixed effect, although our baseline results stay robust with similar significance levels when we replace it with parent lender (the ultimate parent company of the bank) fixed effect.

[7] The SCRisk has a sample standard deviation of 6.18 and an estimated coefficient of 0.005 in our baseline model as indicated in column (5) of Table 2. Since the sample mean value of the natural logarithm of loan spread is 5.11, the reduction in loan spread is e^5.11 – e^(5.11−6.18×0.005) ≈ 5.04 basis points.

annually given the sample mean loan size of $460.78 million.

4.2 Total Cost of Borrowing

Second, we also conduct an alternative test by repeating baseline regressions but replacing the loan spread variable of each loan with Berg et al.'s (2016) total-cost-of-borrowing (TCB) measure. Instead of using the AISD variable as a simple estimation of loan pricing, we use the TCB construction because it considers the complex pricing structure of loan commitments by including a variety of fee types recorded in DealScan loan contracts. Thus it should provide a more comprehensive estimation of loan lending cost than the simple loan interest spread measured by AISD. As predicted, the results in Table 3 again indicate that supply chain risk proxied by the $SCRisk$ score is positively associated with loan costs across all model specifications. Holding all else conditions constant, a one-standard-deviation increase in the SCRisk value increases the total cost of borrowing by 4.54 basis points.

[Insert Table 3 about here]

4.3 Loan Collateralization

To investigate our Hypothesis 2, next, we provide the Logit regression results that relate supply chain risk to the collateral requirement proxied by the secured dummy variable. The model setting is the same as described in equation (1) except that the dependent variable is replaced and the natural logarithm form of loan spread is added as an extra control variable.

The results in columns (1) to (3) of Table 3 indicate that the probability of a loan being secured is significantly higher when supply chain risk is high with a coefficient of about 0.013 (t-stat = 2.08) in our sample. This implies that the marginal effect of supply chain risk is 0.0803, or the likelihood of collateral requirement in loan contracts is 8.03 percent higher for one-standard-deviation higher supply chain risk. Additionally, the results in columns (4) to (6) show further that the loan secured probability is even more sensitive to the change of supply chain risk (*dif_SCRisk*) with both higher coefficients and more significant t-statistics. In summary, the results suggest that bank creditors are more likely to ask for collateral when borrower firms are exposed to larger supply chain risk, which confirms Hypothesis 2: collateralization helps ease lending risk and banks' concern about potential default.

[Insert Table 4 about here]

5. Robustness Checks

Following the baseline test results in section 4.1, next, we conduct a series of robustness checks to further establish the relationship between supply chain risk and bank loan cost, including adding and switching control variables, excluding the observations during the global financial crisis (GFC) of 2007–2009, and applying an alternative loan cost measurement. We also address the possible endogeneity issue via a two-stage least-squares test.

5.1 Adding Customer Concentration as An Extra Control

Our first check is about the customer concentration of borrower firms which is expected to cause a larger loan spread due to its negative influence on creditability and financial constraints (Campello & Gao, 2017). Lenders may see high customer concentration as an undiversified risk in the supply chain connection and may increase the cost of capital as it leads to limited profitability and a high dependence on a small number of large customers (Dhaliwal et al., 2016). To account for such a possibility, we control for customer concentration using three different measures, *CustomerSales*, *CustomerHHI, and CustomerSize* as below:

$$CustomerSales_{i,t} = \sum_{j=1}^{n_i} \%Sales_{i,j,t} \tag{2}$$

$$CustomerHHI_{i,t} = \sum_{j=1}^{n_i} \%Sales_{i,j,t}^2 \tag{3}$$

$$CustomerSize_{i,t} = \sum_{j=1}^{n_i} \%Sales_{i,j,t} \times Size_{j,t} \tag{4}$$

where n_i is the number of firm i's (reported) major customers, $\%Sales_{i,j,t}$ is the sales proportion from firm i to its customer j scaled by i's total sales in year t, and $Size_{j,t}$ is the firm size of customer j in year t.

The results are reported in Panel A of Table 5. As expected, the results show that the coefficients of supply chain risk remain positive and significant with similar-sized estimations in the baseline results. This also aligns with the opinion that customer concentration only partially reflects the overall supply chain risk of a supplier firm (Dhaliwal et al., 2016; Ma et al., 2020).

5.2 Alternative Model Settings and Sample Matching

Furthermore, we conduct a few additional tests applying different model settings or alternative samples to check the robustness of our baseline result. The results are documented in Panel B of Table 5. First, the coefficient value of SCRisk also maintains its magnitude and significance if we switch the estimation model setting to the baseline model of Campello and Gao (2017), which uses a different group of control variables from those we use, including both borrower firm controls and macroeconomic controls.

Next, to ensure that lenders use the most current accounting information to evaluate borrowers, we also follow the modified matching procedure designed by Bharath et al. (2011) to merge control variables constructed from Compustat data in an alternative way. Particularly, if the loan is activated at least six months after the fiscal year ending months in the calendar year t, we use Compustat data from the fiscal year t. Otherwise, we keep using the data from the fiscal year $t-1$. The baseline model results are robust to such change as the coefficient remains barely changed, except that *t*-statistics decrease to between 1.85 and 2.65 under different control specifications.

Finally, we construct a sub-sample by keeping only non-GFC-period observations based on the National Bureau of Economic Research (NBER) business cycle dating[8] record. This allows us to exclude the potential influence induced by the 2007–2009 global financial crisis (Cai & Zhu, 2020; Croci et al., 2021). Unsurprisingly, we find that re-running the baseline regression using the non-GFC sample shows essentially the same "risk-spread" association. Thus the exclusion does not alter our result in Table 2.

5.3 2SLS Test

Next, we further address the potential endogeneity issue to establish the effect of supply chain risk on loan terms. Unobservable factors can mutually correlate with both supply chain risk exposure and loan lending outcomes, which may bias model estimates. For instance, those firms with higher SCRisk value may be the ones with worse prospects and thus face higher loan cost premiums by their lenders. Moreover, considering reverse causality, concerns about debt lending conditions may also bias the supply chain risk information disclosure of the borrower firms. In other words, management may strategically and selectively discuss the supply chain status in the earnings conference calls.

Therefore, to address endogeneity, we exploit the two-stage least-squares regression test by using the maximum SCRisk values of a borrower firm's observed supply chain stakeholders as instruments,

[8] NBER maintain the chronology to identify the dates of peaks and troughs that frame economic recessions (downturns) and expansions. See more details and exact calendar record from https://www.nber.org/research/business-cycle-dating.

motivated by the method of Ersahin et al. (2024a). Utilizing the stakeholders' SCRisk as instruments fits into the network and integration nature of the supply chain that the daily operation of a firm could be disturbed as long as any stakeholder of the targeted firm is experiencing high uncertainty or exposed to severe supply chain risks. More importantly, the financial prospects or future strategies of a borrower firm's stakeholders are unlikely to affect supply chain discussion or information disclosure in its earnings calls. In other words, the instrument variables can be considered exogenous to the operational conditions of our concerned borrower firms.

The supply chain relationship is identified using the Factset Revere database, as it records the supply chain relationship including supplier and customer firm identification for the focal firms. The main data source of Factset Revere is the mandatory disclosure required in both Statement of Financial Accounting Standard (SFAS) 14 in 1976 and SFAS 131 in 1977 (Campello & Gao, 2017; Qiu et al., 2024) for public firms to report their large customer firms that account for 10% or more sales of the financial year, while it collects supplement information from investor presentations, press releases, and other public sources (Crosignani et al., 2023; Ersahin et al., 2024a). This allows us to identify and match a firm's major customers as well as suppliers annually. Therefore, we construct alternative SCRisk values for a target firm i as below:

$$SCRisk\_stakeholder_{i,t} = Max(SCRisk_{ij,t})^{9} \tag{5}$$

where $SCRisk_{ij,t}$ represent the SCRisk value of stakeholder firm j of target firm i in year t, including both customers and suppliers with available records in the Factset Revere dataset.

Table 6 reports two sets of 2SLS test results. As shown in columns (1) and (3), the effect of the instrument variable on a firm's SCRisk in the first stage is positive and significant. The results remain robust after controlling for the macro environment by employing either yearly-average macroeconomic factors or year fixed effects. Thus, it confirms that information from both upstream and downstream of the supply chain effectively helps predict the risk of the borrower firms. Next, the second-stage regression result in columns (2) and (4) further verifies our baseline findings that the loan spread of borrower firms increases following the increases in supply chain risk.

[Insert Table 6 about here]

[9] We also measure the three stakeholders' SCRisk values by taking the mean value instead of taking the maximum value—the results maintain comparable coefficients and similar significance overall.

6. Additional Results

Having determined that a significant loan cost increase is associated with higher supply chain risk, we conduct two extended analyses to further explore the connection. In the first analysis, we document the cross-sectionally varying relationship between supply chain risk and bank loan cost, as it is more pronounced when the borrower firms have less or no prior relationship with their bank lenders. Also, the relationship is especially significant if the banks are relatively smaller, or accumulate less industry-specialized knowledge about the borrower firms. Second, we find evidence that banks also learn from earnings calls of their borrower firms via analyst research to help price the supply chain risk more efficiently in loan contracts.

6.1 Does Banks' Response Vary in Cross-section?

We test if the relationship between supply chain risk and bank loan cost varies cross-sectionally in our sample. This allows us to gauge if banks perceive the supply chain risk and price it consistently, and if not, in what cases the bank lenders are concerned more about the supply chain condition of their borrower firms and ask for higher loan spread in loan contracts as risk compensation.

To answer the question, we conduct sub-sample dual tests based on a series of lead lender bank characteristics. Specifically, we classify the baseline sample reported in section 3.2 into two groups based on the mean value of bank characteristics that may affect the information asymmetry between the borrower firms and their bank lenders, including prior lending relationship (Bharath et al., 2011), bank size, and industry expertise (Lin et al., 2012). We also split the sample into two groups based on the dummy whether the borrower firms have a prior relationship with their lead lenders or not. We then re-run the baseline model regression on the subsamples to compare the relationship between supply chain risk exposure and loan spread under those different conditions.

[Insert Table 7 about here]

Panel A of Table 7 reports the sub-sample results based on prior lending relationships[10]. Following the methods of Bharath et al. (2011), we define the dummy variable *REL(Dummy)* to equal one as long as the firm borrows from the same lead lender in the last five years, otherwise zero. The continuous variable *REL(Amount)* is calculated as the loan amount led by the same lead lender to the borrower,

[10] We report results in Table 7 of REL(Dummy) and REL(Amount). The results stay robust if we alternatively use REL(Number), another prior lending relationship indicator in Bharath et al. (2011), as the sub-sample criteria.

scaled by the total amount of loans to the borrower in the last five years. We find that the association between supply chain risk and loan spread is only significant (t-stat = 3.26 and 2.71) when the borrower firms have relatively low or completely no prior loan lending connections with the bank lenders before the loan contracts are activated over the past five years. On the contrary, the influence of supply chain risk on the loan interest spread is much weaker when the prior relationship is strong, as both the statistical significance and economic consequences are almost eliminated in columns (2) and (4).

Moreover, we also split the sample based on the mean value of bank size and bank industry expertise, and report the results in Panel B of Table 7. Following the method of Lin et al. (2012), we measure the bank size as the total amount of loan lent by the lender throughout the whole sample period, while the bank industry expertise is measured by the loan amount it lent in the industry that the borrower belongs to, divided by the total amount of all available loans issued in the same industry over the past five years. We take the mean value of bank size and industry expertise for all lead lenders in each loan tranche contract. The results indicate that banks require significantly higher loan interest spreads when they are smaller or when they have lower expertise knowledge on the borrower firms' industry. Especially, compared to the baseline results, the pattern (coefficient = 0.010) is magnified to twice as much when bank lending operations are smaller.

In summary, Table 7 implies that bank lenders with specific characteristics are more concerned about the supply chain risk of their borrowers, which is reflected in the loan pricing and leads to exaggerated loan spread in response to the variation of supply chain risk. The more pronounced response to supply chain risk can be further attributed to several reasons. First, those banks with those specific characteristics suffer from larger information asymmetry with their borrower firms (Bharath et al., 2011; Lin et al., 2012), thus they have to execute a more cautious and risk-averse contracting strategy that asks for higher and exaggerated compensation of the risk, which partially compensates the information disadvantage brought by supply chain complexity. However, the information asymmetry and required risk premium could be alleviated if bank lenders possessed information advantage by accumulating sufficient knowledge (M. Gao et al., 2024).

Second, due to shortcomings such as smaller lending service size and insufficient upfront information accumulation, those banks need to incur more effort in ex-ante investigation and ex-post monitoring procedures, as well as higher friction costs in conducting them. Third, smaller banks could be less capable to afford the repayment default or other negative consequences raised by potential supply chain disruptions. This disadvantage may also lead to more conservative pricing strategies in their loan contracts. In conclusion, the cross-sectional variability emphasizes that the bank credit market takes elaborate risk management practices that adaptively respond to the supply chain risk.

6.2 Do Banks Learn from Earnings Call Information?

Another question of interest is whether bank creditors acquire supply chain information from their borrowers' earnings conference calls. Given bank creditors and financial institutions usually possess private information sources or institution-owned knowledge cumulation (Bharath et al., 2011; M. Gao et al., 2024; Lin et al., 2012), the SCRisk score derived from earnings call may be merely an external proxy of the firm-level supply chain risk. Nonetheless, it is also possible that the earnings calls act as an important supplement to private information as bank creditors collect information in the due diligence assessment and loan pricing.

We apply two methods to investigate this question. First, using data from the I/B/E/S database, we construct an analyst coverage variable following the method of Hallman et al. (2023). Then we add the variable into the baseline equation with an extra interaction term as below:

$$\begin{aligned}\ln\left(Loan_{Spread}{}_{l,i,t}\right) &= \beta_1 SCRisk_{i,t-1} + \beta_2 (AC_{i,t-1} * SCRisk_{i,t-1}) + \beta_3 AC_{i,t-1} \\ &+ \beta_4 Controls_{i,t-1} + Fixed\ Effects + \varepsilon_{l,i,t}\end{aligned} \quad (6)$$

where $AC_{i,t-1}$ is the monthly number of analyst forecast estimates for firm i in month $t-1$. The result in Panel A of Table 8 shows that β_1 is significantly positive (t-stat ranges from 3.10 to 3.50), demonstrating that the extent of comovement between $SCRisk$ and loan interest spread is positively dependent on the number of analysts following the firm. This suggests that the banks at least partially depend on external financial analysts to gather unique information about supply chain risk. On the other side, the improvement in loan spread due to the same increase in supply chain risk is more pronounced when more analysts are focusing on the corresponding borrower firm. The negative β_3 (coefficient = -0.006, t-value = -2.20) in column (3) also verifies the empirical findings of Hallman et al. (2023) that analyst coverage reduces loan interest spread.

<u>**[Insert Table 8 about here]**</u>

Second, we also divide the baseline sample into high- and low-coverage groups in each year based on the annual median value of analyst coverage and then run baseline regressions separately. Panel B of

Table 8 shows that the coefficient on supply chain risk is significantly positive (t-stat = 3.32) only in the high-AC group, while we cannot observe an equivalent pattern in the low-AC group (t-stat = -0.07). Also, we find that the t-value of the difference between SCRisk coefficients in the two groups is 3.02, which statistically proves that bank creditors respond differently to the supply chain risk of borrower firms with different analyst coverage in their loan contract pricing. This may also suggest that bank creditors are more capable of pricing supply chain risk effectively in their lending contracts when sufficient analysts are available to help analyze the earnings calls of borrower firms and deliver information to the banks.

This finding is in line with the conference-call-based nature of the SCRisk dataset, as well as the conclusion of Hallman et al. (2023) that analyst research helps bank creditors to better conduct due diligence assessment and alleviate information asymmetry. It also shows that private knowledge does not comprehensively help banks to clarify the supply chain health and potential risks, which also reflects the high complexity of supply chain risk. In the meantime, earnings calls and analyst research add to the information collection and help banks to better price the supply chain risk in loan lending.

7. Conclusion

Recent literature explores the wide influence of supply chain risk on firm operations and financing. In this study, we investigate how banks respond to the supply chain health of their borrowers by examining the bank loan cost of U.S.-listed firms. Specifically, we find that supply chain risk leads to higher loan interest spread. Such a relationship varies in cross-section, as the response of loan spread to supply chain risk is exceptionally prominent when the information asymmetry is larger between the borrower firms and their bank lenders. Additionally, we prove that banks do acquire supplementary information from earnings calls via analyst research, by which they form supply chain risk recognition for their borrower firms and effectively price the risk in loan lending. For non-pricing terms, we gauge a higher likelihood of collateral requirement with higher risk exposure. Overall, the evidence documented in our study supports that the bank market has realized the disturbance of supply chain risk to firm operations and treats the risk as an unfavourable element of borrower firms by incorporating it into their loan contract terms.

Our findings point out significant practical implications, as the analysis results emphasize the importance of supply chain risk assessment and management for firms, which could also be meaningful to the additional screening considerations for banks. Our analysis underscores the critical role that supply chain stability plays in corporate finance and highlights the need for businesses to manage these risks proactively. The industry should recognize that supply chain risk is not only vital for firm operations flexibility and production performance, but also has become one of the main concerns in corporate quality assessment that greatly influences financing costs. It also provides additional incentives for firms to cooperate more closely and decrease the negative impact of supply chain risk collaboratively. On the other side, bank creditors are encouraged to improve their screening and evaluating procedures by collecting more comprehensive information about the supply chain of borrowers from various information channels. Such a development could help increase loan pricing accuracy and efficiency, as well as avoid potential losses from information asymmetry.

There are multiple directions future research could explore. For example, scholars might examine the reasoning of supply chain risk from specific segment departments. Another is to further categorize supply chain risk based on its source (e.g., natural disaster, pandemic, labor shortage, transportation delay, etc.), then estimate and compare their separate impacts on bank loan costs. The comparison could be helpful to identify the key operation node that concerns the bank creditors most and enhance supply chain management correspondingly. Alternatively, our analysis focuses on private bank loan contracts, while future work might include the influence of supply chain risk on other corporate financing tools. Another possible direction is to increase the sample coverage, as only public firms with available earnings call data are included in our research. It would be useful to learn if the same connection exists for private and small business firms.

References

[1] Baldwin, R., & Freeman, R. (2022). Risks and global supply chains: What we know and what we need to know. *Annual Review of Economics*, *14*(1), 153–180.

[2] Berg, T., Saunders, A., & Steffen, S. (2016). The total cost of corporate borrowing in the loan market: Don't ignore the fees. *The Journal of Finance*, *71*(3), 1357–1392.

[3] Bharath, S. T., Dahiya, S., Saunders, A., & Srinivasan, A. (2011). Lending relationships and loan contract terms. *The Review of Financial Studies*, *24*(4), 1141–1203.

[4] Cai, K., & Zhu, H. (2020). Customer-supplier relationships and the cost of debt. *Journal of*

Banking & Finance, *110*, 105686.

[5] Campello, M., & Gao, J. (2017). Customer concentration and loan contract terms. *Journal of Financial Economics*, *123*(1), 108–136.

[6] Cao, J., Li, G., Wermers, R., Zhan, X., & Zhou, L. (2023). Do insurers listen to earnings conference calls? Evidence from the corporate bond market. *Unpublished Working Paper. Social Science Research Network.*

[7] Carvalho, D., Gao, J., & Ma, P. (2023). Loan spreads and credit cycles: The role of lenders' personal economic experiences. *Journal of Financial Economics*, *148*(2), 118–149.

[8] Cen, L., Dasgupta, S., Elkamhi, R., & Pungaliya, R. S. (2016). Reputation and loan contract terms: The role of principal customers. *Review of Finance*, *20*(2), 501–533.

[9] Chava, S., & Roberts, M. R. (2008). How does financing impact investment? The role of debt covenants. *The Journal of Finance*, *63*(5), 2085–2121.

[10] Choi, T. Y., Netland, T. H., Sanders, N., Sodhi, M. S., & Wagner, S. M. (2023). Just-in-time for supply chains in turbulent times. *Production and Operations Management*, *32*(7), 2331–2340.

[11] Chopra, S., & Sodhi, M. S. (2014). Reducing the risk of supply chain disruptions. *MIT Sloan Management Review*. https://sloanreview.mit.edu/article/reducing-the-risk-of-supply-chain-disruptions/

[12] Croci, E., Degl'Innocenti, M., & Zhou, S. (2021). Large customer-supplier links and syndicate loan structure. *Journal of Corporate Finance*, *66*, 101844.

[13] Crosignani, M., Macchiavelli, M., & Silva, A. F. (2023). Pirates without borders: The propagation of cyberattacks through firms' supply chains. *Journal of Financial Economics*, *147*(2), 432–448.

[14] Demerjian, P. R., & Owens, E. L. (2016). Measuring the probability of financial covenant violation in private debt contracts. *Journal of Accounting and Economics*, *61*(2–3), 433–447.

[15] Dhaliwal, D., Judd, J. S., Serfling, M., & Shaikh, S. (2016). Customer concentration risk and the cost of equity capital. *Journal of Accounting and Economics*, *61*(1), 23–48.

[16] Ersahin, N., Giannetti, M., & Huang, R. (2024a). Supply chain risk: Changes in supplier composition and vertical integration. *Journal of International Economics*, *147*, 103854.

[17] Ersahin, N., Giannetti, M., & Huang, R. (2024b). Trade credit and the stability of supply chains. *Journal of Financial Economics*, *155*, 103830.

[18] Florackis, C., Louca, C., Michaely, R., & Weber, M. (2023). Cybersecurity risk. *The Review of*

Financial Studies, *36*(1), 351–407.

[19] Gad, M., Nikolaev, V., Tahoun, A., & Van Lent, L. (2024). Firm-level political risk and credit markets. *Journal of Accounting and Economics*, *77*(2–3), 101642.

[20] Gao, H., Li, K., & Ma, Y. (2021). Stakeholder orientation and the cost of debt: Evidence from state-level adoption of constituency statutes. *Journal of Financial and Quantitative Analysis*, *56*(6), 1908–1944.

[21] Gao, M., Huang, Y., Ongena, S., & Wu, E. (2024). Borrower Technology Similarity and Bank Loan Contracting. *Unpublished Working Paper. Swiss Finance Institute Research Paper Series*.

[22] Graves, S. C., Tomlin, B. T., & Willems, S. P. (2022). Supply chain challenges in the post–Covid Era. *Production and Operations Management*, *31*(12), 4319–4332.

[23] Hallman, N., Howe, J. S., & Wang, W. (2023). Analyst coverage and syndicated lending. *Review of Accounting Studies*, *28*(3), 1531–1569.

[24] Hassan, T. A., Hollander, S., Van Lent, L., & Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, *134*(4), 2135–2202.

[25] Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501–522.

[26] Hendricks, K. B., & Singhal, V. R. (2005a). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations Management*, *14*(1), 35–52.

[27] Hendricks, K. B., & Singhal, V. R. (2005b). Association between supply chain glitches and operating performance. *Management Science*, *51*(5), 695–711.

[28] Herpfer, C. (2021). The role of bankers in the U.S. syndicated loan market. *Journal of Accounting and Economics*, *71*(2–3), 101383.

[29] Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research*, *53*(16), 5031–5069.

[30] Huang, H. H., Kerstein, J., Wang, C., & Wu, F. (Harry). (2022). Firm climate risk, risk management, and bank loan financing. *Strategic Management Journal*, *43*(13), 2849–2880.

[31] Huang, Y., Lin, C., Liu, S., & Tang, H. (2023). Trade networks and firm value: Evidence from the U.S.-China trade war. *Journal of International Economics*, *145*, 103811.

[32] Jacobs, B. W., Singhal, V. R., & Zhan, X. (2022). Stock market reaction to global supply chain

disruptions from the 2018 US government ban on ZTE. *Journal of Operations Management*, *68*(8), 903–927.

[33] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360.

[34] Joglekar, N., & Lévesque, M. (2013). The role of operations management across the entrepreneurial value chain. *Production and Operations Management*, *22*(6), 1321–1335.

[35] Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, *14*(1), 53–68.

[36] Kolay, M., Lemmon, M., & Tashjian, E. (2016). Spreading the misery? Sources of bankruptcy spillover in the supply chain. *Journal of Financial and Quantitative Analysis*, *51*(6), 1955–1990.

[37] Kouvelis, P., Chambers, C., & Wang, H. (2006). Supply chain management research and Production and Operations Management: Review, trends, and opportunities. *Production and Operations Management*, *15*(3), 449–469.

[38] Leland, H. E. (1998). Agency costs, risk management, and capital structure. *The Journal of Finance*, *53*(4), 1213–1243.

[39] Li, K., Mai, F., Shen, R., & Yan, X. (2021). Measuring corporate culture using machine learning. *The Review of Financial Studies*, *34*(7), 3265–3315.

[40] Lin, C., Ma, Y., Malatesta, P., & Xuan, Y. (2012). Corporate ownership structure and bank loan syndicate structure. *Journal of Financial Economics*, *104*(1), 1–22.

[41] Ma, X., Wang, W., Wu, J., & Zhang, W. (2020). Corporate customer concentration and stock price crash risk. *Journal of Banking & Finance*, *119*, 105903.

[42] Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

[43] Qiu, B., Xu, F., Yeung, A. C. L., & Zeng, C. (Colin). (2024). Contagious stock price crashes along the supply chain. *Production and Operations Management*, 10591478241254854.

[44] Sanders, N. R., & Ganeshan, R. (2015). Special issue of Production and Operations Management on “big data in supply chain management.” *Production and Operations Management*, *24*(12), 1984–1985.

[45] Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*, *78*(3), 1449–1498.

[46] Singhal, K., & Singhal, J. (2012). Imperatives of the science of operations and supply-chain management. *Journal of Operations Management*, *30*(3), 237–244.

[47] Sodhi, M. S., Son, B.-G., & Tang, C. S. (2012). Researchers' Perspectives on Supply Chain Risk Management. *Production and Operations Management*, *21*(1), 1–13.

[48] Sodhi, M. S., & Tang, C. S. (2019). Research opportunities in supply chain transparency. *Production and Operations Management*, *28*(12), 2946–2959.

[49] Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science*, *52*(5), 639–657.

[50] Wu, D. (Andrew). (2024). Text-based measure of supply chain risk exposure. *Management Science*, *70*(7).

Appendix I: Variable Definition

Variable	Definition	Data Source
Panel A: Borrower (Firm) Level Variables		
SCRisk	Firm's yearly exposure to supply chain risk.	Ersahin et al. (2024)
Size	The natural logarithm of total assets, deflated as in 2005 dollars.	Compustat
Profitability	The ratio of EBITDA and total assets.	Compustat
Tangibility	The ratio of property, plant, and equipment and total assets.	Compustat
Leverage	Book leverage, the ratio of total debt and total assets.	Compustat
Market-to-book	The ratio of adjusted market value and total assets, calculated as (stock price × shares outstanding + total assets – book equity) / total assets.	Compustat
Altman Z-score	The modified Altman's Z-score without leverage, calculated as (1.2 × working capital + 1.4 × retained earnings + 3.3 × pretax-income + 0.999 × total sales) / total assets.	Compustat
Cash holding	The ratio of cash and marketable securities and total assets.	Compustat
Credit ratings	A dummy indicator that equals to one if the firm has a public credit rating, zero otherwise.	S&P Credit Ratings
CustomerSales	Total percentage sales to all reported major customers.	Compustat, Customer Segment
CustomerHHI	The Herfindahl index of sales to all reported major customers.	Compustat, Customer Segment
CustomerSize	The total size of all major customers, weighted by the firm's percentage sales to customers.	Compustat, Customer Segment
Analyst Coverage	The number of analysts covering the borrowing firm.	I/B/E/S
Panel B: Loan Level Variables		
Loan Spread	All-in-spread-drawn (AISD), the additional basis points required in loan contracts over LIBOR.	DealScan
Loan Maturity	Total number of months to maturity of a loan tranche.	DealScan
Loan Size	Total loan amount in USD million of a loan tranche, deflated as in 2005 dollars.	DealScan
Loan Type	A dummy indicator that equals to one if a loan is a term loan contract, otherwise zero if it is a revolver loan contract.	DealScan

Secured	A dummy indicator that equals to one if the loan tranche is secured, otherwise zero.	DealScan
TCB	Total cost of borrowing, the yearly total cost from a specific loan contract, constructed by including all potential fees charged by lenders, following the method of Berg et al. (2016).	DealScan
REL(Dummy)	Prior lending relationship dummy indicator, a dummy indicator that equals to one if the firm borrows from the same lead lender in the last five years, otherwise zero.	DealScan
REL(Amount)	Prior lending relationship continuous indicator, calculated as the loan amount led by the same lead lender to the borrower, scaled by the total amount of loans to the borrower in the last five years.	DealScan
Bank Size	The total amount of loan lent by the lender in the whole sample period.	DealScan
Bank Industry Expertise	The average of industry expertise ratios of all lead lenders in the loan tranche. The industry experience of a lender is calculated as the loan amount it lent in the industry that the borrower belongs to, divided by the total amount of all available loans issued in the same industry over the past five years.	Compustat, DealScan
Panel C: Macroeconomic Factors		
Credit Spread	The yield spread between average AAA- and BBB-rated corporate bonds in the U.S. market.	FRED
Term Spread	The yield spread between 10-year Treasury bonds and 3-month Treasury bills.	FRED

Table 1: Summary Statistics

Note: The table provides summary statistics of our loan sample from January 2003 to June 2020. Borrower firm-level characteristics are presented in Panel A and loan-level characteristics are presented in Panel B. Definitions of the variables are provided in Appendix I. Firm Size and Loan Size are deflated in 2005 dollars. All continuous variables are winsorized by year at the 1st and 99th percentiles.

Variable	Mean	Std. Dev.	P10	P25	Median	P75	P90	#Obs
Panel A: Borrower (firm) level variables								
SCRisk	3.53	6.18	0.64	1.08	1.93	3.42	6.47	9,879
Size	21.53	1.59	19.51	20.36	21.44	22.60	23.77	9,879
Profitability	0.13	0.07	0.06	0.09	0.13	0.17	0.22	9,879
Tangibility	0.30	0.24	0.05	0.10	0.21	0.47	0.69	9,879
Leverage	0.29	0.20	0.02	0.15	0.27	0.41	0.56	9,879
Market-to-book	1.83	0.98	1.03	1.21	1.53	2.09	2.98	9,879
Altman Z-score	1.60	1.28	0.24	0.78	1.56	2.38	3.14	9,879
Cash Holding	0.11	0.12	0.01	0.02	0.06	0.14	0.27	9,879
Credit Ratings	0.55	0.50	0.00	0.00	1.00	1.00	1.00	9,879
Panel B: Loan level characteristics								
Loan Spread	212.64	147.66	60.00	112.50	176.00	275.00	400.00	9,879
Loan Maturity	53.20	20.16	17.00	39.00	60.00	60.00	78.00	9,879
Loan Size	460.78	675.20	0.58	84.83	223.85	535.86	1145.70	9,879
# Covenants	1.02	1.12	0.00	0.00	1.00	2.00	2.00	9,879
Loan Type	0.36	0.48	0.00	0.00	0.00	1.00	1.00	9,879
Secured	0.49	0.50	0.00	0.00	0.00	1.00	1.00	9,879

Table 2: Supply Chain Risk and Loan Spread

Note: The table reports the OLS regression results in which loan spread (All-in-spread-drawn) is the dependent variable and supply chain risk (SCRisk) is the main independent variable. Specifically, column (1) utilizes a single independent variable only, while column (2) through column (4) adds borrower firm characteristics, loan characteristics, and macro factors as control variables correspondingly. Definitions of the variables are provided in Appendix I. Industry is classified as four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	Natural Logarithm of Loan Spread			
	(1)	(2)	(3)	(4)
SCRisk	0.007***	0.007***	0.007***	0.005***
	(4.16)	(3.84)	(3.91)	(2.98)
Size		-0.182***	-0.123***	-0.113***
		(-9.29)	(-8.33)	(-6.69)
Profitability		-0.917***	-0.890***	-1.089***
		(-3.53)	(-3.82)	(-6.35)
Tangibility		-0.229	-0.145	-0.217
		(-1.55)	(-1.03)	(-1.65)
Leverage		0.805***	0.728***	0.686***
		(7.55)	(7.67)	(6.59)
Market-to-book		-0.144***	-0.128***	-0.076***
		(-4.68)	(-4.31)	(-3.78)
Altman Z-score		-0.052***	-0.046***	-0.041***
		(-3.67)	(-3.66)	(-3.09)
Cash holding		0.306**	0.202	0.057
		(2.17)	(1.51)	(0.47)
Credit ratings dummy		0.042	0.028	0.039
		(1.18)	(0.87)	(1.27)
ln(Loan Maturity)			0.075**	0.139***
			(2.06)	(4.29)
ln(Loan Size)			-0.127***	-0.118***
			(-7.76)	(-7.24)
Loan Type			0.245***	0.244***
			(8.81)	(10.62)
Credit Spread				-0.214***
				(-6.80)
Term Spread				0.075***
				(3.42)
Borrower Industry FE	Yes	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes	Yes
Observations	9,879	9,879	9,879	9,879
Adjusted R-squared	0.484	0.599	0.642	0.683

Table 3: Supply Chain Risk and Total Cost of Borrowing

Note: The table reports the OLS regression results in which total cost of borrowing (TCB) is the dependent variable and supply chain risk (SCRisk) is the main independent variable. TCB is constructed using DealScan data following the method of Berg et al. (2016). Borrower characteristics, loan characteristics, and macro factors are added as control variables correspondingly. Definitions of the variables are provided in Appendix I. Industry is classified as four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	Total Cost of Borrowing (TCB)			
	(1)	(2)	(3)	(4)
SCRisk	0.899**	0.840**	0.739**	0.587*
	(2.13)	(2.19)	(2.08)	(1.83)
Size		-12.997***	-12.798***	-11.780***

		(-6.28)	(-4.65)	(-4.70)
Profitability		-58.642	-62.761	-106.689***
		(-0.95)	(-1.22)	(-3.07)
Tangibility		-43.027*	-2.934	-8.685
		(-1.91)	(-0.16)	(-0.53)
Leverage		166.529***	114.365***	109.392***
		(8.51)	(7.24)	(6.86)
Market-to-book		-14.415***	-13.190***	-6.138***
		(-3.56)	(-2.88)	(-2.60)
Altman Z-score		-12.762***	-8.226***	-7.121***
		(-4.17)	(-4.69)	(-3.87)
Cash holding		17.797	32.053*	13.142
		(0.77)	(1.77)	(0.81)
Credit ratings dummy		-3.87	-6.142	-4.331
		(-0.57)	(-1.25)	(-0.94)
ln(Loan Maturity)			-19.228***	-12.331**
			(-2.68)	(-2.13)
ln(Loan Size)			-4.005	-2.910
			(-1.52)	(-1.10)
Loan Type			194.839***	194.694***
			(18.43)	(17.56)
Credit Spread				-27.596***
				(-6.12)
Term Spread				5.558***
				(2.68)
Borrower Industry FE	Yes	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes	Yes
Observations	9,249	9,249	9,249	9,249
Adjusted R-squared	0.313	0.357	0.691	0.703

Table 4: Supply Chain Risk and Loan Collateral

Note: The table reports the Logit regression results in which loan secured dummy (whether the loan requires collateral or not) is the dependent variable. Specifically, columns (1) to (3) utilize the level value of SCRisk and SCSentiment, while columns (4) to (6) utilize the first difference value of SCRisk and SCSentiment. Borrower characteristics, loan characteristics, and macro factors are added as control variables correspondingly. Definitions of the variables are provided in Appendix I. Industry is classified as four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	Secured Dummy Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
SCRisk	0.020**	0.013**	0.013**			
	(2.48)	(2.02)	(2.08)			
dif_SCRisk				0.020**	0.017**	0.017**
				(2.28)	(2.53)	(2.48)
Size	-0.689***	-0.564***	-0.563***	-0.678***	-0.560***	-0.560***
	(-12.568)	(-12.49)	(-12.08)	(-11.42)	(-10.31)	(-10.05)
Profitability	-1.466	-1.072	-0.723	-1.247	-0.830	-0.411
	(-1.27)	(-0.81)	(-0.57)	(-0.87)	(-0.53)	(-0.28)
Tangibility	-0.659	-0.543	-0.497	-0.492	-0.556	-0.489

	(-1.33)	(-1.12)	(-1.01)	(-0.81)	(-0.93)	(-0.81)
Leverage	2.644***	1.278**	1.187**	2.747***	1.493***	1.396***
	(3.98)	(2.46)	(2.39)	(4.23)	(2.81)	(2.79)
Market-to-book	-0.459***	-0.241**	-0.277**	-0.460	-0.274**	-0.316**
	(-4.40)	(-2.18)	(-2.47)	(-0.81)	(-2.20)	(-2.58)
Altman Z-score	-0.268***	-0.141*	-0.142*	-0.237**	-0.107	-0.106
	(-2.87)	(-1.70)	(-1.70)	(-2.17)	(-1.09)	(-1.07)
Cash holding	1.976***	1.610***	1.712***	2.057***	1.659***	1.786***
	(4.99)	(3.50)	(3.62)	(4.95)	(2.84)	(3.12)
Credit ratings dummy	0.501***	0.465***	0.457***	0.502**	0.450**	0.439**
	(2.79)	(2.87)	(2.77)	(2.56)	(2.40)	(2.34)
ln(Loan Spread)		1.846***	2.024***		1.768***	1.975***
		(9.97)	(10.91)		(9.04)	(9.47)
ln(Loan Maturity)		0.725***	0.626***		0.622***	0.518***
		(5.09)	(4.24)		(4.47)	(3.56)
ln(Loan Size)		0.219***	0.226***		0.233***	0.243***
		(4.37)	(4.54)		(3.92)	(4.11)
Loan Type		0.054	0.023		0.053	0.010
		(0.32)	(0.14)		(0.28)	(0.06)
Credit Spread			0.245**			0.299**
			(2.00)			(2.22)
Term Spread			-0.102			-0.093
			(-1.35)			(-0.95)
Borrower Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,879	9,879	9,879	8,517	8,517	8,517
Cox & Snell R-squared	0.561	0.592	0.594	0.573	0.598	0.600
Nagelkerke R-squared	0.748	0.790	0.792	0.764	0.798	0.800

Table 5: Robustness Checks

Note: The table reports the robustness checks of OLS regression results in which loan spread (All-in-spread-drawn) is the dependent variable and supply chain risk (SCRisk) is the main independent variable. Specifically, columns (1) to (3) of panel A add customer concentration indicators from Campello and Gao (2017) as extra control variables separately. Panel B provides alternative tests, where column (1) uses a sample constructed by the matching procedure of Bharath et al. (2011), column (2) uses control variables of Campello and Gao (2017), and column (3) uses a sample by excluding observations from the period of 2008 global financial crisis. Definitions of the variables are provided in Appendix I. Industry is classified as four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Adding Customer Concentration as Extra Controls			
Dep. Var.	Natural Logarithm of Loan Spread		
	(1)	(2)	(3)
SCRisk	0.007***	0.007***	0.008***
	(2.86)	(2.83)	(3.00)
CustomerSales	0.271**		
	(2.08)		
CustomerHHI		0.458	
		(1.52)	
CustomerSales			0.035***

			(2.59)
Firm-level Controls	Yes	Yes	Yes
Loan-level Controls	Yes	Yes	Yes
Macro-level Controls	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes
Observations	2,172	2,172	2,131
Adjusted R-squared	0.716	0.715	0.724
Panel B: Alternative Control or Sampling Settings			
Dep. Var.	Natural Logarithm of Loan Spread		
Alternative Setting	Bharath et al. (2011)	Campello and Gao (2017)	Non-GFC-period Sample
	(1)	(2)	(3)
SCRisk	0.006***	0.004**	0.005***
	(3.18)	(2.25)	(2.78)
Firm-level Controls	Yes	Yes	Yes
Loan-level Controls	Yes	Yes	Yes
Macro-level Controls	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes
Observations	9,422	9,879	8,641
Adjusted R-squared	0.676	0.689	0.707

Table 6: 2SLS Test on Supply Chain Risk and Loan Spread

Note: The table reports the two-stage least-squares regression test results in which loan spread (all-in-spread-drawn) is the dependent variable and supply chain risk (SCRisk) is the main independent variable, while the maximum SCRisk of the targeted firm's stakeholders is the instrumental variable. Specifically, column (1) reports the first-stage regression result adding industry fixed effect, and column (2) reports the second-stage regression results using the predicted SCRisk value of (1) as the main independent value. Column (3) reports the first second-stage regression result adding industry and year fixed effect, and column (4) reports the second-stage regression results using the predicted SCRisk value of (3) as the main independent value. Definitions of the variables are provided in Appendix I. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	SCRisk of Focal Firms	Natural Logarithm of Loan Spread	SCRisk of Focal Firms	Natural Logarithm of Loan Spread
	(1)	(2)	(3)	(4)
	First stage	Second stage	First stage	Second stage
Predicted SCRisk		0.013*		0.018**
		(1.80)		(2.47)
SCRisk_Stakeholder	0.035***		0.012*	
	(5.22)		(1.89)	
Firm-level Controls	Yes	Yes	Yes	Yes
Loan-level Controls	-	Yes	-	Yes
Macro-level Controls	Yes	Yes	-	Yes
Year FE	-	-	Yes	-
Borrower Industry FE	Yes	Yes	Yes	Yes
Bank Lender FE	-	Yes	-	Yes
Observations	15,405	3,503	15,405	3,503
Adjusted R-squared	0.039	0.712	0.076	0.714

Table 7: Sub-sample Tests

Note: The table reports the sub-sample test of OLS regression results in which loan spread (All-in-spread-drawn) is the dependent variable and supply chain risk (SCRisk) is the main independent variable. Specifically, panel A distinguishes the baseline sample by firms' prior relationship with the lead lenders of their bank loan contract, where on the left the sample is distinguished by having a prior relationship or not, and on the right the sample is distinguished by the mean value of relationship indicator. The two relationship indicators are constructed based on the method of Bharath et al. (2011). Panel B distinguishes the baseline sample based on the mean value of two lenders' characteristics, where the bank size and the bank industry expertise are constructed based on the method of Lin et al. (2012). Definitions of the variables are provided in Appendix I. Industry is classified as a four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Distinguished by Firm Prior Relationship with Bank				
Criteria	**REL(Dummy)**		**REL(Amount)**	
	No Relationship	With Relationship	Low Relationship	High Relationship
	(1)	(2)	(3)	(4)
SCRisk	0.005***	0.002	0.005***	0.001
	(3.26)	(1.05)	(2.71)	(0.43)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes	Yes
Observations	5,483	4,396	6,482	3,397
Adjusted R-squared	0.673	0.746	0.677	0.747
Panel B: Distinguished by Bank Characteristics				
Criteria	**Bank Size**		**Bank Industry Expertise**	
	Small Bank	Large Bank	Low Expertise	High Expertise
	(1)	(2)	(3)	(4)
SCRisk	0.010***	0.002	0.005**	0.001
	(4.11)	(0.84)	(2.535)	(0.36)
Firm controls	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Borrower Industry FE	Yes	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes	Yes
Observations	5,402	4,477	4,694	3,639
Adjusted R-squared	0.692	0.702	0.684	0.713

Table 8: Influence of Analyst Coverage

Note: The table reports the influence of analyst coverage on the relationship between supply chain risk and bank loan spread. Specifically, Panel A reports the OLS regression results in which loan spread (All-in-spread-drawn) is the dependent variable, while supply chain risk (SCRisk) and analyst coverage (AC), as well as their interaction term are the main independent variables. Panel B reports the subsample test results by dividing the baseline sample into high- and low-coverage groups in each year based on the annual median value of analyst coverage and then running baseline regressions separately. Definitions of the variables are provided in Appendix I. Industry is classified as a four-digit SIC code and the lenders are classified by lead lenders. Heteroskedasticity-robust t-statistics in parentheses are clustered at the borrower and year level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Add Analyst Coverage as an Interaction Term			
Dep. Var.	Natural Logarithm of Loan Spread		
	(1)	(2)	(3)
SCRisk	-0.002	-0.001	-0.004
	(-0.88)	(-0.52)	(-1.43)
SCRisk*Analyst_coverage	0.001***	0.001***	0.001***

	(3.10)	(3.21)	(3.50)
Analyst_coverage	-0.004	-0.004	-0.006**
	(-1.26)	(-1.19)	(-2.20)
Firm Controls	Yes	Yes	Yes
Loan Controls	-	Yes	Yes
Macro Controls	-	-	Yes
Borrower Industry FE	Yes	Yes	Yes
Bank Lender FE	Yes	Yes	Yes
Observations	9,024	9,024	9,024
Adjusted R-squared	0.552	0.604	0.651

Panel B: Sub-sample Test Based on Analyst Coverage

	High AC Group	Low AC Group
	(1)	(2)
SCRisk	0.010***	-0.000
	(3.32)	(-0.07)
Firm controls	Yes	Yes
Loan controls	Yes	Yes
Macro controls	Yes	Yes
Borrower Industry FE	Yes	Yes
Bank Lender FE	Yes	Yes
Observations	4,087	4,937
Adjusted R-squared	0.723	0.674