Mind the Cost of “Disturbia”:

Firm-level Supply Chain Risk and the Bank Loan Cost

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Abstract

We investigate how the credit market evaluates firm-level supply chain risk. We reveal that supply chain risk is associated with unfavorable loan condition changes, including a significant increase in the loan interest spread and collateralization requirement. The relationship with loan spread is more significant when global supply chain pressure or geopolitical risk is high. We further find that the influence of such risk on borrower firms can be delivered from their supply chain stakeholders, especially suppliers. Additionally, we observe that the relationship with bank creditors decreases by amount but not length after the supply chain risk information is renewed at a higher level. Overall, our results show that bank creditors learn from borrowers’ earnings call about this risk exposure information, and treat it as an unfavourable factor by incorporating it in the loan contracts, which emphasizes the importance of supply chain risk management.

Keywords: Supply chain, Bank loan, Loan interest spread, Risk factor, Information asymmetry, Information disclosure

JEL classifications: D82, G20, G21, G24, G30, G32

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1. Introduction

The importance of supply chains to firm operations cannot be overstated. Modern corporate production and operation are heavily reliant on supply chain that have been meticulously optimized and connected to improve efficiency and minimize costs. However, the complexity and interdependence characteristics of the supply chain make firms vulnerable to the negative influence delivered by events like the COVID-19 pandemic, the China-America trade war, the Russia-Ukraine conflict, and natural disasters like earthquakes and hurricanes. The disturbance can significantly impact business operations not confined to the manufacturer industry alone, as even minor shocks can propagate and be exaggerated throughout the whole supply chain. According to industrial research by JP Morgan, "*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*", which widely disrupt various industries, including metals and mining, chemical supply, the automotive sector, semiconductor, and technology industries[1]. It is also noteworthy that supply chain risk exposure could be different at the firm level (Ersahin et al., 2024a; Wu, 2023) because product manufacturing is subject to the supply of different materials, while plant address could be subject to different logistics and climate risks – even similar firms may have different risk exposures due to differentiated positioning in the supply chain and corporate strategy. Despite this, there is still limited understanding in the literature about firms' exposure to the overall supply chain risks (Hendricks & Singhal, 2005; Sodhi et al., 2012) and how this risk exposure affects firm operations.

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 have launched specialized supply chain financing (SCF) programs in recent years to not only provide liquidity to both listed firms and SMEs but also further assist their clients in supporting supplier-customer relationships and maintaining production and operation continuity. Therefore, it is reasonable to conjecture that banks have long been aware of the disturbing impact of supply chain risk on their business activities, especially loan lending services. They likely incorporate related information into

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

their screening and risk assessment process, potentially influencing interest spread pricing and other loan terms. However, it remains unclear in the literature about how the banking credit market assesses the supply chain risks perceived by borrower firms, and how the risk status quantitatively alters their loan contracting.

Following the discussion above, this study examines how the credit market evaluates the supply chain health of their firm borrowers, showing how supply chain risk exposure affects a firm's creditworthiness and banking relationships. The detailed loan-level data allows us to investigate how the supply chain risk information disclosed from earnings conference calls influences the loan negotiation between the firms and their bank creditors. We empirically examine the impact of supply chain risk on a series of loan terms, including loan spread, collateral requirements, and covenant terms. We also examine the impact of supply chain risk on future relationships with banks. Our results are novel in revealing extra loan costs associated with firms' exposure to supply chain risk. Our analysis also identifies the contangious effect of such risk from borrowers' supply chain network. This emphasizes the importance of corporate supply chain risk management.

To perform our tests, we utilize the SCRisk dataset developed by Ersahin et al. (2024a). Based on a natural language process algorithm, the firm-year level dataset captures stakeholders' risk concerns about supply chain issues through earnings conference call transcripts. Our bank loan information including pricing and non-pricing terms is sourced from the DealScan LoanConnector database. A comprehensive test sample is formed with 4,100 loan tranche observations negotiated between 1,009 borrower firms from 2003 to 2020. We add to this data information on firm-level characteristics and macroeconomic factor data to further sharpen our inferences.

Our baseline results can be briefed 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 effects, a one-standard-deviation increase in supply chain risk leads to 5.85 basis points higher interest spreads on bank loans, or a 2.41% higher loan markup compared to an average spread of 242.69 basis points. Additionally, the same shift leads to a 3.6% higher likelihood of collateral requirement and an 8.5% reduction in the future loan amount from the same lead lender.

We also examine the spillover effect of supply chain risk on loan spreads through the supply chain network. We find that loan spreads of targeted borrower firms are also sensitive to the supply chain risk of their partners, while the impact on loan spread delivered from their suppliers could be more than three times higher than the original impact from their own supply chain risk.

The sub-period analysis indicates that the relationship between supply chain risk and loan spread concentrates on specific periods when the supply chain is more vulnerable and glitches are more likely to happen, such as high global supply chain pressure periods and high geopolitical risk periods. This indicates additional information asymmetry in periods when the market-level supply chain is more volatile, so the bank creditors need to pay more attention to the supply chain element during the ex-ante screening and assessment procedures. These results bring further support to our view that the supply chain risk is treated as an unfavourable element in the loan consideration and has been incorporated in contract pricing.

Finally, we investigate and show that banks learn from the earnings call of borrower firms as a supplementary way to identify supply chain risk. We prove that beyond private connections, 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' supply chain health and price their loan contracts with the risk information more effectively.

Our study contributes to the existing literature in the following ways. First, it extends the growing literature about supply chain management. To the best of our knowledge, it is the first study to investigate the impact of supply chain risk on firm loan financing. Previous literature has recorded a series of financial and operational performance factors that can be affected via the supply chain network, such as stock price performance (Cohen & Frazzini, 2008; Hendricks & Singhal, 2003; Qiu et al., 2024), bankruptcy risk (Kolay et al., 2016), strategy policy and investment (Ersahin et al., 2024a), corporate innovation (Chu et al., 2019), asset and inventory buffers (Hendricks & Singhal, 2005; Wu, 2023), and shareholder value (Hendricks & Singhal, 2003). Given the vital role of loan lending in corporate financing, our study establishes a linkage between supply chain risk and firm cost of debt. In response to the calling of Sodhi et al. (2012), it helps to narrow the gap between theoretical and empirical research in supply chain risk. What's more, the incremental loan cost induced by the risk emphasizes the necessity of supply chain risk management (SCRM), as the risk not only varies by industry but also shows considerable differences in firm-level due to product characteristics, commercial strategies, and distribution channels (Baldwin & Freeman, 2022; Ersahin et al., 2024a). The linkage to bank loan supplies also aligns with the findings of Ersahin et al. (2024b), as they identify the more intensive trade credit flow associated with operation shocks in the production network. This emphasizes the importance of financial liquidity in enhancing production network stability.

Second, this study also contributes to the literature on the key factors of bank loan financing. Various unique determinants of bank loan terms have been studied in the literature, 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 (Huang et al., 2022), corporate social responsibility (H. Gao et al., 2021), tax avoidance (Hasan et al., 2014). Complementing the prior literature, our analysis connects it with the supply chain condition of borrower firms and provides fresh evidence on the role of supply chain risk in bank assessment and loan contract negotiation.

Our paper is closely related to Campello and Gao (2017), who also investigate the impact of supply chain conditions on loan borrowing by examining the firm-level customer concentration. Our studies are different in the following ways. First, regarding indicators, they focus on customer-side profiles, especially the customer distribution of supplier firms. However, customer concentration represents only a limited part of the supply chain situation. More importantly, it is not necessarily perceived as a signal of risk (Croci et al., 2021; Dhaliwal et al., 2016; Ma et al., 2020): for example, literature also records conflicting evidence that stronger and persistent customer-supplier link positively affects suppliers' loan lending conditions due to its benefit on supply chain stability (Cen et al., 2016), while Croci et al.(2021) find its controversial 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 the suppliers in bond issuance, as customers help screen and monitor the quality of supplier firms, which reduces information asymmetry between the suppliers and their bond-holders. Employing an overall risk measurement, our study examines the direct influence of supply chain health on loan lending and shows that bank creditors treat supply chain risk as a pure risky element in loan decisions. Second, regarding sample construction, Campello and Gao (2017) focus only on the manufacturer industry, while our study applies a sample covering more industries in the U.S. market. This allows us to examine the capacious impact of supply chain risk. Third, we find additional evidence that supply chain risk leads to more collateral requirements, as well as the spillover effect of such risk in the supply chain network. We also find the time-varying evidence of the relationship between the risk and loan spreads, which extends the understanding of how the bank creditors evaluate the supply chain health of their borrower clients.

Broadly speaking, considering the call-transcript-based nature of the supply chain risk measure, our study adds to the emerging literature that applies qualitative information in the financial-economic area, e.g., newspaper (Caldara & Iacoviello, 2022), earnings conference call (Hassan et al., 2019; Sautner et al., 2023), and 10-K files (Lopez-Lira, 2023). These studies provide novel evidence on how soft communication disclosures could help eliminate information asymmetry in the market, and how the stakeholders could digest and utilize information in identifying corporate culture (Li et al., 2021), management sentiment (Loughran & Mcdonald, 2011), as well as non-traditional corporate risks (Florackis et al., 2023; Harford et al., 2023). The earnings call is informative as it captures information about specific topics concerning firm stakeholders. In recent work, Cao et al. (2023) find that insurance companies also adjust their corporate bond investment based on their learning from earnings calls, as it contains information that helps predict the default risk of bond issuers. In our case, our analysis highlights that in addition to investors and bond issuers, earning calls could also benefit bank creditors' loan lending decisions by delivering them more information about supply chain risk exposure, so that the banks could adjust loan spread effectively in response to the disclosed risk of their 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 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 one of the major concerns for banks and incorporated into loan contracting through various ways.

First, negative shocks in the supply chain could lead to unexpected losses to banks. A loan contract can be treated as an implicit put option written by banks (Huang et al., 2022; Merton, 1974) when the loan is credited to limited liability corporations. On the other side, extreme events, such as COVID-19, the Tohoku earthquake in 2011, Hurricane Sandy in 2012, and the West Coast port strike in 2015 would cause supply chain glitches that disrupt firm operations and incur significant losses (Hendricks & Singhal, 2003, 2005). When similar events happen, the negative impacts on borrower firms' business prospects would leave the put options in the money and leave banks' payoff at risk in case of delinquency and default.

Second, supply chain risk may be associated with higher agency costs for banks (Jensen & Meckling, 1976; Leland, 1998), which arises from the potential impairment of existing debt claims, which further decreases the stability of repayment including both loan interest and principal. For example, if supply chain risk negatively affects the financial performance of borrowers, managers are then 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 delivers larger cash flow volatility and default risk from the firm borrowers to their bank creditors, but the latter cannot share the potential benefits equivalently from such risk exposure.

What's more, the supply chain risk exacerbates information asymmetries between borrowers and lenders, which increases the ex-ante information collection costs and the ex-post supervisory and monitory costs for banks (Bharath et al., 2011; Lin et al., 2012). 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). The complexity of supply chain risk may prevent stakeholders from identifying and quantifying its negative impact comprehensively, 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 a more rigorous appraisal process resulting from tougher access to information, as well as more frequent information tracking and monitoring.

2.2 Loan Spread

Based on the discussion above, supply chain risk implies a worse, unfavourable part of the firm status and induces uncertainty in its financial condition and operation continuity. Thus, the disclosed supply chain risk information could be a "risky" signal to raise the concern of bank creditors in loan consideration. This will result in an adverse position for borrower firms in loan contract negotiation, which will be considered in both pricing and non-pricing terms in the loan contracting.

As the pricing term, loan spread is the main pricing tool for bank creditors to incorporate the unfavourable situation of borrowers as well as the default risk it brings into loan contracts. In other words, by demanding a higher interest spread rate, banks would expect to offset the potential losses caused by the higher supply chain risk, in case future loan payments cannot be fulfilled. For instance, Hendricks and Singhal (2005) record the wide negative influence of supply chain glitches on firm operational performance, including revenues, costs, and asset utilization. In the meantime, the spread is also taken as compensation for the higher cost raised from higher supply chain risk in their ex-ante information collection and ex-post monitoring procedures. Combining the upper discussion, 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

In addition to pricing terms, loan contracts may also adjust non-pricing terms as an extra risk management tool to mitigate agency conflicts and information fractions. In the presence of great uncertainty about the supply chain status, it is difficult for bank creditors to collect comprehensive information and monitor the financial status change and operational situation of borrowers, which may lead to post-contractual opportunism and cause damage to the welfare of lenders (Chava & Roberts, 2008; Demerjian & Owens, 2016). Therefore, they are motivated to require asset control rights via non-pricing terms as a complement to pricing mechanisms to coordinate loan transactions and maintain the survival of loan contracts. This unique characteristic reflects the flexibility of the loan contracting dynamic. Related literature has shown that bank credit could implement constraints on borrowers by 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 (Huang et al., 2022).

Therefore, our second hypothesis is that a higher likelihood of loan secured would be applied in dealing with higher supply chain risk. Notice that it remains unclear whether higher supply chain risk similarly affects other non-pricing terms, such as loan size, loan maturity, and the number of covenants. While collateral provides a straightforward solution to risk mitigation, the effects of supply chain risk on other aspects of the loan contract are less predictable. This ambiguity arises from the complex negotiation strategies that balance pricing and non-pricing terms, which vary based on individual firm circumstances and lender preferences. However, the potential impairment of property from supply chain shocks justifies banks' requirement for a larger package of collateral pledged in exchange for loans. Additionally, it also prevents opportunistic divestiture of pledged assets during high-risk periods, which helps to maintain the productive capacity and repayment ability of enterprises (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): Higher supply chain risk is associated with a higher likelihood of loans being collateralized.

3. Sample Construction and Summary Statistics

3.1 Data Sources

We combine a variety of data sources in sample construction, mainly including firm-level supply chain risk data, loan tranche data, as well as different levels of control variables.

We proxy the firm-level supply chain risk using the novel SCRisk scores dataset developed by Ersahin et al. (2024a). Applying textual analysis technology[2], the SCRisk score dataset 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. Specifically, they calculate the number of supply chain bigrams that appear in the transcript context based on the similar risk-quantification method of Hassan et al. (2019) as below:

$$SCRisk_{it} = \frac{\sum_{b}^{B_{i,t}} I[b \in S \backslash N] \times I(|b-r| < 10) \times \frac{f_{b,S}}{B_S}}{B_{i,t}} \tag{1}$$

where $I[]$ is an indicator function to identify bigram b contained in supply chain dictionary S (but not in corporate finance dictionary N) within 10 words around risk unigrams r from Hassan et al. (2019). $f_{b,S}$ is the frequency of the term b in the supply chain training library, and B_S is the total number of terms in the supply chain training library. Note that although earnings conference calls are usually held quarterly responding to the earnings announcement schedule in the U.S. market, the SCRisk dataset is constructed at a yearly frequency to avoid the disruption of potential seasonal factors

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

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. In addition, Ersahin et al. (2024a) also provide a $SCSentiment$ score measurement based on the sentiment dictionary (Loughran & Mcdonald, 2011) to capture the sentiment about supply chain discussion among conference calls. To differentiate the two kinds of data, they empirically confirm and interpret the $SCRisk$ scores as the uncertainty and fear of future supply chain shocks, while $SCSentiment$ scores can be treated as the realization of supply chain shocks during the previous year.

Note that the SCRisk dataset is available from 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 2003 January. The ending of our sample (2020 December) is limited by the link table of Chava and Roberts (2008) which we use to match the loan data with Compustat and SCRisk data in firm-year level.

Our bank loan data is obtained from the WRDS-Refinitiv LoanConnector 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 and accounting information of matched borrower firms is collected from the CRSP/Compustat Merged 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. Regarding the loan type issue, we only include term and revolver loans to avoid the potential interference of various fee structures and restrictive pricing policies, also because these types of loans have more detailed information in the database (Berg et al., 2016; Campello & Gao, 2017). Considering their larger access to financing resources, we also exclude all financial service firms (SIC codes 6000 to 6999) from the sample, following the method of previous literature (e.g., Berg et al. (2016), Chava and Roberts (2008)).

3.2 Summary Statistics

Besides our main dependent variable, the *SCRisk* score[3], 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 and Gao (2017), Chava and Roberts (2008), and 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 yield spread between average AAA-rated corporate bonds and average BBB-rated corporate 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 amount) in the year 2005 dollars. Also, we lag all dependent variables for one period to ensure all 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 additionally. Detailed variable definitions are provided in the Appendix.

[Insert Table 1 about here]

[Summary Statistics]

Table 1 reports the summary statistics of our sample. The baseline test sample covers 4,100 loan tranches from 1,009 firms. The earliest (latest) loan tranche in our sample was activated on January 10th, 2003 (June 30th, 2020). The median loan in our sample has a loan spread of 243 bps over the LIBOR, a maturity of 55 months, and a loan size of $350 million (deflated in 2005 USD currency). In

[3] 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.

the sample, about 61 percent of loan tranches have collateral (secured), while 38 percent of loan tranches are term loans.

Regarding firm-level characteristics, the median book value of total assets (deflated in 2005 USD currency) is \$1.39 billion, and the median book leverage ratio is 30%. In terms of performance, the median profitability measured as the ratio of EBITDA to total assets is 13%, and the median modified Z-score is 1.36. About 44 percent of observations have a credit rating (when the loan is activated) in the S&P crediting rating database. SCRisk (SCSentiment) score ranges from 0.00 (-490.18) to 84.30 (854.72). In terms of macroeconomic factors, the median credit spread is 96.04 bps, while the median term spread is 196.14 bps.

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 analyse the relationship between the change in loan spread and supply chain risk by running loan-level panel regressions with a set of control variables, industry, and lender fixed effects. We then analyse 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 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:

$$\begin{aligned} \ln\left(Loan\_Spread_{l,i,t}\right) &= \beta_1 SCRisk_{i,t-1} + \beta_2 Firm\_controls_{i,t-1} \\ &+ \beta_3 Loan\_controls_{i,l,t-1} + \beta_4 Macro\_factors_{t-1} \\ &+ Fixed\ Effects + \varepsilon_{l,i,t} \end{aligned} \tag{2}$$

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[4] 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 (Campello & Gao, 2017), so we also include bank (lender) fixed effects[5]. 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]

[Supply Chain Risk and Loan Spread]

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, thus the loan spreads are positively associated with supply chain risk, and such a relationship stays statistically significant at the 1% level (t-stat = 2.22) 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 5.85 basis points[6]. Economically, it represents a sizable incremental loan cost of 205,042 USD dollars annually given the sample mean loan size of $350.5 million.

Nevertheless, it is noticeable that loan spread barely changes with the variation of supply chain sentiment (SCSentiment) in our sample. This may imply that in loan contract decisions, bank creditors are not concerned about the salvation of recent supply chain glitches, but care more about the negative

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[4] We mainly report the empirical results using 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 two-digit SIC code and NAICS code.

[5] 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.

[6] The SCRisk has a sample standard deviation of 6.05 and an estimated coefficient of 0.005 in our baseline model. Since the sample mean value of the natural logarithm of loan spread is 5.28, the reduction in loan spread is e^5.28 – e^(5.28−6.05×0.005) ≈ 5.85 basis points.

influence of potential risk factors in the future.

4.2 Loan Collateralization

In response to our hypothesis H2, 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 (2). 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 0.025 (t-stat = 2.54) in our sample. This implies that the marginal effect of supply chain risk is 0.036, or the likelihood of collateral requirement in loan contracts is 3.6 percent higher for one-standard-deviation higher supply chain risk. The results in columns (4) to (6) furtherly show 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 assets pledged in the case that borrower firms are exposed to larger supply chain risk, which confirms the hypothesis H2 as collateralization helps ease lending risk and banks' concern of potential default.

[Insert Table 3 about here]

[Supply Chain Risk and Loan Collateral]

4.3 Future Relationship with Banks

We also examine whether the relationship between the borrower firms and their bank creditors changes after supply chain risk information is renewed based on the method of Campello and Gao (2017). Similarly, we also target *FutureLoans* and *FutureDuration* as measurements of the relationship with borrowers' lead lender banks in the existing loan contracts. The results are reported in Table 4.

Interestingly, we find that the intensity of the relationship (*FutureLoans*) is significantly decreased associated with the increasing supply chain risk, while the length (*FutureDuration*) remains barely unchanged. Specifically, column (2) in Table 4 suggests that a one-standard-deviation increase in supply chain risk is associated with a decline in the amount of future lending extended by the same bank (scaled by their current loan amount) equivalent to 8.5% of the sample mean (t-stat = -2.06). However, columns (3) and (4) demonstrate that the time length of future relationships does not change significantly with the variation of supply chain risk.

[Insert Table 4 about here]

[Supply Chain Risk and Future Relationship with Banks]

Taking the results together, our findings suggest that the supply chain risk of borrower firms encourages banks to adopt a more conservative attitude in their future lending decisions reflected by a dual strategy, which is different from the monotonous influences on bank relationships caused by customer concentration as discussed in Campello and Gao (2017). On the one side, the conservation results in a considerable reduction of loan amounts in the future. On the other hand, the relative stability in the lending relationship length indicates that banks do not necessarily cut off or shorten their ties with firms experiencing higher supply chain risks. The long-term strategy reflects the fact that banks only mitigate potential credit risk from supply chain factors by adjusting the scale of loan debt in response to borrower firms' supply chain vulnerabilities but continue to provide financial support to their clients. The nuanced strategy that banks take in dealing with supply chain risk also highlights their desire to balance risk mitigation with economic benefits while maintaining enduring client relationships.

5. Robustness Checks

Following the baseline test results in section 4.1, next, a series of robustness checks are conducted to further establish the relationship between supply chain risk and loan spread, including adding and switching control variables, as well as applying an alternative loan cost measurement.

5.1 Adding Customer Concentration as 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). High customer concentration could also be seen as an undiversified risk in the supply chain 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 two different measures, *CustomerSales* and *CustomerHHI*[7] following the equation from Campello and Gao (2017) as below:

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

$$CustomerHHI_{i,t} = \sum_{j=1}^{n_i} \%Sales_{i,j,t}^2 \tag{4}$$

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

The results are reported in columns (6) and (7) of Table 2. As expected, our results show that the coefficients of supply chain risk remain positive and significant with similar-sized estimations in the baseline results. What's more, it can be observed that the coefficients of $CustomerSales$ and $CustomerHHI$ are no longer significant in our model, which implies that the explanatory power of customer concentration is absorbed by the overall supply chain risk. This also aligns with the opinion that customer concentration is a part of overall supply chain risk (Dhaliwal et al., 2016; Ma et al., 2020).

5.2 Total Cost of Borrowing Test

Second, we also conduct an alternative test by repeating baseline regressions but replacing the loan spread variable of each loan with the total-cost-of-borrowing (TCB) measure of Berg et al. (2016). Instead of using the AISD spread as a simple estimation of loan pricing, the TCB construction considers the complex pricing structure of loan commitments by including a variety of fee types recorded in DealScan loan contracts. Therefore, it should provide a more comprehensive cost of loan debt estimation than the simple loan interest spread measured by AISD.

[Insert Table 5 about here]

[7] We choose to not include the *CustomerSize* in the test as Campello and Gao (2017) do because the variable construction requires non-absence of firm size variable of customer firms, which largely reduce the test sample size after merging with both DealScan and SCRisk data variables.

[Supply Chain Risk and Total Cost of Borrowing (TCB)]

As predicted, the results in Table 5 again show that supply chain risk proxied by the $SCRisk$ score is positively associated with loan costs across all model specifications. Additionally, we find that the TCB cost is also consistently sensitive to the change (first difference) of $SCRisk$ value over the year. This suggests that bank creditors not only care about the individual supply chain risk status of each year but also incorporate the risk changes into their loan pricing decisions.

5.3 Other Tests Using Alternative Model Settings and Sample

Furthermore, we conduct a few additional tests applying different model settings or alternative samples to check the robustness of our baseline result.

First, the coefficient value of *SCRisk* also maintains its magnitude and significance if we switch to the baseline model setting of Campello and Gao (2017), which uses a different set of group of control variables as we do.

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 calendar year t, then we use Compustat data from fiscal year t. Otherwise, we keep using the data from fiscal year $t-1$. The baseline model results are robust to such change as the coefficient remains barely unchanged, except that t-statistics decrease to between 1.85 and 2.65 under different control specifications.

Finally, we further made a sub-sample by keeping only non-GFC-period observations based on the National Bureau of Economic 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 the "risk-spread" association remains nearly unchanged by re-running the baseline regression using the non-GFC sample (coefficient = 0.005, t-stat = 2.07), thus the exclusion does not alter our result in Table 2.

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

6. Additional Results

6.1 Does Stakeholders' SCRisk Matter?

Various research has discussed the spillover effect of risk factors along the supply chain network (e.g., Crosignani et al., 2023; Kolay et al., 2016; Qiu et al., 2024). Therefore, it is natural to infer that the supply chain risk may also be influential among the network due to its externality nature. In light of the spirit of prior literature, we then examine if the loan spread of the targeted borrower firm also responds equivalently to the supply chain risk of their stakeholders.

We identify the alternative SCRisk values for a borrower firm by identifying its observed supply chain stakeholders and then merging them with the original SCRisk score dataset. The supply chain relationship is constructed using the Compustat segment file, as it records customer firms that account for 10% or more sales of the targeted firms as the latter ones are required to disclose. This allows us to identify major customers of a firm, and a group of available suppliers reversely through the same channel. Next, we construct alternative SCRisk values for a target firm i as below:

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

where $SCRisk_{ij,t}$ represents the $SCRisk$ value of stakeholder firm j of target firm i in year t. With this approach, three different variables are calculated yearly for each borrower firm i: (1) $SCRisk\_customer$ for all its disclosed customers, (2) $SCRisk\_supplier$ for all its available suppliers, and (3) $SCRisk\_stakeholder$ for all available customers and suppliers. The correlation matrix reported in Table 6 suggests these three alternative SCRisk values are rarely correlated with the original SCRisk, which suggests there is high heterogeneity of firm-level supply chain risk even within a supply chain (Ersahin et al., 2024a). It is also noticeable that the supply chain risk of suppliers dominates the overall supply chain risk due to the high correlation (0.924) between $SCRisk\_supplier$ and $SCRisk\_stakeholder$.

[9] We also measure the three alternative SCRisk values by taking the mean value instead of taking the maximum value – the results in Table 6 and 7 maintains comparable coefficients and similar significance overall.

[Insert Table 6 about here]

[Correlation Matrix of Different Stakeholders' SCRisk]

Next, to examine the relationship between different stakeholders' supply chain risk with the loan spread, we replace the original $SCRisk$ with these stakeholders' $SCRisk$ value in the baseline model described in section 4.1. Columns (1) to (3) of Table 7 show that the loan spread of borrower firms is significantly higher when their supplier or customer partners are exposed to higher supply chain risks. The coefficients (0.007) are similar to the baseline model estimation, compared to the results in Table 2. Columns (4) to (6) focus on the spillover effect of risk from suppliers, and it is noticeable that bank creditors seem to be more sensitive to the supply chain risk of borrowers' suppliers, as the coefficients (0.023 to 0.028) are about 3.5 times larger than the original ones in the baseline results while keeping a comparable significance. However, we cannot observe an equivalent response of loan spread to the supply chain risk of borrowers' customers in columns (7) to (9).

[Insert Table 7 about here]

[Stakeholders' Supply Chain Risk and Loan Spread]

Overall, the results confirm that supply chain risk can be delivered among the supplier-customer network and severely alter the loan spread of targeted firms. This also outlines the important impact of supply chain disruption on firm financing costs. Aligning with the findings of Ersahin et al. (2024a), our analysis agrees that the negative impact of supply chain risk is mainly delivered from suppliers instead of customer partners. Moreover, the influence on loan interest spread is even more exaggerated when we focus on the spillover effect of suppliers' risk.

6.2 Does Banks' Response Vary in Time Series?

Having determined that there is a significant loan spread increase associated with higher supply chain risk, next, we test if such a relationship is time-dependent over the sample period. This allows us to gauge if banks perceive the supply chain risk and price it in loan contracts consistently.

We determine our whole sample into dual sub-sample periods based on a series of time series criteria that may affect the influence of supply chain risk, including the Global Supply Chain Pressure (GSCPI)

Index[10], Geopolitical Risk (GPR) Index (Caldara & Iacoviello, 2022). Specifically, we classify months into high-risk (high-pressure) periods if they have index values that are above the top (under the bottom) third of the index throughout the sample period. We then re-run the baseline model tests on the subsamples to compare the relationship between supply chain risk exposure and loan spreads under those different conditions. The subsample test results are reported in Table 8.

[Insert Table 8 about here]

[Supply Chain Risk and Loan Spread in Different Periods]

Panel A of Table 9 reports high- and low-GSCPI period sub-sample results. We find that the relationship between supply chain risk and loan spread is only significant during the high-pressure period (t-stat = 2.16), while the coefficient is amplified to 0.012 -- as a comparison, the baseline model in column (5) of Table 2 records a coefficient of 0.005 only. On the other side, the pattern is almost eliminated in the low-GSCPI period, as indicated by a non-positive and non-significant coefficient. Similarly, we classify the sample by geopolitical risk index in Panel B and find that the magnitude of such a relationship expands significantly in the high-risk period but disappears in the low-risk period. Two-sample differentiation t-test with t-statistics of 2.03 and 2.39 also confirms the significance of such differences in two groups of sub-samples.

In summary, Table 8 implies that bank creditors are more concerned about the supply chain risk of their borrowers when the GSCPI or GPR index value stays at a relatively high level, which is reflected in the loan pricing and leads to more exaggerated loan spreads in response to the variation of supply chain risk. For reasoning, the rising coefficient could mean additional information asymmetry in specific periods, so the bank creditors need to pay more attention to the supply chain element during the ex-ante screening and assessment procedures. Therefore, they are more sensitive and cautious about potential repayment default sourced from borrowers' supply chain disruption. On the other side, it may also be attributed to the additional information friction cost of bank creditors (Bharath et al., 2011; Lin et al., 2012), as the complexity of supply chain status would further increase in those periods and require banks to take more effort in the ex-post tracking and monitoring procedures to collect the information on borrowers' operational situation. Consequently, banks tend to demand higher loan

[10] The GSCPI index is developed by the Federal Reserve Bank of New York. Its goal is to provide a parsimonious measure to gauge the role of supply chain constraints and disruptions to global economic outcome by integrating a series of transportation cost data and manufacturing indicators. See more details from https://www.newyorkfed.org/research/policy/gscpi#/overview.

spreads as extra compensation for equivalent supply chain risk of borrower firms in those periods.

Overall, the subsample tests demonstrate that the incremental loan spread of borrowers associated with its firm-level supply chain risk varies in different periods, which indicates the time-varying nature of the interest premium for supply chain risk required by the bank credit market. The exaggerated coefficients also support the literature (Baldwin & Freeman, 2022; Ersahin et al., 2024a) that the global supply chain network can be severely affected by geopolitical and transportation factors, which further increases the complexity of due diligence and risk management. In conclusion, the time-series variability highlights the fact that banks take adaptive risk management practices that respond to the supply chain risk under the changing macroeconomic landscape.

6.3 Do Banks Learn from Earnings Call Information?

Another question of interest is whether bank creditors acquire supply chain information from the earnings conference calls of their borrowers. We are curious because banks and large 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). In other words, we wonder whether (1) the firm-level SCRisk score is merely an external proxy of supply chain risk level, while banks do not necessarily gain any supply chain information from the earnings calls, or (2) besides the private information channel, bank creditors also learn from calls as a supplementary channel to 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 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:

$$\begin{aligned}\ln\left(Loan_{Spread}{}_{l,i,t}\right) &= \beta_1(Analyst\_coverage_{i,t-1} * SCRisk_{i,t-1}) \\ &+ \beta_2 SCRisk_{i,t-1} + \beta_3 Analyst\_coverage_{i,t-1} \\ &+ \beta_4 Firm\_controls_{i,t-1} + \beta_5 Loan\_controls_{i,l,t-1} \\ &+ \beta_5 Macro\_factors_{t-1} + Fixed\ Effects + \varepsilon_{l,i,t}\end{aligned} \tag{6}$$

where $Analyst\_coverage_{i,t-1}$ is the monthly number of analyst forecast estimates for firm i in month $t-1$. The result shows that β_1 is significantly positive (coefficient value = 0.0004, t-stat = 3.85), demonstrating that the extent of comovement between $SCRisk$ and loan interest spread is positively dependent on the number of analysts following the firm. This also suggests that the banks at least partially depend on external financial analysts to gather unique information about supply chain risk, also that 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 = -0.014, t-value = -3.89) also verifies the empirical findings of Hallman et al. (2023) that analyst coverage reduces loan interest spread.

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. The results show that the coefficient on supply chain risk is significantly positive (t-stat = 3.26) only in the high-coverage group, while we cannot observe an equivalent pattern in the low-coverage group. Also, the t-value of the differentiate test for the coefficient of two samples is 3.33, which statistically proves the different loan spread responses to supply chain risk of borrower firms with different analyst coverage. This suggests that bank creditors are only capable of pricing supply chain risk effectively in their lending contracts when sufficient analysts are available to help analyse and deliver information from the earnings calls of borrower firms to the banks.

This finding is in line with the conference-call-based nature of the SCRisk dataset, as well as the findings 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 bank private knowledge does not comprehensively help 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. Concluding Remarks

Recent literature explores the wide influence of supply chain risk on firm operations and financing. In this study, we examine the variation of bank loan cost associated with supply chain risk.

Our study investigates how banks respond to the supply chain health of their borrowers by examining the pricing and non-pricing terms in the loan contracts of the US-listed firms. Specifically, we find that supply chain risk leads to higher loan interest spread. Such a relationship is time-varying, as the response of loan spread to supply chain risk is exceptionally prominent in specific periods. We further identify the spillover effect of this risk on loan spreads, which is mainly driven by the supplier side of borrower firms. 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 find a higher likelihood of collateral requirement with higher risk exposure, or the increase of such risk exposure. We also gauge how the updated risk affects the borrowers' future relationship with their lender banks, as banks choose to maintain the length but reduce the intensity of the relationship. The analysis of non-pricing terms indicates that the bank market has realized the disturbance of supply chain risk to firm operations and future loan repayments, but continues to provide a modest level of financial liquidity support under the supply chain uncertainty. Overall, the evidence revealed in our study supports that banks treat supply chain risk as an unfavorable element of borrower firms and have incorporated it into the loan contract terms.

Our findings point out significant practical implications, as the analysis results emphasize the importance of supply chain risk identification 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 financial performance but also has become one of the main concerns in corporate credit quality assessment that greatly influences financing costs. On the other side, bank creditors are also encouraged to modify their screening and evaluating procedures by collecting more comprehensive information about the supply chain of applied borrowers from various information channels. Such a development could help increase loan pricing accuracy and efficiency, as well as avoid potential losses from the high information asymmetry.

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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)
SCSentiment	Firm's yearly sentiment of supply chain topic	Ersahin et al. (2024)
Size	The natural logarithm of total assets (*at*), deflated as in 2005 dollars	Compustat
Profitability	The ratio of EBITDA and total assets	Compustat
Tangibility	The ratio of property, plant, and equipment (*ppent*) and total assets	Compustat
Leverage	Book leverage, the ratio of total debt (*dlcc* + *dlt*) and total assets	Compustat
Market-to-book	The ratio of adjusted market value and total assets, calculated as (stock price (*prcc*) × shares outstanding (*csho*) + total assets – book equity (*ceq*)) / total assets	Compustat
Altman Z-score	The modified Altman's Z-score without leverage, calculated as (1.2 × working capital (*wcap*) + 1.4 × retained earnings (*re*) + 3.3 × pretax-income (*pi*) + 0.999 × total sales (*sale*)) / total assets	Compustat
Cash holding	The ratio of cash and marketable securities (*che*) 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
Analyst Coverage	Number of forecast estimates submitted for each month, recorded in the I/B/E/S system.	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 dollars of a loan tranche deflated as in 2005 dollars	DealScan
Loan Type	A dummy indicator that equals to one if the loan is a term loan, otherwise zero if it is a revolver	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
CustomerSales	Total percentage sales to all reported major customers	Compustat Segment
CustomerHHI	The Herfindahl index of sales to all reported major customers	Compustat Segment
FutureLoans	The total amount of loan facilities issued by the same bank in the future, scaled by the current total loan amount	DealScan
FutureDuration	The total number of months until the last loan is extended by the same bank (since the borrower firm updates its SCRisk at the beginning of each year)	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	3.34	6.05	0.62	1.05	1.84	3.29	6.13	4,100
SCSentiment	37.19	86.93	-9.39	2.97	14.85	36.90	103.20	4,100
Size	21.05	1.46	19.22	19.99	21.03	21.99	23.08	4,100
Profitability	0.13	0.08	0.05	0.09	0.12	0.17	0.22	4,100
Tangibility	0.31	0.26	0.04	0.09	0.22	0.52	0.72	4,100
Leverage	0.30	0.21	0.00	0.13	0.28	0.42	0.57	4,100
Market-to-book	1.77	0.96	1.01	1.18	1.49	2.01	2.82	4,100
Altman Z-score	1.36	1.45	-0.01	0.60	1.36	2.14	2.99	4,100
Cash holding	0.12	0.14	0.01	0.02	0.07	0.15	0.30	4,100
Credit ratings	0.44	0.50	0.00	0.00	0.00	1.00	1.00	4,100
Panel B: Loan level characteristics								
Loan Spread	242.69	156.48	75.00	129.38	200.00	325.00	450.00	4,100
ln(Loan Spread)	5.28	0.70	4.32	4.86	5.30	5.78	6.11	4,100
Loan Maturity	55.00	19.62	24.00	46.00	60.00	60.00	84.00	4,100
ln(Loan Maturity)	3.91	0.53	3.18	3.83	4.09	4.09	4.43	4,100
Loan Size	350.05	584.64	25.84	67.16	173.63	402.93	849.09	4,100
ln(Loan Size)	18.88	1.34	17.07	18.02	18.97	19.81	20.56	4,100
# Covenants	1.14	1.17	0.00	0.00	1.00	2.00	3.00	4,100
Loan Type	0.38	0.49	0.00	0.00	0.00	1.00	1.00	4,100
Secured	0.61	0.49	0.00	0.00	1.00	1.00	1.00	4,100

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 columns (2) through (5) add SCSentiment, borrower characteristics, loan characteristics, and macro factors as control variables correspondingly. Columns (6) and (7) further add CustomerSales and CustomerHHI as extra control as in Campello and Gao (2017). Definitions of the variables are provided in Appendix I. All regressions use industry-fixed effects and lender-fixed effects. Industry is classified by four-digit SIC codes 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)	(5)	(6)	(7)
SCRisk	0.007**	0.007**	0.007***	0.006***	0.005**	0.011**	0.009**
	(2.88)	(2.82)	(3.60)	(3.08)	(2.22)	(2.53)	(2.22)
SCSentiment		0.000	0.000	-0.000	0.005	0.000	0.000
		(-0.97)	(-1.16)	(-1.09)	(-0.94)	(-1.10)	(-1.33)
CustomerSales						0.172	
						(0.86)	
CustomerHHI							-0.138
							(-0.29)
Size			-0.167***	-0.128***	-0.131***	-0.159**	-0.162***
			(-7.39)	(-6.59)	(-6.33)	(-3.46)	(-3.60)
Profitability			-0.985***	-0.959***	-1.074***	-1.581***	-1.616***
			(-3.21)	(-3.33)	(-3.68)	(-5.63)	(-6.46)
Tangibility			-0.319**	-0.277*	-0.309**	-0.561	-0.583*
			(-2.01)	(-1.96)	(-2.17)	(-1.82)	(-1.88)
Leverage			0.719***	0.652***	0.612***	0.783***	0.814***
			(4.76)	(4.86)	(4.62)	(5.31)	(5.77)
Market-to-book			-0.158***	-0.144***	-0.110***	-0.101**	-0.102***
			(-4.68)	(-4.89)	(-4.89)	(-2.96)	(-2.91)
Altman Z-score			-0.017	-0.013	-0.013	0.024	0.027
			(-1.16)	(-0.96)	(-0.87)	(1.16)	(1.21)
Cash holding			0.055	0.003	-0.075	0.039	0.127
			(0.24)	(0.02)	(-0.36)	(0.25)	(0.84)
Credit ratings			0.019	0.016	0.030	0.129**	0.112*
			(0.49)	(0.40)	(0.86)	(1.99)	(1.76)
ln(Loan Maturity)				0.015	0.073**	0.117	0.122*
				(0.38)	(2.01)	(1.57)	(1.70)
ln(Loan Size)				-0.084***	-0.074***	-0.097***	-0.097***
				(-5.56)	(-5.26)	(-5.74)	(-5.85)
Loan Type				0.232***	0.222***	0.228***	0.230***
				(9.67)	(10.63)	(7.52)	(7.58)
Credit Spread					-0.138***	-0.065	-0.065
					(-3.53)	(-1.21)	(-1.17)
Term Spread					0.082***	0.101***	0.100
					(4.55)	(4.22)	(4.19)
Observations	4,100	4,100	4,100	4,100	4,100	927	927
Adjusted R-squared	0.537	0.537	0.637	0.668	0.700	0.699	0.698

Table 3: 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. All regressions use industry-fixed effects and lender-fixed effects. The industry is classified by four-digit SIC codes 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	0.029**	0.023**	0.025**			
	(2.52)	(2.31)	(2.54)			
dif_SCRisk				0.033***	0.031***	0.030***
				(2.95)	(3.02)	(3.32)
SCSentiment	-0.001	0.000	-0.001			
	(-1.19)	(-0.62)	(-0.72)			
dif_SCSentiment				-0.001	-0.001	-0.001
				(-1.10)	(-1.18)	(-1.30)
Size	-0.723***	-0.622***	-0.610***	-0.678***	-0.609***	-0.593***
	(-5.42)	(-3.75)	(-3.69)	(-5.02)	(-3.73)	(-3.64)
Profitability	-2.410	-2.111	-1.605	-2.408	-2.013	-1.446
	(-1.28)	(-0.99)	(-0.78)	(-1.02)	(-0.82)	(-0.62)
Tangibility	-1.838***	-1.557**	-1.536**	-1.742*	-1.569*	-1.557*
	(-2.63)	(-2.18)	(-2.14)	(-1.74)	(-1.65)	(-1.65)
Leverage	2.230**	0.503	0.388	2.220**	0.463	0.323
	(2.54)	(0.63)	(0.53)	(2.27)	(0.49)	(0.36)
Market-to-book	-0.415**	-0.190	-0.211	-0.419**	-0.199	-0.230
	(-2.55)	(-1.28)	(-1.40)	(-2.10)	(-1.13)	(-1.23)
Altman Z-score	-0.254**	-0.160	-0.178	-0.241	-0.160	-0.184
	(-2.02)	(-1.24)	(-1.41)	(-1.60)	(-1.03)	(-1.18)
Cash holding	1.077	0.794	0.874	1.014	0.761	0.876
	(1.19)	(0.75)	(0.83)	(0.94)	(0.50)	(0.57)
Credit ratings dummy	0.819***	0.721***	0.714***	0.883***	0.745***	0.769***
	(2.92)	(2.85)	(2.80)	(3.04)	(2.64)	(2.76)
ln(Loan Spread)		1.743***	2.048***		1.81***	2.181***
		(7.29)	(7.70)		(5.54)	(6.29)
ln(Loan Maturity)		0.806***	0.670***		0.636***	0.483**
		(3.80)	(3.26)		(2.82)	(2.17)
ln(Loan Size)		0.293***	0.296***		0.370***	0.379***
		(2.73)	(2.84)		(3.52)	(3.68)
Loan Type		0.417**	0.392*		0.413*	0.387
		(1.97)	(1.83)		(1.75)	(1.61)
Credit Spread			0.264			0.269
			(1.54)			(1.28)
Term Spread			-0.267***			-0.321**
			(-3.36)			(-2.52)
Observations	4,100	4,100	4,100	3,414	3,414	3,414
Cox & Snell R-squared	0.567	0.593	0.596	0.581	0.604	0.608
Nagelkerke R-squared	0.768	0.804	0.808	0.785	0.816	0.821

Table 4: Supply Chain Risk and Future Relationship with Banks

Note: The table reports the OLS regression results in which future relationship with banks is the dependent variable and supply chain risk (SCRisk) is the main independent variable. Specifically, columns (1) and (2) utilize the *FutureLoans* ratio as the dependent variable, while columns (3) and (4) utilize the *FutureDuration* as the dependent variable. Definitions of the variables are provided in Appendix I. All regressions use industry-fixed effects and lender-fixed effects. The industry is classified by four-digit SIC codes 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.	FutureLoans		FutureDuration	
	(1)	(2)	(3)	(4)
SCRisk	-0.038**	-0.037**	-0.001	-0.003
	(-2.17)	(-2.06)	(-0.19)	(-0.38)
SCSentiment	-0.001	-0.001	-0.000	-0.000
	(-1.55)	(-1.51)	(-0.33)	(-0.11)
Size	0.066	0.055	-0.089	-0.096
	(0.35)	(0.28)	(-1.47)	(-1.64)
Profitability	3.357**	3.676**	0.603	0.608
	(2.28)	(2.57)	(0.85)	(0.88)
Tangibility	-1.111	-1.113	0.296	0.242
	(-1.02)	(-1.00)	(1.09)	(0.86)
Leverage	-0.448	-0.509	-0.372	-0.493
	(-0.44)	(-0.53)	(-0.94)	(-1.35)
Market-to-book	0.142	0.077	0.113**	0.137**
	(1.15)	(0.68)	(2.19)	(2.45)
Altman Z-score	0.017	0.012	0.019	0.019
	(0.23)	(0.16)	(0.50)	(0.51)
Cash holding	-0.709	-0.584	1.264	0.830
	(-0.72)	(-0.67)	(1.62)	(1.10)
Credit ratings	-0.570	-0.615	0.022	0.025
	(-0.95)	(-1.00)	(0.20)	(0.22)
Credit Spread		0.360***		0.046
		(2.95)		(0.59)
Term Spread		0.158*		0.145***
		(1.76)		(2.98)
Observations	915	915	915	915
Adjusted R-squared	0.114	0.130	0.173	0.194

Table 5: 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). 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. All regressions use industry-fixed effects and lender-fixed effects. Industry is classified by four-digit SIC codes 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)	(5)	(6)
SCRisk	2.021**	1.502**	1.334*			
	(2.28)	(2.11)	(1.89)			
dif_SCRisk				1.858**	1.507**	1.464***
				(2.53)	(2.50)	(2.58)
SCSentiment	-0.045	-0.018	-0.013			
	(-1.07)	(-0.57)	(-0.41)			
dif_SCSentiment				0.002	0.030	0.033
				(0.07)	(1.17)	(1.39)
Size	-14.709***	-16.497***	-16.521***	-14.040***	-16.822***	-16.767***
	(-3.70)	(-4.87)	(-5.65)	(-3.45)	(-4.75)	(-5.46)
Profitability	-126.761	-165.659**	-205.325**	-195.390*	-207.091***	-238.51***
	(-1.13)	(-2.16)	(-2.48)	(-1.71)	(-2.62)	(-2.73)
Tangibility	-40.060	-3.157	-3.312	-31.502	9.626	6.065
	(-1.13)	(-0.13)	(-0.15)	(-0.77)	(0.32)	(0.22)
Leverage	204.801***	154.601***	148.235***	207.580***	158.630***	153.066***
	(6.57)	(7.25)	(7.25)	(5.85)	(7.02)	(7.50)
Market-to-book	-15.376**	-11.489**	-6.255	-10.757*	-9.262	-4.844
	(-2.39)	(-2.03)	(-1.29)	(-1.77)	(-1.63)	(-1.03)
Altman Z-score	-13.186**	-5.551	-4.931	-9.682	-3.895	-3.481
	(-2.00)	(-1.23)	(-1.16)	(-1.54)	(-0.82)	(-0.78)
Cash holding	13.624	18.027	6.016	-1.578	3.927	-9.506
	(0.36)	(0.62)	(0.23)	(-0.35)	(0.12)	(-0.34)
Credit ratings	1.833	-5.423	-2.131	2.212	-6.946	-3.926
	(0.43)	(-1.55)	(-0.65)	(0.38)	(-1.57)	(-0.99)
ln(Loan Maturity)		-24.714***	-17.599**		-25.787**	-19.023*
		(-3.16)	(-2.33)		(-2.39)	(-1.84)
ln(Loan Size)		-0.910	0.411		-0.314	0.905
		(-0.27)	(0.13)		(-0.08)	(0.25)
Loan Type		209.333***	207.935***		208.659***	207.472***
		(15.49)	(14.95)		(13.89)	(13.48)
Credit Spread			-23.596***			-19.131***
			(-4.22)			(-3.24)
Term Spread			6.520***			7.588***
			(2.82)			(3.21)
Observations	3,599	3,599	3,599	3,094	3,094	3,094
Adjusted R-squared	0.356	0.698	0.706	0.352	0.695	0.701

Table 6: Correlation Matrix of Different Supply Chain Risk

The table reports the correlation matrix of supply chain risk (SCRisk) from different groups of supply chain stakeholders of the target firm. Supply chain relationships are identified using the Compustat Customer Segment database. SCRisk_supplier represents the maximum SCRisk value of all available suppliers of the target firm. SCRisk_customer represents the maximum SCRisk value of all available customers of the target firm. SCRisk_stakeholder represents the maximum SCRisk value of all available suppliers and customers of the target firm.

	SCRisk	SCRisk_supplier	SCRisk_customer	SCRisk_stakeholder
SCRisk	1.000	-	-	-
SCRisk_supplier	0.029	1.000	-	-
SCRisk_customer	0.119	0.050	1.000	-
SCRisk_stakeholder	0.045	0.924	0.407	1.000

Table 7: Stakeholders' 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, while supply chain risk (SCRisk) and sentiment (SCSentiment) from different groups of stakeholders are the main independent variables. Specifically, columns (1) to (3) use the max SCRisk and SCSentiment value of all available customers and suppliers from the Compustat database. Columns (4) to (6) use the max SCRisk and SCSentiment value of all available suppliers. Columns (7) to (9) use the max SCRisk and SCSentiment value of all available customers. Definitions of the variables are provided in Appendix I. All regressions use industry-fixed effects and lender-fixed effects. The industry is classified by four-digit SIC codes 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								
Main Indep. Var.	Max SCRisk of Stakeholders			Max SCRisk of Suppliers			Max SCRisk of Customers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SCRisk_stakeholder	0.007**	0.007**	0.007***						
	(2.18)	(2.50)	(2.85)						
SCRisk_supplier				0.028**	0.028**	0.023*			
				(2.29)	(2.22)	(1.78)			
SCRisk_customer							0.004	0.004	0.004
							(1.02)	(1.18)	(1.13)
SCSentiment_stakeholder	0.000	0.000	0.000						
	(0.44)	(0.41)	(0.66)						
SCSentiment_supplier				-0.000	-0.000	-0.000			
				(-0.69)	(-0.74)	(-1.08)			
SCSentiment_customer							0.000	0.000	0.000
							(0.81)	(0.96)	(1.03)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls		Yes	Yes		Yes	Yes		Yes	Yes
Macro Controls			Yes			Yes			Yes
Observations	2,654	2,654	2,654	1,063	1,063	1,063	1,794	1,794	1,794
Adjusted R-squared	0.670	0.706	0.728	0.778	0.791	0.809	0.653	0.697	0.716

Table 8: Supply Chain Risk and Loan Spread in Different Periods

Note: The table reports the sub-sample test results in which loan spread is the dependent variable and supply chain risk (SCRisk) and sentiment (SCSentiment) are the main independent variables. The test samples are distinguished in time series using a baseline sample as described in Table 1: Panel A divides the sample on the basis of the periods that are above the top (under the bottom) third of the Global Supply Chain Pressure (GSCPI) index. Panel B divides the sample on the basis of the periods that are above the top (under the bottom) third of the Geopolitical Risk (GPR) index. All regressions utilize control and fixed effect settings same as baseline results in Table 2. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Distinguished by the Global Supply Chain Pressure Index (GSCPI)			
	High-pressure period	Low-pressure period	t-stat of difference
	(1)	(2)	
SCRisk	0.012**	-0.003	
	(2.16)	(-0.64)	(2.03)**
Observations	1,413	1,366	
Adjusted R-squared	0.768	0.764	
Panel B: Distinguished by Geopolitical Risk (GPR) Index			
	High-risk period	Low-risk period	t-stat of difference
	(1)	(2)	
SCRisk	0.010***	-0.004	
	(2.81)	(-0.89)	(2.39)**
Observations	1,415	1,338	
Adjusted R-squared	0.737	0.727	