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Supply Chain Disruption Risk and Credit Spead of Corporate Bond

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Abstract

Supply chain disruptions have emerged as a major source of firm-level operational risk, yet their pricing implications in corporate bonds remain insufficiently understood. Using a comprehensive text-based measure of supply chain disruption risk constructed from firm-level disclosures and a large panel of transaction-level bond data in China, this paper provides systematic evidence that supply chain disruption risk significantly increases corporate bond credit spreads. Results remain robust to a battery of endogeneity and extensive robustness tests. Mechanism analysis reveals that supply chain disruption risk increases credit spread by deteriorating firms' operational efficiency and impairing solvency. These effects are amplified among bonds with longer maturities and lower credit ratings, non-state-owned enterprises, manufacturing firms, and firms with concentrated or opaque supply chains. Moreover, our results document strong upstream and downstream spillover effects: disruption risks originating from suppliers and customers propagate through supply chain networks and significantly elevate credit spreads for connected firms. Overall, our findings shed new light on the financial consequences of supply chain disruption risk and offer policy implications for risk management, disclosure regulation, and macro-financial stability.

Keywords: Supply chain disruptions risk; credit spread; operational efficiency; solvency

1 Introduction

Over the past several decades, firms have increasingly relied on sophisticated supply chain networks to reduce costs and enhance production efficiency, thereby supporting profitability and business continuity. However, this interdependence has simultaneously exposed firms to heightened and more systemic supply chain risks (Tang, 2006; Cao and Zhang, 2011; Brindley, 2017). Among these risks, supply chain disruption risk has received particular attention due to its substantial destructive impact, long-term performance deterioration, and severe economic consequences (Revilla and Sáenz, 2014; Todo et al., 2015). Existing research shows that supply chain disruptions not only inflict substantial financial losses but may persistently affect supply chain performance for years (Baghersad and Zobel, 2021). For example, the 2018 U.S.–China trade war and the 2020 COVID-19 pandemic triggered global supply chain breakdowns that profoundly reshaped corporate and national supply chain management strategies (Ye et al., 2024; Li et al., 2025). Not surprisingly, supply chain disruption risk has become a central concern for firms and investors over the past decade (Kim et al., 2015).

Prior research revealed multiple consequences of supply chain disruptions. A strand of literature focuses on stock-market impacts. Hendricks et al. (2020), using the 2011 Great East Japan Earthquake as a quasi-natural experiment, show that supply chain disruptions exert significant short-term negative effects on both Japanese firms and their business partners. Hendricks & Singhal (2005a) further document that supply chain disruptions reduce long-term stock returns and increase equity risk. Other studies examine financial performance. Hendricks and Singhal (2005b) show that firms unable to recover quickly from disruptions experience deterioration in revenue, sales, costs, and inventories, thereby weakening operational performance. Wang et al. (2024) find that firms exposed to COVID-19-related disruptions suffered sharp declines in shareholder value and significantly weaker performance in the subsequent year. Firms highly dependent on supply chains often adjust inventory strategies to strengthen resilience post-disruption (Ambulkar et al., 2015; Gunessee et al., 2018). A further line

of research explores risk-management responses. Manufacturing firms increasingly diversify their supply chains to effectively mitigate disruption-related shocks (Wang et al., 2024). Yet diversification comes at a cost: lower supply-chain concentration increases debt financing costs. Firms incur explicit costs, such as higher debt costs, to hedge disruption risk. Other evidence shows that vertical integration can reduce firms' bond yields by enhancing supply-chain control (Li et al., 2025).

However, whether supply chain disruption risk itself is priced into firms' debt financing costs remains largely unexplored. Although Li et al. (2025) mention bond yields, their analysis focuses on vertical integration rather than on the pricing of disruption risk in credit spreads. Motivated by this gap, this paper examines whether a firm's supply chain disruption risk is reflected in its corporate bond credit spread. This paper investigates this question for three key reasons. First, advancements in artificial intelligence have made textual disclosures an important source of information for investors in pricing firm risk, and supply chain disruption risk is well-suited for measurement using these techniques (Bochkay and Levine, 2019). Our approach differs from traditional measures that rely on vague numerical proxies. Instead, we focus on textual information disclosed in firms' Management Discussion and Analysis (MD&A) sections, which provide clear insights into managerial perceptions of supply chain disruption risk. Second, relative to stock returns, the secondary-market corporate bond credit spread, defined as the difference between a bond's yield to maturity and the yield on a risk-free Treasury of comparable maturity, provides a more direct and accurate measure of a firm's default risk, including the component arising from supply chain disruptions (Campbell and Taksler, 2003; Campello et al., 2008; Augustin et al., 2024). Third, corporate bond yields depend on expected cash flows and discount rates and thus serve as forward-looking indicators that capture real-time changes in firm risk (Li et al., 2025). Therefore, examining corporate bond spreads offers an effective channel to assess the cost firms bear due to disruption risk.

This paper structures analysis in three steps. Firstly, we use word-embedding models

for natural language processing (NLP) to measure firms' supply chain disruption risk. Following Bochkay et al. (2023), we apply word-embedding techniques to MD&A texts, which is an important and reliable source of information on supply chain-related risks (Cen et al., 2018; Chiu et al., 2019). Word-embedding models capture semantic similarity and reduce text dimensionality, making them particularly suitable for Chinese textual analysis in contexts lacking mature domain dictionaries (Loughran & McDonald, 2016; Li et al., 2021). Secondly, we calculate firms' daily credit spreads using secondary-market bond transaction data and Treasury yields. Thirdly, we empirically test the impact of supply chain disruption risk on corporate bond credit spreads and further investigate two transmission mechanisms (solvency and operational efficiency) along with an array of robustness checks and heterogeneity analysis. Moreover, we also test whether a firm's supply chain disruption risk spills over to its upstream and downstream counterparties, contributing to broader supply chain externalities.

Our findings reveal a significantly positive relationship between supply chain disruption risk and corporate bond credit spreads. The increase in risk premia indicates that firms exposed to higher disruption risk face greater debt costs and credit-risk charges. Our contributions are threefold. Firstly, we enrich the literature on supply chain disruption risk by examining the pricing of ex-ante disruption risk rather than the effects of realized disruptions (Revilla & Sáenz, 2014; Todo et al., 2015). Secondly, we introduce a novel textual-analysis-based measure of disruption risk to supply chain research, extending the applications of NLP in corporate finance. Thirdly, we contribute to studies on debt financing costs and credit risk by showing that investors incorporate supply chain disruption risk into corporate bond risk premia, with important implications for debt management and investment decisions.

The remainder of the paper structured as follows. Section 2 reviews related literature and develops hypotheses. Section 3 describes the data and empirical design. Section 4 presents the main results and robustness checks. Section 5 provides additional analysis, including mechanism and heterogeneity tests. Section 6 concludes with key findings

and practical implications.

2 Literature Review and Hypothesis Development

Corporate bond credit spreads reflect the excess compensation required by investors for bearing issuer default risk. Traditional theories posit that spreads are primarily driven by financial leverage, asset volatility, and risk-free interest rates (Merton, 1974; Elton et al., 2001; Campello et al., 2008). However, these classical factors account for only a limited fraction of the observed credit-spread variation, especially for investment-grade bonds, leading to the well-known "credit-spread puzzle," which suggests that important risk factors remain unpriced or underpriced (Huang et al., 2024).

Supply chain disruption risk, an emerging class of non-financial operational risk, has recently garnered significant attention. Disruptions, including natural disasters, geopolitical conflicts, and supplier bankruptcies, may impair production and delivery, raise operating costs, and heighten uncertainty, thereby undermining the stability of future cash flows (Shekarian et al., 2020; Gunessee et al., 2018). Such risks may also erode confidence in managerial capability and risk-control effectiveness, increasing required risk premia. Empirical evidence supports the link between supply chain disruption and credit risk. During COVID-19, frequent supply chain disruptions in China significantly elevated firms' credit-risk premia (Wang et al., 2024). Internationally, disruptions in China's supply chain propagated to U.S. firms with business ties, widening their CDS spreads, which subsequently narrowed as disruptions eased (Luo et al., 2025). Supply chain risks also exhibit contagion effects: liquidity constraints, fundamental deterioration, or financial distress among upstream suppliers or downstream customers transmit through supply chain networks and exacerbate core-firm credit risk (Barrot, 2016). Moreover, firms with higher financial or operating leverage or those operating in highly competitive markets tend to be more sensitive to disruptions (Ağca et al., 2023).

Although theory and evidence suggest a relationship between supply chain disruptions

and credit risk, large-sample empirical research linking credit spreads to disruption risk rather than realized disruptions remains scarce. Prior research has focused on stock-price volatility, CDS spreads, or yield-curve reactions (Chod, 2017), and has documented explore heterogeneous effects of supply chain uncertainty on bond yields (Chen & Liao, 2017). Hence, the extent to which supply chain disruption risk is priced in corporate bond credit spreads remains an open question. Based on risk-premium theory (Merton, 1974), supply chain disruption risk raises the uncertainty of future cash flows. When investors perceive heightened disruption risk, they demand greater compensation, widening corporate bond credit spreads. Thus, this paper proposes the first hypothesis H1.

H1: Higher supply chain disruption risk leads to larger corporate bond credit spreads.

As shown in Figure 1, supply chain disruption risk may indirectly widen credit spreads by reducing firms' operational efficiency. Operational efficiency reflects the ability to convert assets into revenue and cash flows. Disruptions induce production delays, inventory accumulation, and order postponements, lowering asset turnover and profitability (Hendricks & Singhal, 2005). Schmidt and Raman (2012) argue that highly efficient supply chains with low redundancy are more fragile because higher efficiency implies lower elasticity. On the demand side, Chen and Liao (2017) show that uncertainty in customers' production efficiency is positively related to corporate bond yield spreads, reinforcing the idea that instability within downstream operations can transmit upward and elevate credit risk. From a resource-based perspective, firms rely on external supply-chain relationships and financing to obtain efficiency advantages; disruption risk undermines these capabilities, damaging competitiveness and signalling weakness to bond markets (Figure 1). Thus, this paper proposes the second hypothesis H2.

H2: Supply chain disruption risk increases corporate bond credit spreads by reducing operational efficiency.

As illustrated in Figure 1, supply chain disruption risk may impair firms' solvency, an important additional determinant of credit spreads. Solvency depends on stable operating cash flows, which disruptions weaken through two channels: lower cash inflows due to reduced sales and higher cash outflows due to emergency procurement or alternative logistics (Ağca et al., 2023). Disruptions may further trigger liquidity deterioration and debt-rollover risk, increasing default probability. Credit rating agencies emphasize cash-flow stability and debt-payment capability; thus, weakened solvency is rapidly priced into credit spreads. Thus, this paper proposes the third hypothesis H3.

H3: Supply chain disruption risk widens corporate bond credit spreads by weakening solvency.

Insert Figure1 here

3 Research Design

3.1 Empirical Model

To examine the effect of supply chain disruption risk on corporate bond credit spreads, we estimate a panel fixed-effects model as shown in equation (1) :

$$Spread_{i,j,d} = \alpha_0 + \alpha_1 SCDRisk_{j,y} + \alpha_2 Controls + Year_Month\ FE + City\ FE + Industry\ FE + \varepsilon_{i,j,d} \quad (1)$$

where $\boldsymbol{i}$, $\boldsymbol{j}$, $\boldsymbol{y}$ and $\boldsymbol{d}$ denote the bond, firm, year and trading day respectively. $\boldsymbol{Spread_{i,j,d}}$ is the daily credit spread of bond $\boldsymbol{i}$ issued by firm $\boldsymbol{j}$. $\boldsymbol{SCDRisk_{j,y}}$ represents the firm-level supply chain disruption risk in year $\boldsymbol{y}$. The vector $\boldsymbol{Controls}$ includes bond-level, firm-level, and city-level control variables. The empirical model absorbs year–month, city, and industry fixed effects to address unobserved heterogeneity across time, regions, and industries. $\boldsymbol{\varepsilon_{i,j,d}}$ is the error term to capture residual idiosyncratic shocks. To address heteroskedasticity and serial correlation inherent in panel data, we also cluster standard errors at the firm × year–month level, which is consistent with recent empirical credit-risk studies and mitigates downward

bias in inference.

Insert Table 1 here

3.2 Data Description

Following the China Securities Regulatory Commission's 2015 revision of the Administrative Measures for the Issuance and Trading of Corporate Bonds, which expanded access to corporate bond financing and deepened secondary market activity, we construct our sample using corporate bond transactions from 2015 to 2023. The data sources include *Wind*, *iFind*, *CSMAR*, *CNRDS*, and the China City Statistical Yearbook. Consistent with the literature, we apply the following filters: (1) retain only firms listed on the Shanghai and Shenzhen A-share markets; (2) include corporate bonds, enterprise bonds, and medium-term notes traded in the secondary market; (3) exclude firms in the financial and real estate industries; (4) remove ST and PT firms; (5) drop observations with missing key variables (bond characteristics, financial indicators, city characteristics); (6) compute credit spreads as the difference between corporate bond yields and yields on matched-maturity Chinese government bonds and remove extreme outliers. The final dataset contains 153,031 bond–day observations issued by non-financial listed firms, providing a representative coverage of China's corporate bond market during the sample period.

Insert Table 2 here

3.3 Variable Construction

3.3.1 Dependent Variable: Credit Spread

Credit spreads represent the excess yield on corporate bonds relative to risk-free government securities of comparable maturities. Following standard practice, we use daily yields on Chinese government bonds from the *ChinaBond* platform as the risk-free benchmark, given their negligible default risk. The credit spread is defined as the difference between *YTM* of corporate bond and *YTM* of treasury with the same term to maturity, which captures the market's required compensation for firm-specific credit risk as the *YTM* of treasury represents the risk-free rate.

3.3.2 Independent Variable: Supply Chain Disruption Risk

To construct firm-level supply chain disruption risk, we develop a text-based measure using the MD&A sections of firms' annual reports. The first step is *Text Extraction and Tokenization*. We collect MD&A texts from corporate websites and apply Jieba segmentation with stopword lists from HIT and Baidu to retain meaningful content. The second step is *Seed Word Identification*. From manually reviewing 40 randomly selected reports, we compile 22 seed words related to supply chain disruptions (as shown in ***Appendix A***), validated by two research assistants. The third step is *Word2Vec Expansion*. Using a CBOW Word2Vec model trained on the MD&A corpus, we extract 220 candidate terms based on semantic similarity to the seed words. After applying a cosine similarity threshold of 0.6, we finalize a lexicon of 72 disruption-related terms. The last step is *Risk Index Construction*. We construct our primary disruption-risk proxy, *SCDRisk*, by counting the frequency of disruption-related terms in each firm's MD&A and normalizing by total MD&A word count. To verify robustness, we also form two alternative indices, *SCDRisk2* and *SCDRisk3*, using cosine-similarity thresholds of 0.5 and 0.7, respectively. The full lexicon and construction details are reported in ***Appendix A***.

4 Empirical Results

4.1 Main Results

Table 3 reports regressions estimating the effect of supply chain disruption risk on corporate bond credit spreads. The dependent variable is the secondary-market credit spread, capturing changes in firms' financing costs. Column (1) includes only the core explanatory variable, *SCDRisk*, which reflects the severity of firms' supply chain disruption risk. All regressions include year-month, industry, and city fixed effects to control for systematic variation due to time trends, sectoral structure, and regional characteristics. Column (2) adds bond-level controls; column (3) incorporates firm-level controls (e.g., size, leverage, financial condition); column (4) further includes city-level controls.

Results indicate positive and statistically significant relationship between disruption risk and credit spreads. In column (4), the coefficient on *SCDRisk* is 6.566, which is significant at the 1% level. This implies that a one-standard-deviation increase in supply chain disruption risk is associated with an average increase of approximately 6.57 basis points in credit spreads. These findings support H1 and suggest that investors incorporate supply chain disruption risk into credit-risk pricing. Control variables exhibit the expected signs, reinforcing the robustness of the results. Overall, the results indicate that supply chain disruption risk has become a key priced factor in China's corporate bond market.

Insert Table 3 here

4.2 Robustness Tests

4.2.1 Endogeneity Concerns

Although our baseline specification includes an extensive set of control variables covering bond characteristics, firm fundamentals, and city-level attributes, and further incorporates year–month, industry, and city fixed effects, unobservable confounders may still bias the estimates. To mitigate potential endogeneity in the relationship between supply chain disruption risk and credit spreads, we re-estimate the baseline model using an instrumental variables (IV) approach.

First, following Xu et al. (2014), we construct two external instruments for IV estimation: the annual city–industry mean (*Iv1*) and median (*Iv2*) of supply chain disruption risk. These instruments are theoretically justifiable because the average disruption exposure of firms operating in the same city and industry affects an individual firm's supply chain risk but is plausibly orthogonal to its idiosyncratic credit spread, satisfying the exclusion condition. In addition, motivated by Lewbel's (1997) heteroskedasticity-based identification strategy, we construct two additional instruments by taking the cubic deviations of firm-level disruption risk from the city–province industry mean value (*Iv3*) and median value (*Iv4*). These Lewbel-type instruments exploit the presence of heteroskedasticity in the data to generate valid

instruments exogenously, thereby strengthening identification and improving robustness.

Tables 4 and 5 report the two-stage least squares (2SLS) estimates using all four instruments. The first-stage results in columns (1) and (3) indicate that the instruments are strongly correlated with firm-level disruption risk at the 1% significance level. Moreover, the reported Cragg–Donald Wald F-statistics and Kleibergen–Paap rk LM statistics exceed the conventional critical values, confirming that the instruments are neither weak nor underidentified. The second-stage regressions in columns (2) and (4) show that the fitted values of disruption risk remain positively and significantly associated with corporate bond spreads at the 1% level, fully consistent with the baseline findings and supportive of our theoretical predictions.

Collectively, the IV estimates alleviate endogeneity concerns and reinforce the causal interpretation that higher supply chain disruption risk leads to wider credit spreads.

Insert Table 4 here

Insert Table 5 here

4.2.2 Alternative Independent Variables

To further assess robustness, we replace daily credit spread data with monthly aggregated spreads. Specifically, we compute weights based on the proportion of each bond's daily trading volume relative to its monthly volume, and alternatively, based on the proportion of daily trading value relative to the monthly total. We then construct two monthly measures—*Spread_volume* and *Spread_amount*—as weighted averages of daily credit spreads. After merging these monthly spreads with disruption-risk data, we obtain a bond–month panel consisting of 44,701 observations. Keeping all other variables unchanged, we re-estimate the regressions. As reported in Table 6, the results remain strongly significant, demonstrating that the positive relationship between disruption risk and credit spreads is not driven by high-frequency fluctuations in daily trading data.

Insert Table 6 here

4.2.3 Alternative Dependent Variables

Our baseline measure of disruption risk, *SCDRisk*, is constructed based on a similarity threshold of 0.6 in the word-embedding lexicon. To evaluate whether our findings depend on this specific threshold, we follow Jiang et al. (2024) and construct two alternative indices—*SCDRisk2* and *SCDRisk3*—using similarity thresholds of 0.5 and 0.7, respectively. Regression results reported in Table 7 show that, except for column (5), the coefficients remain positive and statistically significant at the 5% level or better. These findings demonstrate that our conclusions are not sensitive to the particular similarity threshold used in constructing the textual risk measure.

Insert Table 7 here

4.2.4 Other Robustness Tests

Beyond the aforementioned analysis, this paper conducts three additional robustness checks. Firstly, this paper uses high-dimensional fixed effects. To account for potential time-varying heterogeneity across industries, we augment the baseline fixed-effect structure by including industry × year–month fixed effects. This controls for dynamic sectoral shocks that may jointly affect supply chain risk and credit spreads. Secondly, this paper considers alternative clustering levels in empirical tests. We re-estimate models using alternative clustering schemes—bond × year–month, city × year–month, and industry × year–month—to ensure that our inference is not driven by a particular clustering dimension. Results remain qualitatively unchanged. Thirdly, this paper exclude the pandemic period of COVID-19. Considering that COVID-19 may have exerted unprecedented shocks on China's financial markets around the end of 2019, we re-estimate the regressions after excluding all post-2019 observations. To reduce the length of this paper, results of robustness tests are presented in ***Appendix B*** where the results continue to hold, indicating that our findings are not driven by pandemic-related distortions. Taken together, the robustness tests consistently confirm that supply chain disruption risk is a significant and stable determinant of corporate bond credit spreads.

4.3 Mechanism Analysis

4.3.1 Decline in Operational Efficiency

Operational efficiency constitutes a key transmission channel through which supply chain disruption risk is priced in the bond market. We examine three dimensions of operational performance that capture how disruption risk affects firms' ability to convert resources into cash flows. The variables constructed to reflect firm operational performance are *Operating Cash Ratio (OCR)*, *Accounts Receivable Turnover Ratio (ARTR)*, *Accounts Payable Turnover Ratio (APTR)*.

The *Operating Cash Ratio (OCR)*, which is defined as working capital divided by operating cash flow, captures the extent to which firms must tie up liquidity to sustain operations. A higher ratio indicates that a larger amount of working capital is required to generate a unit of operating cash flow, reflecting lower capital-use efficiency. *Accounts Receivable Turnover Ratio (ARTR)*, measured as the ratio of revenue to accounts receivable, decreases when customers delay payments, signaling slower cash conversion and rising liquidity risk. *Accounts payable Turnover Ratio (APTR)*, defined as revenue divided by accounts payable, rises when suppliers accelerate collection efforts, indicating heightened pressure on firms' short-term funding cycles. All variables are constructed from firms' annual report disclosures obtained from the *CSMAR* database.

Then, we empirically test impact of *SCDRisk* on the three operational-efficiency indicators. As reported in Table 8, columns (1)–(3), all coefficients are significant at the 1% level. Specifically, the positive coefficient in column (1) indicates that higher disruption risk increases firms' working-capital requirements, reducing cash-conversion efficiency. Column (2) shows a significant negative effect on accounts receivable turnover, consistent with downstream customers extending payment periods and slowing fund recovery. Column (3) reports a significant positive effect on accounts payable turnover, reflecting pressure from upstream suppliers to expedite repayment.

Collectively, these results confirm that operational inefficiency is a central pathway

through which supply chain disruption risk translates into higher credit spreads. By impairing capital-use efficiency, lengthening receivable cycles, and shortening payable cycles, disruption risk diminishes firms' operating liquidity and weakens their overall operational resilience. Bond investors interpret these signals as deterioration in liquidity and operational fundamentals, demanding higher compensation for the associated credit risk. This mechanism ultimately manifests as wider corporate bond credit spreads.

Insert Table 8 here

4.3.2 Impaired Solvency

Solvency is a fundamental dimension through which external investors evaluate corporate creditworthiness. Accordingly, we analyze how supply chain disruption risk affects solvency along three dimensions: *Cash Flow Interest Coverage Ratio (CFICR)*, *Equity Multiplier (EM)* and *Cash-to-Short-Term-Debt Ratio (CSTDR)*.

Firstly, the *Cash Flow Interest Coverage Ratio (CFICR)* measured by operating cash flow divided by interest-bearing debt due in the near term, reflects a firm's ability to service interest obligations using internally generated cash. Lower values indicate insufficient cash-flow protection. Secondly, the *Equity Multiplier (EM)* measured by total assets divided by shareholders' equity, captures balance-sheet leverage; higher values reflect greater reliance on debt financing and heightened financial risk. Thirdly, the *Cash-to-Short-Term-Debt Ratio (CSTDR)*, defined as cash holdings relative to short-term interest-bearing debt, directly reflects the firm's ability to meet short-term repayment obligations. All measures are computed from annual financial statements sourced from the *CSMAR* database.

To identify how disruption risk affects solvency, we empirically investigate the effect of *SCFRisk* on *CFICR*, *EM*, and *CSTDR* separately. Table 9 shows that disruption risk significantly weakens all three aspects of solvency. Column (1) indicates that higher disruption risk is associated with a significantly lower *CFICR*, implying that disrupted operations constrain cash inflows and compress firms' capacity to service interest payments. Column (2) shows a significant positive relationship between disruption risk

and *EM*, suggesting that firms increasingly rely on debt financing to buffer operational shocks, thereby elevating leverage-related risk. Column (3) reports a significant negative association between disruption risk and *CSTDR*, reflecting a decline in short-term liquidity reserves and reduced flexibility to meet maturing obligations.

Taking together, these results demonstrate that supply chain disruption risk undermines solvency through multiple channels: weakening cash-flow protection, increasing leverage, and tightening short-term liquidity. Investors incorporate these adverse signals into their assessment of firm credit quality and demand higher credit risk premia, ultimately resulting in wider corporate bond credit spreads.

Insert Table 9 here

5. Expansive Analysis

5.1 Heterogeneity by Bond Characteristics

In this section, we investigate whether the effect of supply chain disruption risk on credit spreads varies with bond maturity and credit rating. As reported in Table 10, we divide the full sample into two subsamples along two dimensions. First, we classify bonds with remaining maturity of at least one year as long-term, while those with less than one year as short-term. Second, we split the sample into AAA-rated and non-AAA-rated bonds.

The results reveal pronounced heterogeneity. From the maturity perspective, supply chain disruption risk exerts a significantly stronger effect on long-term bonds. Column (1) shows a positive and highly significant coefficient at the 1% level, whereas the effect in column (2) for short-term bonds is statistically insignificant. The p-value of 0.000 for the between-group test further confirms that the difference is economically and statistically meaningful. This pattern indicates that long-term bonds face a longer horizon of uncertainty and are more exposed to the cumulative effects of disruptions, prompting investors to demand higher risk premia. From the perspective of credit

quality, the effect of disruption risk is substantially more pronounced for lower-rated bonds. Column (3) shows an insignificant coefficient for AAA bonds, whereas column (4) reports a positive and significant effect at the 1% level for non-AAA bonds, with the between-group difference again significant at the 0.000 level. This suggests that lower-rated bonds with weaker credit fundamentals are more vulnerable to adverse shocks, and the market reacts more strongly to changes in their underlying operational risk.

Overall, these findings align with theoretical expectations: investors incorporate maturity structure and credit quality in pricing supply chain disruption risk and require higher compensation for bonds with greater exposure to potential disruptions.

Insert Table 10 here

5.2 Heterogeneity by Firm Characteristics

At the firm level, we further examine whether ownership structure and industry classification affect the transmission of disruption risk to credit spreads. Accordingly, we divide the sample by ownership type (state-owned vs. non-state-owned enterprises) and industry group (manufacturing vs. non-manufacturing) and conduct subgroup regressions.

The results indicate sharp heterogeneity across firm types. Columns (1) and (2) of Table 11 show that the coefficient on *SCDRisk* is significantly negative for state-owned enterprises (SOEs) but significantly positive for non-SOEs, both at the 1% level. This pattern is consistent with the notion that SOEs benefit from implicit government guarantees and preferential access to financing, which buffer the adverse effects of supply chain shocks. In contrast, non-SOEs face tighter financial constraints and weaker shock-absorption capacity, making their credit spreads more sensitive to disruption risk. Similarly, columns (3) and (4) reveal meaningful heterogeneity across industry groups. The effect of disruption risk is positive and significant at the 1% level for manufacturing firms, while for non-manufacturing firms the coefficient remains positive but only marginally significant at the 5% level. All findings are confirmed by

a bootstrap-based between-group test (500 random resamples), ensuring robustness.

These results suggest that manufacturing firms with greater supply chain reliance and more complex production processes are more exposed to disruption-induced risks and therefore command higher credit risk premia. This asymmetric transmission pattern underscores the importance of identifying vulnerable firm types and implementing targeted risk-management strategies.

Insert Table 11 here

5.3 Heterogeneity by Supply Chain Characteristics

At the supply chain level, following Li et al. (2024) and Wang et al. (2024), we construct two key indicators to capture firms' supply chain attributes. The first indicator is supply chain concentration, which equals 1 if the share of revenue attributable to the top five suppliers or customers exceeds the annual industry mean, and 0 otherwise. The second indicator is supply chain transparency, which equals 1 if the number of suppliers or customers disclosed in a firm's annual report exceeds the annual industry average, and 0 otherwise. Based on these measures, we classify firms into high- vs. low-concentration groups and high- vs. low-transparency groups.

Columns (1) and (2) in Table 12 show that the effect of supply chain disruption risk is significant only in the high-concentration group, while the coefficient is insignificant and negative in the low-concentration group. This suggests that firms heavily dependent on a small set of core suppliers or customers are more vulnerable to disruptions. When disruptions occur, these firms face more severe operational and cash flow impacts, prompting bond investors to demand higher risk premia. This finding is consistent with the view that high concentration acts as a risk amplifier, exacerbating profitability volatility and information asymmetry, as documented in prior research. Similarly, columns (3) and (4) indicate substantial divergence across transparency levels. The effect of disruption risk is significant at the 1% level for firms with low transparency whereas it is insignificant for firms with high transparency. This suggests that greater supply chain disclosure mitigates information asymmetry and enables investors to

better assess firms' actual exposure to supply chain risks, reducing the magnitude of credit spread increases. Hence, firms with higher transparency not only enhance their resilience to supply chain shocks but also improve their financing conditions and reduce their borrowing costs.

Insert Table 12 here

5.4 Spillover Effects along the Supply Chain Network

To further examine the propagation of disruption risk through upstream and downstream chains, we construct weighted spillover measures based on the strength of linkages in firms' supply networks. Using supplier and customer information disclosed in the *CSMAR* database, we design two upstream indicators. The first, *Risk_up_total*, weights each supplier's disruption risk (*SCDRisk*) by its share in the firm's top-five procurement costs, capturing the aggregated upstream spillover transmitted via the cost chain. The second, *Risk_up_sum*, weights risk by each supplier's share of total disclosed procurement, reflecting concentration-induced amplification of upstream exposure. Similarly, on the downstream side, we construct *Risk_down_total*, which weights customer risks by the share of top-five sales in firm revenue, and *Risk_down_sum*, which uses customers' shares of total disclosed sales. These measures capture the overall and concentration-driven spillovers transmitted via the revenue chain.

Given potential sample selection bias arising from incomplete supply chain disclosures, we re-estimate the baseline model using the refined sample and report the results in columns (3) and (6). As shown in columns (1)–(2) and (4)–(5) of Table 13, supply chain disruption risk significantly increases credit spreads for both upstream-connected and downstream-connected firms. This confirms that disruption risk propagates through the supply chain network, generating substantial spillover effects that elevate credit risk premia not only for directly affected firms but also for their supply chain partners.

Overall, these findings demonstrate that supply chain disruption risk has both direct and network-driven effects, collectively contributing to higher credit spreads across the

bond market.

6. Conclusion

This paper demonstrates that supply chain disruption risk is an important and systematically priced component of corporate credit risk. Using a novel, text-based measure of disruption exposure and high-frequency bond-level credit spreads, we show that supply chain disruption risk exerts a statistically and economically significant impact on firms' credit spread. The results remain robust under various robustness tests. This paper identifies two core mechanisms of supply chain disruption risk influencing bond pricing: operational efficiency deterioration and solvency impairment. The effect of supply chain disruption risk on credit spreads is highly heterogeneous. Long-term and lower-rated bonds, non-state-owned and manufacturing firms, and firms with concentrated or opaque supply chains exhibit substantially stronger sensitivity to supply chain disruption risk. These results underscore the role of firm-level characteristics and supply chain structure in shaping vulnerability to supply chain shocks. In addition, we document significant spillover effects: risk originating from upstream suppliers and downstream customers propagates through supply chain networks and meaningfully increases credit spreads for connected firms. This network transmission mechanism suggests that supply chain fragility has broader implications for market-wide credit conditions.

Taken together, our results highlight the importance of supply chain disruption risk not only for operational stability but also for financial stability, suggesting that firms, investors, and regulators should place greater emphasis on supply chain resilience. The findings also offer new insights for credit risk modeling, corporate finance, and macro-finance research by linking real-side production networks with financial market pricing. Future work may extend this analysis to international settings, explore dynamic responses to global supply shocks, and integrate supply chain network features into

structural models of credit risk.

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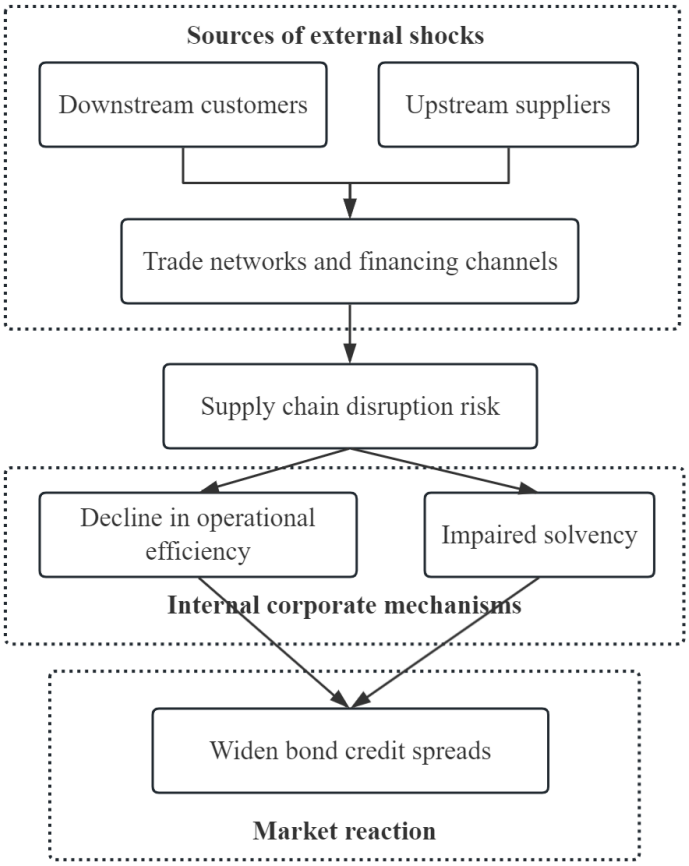


Fig. 1. Figure of transmission framework.

Note: This figure, developed by the authors, depicts the transmission mechanism of supply chain disruption risk on bond credit spreads.Shocks from downstream customers and upstream suppliers propagate through trade and financing channels, generating disruption risk that affects firms' internal operations by reducing efficiency and impairing solvency. These effects collectively result in wider bond credit spreads, reflecting the market's response.

Table 1
Definition of variables

	Variables	Definition
Dependent Variables	*Spread*	The difference between the yield to maturity of a corporate bond with a given residual maturity and the yield of a government bond with the same residual maturity on the same trading day.
Independent Variables	*SCDRisk*	Word frequency of supply chain disruption risk in MD&A / total MD&A words (lexicon based on similarity threshold = 0.6).
Control Variables	*Maturity*	A bond's time to maturity
	Bondsize	The natural logarithm of the total bond amount
	Bondtime	The natural logarithm of the number of bond transactions
	Bondtype	A dummy variable that equals 1 if the bond is a medium term note, and 0 otherwise.
	Bondrate	A dummy variable that equals 1 if the bond is rated AAA, and 0 otherwise.
	Roa	Return on total assets.
	Lev	Total liabilities / total assets.
	Size	The natural logarithm of total assets.
	Growth	(Operating revenue - previous year's operating revenue) / previous year's operating revenue
	Fixed	Fixed assets / total assets
	Top10	Shareholding ratio of the top ten shareholders
	Age	Year since listing
	Salary	The natural logarithm of total executive compensation.
	Gdp	The natural logarithm of regional gross domestic product
	Gov	General budgetary fiscal expenditure / general budgetary fiscal revenue
	Fin	(Total deposits + total loans of regional financial institutions) / regional GDP

Note: This table provides the definitions of the main variables used in this study.

Table 2
The descriptive statistics of variables

Variables	Obs.	Mean	SD	Min	p25	p50	p75	Max
Spread	153031	1.990	1.588	0.293	0.775	1.389	2.851	6.930
SCDRisk	153031	0.024	0.009	0.008	0.017	0.022	0.028	0.055
Maturity	153031	1.629	1.366	0.030	0.644	1.340	2.240	7.810
Bondsize	153031	15.980	2.856	6.908	14.690	16.810	17.910	20.130
Bondtime	153031	1.381	0.831	0.693	0.693	1.099	1.609	4.615
Bondtype	153031	0.323	0.468	0.000	0.000	0.000	1.000	1.000
Bondrate	153031	0.623	0.485	0.000	0.000	1.000	1.000	1.000
Roa	153031	0.023	0.041	-0.140	0.010	0.022	0.041	0.141
Lev	153031	0.609	0.137	0.233	0.515	0.628	0.718	0.895
Size	153031	25.140	1.639	21.770	23.880	25.060	26.380	28.500
Growth	153031	0.114	0.253	-0.400	-0.018	0.086	0.194	1.131
Fixed	153031	0.315	0.224	0.006	0.104	0.302	0.507	0.805
Top10	153031	66.840	0.171	0.184	0.540	0.681	0.801	1.010
Age	153031	2.700	0.517	0.693	2.398	2.833	3.091	3.434
Salary	153031	15.670	0.840	13.370	15.200	15.680	16.210	17.890
Gdp	153031	27.850	1.133	25.340	26.960	28.200	28.890	29.180
Gov	153031	1.513	0.548	0.989	1.219	1.298	1.570	4.095
Fin	153031	1.897	0.662	0.531	1.495	2.080	2.273	3.711

Note: Variables are the variable names; Obs. is the number of observations; Mean and SD are the sample mean and standard deviation; Min and Max are the minimum and maximum values; p25, p50, and p75 indicate the 25th percentile, median, and 75th percentile, respectively.

Table 3
Estimation results of the baseline regression

	Spread			
	(1)	(2)	(3)	(4)
SCDRisk	7.982***	10.650***	6.017***	6.566***
	(1.742)	(1.614)	(1.586)	(1.581)
Maturity		-0.091***	-0.065***	-0.064***
		(0.006)	(0.005)	(0.005)
Bondsize		-0.070***	-0.067***	-0.068***
		(0.003)	(0.003)	(0.003)
Bondtime		0.327***	0.284***	0.283***
		(0.013)	(0.012)	(0.012)
Bondtype		0.532***	0.596***	0.598***
		(0.021)	(0.021)	(0.021)
Bondrate		-0.446***	-0.080***	-0.090***
		(0.031)	(0.031)	(0.030)
Roa			-4.058***	-4.050***
			(0.346)	(0.348)
Lev			1.608***	1.724***
			(0.121)	(0.123)
Size			-0.303***	-0.287***
			(0.015)	(0.015)
Growth			0.173***	0.159***
			(0.041)	(0.041)
Fixed			-0.021	-0.009
			(0.088)	(0.087)
Top10			-1.393***	-1.318***
			(0.102)	(0.100)
Age			-0.414***	-0.399***
			(0.024)	(0.023)
Salary			0.012	-0.003
			(0.019)	(0.019)
Gdp				-1.204***
				(0.173)
Gov				0.151**
				(0.075)
Fin				-0.480***
				(0.073)
Constant	1.801***	2.653***	11.067***	44.970***
	(0.043)	(0.067)	(0.397)	(4.904)
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	153031	153031	153031	153031
Adj R-squared	0.425	0.470	0.519	0.522

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 4
Addressing endogeneity using instrumental variables Iv1 and Iv2

	SCDRisk	*Spread*	*SCDRisk*	*Spread*
	First_stage	Second_stage	First_stage	Second_stage
	(1)	(2)	(3)	(4)
Iv1	0.993***			
	(0.004)			
Iv2			0.912***	
			(0.005)	
SCDRisk		5.453***		4.848**
		(1.831)		(1.888)
Constant	0.023***	45.206***	0.023***	45.155***
	(0.007)	(5.018)	(0.009)	(5.016)
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	153031	153031	153031	153031
Adj R-squared	0.510		0.523	
Cragg-Donald Wald F-statistics	67632.52***		33712.16***	
Kleibergen-Paap rk LM statistic	2540.22***		2366.70***	
P-Value	0.000***		0.000***	

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 5
Addressing endogeneity using instrumental variables Iv3 and Iv4

	SCDRisk	*Spread*	*SCDRisk*	*Spread*
	First_stage	Second_stage	First_stage	Second_stage
	(1)	(2)	(3)	(4)
Iv3	73.332***			
	(1.347)			
Iv4			41.003***	
			(1.208)	
SCDRisk		7.555***		16.345***
		(2.849)		(4.150)
Constant	-0.097***	45.384***	-0.081***	46.129***
	(0.023)	(5.017)	(0.024)	(5.060)
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	153031	153031	153031	153031
Adj R-squared	0.523		0.522	
Cragg-Donald Wald F-statistics	2961.97***		1152.037***	
Kleibergen-Paaprk LM statistic	611.50***		430.93***	
P-Value	0.000***		0.000***	

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 6
Robustness tests: alternative dependent variables

	Spread_volume				*Spread_amount*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCDRisk	12.587***	15.471***	11.620***	11.920***	12.589***	15.473***	11.623***	11.922***
	(1.258)	(1.229)	(1.258)	(1.254)	(1.258)	(1.229)	(1.258)	(1.254)
Constant	1.477***	2.096***	7.548***	32.643***	1.477***	2.095***	7.548***	32.638***
	(0.030)	(0.056)	(0.306)	(3.544)	(0.030)	(0.056)	(0.306)	(3.543)
Bond-specific Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm-specific Controls	No	No	Yes	Yes	No	No	Yes	Yes
City-specific Controls	No	No	No	Yes	No	No	No	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44701	44701	44701	44701	44701	44701	44701	44701
Adj R-squared	0.297	0.348	0.387	0.389	0.297	0.348	0.387	0.389

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 7
Robustness tests: alternative independent variables

	Spread							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCDRisk2	3.163***	4.476***	1.919***	1.975***				
	(0.633)	(0.579)	(0.541)	(0.538)				
SCDRisk3					2.937	9.951***	5.674**	6.152***
					(2.600)	(2.443)	(2.341)	(2.332)
Constant	1.719***	2.519***	10.985***	44.331***	1.948***	2.763***	11.167***	44.474***
	(0.055)	(0.070)	(0.398)	(4.921)	(0.039)	(0.063)	(0.391)	(4.901)
Bond-specific Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm-specific Controls	No	No	Yes	Yes	No	No	Yes	Yes
City-specific Controls	No	No	No	Yes	No	No	No	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153031	153031	153031	153031	153031	153031	153031	153031
Adj R-squared	0.425	0.470	0.519	0.522	0.424	0.468	0.519	0.521

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 8
Mechanism analysis: estimation results of operating efficiency

	OCR	*ARTR*	*APTR*
	(1)	(2)	(3)
SCDRisk	1.382***	-0.908***	2.842***
	(0.189)	(0.229)	(0.277)
Maturity	-0.002***	0.001	0.022***
	(0.001)	(0.001)	(0.002)
Bondsize	-0.001**	-0.001***	-0.009***
	(0.000)	(0.000)	(0.001)
Bondtime	-0.004***	-0.000	0.018***
	(0.001)	(0.001)	(0.003)
Bondtype	0.013***	0.007***	-0.008***
	(0.002)	(0.002)	(0.003)
Bondrate	0.004	0.024***	-0.007*
	(0.003)	(0.004)	(0.004)
Roa	0.165***	0.717***	0.798***
	(0.051)	(0.057)	(0.117)
Lev	-0.107***	0.085***	-0.317***
	(0.016)	(0.021)	(0.031)
Size	0.018***	0.000	0.024***
	(0.002)	(0.002)	(0.003)
Growth	0.012**	-0.009	-0.027
	(0.005)	(0.007)	(0.020)
Fixed	-0.045***	0.223***	0.515***
	(0.013)	(0.013)	(0.050)
Top10	-0.074***	0.031**	-0.018
	(0.019)	(0.016)	(0.016)
Age	-0.010***	-0.021**	0.034***
	(0.003)	(0.011)	(0.005)
Salary	-0.020***	-0.031***	-0.001
	(0.004)	(0.003)	(0.004)
Gdp	0.039	0.104***	-0.034*
	(0.028)	(0.018)	(0.018)
Gov	-0.006	-0.002	-0.005
	(0.011)	(0.009)	(0.008)
Fin	0.032***	-0.030***	0.130***
	(0.011)	(0.009)	(0.022)
Constant	-1.158	-2.252***	0.179
	(0.784)	(0.515)	(0.470)
Year-Month FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	153031	153031	153031
Adj R-squared	0.230	0.710	0.360

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 9
Mechanism analysis: estimation results of solvency

	CFICR	*EM*	*CSTDR*
	(1)	(2)	(3)
SCDRisk	-11.330***	3.805***	-1.498***
	(2.784)	(0.676)	(0.434)
Maturity	0.022**	0.004***	0.004***
	(0.010)	(0.002)	(0.001)
Bondsize	-0.003	-0.010***	0.001
	(0.004)	(0.001)	(0.001)
Bondtime	0.017	0.012***	-0.009***
	(0.013)	(0.004)	(0.002)
Bondtype	-0.098***	0.032***	0.015***
	(0.024)	(0.006)	(0.005)
Bondrate	0.145***	-0.019*	0.013*
	(0.039)	(0.011)	(0.008)
Roa	9.639***	-0.356*	1.259***
	(0.679)	(0.200)	(0.100)
Lev	-4.644***	6.475***	-0.459***
	(0.251)	(0.071)	(0.037)
Size	-0.149***	-0.023***	0.057***
	(0.030)	(0.007)	(0.005)
Growth	-0.071	0.026	-0.019*
	(0.082)	(0.023)	(0.010)
Fixed	2.582***	-0.803***	-0.298***
	(0.235)	(0.056)	(0.027)
Top10	1.717***	0.107**	-0.055*
	(0.180)	(0.045)	(0.030)
Age	0.077**	0.037***	-0.019***
	(0.039)	(0.007)	(0.006)
Salary	-0.253***	-0.122***	-0.063***
	(0.031)	(0.010)	(0.006)
Gdp	1.039***	-0.306***	0.033
	(0.194)	(0.039)	(0.024)
Gov	0.237**	0.021	0.023*
	(0.100)	(0.020)	(0.013)
Fin	0.507***	0.051**	-0.057***
	(0.110)	(0.026)	(0.016)
Constant	-20.561***	9.966***	-0.600
	(5.507)	(1.135)	(0.701)
Year-Month FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	153031	153031	153031
Adj R-squared	0.400	0.909	0.472

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 10
Results of the bond-level heterogeneities: bond maturity and bond rating

	Spread			
	Long-term maturity		*AAA-rated*	
	Yes	*No*	*Yes*	*No*
	(1)	(2)	(3)	(4)
SCDRisk	12.097***	-0.521	2.940	12.375***
	(1.887)	(2.096)	(1.857)	(2.253)
p-value for equality test	0.000***		0.000***	
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	93,601	59,424	95,382	57,649
Adj R-squared	0.529	0.545	0.341	0.613

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 11
Results of the firm-level heterogeneities: ownership type and industry attributes

	Spread			
	SOE		*Manufacturing*	
	Yes	*No*	*Yes*	*No*
	(1)	(2)	(3)	(4)
SCDRisk	-18.483***	10.325***	16.385***	5.210**
	(3.023)	(1.679)	(2.262)	(2.015)
p-value for equality test	0.000***		0.000***	
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	28,752	124,278	59,732	93,298
Adj R-squared	0.695	0.511	0.586	0.487

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 12

Results of the supply chain-level heterogeneities: concentration and transparency

	Spread			
	Concentration		*Transparency*	
	Higher	*Lower*	*Higher*	*Lower*
	(1)	(2)	(3)	(4)
SCDRisk	8.281***	-0.597	0.390	8.197***
	(2.274)	(1.838)	(2.476)	(1.914)
p-value for equality test	0.000***		0.000***	
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	71,967	81,062	53,236	99,794
Adj R-squared	0.6004	0.5053	0.628	0.526

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.

Table 13
Results of supply-chain upstream and downstream spillover effects

	Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
Risk_up_total	46.297**					
	(18.874)					
Risk_up_sum		21.920***				
		(2.591)				
Risk_down_total				28.560**		
				(13.833)		
Risk_down_sum					10.233***	
					(2.749)	
SCDRisk			21.453***			10.111***
			(2.625)			(2.757)
Constant	19.885***	25.352***	25.112***	28.276***	31.646***	31.518***
	(6.846)	(7.144)	(7.141)	(6.571)	(6.208)	(6.200)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46678	46678	46678	63650	63650	63650
Adj R-squared	0.620	0.620	0.620	0.481	0.481	0.481

Notes: *, **, and *** denote significance at the 10%, 5%, and 1% levels; regressions include year-month, city, and industry fixed effects, with robust standard errors clustered at the firm × year-month level in parentheses.