Climate Risk in the Supply Chain: Evidence from Cost of Debt

Chenchen Huang, Enrico Onali, Yunfan Sheng and Ru Xie*

Abstract

We document that customers' climate risk leads to unfavorable bank loan pricing for their suppliers. We explain this result with a simple theoretical model, confirmed by empirical findings, based on a novel liquidity-risk channel: suppliers extend trade credit to customers hit by climate-related shocks, especially if they cannot easily switch to other customers or if their bargaining power is low. Trade credit reduces a supplier's cash flows, and this form of liquidity risk leads their banks to require higher interest payments. Consistent with this channel, lenders' attention toward climate disasters also contributes to the increased loan spreads.

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*Chenchen Huang (ch2651@bath.ac.uk), Yunfan Sheng (ys2605@bath.ac.uk) and Ru Xie (r.xie@bath.ac.uk) are with School of Management, University of Bath; Enrico Onali (e.onali@bristol.ac.uk) is with Business School, University of Bristol. We are grateful for the constructive and helpful comments received on earlier versions of this work from participants at the 8th Shanghai-Edinburgh-London-Cape Town Green Finance and Accounting Conference (June 1, Shanghai, China), the International Risk Management Conference (June 24, Milan, Italy), and the Doctoral Finance Symposium (July 2024, Reading, UK). Comments and suggestions are welcome. Errors and omissions remain the responsibility of the authors.

1 Introduction

As global climate conditions become increasingly volatile, with more frequent and extreme weather events such as heatwaves, floods, and wildfires, firms and their supply chains face heightened risks of disruption (Barrot and Sauvagnat, 2016; Carvalho et al., 2021).[1] These disruptions have raised significant concerns about the stability of the financial system due to liquidity shortfalls following climate disaster shocks. In response, regulators and institutions are revisiting risk frameworks by integrating climate-specific capital buffers and scenario-based stress tests. Initiatives such as the Federal Reserve's climate scenario analysis and the European Central Bank's stress test underscore systemic vulnerabilities, including liquidity disruptions and credit risks associated with climate change risk (European Central Bank, 2021; Federal Reserve, 2024). Commercial banks are increasingly factoring the impacts of climate disasters into credit risk assessments,[2] evidenced by the findings of prior empirical studies that banks are pricing climate-related physical risks into lending decisions (Schüwer et al., 2019; Javadi et al., 2023; Huang et al., 2022; Correa et al., 2022). However, despite this focus on client-level climate risks, the indirect risks propagated through supply chains remain underexplored, even as institutions highlight that supply chain disruptions caused by physical risks can significantly strain borrowers' cash flows and further banks' liquidity profiles.[3] With this, in this study, we investigate, both theoretically and empirically, whether and how banks evaluate the climate risk from the supply chain of the clients.

The relationships between suppliers and their main customers are essential for a modern economy. Within these complex networks, major customers play a pivotal role, significantly influencing the stability and efficiency of supply chains.[4] Customers' concentration and bargaining power can affect suppliers performance and risk (Banerjee et al., 2008; Dhaliwal et al., 2016; Campello and Gao, 2017; Itzkowitz, 2013; Chen et al., 2023). Such empirical investigations find theoretical justification in contributions highlighting the importance of relation-specific investments in the supply chain dynamics (Titman, 1984). Recent contributions, however, go one step further and show that bankruptcy risk and adverse credit

[1] For example, the direct and indirect economic damages of the 2018 wildfire in California amounted to $148.5 billion, which is approximately 1.5% of California's annual GDP (Wang et al., 2021). Reuters reported that "Supply chain disruptions resulting from the 2011 earthquake in Japan have forced at least one global automaker to delay the launch of two new models and are forcing other industries to shutter plants and rethink their logistical infrastructure" (Kim and Reynolds, 2011). Prior studies show that climate change is becoming a significant risk with the potential to impose considerable economic costs (e.g., Dell et al., 2014; Dietz et al., 2016; Lesk et al., 2016).

[2] See examples of banks' 10-K statements collected by (Correa et al., 2022)

[3] For example, Basel Committee on Banking Supervision (2024) suggests that "A comprehensive assessment would also include modelling second-round effects such as the propagation of policy or physical risk shocks through supply chains or financial contagion while accounting for the adaptive and mitigation abilities of economic agents."

[4] Approximately 45% of public companies in the U.S. are significantly dependent on at least one major customer, and manufacturers report that nearly 33% of their sales are attributed to a small group of "large customers"(Ellis et al., 2012; Campello and Gao, 2017)

shocks on major customers can indirectly affect the cost of debt for suppliers (Hertzel et al., 2008; Houston et al., 2016; Agca et al., 2022). A critical yet unexplored question is whether climate risk associated with major customers spills over to affect the borrowing costs of their suppliers and how banks account for such indirect risks when evaluating borrowers.

Our central argument on the potential influential mechanism is that natural disasters disrupt the operations of major customers, causing delays in payments to their suppliers and significantly straining the suppliers' liquidity. This liquidity squeeze can cascade through the supply chain, intensifying financial vulnerabilities of interconnected firms.[5] Banks, in turn, assess the increased liquidity risks faced by suppliers as a spillover effect of their customers' financial distress. To mitigate their own exposure, banks factor in this increased risk by raising interest rates to account for the higher probability of default of the affected suppliers. We build a simply framework that integrates supply chain liquidity dynamics, borrowers' liquidity risk and default probability, and a bank payoff model to illustrate how the climate risk of major customers influences suppliers' cost of debt. Our theoretical justification is further supported by prior empirical evidence, indicating that unexpectedly severe weather event impose a significant cash flow shock for firms, where banks charge borrowers for this liquidity shortfall via increased interest rate (Brown et al., 2021). The liquidity problem also propagates along the supply chain through trade credit dynamics and shifts in the supply or demand for goods and services (Costello, 2020; Ersahin et al., 2024).

To test our predictions, we analyze a sample of syndicated loans issued to the US suppliers and construct a de-trended measure of firms' climate risk exposures to local natural disasters.[6] Using supply chain networks, we further identify suppliers' aggregate exposure to their major customers' climate risk. Our final sample consists of 2,952 U.S. supplier-loan observations from 777 unique borrowers over the period 2003–2022. Our baseline results show that banks charge higher loan spreads on suppliers when their major customers are more exposed to climate risk, supporting our prediction that lenders adjust interest rates to account for climate risk within the supply chain. This evidence further complements prior studies, such as Agca et al. (2022), which identifies major customers' climate risk as a significant risk factor in the credit default swap (CDS) market.

We conduct a battery of robustness tests by using alternative measures and samples. First, we

[5] Acemoglu et al. (2012) well document the "cascade effects" in the intersectoral input-output networks, illustrating how productivity shocks to a single sector can propagate both upstream and downstream, ultimately impacting the entire economy.

[6] We focus on the borrowing costs of syndicated loans, which have been one of the most important sources of external finance for firms, approximately representing more than half of the total debt raised in the U.S (Chava et al., 2009; Allen et al., 2013). To capture the unexpected disaster shock to the firms, we construct a measure of excess disaster exposure by eliminating the long-term trends of disaster patterns which are correlated with stable time and spatial characteristics.

employ more granular measures of firms' climate risk exposure at the subsidiary and establishment levels. For the subsidiary level exposure, following Huang et al. (2022), we measure climate risk by using the frequency of climate-related disasters in regions where subsidiaries are located and aggregate this to the firm level using a subsidiary-weighted approach. At the establishment level, we measure climate risk exposure based on factory locations obtained from the TRI (Toxics Release Inventory) database.[7] To avoid the compounding effect of customers' climate risk and suppliers' climate risk in geographically close areas, we use an alternative sample that exclude observations where the customer and supplier are located in the same county.

Next, we carry out several cross-sectional tests to explore the heterogeneity in the impact of major customers' climate risk based on the nature of customer-supplier relationships. We find that the effect on the suppliers' cost of debt is more pronounced when suppliers face higher switching costs, proxied by factors such as durable goods production, low asset redeployability, or high SG&A expenses. Besides, the impact is more evident when customers possess significant bargaining power, measured by 1) customers' market shares, 2) sales concentration from suppliers, and 3) operations in industries with greater market entry barriers and lower competition. These findings align with prior studies indicating that switching cost and bargaining power affect firms' reliance on trade credit in response to shocks (Ersahin et al., 2024), and amplify the propagation of firm-specific idiosyncratic shocks along the production networks (Barrot and Sauvagnat, 2016; Ni et al., 2023). As a result, banks respond more prominently to the shocks arising from such supply chain relationships.

To further investigate the mechanism underlying our main findings, we investigate whether higher loan spreads are set to compensate for the increased liquidity risk faced by suppliers due to their exposures to major customers' climate risk. First, using a Two-Stage Least Squares (2SLS) regression framework, our results indicate that customers' climate risk increases the use of trade credit by customers, which subsequently reduces suppliers' cash flow. Next, our mediation analysis indicates that customers' climate risk indirectly affects suppliers' cost of debt through changing suppliers' cash flow, which supports the liquidity reduction channel we proposed.

To improve our identification of the causality channel underlying our main results, we employ a Difference-in-Differences (DiD) approach with using the occurrence of each disaster as an exogenous shock to customers' climate risk. We find that climate risk affects the cost of suppliers' loans issued within one year following the disaster hitting major customers, but the effect diminishes over time.

[7] The TRI database was established in response to the 1986 Emergency Planning and Community Right-to-Know Act (EPCRA), which requires firms to report their factory locations and pollution data. While this paper does not focus on firms' toxic release data, the database is widely used in prior studies to identify factory locations (e.g., Hsu et al., 2018).

Our findings align with prior studies suggesting that disasters lead to temporary disruptions in firms' operations and liquidity (Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Brown et al., 2021; Ersahin et al., 2024). As an additional test, we explore whether the effect on suppliers' cost of debt is intensified when there is increasing public awareness of climate risk, as prior studies suggest that public attention increases investors' demand for compensation for climate-related risks (Hirshleifer et al., 2011; Huynh and Xia, 2023). By employing the Wall Street Journal (WSJ) index as a measure of media's attention to climate risk (Engle et al., 2020), We find that higher media attention amplifies the adverse impact of customers' climate risk on suppliers' cost of debt. These additional results are consistent with the view that customers' climate risk, rather than other confounding factors, is at the root of our findings.

Finally, we explore whether bankers' prior lending relationships with suppliers' major customers mitigate the impact of customers' climate risks on suppliers' cost of debt. Gao et al. (2022) documents the role of interfirm ownership networks in reducing information asymmetry and enhancing lenders' ability to assess borrowers' creditworthiness. Prior lending relationships with a borrower's major customers may provide lenders with insights into borrowers' exposure to customers' climate risk. Our findings suggest that this type of relationship moderate the positive impact of customers' climate risk on suppliers' cost of debt. Thus, these results suggest that, in addition to a cash-flow channel, an informational channel might also contribute to a higher cost of loans for suppliers whose customers have a higher climate risk.

Our study contributes to prior literature in several aspects. First, it extends the discussions within the climate change literature, which has largely concentrated on how climate risk affects corporate behavior internally. Prior investigations, such as those by Javadi and Masum (2021) and Huang et al. (2022), have illustrated that firms exposed to physical climate risks experience elevated debt financing costs. Similarly, Huynh et al. (2020) identified a significant positive correlation between climate risk and the cost of equity. Earlier studies have investigated the impacts of climate change on firm performance such as firms' cost of sales and financial leverage, with significant findings from Zhang et al. (2018), Ginglinger and Moreau (2023), Nguyen et al. (2022), and Pankratz et al. (2023). Our study builds upon this existing framework by directly investigating the economic impacts of customers' climate risks within supply chain relationships on the borrowing costs of suppliers. This exploration not only deepens our understanding of the financial interdependencies within supply chains but also highlights the extensive economic consequences of climate risks that extend beyond individual corporate boundaries.

Second, we contribute to the expanding literature on supply chain dynamics by investigating how climate change, acting as an exogenous shock, influences perceptions within the syndicated loan market. Existing literature has examined the impact of customer concentration on suppliers' loan terms (Dhaliwal et al., 2016; Campello and Gao, 2017), and further studies have considered how various characteristics of customers, such as earnings performance (Kim et al., 2015), customer bankruptcies (Houston et al., 2016), customer financial restatements (Files and Gurun, 2018), and the identity of the customers (Cohen et al., 2022), affect suppliers' loan terms. These studies highlight the spillover effects of customers' economic conditions within the supply chain. In contrast, our study shifts focus from economic determinants to the spillover effects of customers' climate risks on the supplier's loan term.

Third, our research adds a significant dimension to the banking literature. As the severity of climate issues escalates and their negative impact on economic dynamics becomes more pronounced, it is increasingly crucial for lenders to incorporate climate-related factors into their financial risk assessments of borrowing firms. Evidence from Javadi and Masum (2021), Huang et al. (2022), Correa et al. (2022), and Huang et al. (2024) demonstrates that companies exposed to climate risks face higher loan spread from banks. However, the area of how customers' climate risks impact these conditions remains largely unexplored in banking research. Our study addresses this gap by illustrating that the climate risks associated with a firm's major customers can significantly influence the loan terms offered by banks. This highlights the broader implications of climate risks, extending beyond the direct exposure of borrowing firms to include their supply chain relationships.

The remainder of the paper proceeds as follows. Section 2 introduces the institutional background and presents the conceptual framework. Section 3 describes the data and research methodology. We report main empirical findings in Section 4 and conduct channel analysis in Section 5 and 6. Section 7 concludes.

2 Institutional background and Conceptual Framework

2.1 Institutional Responses to Climate Risks in Banking

The growing imperative to address climate-related financial risks has prompted regulators and financial institutions to revisit the current regulatory frameworks. Recent initiatives, such as the Federal Reserve's 2023 Climate Scenario Analysis (CSA) exercise (Federal Reserve, 2024) and the European Central Bank (ECB) economy-wide climate stress test in 2021 (European Central Bank, 2021), highlight the growing recognition of systemic vulnerabilities linked to climate risks, particularly through the banking sector's interconnectedness with supply chains, regional dependencies, and sectoral concentrations. Both exercises emphasized the systemic implications of climate risks, including disruptions to liquidity, increased credit risk, and financial instability caused by supply chain vulnerabilities.

The Federal Reserve CSA exercise identified significant data and modeling gaps, particularly in capturing indirect impacts of climate risk. The ECB stress test incorporated long-term climate scenarios and explored interactions between transition and physical risks, providing critical insights into the systemic nature of climate risk. They both highlight that existing regulatory standards under the Pillar 1 framework are insufficient to fully capture the unique dimensions of climate-related risks. Standardized approaches lack granular risk weights tailored to climate vulnerabilities, and internal rating-based (IRB) methods often rely on backward-looking data, failing to account for the forward-looking nature of climate risks. To address these gaps, the Basel Committee on Banking Supervision (BCBS), have begun to integrate climate risks into traditional risk frameworks. This includes introducing climate-specific capital buffers and scenario-based stress tests to enhance banks' resilience and incentivize the transition to less climate-sensitive investments (Basel Committee on Banking Supervision, 2024).

In addition, liquidity resilience is a critical issue in the context of climate risks and remains a critical focus for regulators. Current standards, such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), address short- to medium-term liquidity risks but are less effective for long-term climate-related challenges. The Federal Reserve's CSA exercise noted that disruptions in supply chains, caused by physical risks such as floods or wildfires, can significantly strain banks' liquidity profiles. For instance, natural disasters can delay payments from major customers, reducing supplier cash flows and increasing their liquidity risk. The ECB stress test reinforces these findings, emphasizing that climate-related liquidity challenges often concentrate in specific regions and sectors, amplifying systemic vulnerabilities. For instance, banks with concentrated exposures to climate-sensitive regions or industries may face significant tail risks.

In this context, the integration of climate risks into banking practices has profound implications for loan pricing, financial stability, and supply chain dynamics. Climate risks significantly influence loan pricing and financial stability, especially through their impact on supply chains. This occurs as banks adjust loan spreads to reflect heightened credit and liquidity risks, particularly in cases where suppliers are dependent on a few major customers with high climate vulnerabilities. Our paper provides evidence that climate risk exposure in supply chains increases borrowing costs for suppliers. Furthermore, our findings highlight the role of customer concentration and bargaining power in exacerbating financial vulnerabilities. Suppliers heavily reliant on a few major customers face greater risks when climate events disrupt customer operations. To address these challenges, banks should integrate supply chain analyses into risk assessments, incorporating granular data on customer climate risk exposure.

As climate change increasingly intersects with financial stability, regulatory frameworks and banking practices must evolve to address the unique nature of climate-related risks, enabling banks to better navigate the complexities of interconnected risks across supply chains. This comprehensive approach not only strengthens financial resilience, but also aligns banking practices with broader sustainability objectives, ensuring the financial system remains robust despite the increasing climate challenges.

2.2 Literature Review

Studies increasingly highlight the impact of physical climate risks on business operations. For example, Tadasse et al. (2016) document that extreme weather events create volatility in raw material costs, affecting food and energy prices. With the disruption of operations, firms' productivity, liquidity and profitability are negatively affected by climate disasters (Huang et al., 2018; Zhang et al., 2018; Brown et al., 2021; Carvalho et al., 2021; Pankratz et al., 2023). To mitigate these risks, firms are adopting conservative financial strategies, such as maintaining higher cash reserves and adopting more conservative leverage policies to hedge against these risks (Ginglinger and Moreau, 2023; Javadi et al., 2023).

Given the increase in liquidity shortfalls and credit risk after natural disasters, prior studies suggest a positive relationship between firms' exposure to physical climate risk and the cost of external financing. Bondholders of corporate bonds or municipal bonds require higher returns to compensate for firms' high exposure to climate risk, such as sea level rise and severe natural disasters (Painter, 2020; Goldsmith-Pinkham et al., 2023; Huynh and Xia, 2023). Banks incorporate climate risk factors by imposing stricter loan conditions and higher costs, responding to the elevated credit risk driven by the climate disasters (Javadi and Masum, 2021; Huang et al., 2022; Correa et al., 2022). Moreover, Correa et al. (2022), Huynh and Xia (2023), and Huang et al. (2024) uncover the irrational factors, i.e., salience bias, in banks' evaluation of borrowers' climate risk, where the increased interest rate reflects an overreaction to the perceived risk.

This climate-related financial risk can extend to interconnected firms throughout the supply chains (Barrot and Sauvagnat, 2016; Carvalho et al., 2021). Supply chain relationships characterized by greater dependence, such as with reliant suppliers or major customers, are more vulnerable to the propagation of climate risk across production networks. For example, having major customers often require suppliers to make specific investments (Titman, 1984; Banerjee et al., 2008), resulting in significant reliance on the customers' operation and exposing suppliers to greater uncertainty stemming from these major customers. This dependence exacerbates suppliers' liquidity problems when major customers face financial distress caused by idiosyncratic risk (Hertzel et al., 2008; Houston et al., 2016; Lian, 2017). As documented by Campello and Gao (2017), a concentrated customer base can lead to more liquidity problems and high cash flow risks, thereby resulting in high interest rate charged by banks on suppliers' loans to compensate for their increased likelihood of default. When climate risk significantly disrupts major customers' operations and causes liquidity issues, the contagion effect spreads to suppliers through mechanisms such as delayed payments via trade credit and reduced future orders. This, in turn, exacerbates suppliers' default risk by tightening liquidity and diminishing their repayment capacity due to reduced future profitability. Therefore, we conjecture that banks require higher return on suppliers' loans when their major customers suffer from high climate risk.

2.3 Theoretical framework

2.3.1 Basic Framework

We develop a simple theoretical framework to analyze the role played by climate risk of a major customer (ρ) on the supplier's financial stability and the subsequent adjustments in bank loan spreads. The objective is to capture how climate risk propagates across the supply chain and lending relationships. Specifically, we focus on how climate risk of a customer can influence loan pricing via a liquidity channel.

We consider a two-period model with three dates: $t = 0, 1, 2$. There are two firms: *Supplier* and *Customer*, where *Supplier* is the upstream firm and *Customer* is the downstream firm.

At date $t = 0$, *Supplier* delivers an input to *Customer*. The output at each firm is I and aI, where $a > 1$. For simplicity, we assume that there is a homogeneous good or, equivalently, that outputs are expressed in a numeraire. Therefore, the profits of *Supplier* and *Customer* are I and $aI - I$, respectively.

At date $t = 1$, the payment for the input I is to be made. However, if *Customer* experiences a liquidity shock, *Supplier* may act as a liquidity provider, insuring against liquidity shocks that could endanger the survival of their customer relationships (Cunat, 2007; Boissay and Gropp, 2013; Ersahin et al., 2024). Therefore, *Supplier* and *Customer* may renegotiate the credit terms at $t = 1$ to alleviate the financial stress on the *Customer*.

We consider the case where *Customer* is affected by a natural disaster shock that occurs after *Supplier* ships the input at $t = 0$, but before the scheduled payment date $t = 1$. At $t = 1$, we define $(1 - X)$ as the proportion of the payment deferred to $t = 2$ due to financial distress caused by the natural disaster. Thus, XI represents the expected payment at $t = 1$, while $(1 - X)I$ denotes the deferred payment at $t = 2$. Here, we assume that $(1 - X)$ is a function of climate risk ρ, and other factors, denoted as o. Thus, $(1 - X) = f(\rho, o)$, with $\frac{\partial f}{\partial \rho} > 0$, implying that higher climate risk increases the likelihood of a liquidity shock for the *Customer* (Huang et al., 2018; Brown et al., 2021).

Given that the *Supplier* is expected to receive XI at $t = 1$ and $(1 - X)I$ at $t = 2$, the present value of the total payments received by the *Supplier* at $t = 1$ is $XI + (1 - X) \cdot \frac{I}{1+r_c}$, where r_c represents the supplier's cost of capital. For simplicity, we assume r_c is equal to the firm's current cost of debt without climate risk. We present a timeline of payment in Figure 1.

The reduction of expected payment through trade credit can be written as: $I - \left(XI + (1 - X) \cdot \frac{I}{1+r_c}\right) = (1 - X) \cdot I \cdot \frac{r_c}{1+r_c}$. That is, *Supplier* allows *Customer* to delay the payment for part or all of the input purchase I, providing trade credit at a cost below *Supplier*'s cost of debt. Given that $(1 - X) = f(\rho, o)$, the above equation can be written as: $f(\rho, o) \cdot I \cdot \frac{r_c}{1+r_c}$, where $\frac{\partial f}{\partial \rho} > 0$. This indicates that the value of this subsidy depends on the *Customer*'s exposure to climate risk ρ. When ρ increases, the likelihood of delayed payment rises, leading to an increasing liquidity that the *Supplier* extends to the *Customer*.

Firms with a higher default risk tend to pay higher rates for their loans (Valta, 2012). Since the *Customer*'s climate risk reduces the *Supplier*'s liquidity and increases cash flow risk, the *Customer*'s climate risk could also increase default risk. In the appendix, we provide further explanation for why banks would raise the loan spread in response to the *Supplier*'s liquidity reduction. This yields the first set of empirical implications of our simple framework.

Implication 1: Larger climate risk exposure ρ of major customers is associated with greater interest rates when their suppliers borrow from banks.

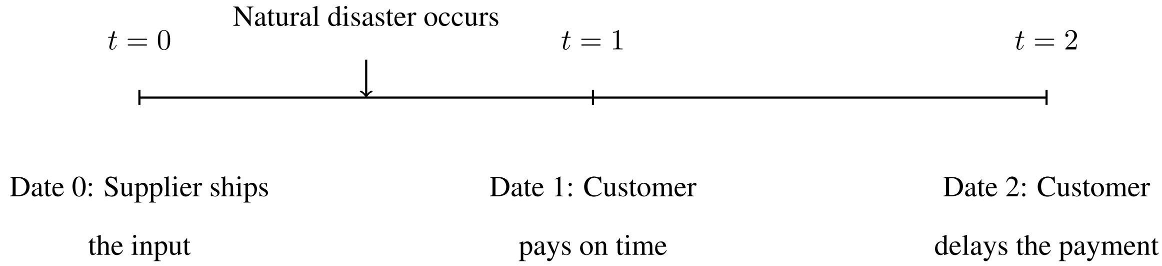

Figure 1: Timeline

2.3.2 Supplier Switching Costs

In the above, we assume that *Supplier* acts as a liquidity provider, insuring *Customer* against liquidity shocks that could endanger their survival. However, the necessary condition for this relationship to exist is the presence of a surplus for *Supplier* when they continue to do business with *Customer*. In other words, there must be a link between *Supplier* and *Customer* that makes it costly for the *Supplier* to lose its current *Customer*.

Following a liquidity shock to *Customer*, the expected payoff loss to the *Supplier* is the subsidy extended to *Customer* through trade credit. At $t = 1$, *Supplier* receives $X \cdot I$ as partial payment, while the remaining $(1 - X) \cdot \frac{I}{1+r_c}$ is deferred to $t = 2$ as trade credit. This deferred payment represents a liquidity reduction for *Supplier*. In such cases, following Maksimovic and Frank (2005), they explained that suppliers have an advantage in liquidating inputs in case of default by their customers, given that they have distribution channels to re-sell inputs. Therefore, *Supplier* can avoid the liquidity reduction by switching to another *Customer* at $t = 1$. Changing *Customer* implies switching costs K. If *Customer* fails to make the agreed payment on time, *Supplier* can retrieve the input associated with the unpaid portion $(1 - X) \cdot I$ and resell them to alternative customers in the market. Thus, *Supplier* switches when *Customer* has experienced a liquidity shock if: $(1 - X) \cdot \frac{I}{1+r_c} < (1 - X) \cdot I - K$, that is, if: $K < (1 - X) \cdot I \cdot \frac{r_c}{1+r_c}$. This can be further simplified as: $K < f(\rho, o) \cdot I \cdot \frac{r_c}{1+r_c}$

This implies that when the *Customer*'s climate risk ρ increases, the *Supplier*'s response depends on their switching costs. If the *Supplier*'s switching costs are low, the *Supplier* can opt to replace the *Customer* to avoid the liquidity reduction caused by the *Customer*'s climate risk. In this case, the expected payoff for the *Supplier* at $t = 1$ is: $X \cdot I + (1 - X) \cdot I - K$. Conversely, when the *Supplier*'s switching costs are high, the *Supplier* is more likely to absorb the liquidity reduction rather than switch customers, making the impact of the *Customer*'s climate risk on the *Supplier*'s liquidity reduction more pronounced. As a result, the *Supplier* faces higher default risk, which may prompt lenders to increase the interest rates for the *Supplier*. This yields the second set of empirical implications of our simple framework.

Implication 2: If the supplier faces high switching costs K in the supply chain, the effect of the customer's climate risk ρ on the interest rates of suppliers will be more pronounced.

2.3.3 Customer Bargaining Power

Customer's bargaining power also plays an important role. The literature argues that an imbalance of bargaining power between suppliers and customers can significantly influence suppliers' contractual terms. Customers with greater bargaining power can negotiate more favorable trade terms, resulting in delayed payments and extended receivable cycles (Fee and Thomas, 2004; Murfin and Njoroge, 2015; Hui et al., 2019; Ersahin et al., 2024). This has drawn attention from financial media. For instance, an analysis conducted for *The Wall Street Journal* noted that "firms with less than $500 million in annual sales generally took longer than in the same period a year ago to collect cash" (*The Wall Street Journal,* *August 31, 2009*).

Building on the above, we predict that customers with greater bargaining power are more likely to negotiate extended payment periods, requiring partial payment at $t = 1$ and deferring the rest to a longer time β, where $\beta \geq 1$ captures the *Customer*'s bargaining power.

In other words, when *Customer*s have greater bargaining power, they can require a longer payment period β. Thus, the expected payoff at $t = 1$ for the *Supplier* is: $X \cdot I + (1 - X) \cdot \frac{I}{(1+r_c)^\beta}$. Consequently, the *Supplier*'s expected payment reduction can be expressed as: $I - \left(X \cdot I + (1 - X) \cdot \frac{I}{(1+r_c)^\beta}\right)$, which is simplified as: $(1 - X) \cdot I \cdot \left(1 - \frac{1}{(1+r_c)^\beta}\right)$. This can be further presented as: $f(\rho, o) \cdot I \cdot \left(1 - \frac{1}{(1+r_c)^\beta}\right)$.

In addition, we predict that when *Customer* have greater bargaining power, they can negotiate for more trade credit at $t = 1$. To simplify the framework, we use the same parameter β as above to reflect the *Customer's* bargaining power. At $t = 1$, the *Customer* pays $\frac{1}{\beta} \cdot X \cdot I$, where $0 < \frac{1}{\beta} \leq 1$. A larger β indicates greater bargaining power, allowing the *Customer* to reduce the payment proportion at $t = 1$. The remaining amount, $\left(1 - \frac{1}{\beta} \cdot X\right) \cdot I$, is deferred as trade credit. Thus, the expected payment at $t = 1$ for the Supplier is: $\frac{1}{\beta} \cdot X \cdot I + \frac{\left(1-\frac{1}{\beta} \cdot X\right) \cdot I}{1+r_c}$. Consequently, the *Supplier's* expected payment reduction can be expressed as:$I - \left(\frac{1}{\beta} \cdot X \cdot I + \frac{\left(1-\frac{1}{\beta} \cdot X\right) \cdot I}{1+r_c}\right)$. This can be simplified as:$I \cdot r_c \cdot \frac{\left(1-\frac{1}{\beta} \cdot X\right)}{1+r_c}$.

Therefore, under conditions of high *Customer's* climate risk ρ, if the *Customer's* bargaining power β is also high, they can demand even longer payment periods and more trade creidt at $t = 1$. This leads to a greater expected payment reduction for the *Supplier*s. As a result, the *Supplier* faces higher default risk, which may prompt lenders to increase the interest rates for *Supplier*s. This yields the third set of empirical implications of our simple framework.

Implication 3: If the *Customer* has higher bargaining power β in the supply chain, the effect of the customer's climate risk ρ on the interest rates of suppliers will be more pronounced.

3 Sample and Research Design

3.1 Sample Construction

We first obtain the syndicated loan data originated between 2003 to 2022 from LPC-DealScan database. Syndicated loan contracts, established between the borrowers and the banks, may include either a single facility or a package of multiple facilities with varying price terms. In our analysis, we consider each loan facility as separate loan contract, since many bank loan price terms and non-price terms vary across facilities. Following Chava and Roberts (2008), we collect borrowers' financial data from Compustat for the fiscal year prior to loan initiation date. This approach guarantees that banks and other private lenders have access to the borrower's risk characteristics before loans are initiated.

We collect the customer-supplier relationship data for the period of 2002 to 2021 from the Compustat's Segment Customer File.[8] Statement of Financial Accounting Standard (SFAS) No. 14 (before 1997) and SFAS No. 131 (after 1997) require firms to disclose all firms that contribute more than 10% of a firm's total sales. The 10% threshold is established to identify customers that have significant economic importance to the reporting firm. Following approach Cohen and Frazzini (2008), we match customers to their corresponding unique identifiers in Compustat and only keep the public customers.[9] We retain only those major customers that individually account for 10% or more of their suppliers' total sales. We identify 7,527 unique supplier-customer relationships and 26,902 customer-supplier-year observations with valid firm identifiers (GVKEY) for both the suppliers and their customers.

The climate risk data is gathered from Spital Hazard Events and Losses Database for the United States (SHELDUS), maintained by Arizona State University (CEMHS,2024). Following Barrot and Sauvagnat (2016), Dessaint and Matray (2017) and Ersahin et al. (2024), we measure a firm's climate risk exposure based on the geographic location of its headquarters and county-level climate disaster data from SHELDUS.

Next, we merge the loan-level data with the supplier-customer data to get the information about the borrowers' and their customers' climate risk. After excluding the borrowers from utility and financial industries, we retain 2,952 borrower (supplier)-facility-year observations with available loan details, financial information and customer's climate risk data. Appendix Table A1 summarizes the sample selection criteria and the corresponding number of remaining observations.

3.2 Variable Definition

3.2.1 Major customers' climate risk

The variable of interest in our study is the major customer's physical climate risk. First, following Huynh et al. (2020) and Javadi and Masum (2021), we measure the firm-specific climate risk based on the exposure to extreme climate events within the county where the firm's headquarter is located. The rationale of this measurement is twofold: Firstly, the firms frequently hit by natural disasters experience significant disruption in their production process and are more susceptible to adverse effects of climate change (Dessaint and Matray, 2017; Hong et al., 2019; Brown et al., 2021; Pankratz et al., 2023);

[8]Compustat's Segment Customer database is commonly used in prior studies on the customer-supplier relationships. See Houston et al. (2016) and Campello and Gao (2017), etc.

[9]Although some suppliers may report customers with less than 10% of their sales, this information is provided on a voluntary basis.

Secondly, prior studies indicate that firms typically conduct their operation and core business activities in close proximity to their headquarters (Pirinsky and Wang, 2006; Collis et al., 2007; Menz et al., 2015).

Following Dessaint and Matray (2017) and Gustafson et al. (2023), we first obtain the county-level natural disaster data from SHELDUS. This database provides detailed information on the type of disaster, the Federal Information Processing Standards (FIPS) code of affected counties, county level dollar damages (e.g., property and crop losses, fatalities) caused by each type of hazard, duration of each type of hazard and the occurrence time (year, quarter, and month) of the event. To ensure that the event is sufficiently salient, following Barrot and Sauvagnat (2016), we restrict the sample to disasters which led to Presidential Disaster Declaration by Federal Emergency Management Agency (FEMA) and caused damage exceeding 1 billion dollars (adjusted for inflation).[10] As hurricanes/tropical storms, floods, and wildfires are closely linked to climate change and together account for the majority of the total damages caused by all climatic disasters (Seneviratne et al., 2012; Alok et al., 2020; Gustafson et al., 2023), we focus on these types of disasters in our analysis. A county is reported as an affected county whenever it is hit by such a billion-dollar natural disaster.

Given that natural disasters may correlate with stable time and spatial characteristics, which could harm its interpretation as a disaster shock, we construct a measure of county-level excess disaster exposure following Gustafson et al. (2023). This measure captures unexpected disaster shock beyond what is tipically anticipated based on historical data. Specifically, we identify the excess disaster for county c in year t by comparing the current level disaster exposure to a historical benchmark derived from 1990 to 1999, which is defined as:

$$\begin{aligned} County\ Excess\ Disaster\ Exposure_{c,t} = \max\{0, &County\ Disaster\ Exposure_{c,t} \\ &- County\ Expected\ Yearly\ Exposure_{c,90s}\} \end{aligned} \tag{1}$$

Where $County\ Disaster\ Exposure_{c,t}$ is an indicator taking value of 1 if a $county_c$ is hit by a natural disaster in year t, and 0 otherwise. $County\ Expected\ Yearly\ Exposure_{c,90s}$ represents the fraction of the ten years in the 1990s that county c experienced a natural disaster. Through comparing $County\ Disaster\ Exposure_{c,t}$ and $County\ Expected\ Yearly\ Exposure_{c,90s}$, we get the measure, $County\ Excess\ Disaster\ Exposure_{c,t}$, capturing whether and to what extent a county c has been exposed to an abnormal level of climate risk in year t than what would have been expected in a typical

[10] We have compared the information provided by SHELDUS with National Centres for Environmental Information (NCEI)'s list of billion-dollars climate disasters in the U.S. We find that the natural disasters name reported in SHELUDUS are consistent.

year of the 1990s. We apply the maximum function to capture only positive deviations, which represent unexpectedly severe exposure, while negative deviations are set to zero, indicating that disaster exposure is within the normal historical range and thus is not highlighted.

We use the county location of headquarters to determine the extent to which a firm is affected by unexpected severe disaster shocks. We rely on the historical location data of firms' headquarters extracted from 10-K fillings, as firms may relocate their headquarters during our sample period (Barrot and Sauvagnat, 2016).[11] Accordingly, we use the excess disaster exposure ($County\ Excess\ Disaster\ Exposure_{c,t}$) of the counties where major customers' headquarters are located to capture their climate risk. As many suppliers could have more than one major customer, we employ a sales-weighted average method to calculate the supplier's aggregate exposure to all the major customers' climate risk in a given year. Following the Patatoukas (2012), the weight is defined as:[12]

$$w_{ijt} = \left(\frac{Sale_{ijt}}{Sale_{it}}\right) / \sum_{j=1}^{n_{it}} \frac{Sale_{ijt}}{Sale_{it}} \tag{2}$$

Where $Sale_{ijt}$ represents the sales of supplier i to customer j in year t, $Sale_{it}$ is the supplier i's total sales in year t. n_{it} is the number of identified major customers of supplier i. Therefore, our measure of overall customers' climate risk can be calculated as follows:

$$Customer\ Climate\ Risk_{it} = \sum_{j=1}^{n_{it}} w_{ijt} \cdot Excess\ Disaster\ Exposure_{jt} \tag{3}$$

Where $Excess\ Diasaster\ Exposure_{jt}$ is the county-level excess disaster exposure of the county where the headquarters of the customer j is located in year t. A high *Customer Climate Risk* suggests that the supplier is exposed to higher climate risk from its major customers.

3.2.2 Control variables

In our baseline regression, we consider a range of control variables which could affect the borrower's (supplier's) cost of debt, at three levels (Graham et al., 2008; Bharath et al., 2011; Kim et al., 2015; Campello and Gao, 2017; Javadi and Masum, 2021; Huang et al., 2022). First, at the supplier firm level, we control for the supplier's own climate risk (*Supplier Climate Risk*) in our regression, as higher climate risk exposure for the borrowing firm can directly lead to increased loan spreads (Javadi

[11] We thank Bill McDonald for sharing the historical location data (https://sraf.nd.edu/data/augmented-10-x-header-data/)

[12] For example, suppose a supplier has two major customers, A and B, with sales to them amounting to 10 and 40, respectively. The supplier's total sales are 100. The weight for customer A would then be calculated as $\left(\frac{10}{100}\right) / \left(\frac{10}{100} + \frac{40}{100}\right) = 0.2$, and the weight for customer B would be $\left(\frac{40}{100}\right) / \left(\frac{10}{100} + \frac{40}{100}\right) = 0.8$.

and Masum, 2021; Huang et al., 2022). We also control for the supplier's fundamental characteristics, including firm size (*Ln(Asset)*), long-term debt to total asset ratio (*Leverage*), book value to market value of equity ratio (*MTB*), the ratio of tangible assets to total assets (*Tangibility*), the ratio of operating income to total assets (*Profitability*), the modified Altman's (1968) Z score (*Zscore*), and whether the firm lacks an S&P long-term issuer rating (*Unrated*), which are in line with prior bank contracting literature (Javadi and Masum, 2021; Campello and Gao, 2017; Huang et al., 2022). Second, given the focus of our study on supply chain, we also control for customers level characteristics that could influence the suppliers' cost of debt, as suggested by prior studies (Kim et al., 2015; Huang et al., 2022). We control for the sales-weighted average leverage of customers (*Customer Leverage*), the sales-weighted average profitability of customer (*Customer Profitability*), and the concentration of customers (*Customer Concentration*) in the regression. Customer concentration is calculated as the sum of sales to all major customers scaled by the supplier's total sales (Banerjee et al., 2008; Campello and Gao, 2017). Third, we control the loan level characteristics, including the natural logarithm of the loan maturity in months (*Ln(Maturity)*), the presence of performance pricing provisions within the loan contract (*Performance Pricing*), and the natural logarithm of loan size (*Ln(Loan Size)*). For instance, Graham et al. (2008) show that lenders demand a liquidity premium for long-term debt, which result in a higher loan spread. Huang et al. (2022) suggest that lenders charge lower rates for larger loan facilities and loans that include performance pricing provisions. To mitigate the impact of outliers, all continuous variables are winsorised at the 1st and 99th percentiles. Appendix Table A2 provides a detailed description of all variables used in our analysis.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for climate risk, suppliers' and customers' characteristics, and loan terms. *Customer Climate Risk* represents the sales-weighted average excess disaster exposure for customers, based on the disaster exposure in the counties where the customers' headquarters are located. The mean of *Customer Climate Risk* is 0.098, indicating the average excess disaster exposure faced by the borrowing firm's (supplier's) customers. The mean of *Supplier Climate Risk* is 0.128, capturing the average excess disaster exposure of suppliers themselves. For the supplier firm characteristics, the mean (median) of the natural logarithm of total assets (*Ln(Asset)*), leverage ratio (*Leverage*), and profitability (*Profitability*) are 7.25 (7.32), 0.25 (0.23), and 0.12 (0.13), respectively. These firm characteristics values are comparable to those reported in previous studies (e.g., Campello and Gao, 2017; Huang et al., 2022). Regarding the customer characteristics, the mean (median) of customer leverage ratio (*Customer Leverage*) and customer profitability (*Customer Profitability*) are 0.22 (0.20) and 0.14 (0.14), respectively. Additionally, the average customer concentration (*Customer Concentration*) is 0.28, implying that, on average, suppliers derive 28% of their sales from their major customers. This value closely aligns with the findings of Campello and Gao (2017), where firms attributed 30% of their sales to major customers. For the bank loan characteristics, the mean (median) of the natural logarithm of loan spread (*Ln(Spread)*) and loan maturity (*Ln(Maturity)*) are 5.3 (5.4) and 3.7 (4.1), respectively, corresponding to 225 (255) basis points and 50 (60) months. These values are consistent with those reported in previous banking literature (e.g., Graham et al., 2008; Huang et al., 2022).

< INSERT TABLE 1 HERE >

3.4 Empirical model

To estimate the impact of major customer's climate risk on the cost of debt for supplier firms, we specify the following regression model:

$$\begin{aligned} Ln(Spread)_{i,k,t} = {} & \beta_0 + \beta_1 Customer\ Climate\ Risk_{i,t-1} + \beta_2 Supplier\ Charcteristics_{i,t-1} \\ & + \beta_3 Customer\ Charcteristics_{i,t-1} + \beta_4 Loan\ Charcteristics_{i,k,t} \\ & + Year\ FE_t + Bank\ FE_g + Loan\ Purpose\ FE_h + Loan\ Type\ FE_l + \epsilon_{i,k,t} \end{aligned} \tag{4}$$

where i represents the borrowing firm (i.e., supplier), k denotes the loan facility, t indicates the year of the loan initiation. The dependent variable, *Ln(Spread)*, is the loan spread in the supplier's loan contract, which is calculated by the natural logarithm of drawn all-in spread in basis points (bps) in excess of LIBOR. *Customer Climate Risk* is the sales-weighted average climate risk of the supplier's (i.e., borrower's) major customers. *Supplier Characteristics, Customer Characteristics, and Loan Characteristics* are the series of control variables discussed in Section 3.3.

Industry FE and *Year FE* stand for the borrower's (i.e., supplier's) industry (based on Fama-French 48 industry classification) and year fixed effects, which account for time-invariant differences across industries, and for time-varying changes that occurs over the years, respectively. Loan purpose fixed effects (*Loan Purpose FE*) and loan type (*Loan Type FE*) are also included to control for the specific purpose and type behind the loans. All models in our analysis are estimated using heteroskedasticity robust standard errors clustered by firm to address potential correlations within firms.

4 Empirical Results

4.1 Baseline Results

Table 2 reports the results of baseline regression model. In column (1), the standalone effect of *Customer Climate Risk* is positive and statistically significant at the 10% level. This effect remains significant as covariates are incrementally added in columns (2) to (5), indicating that there is a contagion effect of customer climate risk on suppliers' cost of debt. The economic magnitude is sizeable: for example, in the full model shown in column (5), a one-standard-deviation increase in customer climate risk is associated with a 15.81 basis points increase in the loan spread.[13] The findings support our main conjecture that bankers account for major customers' climate risk when pricing suppliers' loans, which highlights the role of climate risk along the supply chain as a key factor in borrowers' credit risk evaluations. It further complements prior studies that emphasize firms' own climate risk in determining their cost of capital (Chava, 2014; Javadi and Masum, 2021; Huang et al., 2022; Correa et al., 2022; Huynh and Xia, 2023; Ge et al., 2024).

Among the covariates in our models, we find that borrowers' climate risk (*Supplier Climate Risk*) also shows significantly positive impacts on the loan spread. For example, in column (5), a one-standard-deviation increase in firms' own climate risk is associated with a 4.9 basis points increase in the loan spread. As for other control variables, the empirical results are largely consistent with the findings in the existing literature (e.g., Graham et al. (2008); Javadi and Masum (2021)). Specifically, smaller borrower size, lower profitability, higher leverage, lower market-to-book ratio and lower Z score are associated with higher loan spreads. Consistent with Kim et al. (2015), we find borrowers with more profitable customers can obtain bank loans with lower loan spreads. Besides, loan characteristics such as maturity, size, and performance pricing demonstrate significant effects on loan spread, aligning with findings from previous studies. Overall, our results confirm that banks perceive climate risk along supply chain as a significant factor in assessing borrowers' credit risk, alongside borrowers' own characteristics.

< INSERT TABLE 2 HERE >

[13]This is computed as the difference between the sample mean loan spread and the new resulting spread: $e^{(5.303+0.626\times 0.121)} - e^{5.303} = 15.81$ basis points.

4.2 Cross-sectional heterogeneity: Supplier′ Switching Costs and Customers′ Bargaining Power

As explained by model, the on-average effect of customer climate risk on the cost of debt could vary cross-sectionally. The propensity of a firm to switch from a customer who are affected by natural disaster should be lower if switching costs are high. In such cases, the negative effect of customer climate risk on a supplier's cost of debt is more likely to occur, particularly when it is hard for suppliers to find alternative customers. In addition, extensive research on supply chain supports the premise that higher switching costs increase suppliers' vulnerability to adverse supply chain risks, such as customer concentration (Campello and Gao, 2017), customer financial distress risk (Lian, 2017) and customer credit shock (Agca et al., 2022). Suppliers that making relationship-specific investments are more likely to suffer higher switching costs if their customers fail to uphold their commitments (Titman and Wessels, 1988; Houston et al., 2016). When making specific investments, supplier develop ties with customers, and is costly to find alternative uses for their products, making them more vulnerable to customers' climate shocks. Therefore, we expect that customer climate risk should be more significantly positively related to supplier cost of debt when they substitute the customer in a high cost.

To measure supplier's switching costs, we rely on three different proxies. First, firms in durable industries or those with higher SG&A often manufacture unique products that require specialized servicing (Titman and Wessels, 1988; Banerjee et al., 2008; Hui et al., 2019). Accordingly, we identify whether a firm operates in durable industry, defined by three-digital SIC codes 245, 250-259, 283, 301 and 324-399, and use selling, general and admirative (SG&A) expenses to capture a supplier firm's relationshipspecific investments. Furthermore, we employ the asset redeployability metric constructed by Kim and Kung (2017) as a proxy for switching costs of suppliers. Suppliers with high asset redeployability can redeploy their assets in alternative ways and consequently are less vulnerable to being "held up" by their customers. Based on these variables, we create three sets of subsamples. Firms are assigned to the Yes (No) group if the firms operate in durable (non-durable) goods industry. Similarly, firm are assigned to high (low) group if the value of SG&A or asset redeployability lies above (below) the sample median.

The subsample results are presented in Table 3. The baseline results indicate that the positive impact of major customers' climate risk on suppliers' cost of debt is larger and statistically significant only when suppliers operate in durable goods industry, have higher SG&A expenses, or exhibit higher asset redeployability, as shown in column 1, 3, and 6, respectively. Taken together, these findings align with Implication 2, suggesting that the contagion effect of customers' climate risk on firms' credit risk is more pronounced when firms face higher switching costs in the supply chain relationships.

< INSERT TABLE 3 HERE >

In addition to analyzing supplier-specific heterogeneity, we explore whether customer bargaining power moderates the impact of major customers' climate risk on suppliers' cost of debt, as proposed in Implication 3. The imbalance of bargaining power between suppliers and customers can significantly influence suppliers' contractual terms and financial performance. When facing powerful customers, supplier may be compelled to receive more trade credit for longer periods (Fee and Thomas, 2004; Murfin and Njoroge, 2015; Hui et al., 2019). As explained in the theoretical framework, the favourable contract terms leveraged by powerful customers can exacerbate the supplier's cash flow risks, which in turn increase their default risk. We expect that baseline relationship to be more significant for customers with stronger bargaining power.

We construct three measures of customer's bargaining power from the perspective of market dynamics. First, following Campello and Gao (2017), we proxy the customer bargaining power based on Herfindahl Hirschman index (HHI) of customers' industry sales. Customers operating in more concentrated (less competitive) industries, indicated by a higher HHI, have stronger bargaining power than those in less concentrated industries. Second, prior research suggests that customers with a higher market share have greater bargaining power, which enables them to negotiate more favourable terms, such as more trade credit (e.g., Klapper et al. (2012)). Therefore, we compute market share as the ratio of a customer's sales to the total sales of the customer's industry to capture its bargaining power. The third variable is barriers-to-entry in an industry, calculated as weighted average gross value of property, plant, and equipment for firms in an industry, with weights determined by each firm's sales market share. Customers operating in less fragmented industries with high barriers to entry gain increased market power, which increase their bargaining power relative to suppliers (Hui et al., 2012). For suppliers with multiple customers, we calculate the weightedaverage value of these variables above to capture the overall bargaining power of their customer base. We then partition our full sample into two subsample High or

Low based on the sample median of each attribute measures mentioned above.

Our second empirical test investigates the bargaining effects associated with customer product market competition. If customers operate in industries with lower product competition, they are likely to hold relatively stronger positions when negotiating and contracting with suppliers (Agca et al., 2022; Chen et al., 2023; Ersahin et al., 2024). We use data from the Hoberg-Phillips Data library, which is constructed through textual analysis of product descriptions in firms' 10-K fillings. This dataset provides measures of the intensity of competition that a firm faces from its direct rivals. We start by measuring customers' bargaining power using a customer's product market fluidity proxy developed by Hoberg et al. (2014). The fluidity score captures how competitors are changing the product vocabulary that overlaps with a firm's product descriptions. Customer with a lower fluidity value face less competition from their rivals. In addition to fluidity score, we incorporate two other proxies: similarity score and the TNIC HHI, both developed by Hoberg and Phillips (2016) using text-based network industries analysis. Customers with lower similarity score indicates that customers' products are less similar to their peers in the product market, which implies more direct competitions. A higher TNIC HHI score of customer reflects less competition from their rivals as it indicates greater industry concentration. For each supplier, we calculate a weighted average fluidity, similarity and TNIC HHI values for its major customers. We then partition our full sample into two subsamples High or Low based on the median values of each attribute measures mentioned above.

The subsample results are shown in Table 4, Panel A and Panel B. In Panel A, the positive relationships between customer climate risk and cost of loans remain significant when customers' market share, HHI and barriers-to-entry are high, but become insignificant in the low group. Panel B shows that that baseline relationship is significantly and positively only for the subsample firms whose customers face less product competition from their rivals. Overall, consistent with the conjecture in Implication 3, these results suggest that lenders recognize imbalances in bargaining power and take this into consideration when assessing the potential implication of major customers' climate risk on loan contracts.

< INSERT TABLE 4 HERE >

5 Robustness Check

5.1 A DID approach

In our baseline regression, we employ a continuous measure to quantify firms' abnormal climate risk beyond historical trends. One concern with this approach is that such a continuous de-trended index may capture broader trends unrelated to climate risk, potentially introducing compounding effects into the analysis. To address this, following previous studies (Barrot and Sauvagnat, 2016; Ersahin et al., 2024), we use the occurrence of natural disasters as exogenous and discrete shocks to enable clearer causal inference on how banks respond to disaster-induced disruptions in the supply chain. Since disasters hit firms in different locations at different times during our sample period, we employ a generalized Difference-in-Differences framework to compare the loans of firms whose customers experienced disaster-related disruptions with the loans of those whose customers were unaffected.The DiD model specification is as follows:

$$Ln(Spread)_{i,k,t} = \beta_0 + \beta_1 Shock_{i,t-1} + Controls + Fixed\ Effects + \varepsilon_{i,k,t} \tag{5}$$

Where $\text{Shock}_{i,t-1}$ is a dummy variable that equals one if at least one of the borrower's customers is located in a county hit by a natural disaster in the year prior to the loan issuance, and zero otherwise. We use the same control variables and fixed effects as those in the baseline regression model.

Table 5 reports the results. As shown in Column 1, the coefficient on *Shock* dummy is positive and statistically significant at the 10% level, suggesting that banks increase loan spreads for suppliers (borrowers) in the year following a natural disaster affecting their customers, which is consistent with our baseline findings. The coefficient estimate also indicates that following a natural disaster affecting customers, banks increase the loan spread for suppliers by approximately 16.31 basis points, which is 7.25% of sample's average loan spread of 225bps.

We next use a dynamic model to verify our DiD approach by testing whether there is any pretreatment trend, which should exclude the possibility that the difference between the treatment and control groups in terms of loan spread already exists before the treatment effect. To test this hypothesis, we include 4 *Shock* dummies capturing different time periods: *Shock(-1)*, *Shock(0)*, *Shock(+1)*, *Shock(2+)*. Specifically, *Shock(-1)* equals one if the loan is issued in one year prior to the disaster shock affecting its customers, and zero otherwise. *Shock(0)* equals one if the loan is issued in the same year as the disaster shock affecting its customers, and zero otherwise. *Shock(+1)* equals one if the loan is issued in one year after the disaster shock affecting its customers, and zero otherwise. *Shock(2+)* equals one if the loan is issued in two or more years after the disaster shock affecting its customers, and zero otherwise.

Column 2 of Table 5 presents the results of the dynamic difference-in-differences analysis. The results show that the coefficient on *Shock(-1)* is not statistically significant, indicating that there are no pre-existing trends in the supplier's increasing cost of debt prior to their major customers being hit by natural disasters. The estimates confirm that changes in the supplier's cost of debt do not emerge before the customer was hit by natural disasters. The results also show that the coefficient on *Shock(+1)* is positively and statistically significant, indicating that banks increase loan spreads in the year directly following the disaster. Notably, the coefficient on *Shock(2+)* is insignificant, suggesting that the effect of customers' climate risk on loan spreads diminishes over time. It further implies that the impact of acute disaster shocks is transient rather than persistent, aligning with prior findings that disasters primarily cause temporary disruptions in firms' operations and liquidity (Barrot and Sauvagnat, 2016; Dessaint and Matray, 2017; Brown et al., 2021; Ersahin et al., 2024).

Overall, findings from Table 5 provide evidence that the supplier's cost of debt increases only in the year following a natural disaster affecting their customers and but not before. This result highlights a positive relation between customer climate risk and the supplier's cost of debt, further supporting the robustness of our main results.

< INSERT TABLE 5 HERE >

5.2 Alternative measurements and samples

In our current setting, we follow prior studies to use a firm's headquarter location to determine its exposure to climate risk (Barrot and Sauvagnat, 2016; Javadi and Masum, 2021; Ersahin et al., 2024).[14] However, firms' plants and establishments are not always located in the same county as their headquarters. Our measurement focusing on the headquarter-level exposure might bias the estimates of climate risk impact if it ignores heterogeneity in climate risk exposure across different locations of a firm's operations. To alleviate this issue, we employ more granular measures of firms' climate risk exposure at the subsidiary and establishment level.

For the subsidiary-level exposure, we follow Huang et al. (2022) using the number of climate-

[14]Supporting this, Chaney et al. (2012) argue that a firm's major production plants are usually clustered in the region where the headquarter is located. Using establishments-level data, Barrot and Sauvagnat (2016) find that the average firm has 60% of its employees located in its headquarters.

related disasters in the geographic regions of its subsidiaries. Specifically, we firstly aggregate the number of natural disasters that occurred in each year in each state from the SHELDUS database.[15] Based on subsidiary state location, we then compute a subsidiary-weighted average number of natural disasters to indicate the firm's climate risk.[16] For establishment-level exposure, we follow the methodology of Hsu et al. (2018) and use the U.S. Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database to identify the county locations of the firm's U.S. factories. Building on the approach proposed by Xiong and Png (2019), we match the TRI database with the Compustat database to link facilities to their corresponding parent firms. Using our baseline method, we calculate the excess climate risk for each county where the firm's facilities are located. We then compute a facility-weighted average climate risk to indicate the firm's climate risk.

For each supplier firm, we calculate the sales-weighted average of the subsidiary-level and establishment-level climate risk exposures of its customers to estimate the firm's overall exposure to customer climate risk. The results reported in Columns 1 and 2 of Table 6 correspond to the subsidiary-level and facility-level approaches. The coefficients on customers' climate risk are both positive and statistically significant, indicating an adverse impact of customers' climate risk on corporate loan spread.

In our baseline regression model, we control for the supplier's own climate risk (i.e., borrower's climate risk) to account for the possibility that natural disasters may simultaneously affect both partners in a supply chain link. As an additional robust check, following Carvalho et al. (2021) and Agca et al. (2022), we exclude observations where the customer and supplier are located in the same county, which enables us to better capture the propagation of natural disaster shocks across supply chain-linked firms. Our results shown in Column 3 of Table 6 remain consistent.

< INSERT TABLE 6 HERE >

[15]To keep consistent with our main analysis, we only consider hurricanes/tropical storms, flooding, and wildfire in building this alternative measure.

[16]For example, a company has four subsidiaries: one in Florida and three in Kentucky. As Florida experienced 7 natural disasters in a given year and Kentucky experienced 5, the subsidiary-weighted average is $(1/4 \times 7 + 3/4 \times 5) = 5.5$. After scaling this value by 100, the firm's climate risk for that year is 0.055.

6 Channel Analysis

6.1 2SLS: The impact of customer's climate risk on supplier's liquidity

Our findings so far consistently demonstrate that customers' climate risk significantly increases suppliers' cost of debt. Building on our theoretical model, we propose that the influential channel is that customers' climate risk leads to an increase in trade credit extended by suppliers, which subsequently increases suppliers' liquidity risk. As a result, banks charge higher interest rates to compensate for the increased liquidity risk of borrowers. To test this hypothesis, we employ a Two-Stage Least Squares approach to analyze the relationships among customer climate risk, trade credit usage, and supplier liquidity.

Prior studies suggest that suppliers tend to extend more trade credit to customers impacted by natural disasters (e.g., Ersahin et al., 2024). We, therefore, use customer climate risk in year $t-1$ as an instrumental variable for the endogenous variable, i.e., the change in trade credit between year $t-1$ and t.We calculate the trade credit outstanding as the ratio of accounts receivable to net sales (e.g., Shenoy and Williams, 2017. In the first stage, we regress the change in suppliers' trade credit on customer climate risk, controlling for various firm-level factors on trade credit which are commonly used in prior studies (e.g., Shenoy and Williams, 2017; Ersahin et al., 2024). The exclusion restriction underlying our identification strategy is that customer's climate risk is exogenous and only influences the supplier's liquidity through its effect on the usage of suppliers' trade credit. In the second stage, we regress suppliers' liquidity, proxied by cash flow, on the predicted value from the first-stage regression. We use cash flow as a proxy for the supplier's liquidity, defined as the operating cash flow of suppliers in year t. Formally, we estimated the following system of equations:

$$Change\ in\ Trade\ Credit_{t-1,t} = \beta_1 CustomerClimateRisk_{t-1} + \sum_{i=2}^{n} \beta_i Controls_{t-1} + Fixed\ Effects + \nu \quad (6)$$

$$CashFlow_t = \alpha_1 \widehat{Change\ in\ trade\ credit}_{t-1,t} + \sum_{i=2}^{n} \alpha_i Controls_{t-1} + Fixed\ Effects + u \quad (7)$$

Table 7 presents the result of the 2SLS estimation. Column 1 reports the first-stage regression. The coefficient on *Change in Trade Credit* is positive and significant at 1% significance level, suggesting that customer's climate risk can significantly increase the usage of trade credit provided by suppliers. To mitigate weak instrument concerns, *Customer Climate Risk* must be a sufficiently strong predictor of suppliers' trade credit. The partial F-statistic on *Customer Climate Risk* shown in Column 1 is approximately 18, exceeding the threshold of 16 suggested by Stock and Yogo (2002). It suggests that the results are unlikely to be affected by weak instrument bias, and customer's climate risk performs as a strong and significant predictor of changes in trade credit. Using the fitted value of *Change in Trade Credit* generated from the first stage, we regress the supplier's cash flow on it in the second stage. The coefficient of *Fitted Change in Trade Credit* in Column 2 is significantly negative, indicating that supplier firms' cash flow declines as they extend more trade credit to customers after natural disaster shocks. Overall, our 2SLS results support our proposed explanation of the underlying mechanism, indicating that customer's climate risk propagates through the supply chain via the use of trade credit, ultimately reducing supplier's liquidity.

< INSERT TABLE 7 HERE >

6.2 Mediation effect

Based on the findings in 2SLS, we further investigate whether the reduced liquidity of suppliers due to customer's climate risk results in higher cost for loan contracts. To establish liquidity as the channel underlying the relation between supplier's loan spread and customer's climate risk, we perform a mediation analysis following the framework of Baron and Kenny (1986). This approach has been widely used in prior literature to examine underling mechanisms in various contexts (e.g., Rahaman et al. (2020)).

To demonstrate the mediation effect, three conditions should be met. First, the independent variable *Customer Climate Risk* should have a significant relationship with the dependent variable *Ln(Spread)*. Second, the independent variable *Customer Climate Risk* should significantly relate to the mediator variable *Cash Flow*, acting as the proxy for liquidity. The final step is to regress dependent variable (*Ln(Spread)*) on both the independent variable (*Customer Climate Risk*) and mediator (Cash Flow). If the mediator is statistically significant and the significance of the independent variable decrease in the third regression, the mediator is considered to play a mediating role between *Ln(Spread)* and *Customer Climate Risk*. To examine the significance of mediating effect, we follow Krull and MacKinnon (2001) and employ the Sobel (1982) test.

Table 8 presents the results of mediation analysis. Column 1 reports the results of the first stage analysis, which corresponds to the baseline regression model indicating a significant positive relationship between *Ln(Spread)* in year t and *Customer Climate Risk* in year t-1. Column 2 reports the second stage of the analysis, where the dependent variable is *Cash Flow* in year t. We find that the coefficient on *Customer Climate Risk* is positive and significant, indicating that customer climate risk leads to a reduction in suppliers' (borrowers') cash flow. This result aligns with our theoretical predictions and satisfies the second condition for mediation analysis.

In Column 3, we include both *Customer Climate Risk* and *Cash Flow* as explanatory variables in the regression, with *Ln(Spread)* as the dependent variable. The results reveal a negative and significant relationship between Cash Flow and *Ln(Spread)*, consistent with the expectation that reduced cash flow increases borrowing costs. Notably, while *Customer Climate Risk* remains positively and significantly related to *Ln(Spread)*, its coefficient decreases from 0.121 in Column 1 to 0.097 in Column 3. This reduction captures the mediation effect, as controlling for cash flow accounts for parts of the impact of customer climate risk on loan spread. Specifically, the total effect of *Customer Climate Risk* on *Ln(Spread)* is 0.121 (Column 1), while the direct effect, after accounting for a mediation (indirect) effect of *Cash Flow*, is 0.097 (Column 3). The mediation effect, calculated as the differences between the total effect and the direct effect, is 0.024 (i.e., 0.121-0.097). Thus, after controlling for the variable *Cash Flow*, the total effect of *Customer Climate Risk* declines by approximately 20% (0.024/0.121*100%) between Column 1 and Column 3. Using a Sobel test, we confirm that this mediation effect is significant ($p<0.01$), as reported in Column 3. Overall, these results provide evidence that the role of liquidity as a key channel through which customer climate risk impacts bank loan spreads.

< INSERT TABLE 8 HERE >

7 Additional Analysis

As an additional analysis, we investigate whether the relationship between customers' climate risk and suppliers' cost of debt would be affected by the increased attention to climate change, as prior studies suggest that investors' reaction to natural disasters tend to intensify when the public attention to climate change grows (Hirshleifer et al., 2011; Gustafson et al., 2023). Therefore, we posit that banks' assessments of climate change risk may become pronounced during periods of high public attention to climate change, resulting in higher interest rates for suppliers when natural disasters affect major customers.

To capture attention to climate change, we use two proxies. The first is the WSJ Climate Change News Index constructed by Engle et al. (2020). Based on textual analysis, the WSJ index value quantifies the fraction of Wall Street Journal (WSJ) articles dedicated to the topic of climate change from January 1984 to June 2017. The second measure is based on Google search traffic for the term "climate change," spanning the period from 2004 to 2023. For each proxy, we calculate the median value across the entire sample period. *Above WSJ* and *Above Google Index* are indicators for loans issued in months with above median levels of climate change attention.

In Table 9, we interact customers' climate risk with these two climate change attention indicators. The results show that the coefficient estimates for these interaction terms are significantly positive, suggesting that customers' climate risk on supplier's cost of debt is more pronounced during periods of increased attention to climate change.

< INSERT TABLE 9 HERE >

8 Customers' Lending Relationship with lead banks

Finally, we investigate whether bankers' prior lending relationships with suppliers' major customers mitigate the impact of customers' climate risk on suppliers' cost of debt. Prior research highlights the role of interfirm ownership networks in reducing information asymmetry and enhancing lenders' ability to assess borrowers' creditworthiness (e.g., Gao et al., 2022). Furthermore, repeated interactions with a borrower allow banks to acquire information about the borrower's supply chain partners at a lower marginal cost than would be possible without an existing lending relationship (e.g., Bharath et al., 2007, Hasan et al., 2020). Therefore, we conjecture that prior lending relationships with a borrower's major customers may provide lenders with insights into borrowers' exposure to customers' climate risk.

To test this hypothesis, we construct two variables: Prior 3 and Prior 5. Prior 3 is an indicator variable that equals one if the customer had a loan relationship with the lender within the three years prior to the supplier receiving a loan from the same lender, and zero otherwise. Similarly, Prior 5 is an indicator variable that equals one if the customer had a loan relationship with the lender within the five years prior, and zero otherwise.

In Table 10, we interact customers' climate risk with these prior relationship indicators. The results indicate that the coefficients for these interaction terms are significantly negative, suggesting that prior relationships between lenders and suppliers' major customers mitigate the impact of customer climate risk on the supplier's cost of debt. These results suggest that an informational channel might also contribute to a higher cost of loans for suppliers whose customers have a higher climate risk.

< INSERT TABLE 10 HERE >

9 Conclusions

Using a sample of 2,952 loan facility-year observations for suppliers that disclose their major customer's identities during the period of 2003-2022, we examine whether the climate risk of major customers is associated with supplier's cost of syndicated loans. We find that firms whose customers are more exposed to climate risk pay significantly higher interest rates. Further analysis reveals that the impact of major customers' climate risk on suppliers' loan price terms is more pronounced when: suppliers make more relationship-specific investment or face higher switching costs; customers have greater bargaining power and lower product competitiveness. Our main results remain robust when alternative measures of customers' climate risk and a generalized Difference-in-Differences (DiD) approach are applied. We also find that the increase in spreads for suppliers is driven by the increased liquidity risk faced by suppliers due to their exposures to major customers' climate risk.

Overall, our results suggest that major customers' climate risk is an incrementally important factor affecting a supplier's credit assessments, leading banks to impose higher interest rate on supplier's loans. Furthermore, our findings imply that lenders recognize the economic bonding between customers and suppliers so that the uncertainty of customers' climate risk to bank varies with the nature and attributes of customer-supplier relationships.

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Tables

Table 1. Summary Statistics

The table presents the summary statistics for variables used in the baseline model. The sample contains 2,952 facility-level observations from 2003 to 2022. The dependent variable, $ln(Spread)$, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *Customer Climate Risk* is the sales-weighted average climate risk of major customers, and *Supplier Climate Risk* is the firm's own climate risk. Both customer and supplier climate risks are determined by the unexpected natural disaster shocks experienced in the counties where their headquarters are located. Loan characteristics are measured at year t, while firms' (suppliers') and customers' characteristics are measured at year $t-1$. Continuous variables are winsorised at 1% and 99%. All variables are defined in Appendix 1.

Variable	N	Mean	Std.dev	P25	P50	P75
Firm climate risk variable						
Customer Climate Risk	2952	0.098	0.272	0	0	0
Supplier Climate Risk	2952	0.128	0.319	0	0	0
Borrowing firm characteristics						
Ln (Asset)	2952	7.249	1.719	6.068	7.319	8.415
Leverage	2952	0.25	0.207	0.08	0.226	0.372
MTB	2952	1.778	0.88	1.203	1.535	2.068
Tangibility	2952	0.26	0.228	0.096	0.184	0.344
Profitability	2952	0.122	0.091	0.086	0.126	0.169
Zscore	2952	1.534	1.557	0.92	1.69	2.309
Unrated	2,952	0.849	0.358	1	1	1
Customer firm characteristics						
Customer Leverage	2952	0.222	0.124	0.135	0.207	0.288
Customer Profitability	2952	0.136	0.061	0.087	0.139	0.169
Customer Concentration	2952	0.276	0.185	0.14	0.21	0.348
Loan facility characteristics						
Ln(Spread)	2952	5.303	0.752	4.905	5.416	5.784
Ln(Matruity)	2952	3.761	0.626	3.584	4.094	4.094
Performance Pricing	2952	0.403	0.491	0	0	1
Ln(Loan Size)	2952	5.12	1.607	4.007	5.298	6.215

Table 2. Customers' Climate Risk and Corporate Loan Spread

The table presents the results of analyses examining the relationship between customers' climate risk and supplier's bank loan spread. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *Customer Climate Ris*k is the sales weighted average climate risk of major customers. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.105*	0.110**	0.116*	0.112**	0.121***
	(1.84)	(2.18)	(1.91)	(2.23)	(2.64)
Supplier Climate Risk		0.120**		0.122**	0.077*
		(2.28)		(2.33)	(1.65)
Ln (Asset)		-0.188***		-0.190***	-0.110***
		(-14.01)		(-13.76)	(-6.75)
Leverage		0.616***		0.608***	0.534***
		(7.22)		(7.19)	(7.00)
MTB		-0.147***		-0.149***	-0.135***
		(-6.87)		(-7.00)	(-7.03)
Tangibility		-0.283*		-0.290**	-0.128
		(-1.92)		(-1.99)	(-0.96)
Profitability		-0.895***		-0.859***	-0.846***
		(-3.62)		(-3.47)	(-4.07)
Zscore		-0.038***		-0.039***	-0.027**
		(-2.72)		(-2.77)	(-2.21)
Unrated		-0.188***		-0.186***	-0.144***
		(-4.61)		(-4.58)	(-4.27)
Customer Leverage			0.302*	-0.004	0.008
			(1.85)	(-0.03)	(0.07)
Customer Profitability			-0.299	-0.584**	-0.628***
			(-0.86)	(-2.16)	(-2.59)
Customer Concentration			0.279**	-0.019	0.012
			(2.05)	(-0.20)	(0.14)
Ln(Matruity)					0.076***
					(3.43)
Performance Pricing					-0.182***
					(-5.66)
Ln(Loan Size)					-0.104***
					(-6.18)
Constant	5.742***	7.161***	5.703***	7.295***	6.938***
	(23.15)	(19.99)	(26.28)	(20.56)	(23.31)
Observations	2,952	2,952	2,952	2,952	2,952
Adjusted R^2	0.296	0.445	0.200	0.446	0.554
Year FE	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES
Loan Purpose FE	YES	NO	NO	NO	YES
Loan Type FE	YES	NO	NO	NO	YES
Cluster Firm	YES	YES	YES	YES	YES

Table 3. Supplier's Switching Cost

This table presents the results for the cross-sectional analyses of the association between customers' climate risk and supplier's bank loan spread based on the supplier's switching costs. The dependent variable, Ln(Spread), is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. Customer Climate Risk is the sales weighted average climate risk of major customers. In column (1) and (2), a supplier is classified as a durable goods producer if it operates in industries with SIC codes 245, 250-259, 283, 301, and 324-399. In column (3) and (4), SG&A is caculated as the ratio of the supplier's selling, general and administrative expenses to total assets. In column (5) and (6), asset redeployability reflects the extent to which a firm's assets can be used elsewhere, provided by Kim and Kung (2017). Our sample is split into two sub-samples based on whether supplier is a durable goods produced (Column1 and 2) or the sample median of SG&A and of asset redeployability (Column 3 to 6). Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Supplier is a Duarable Goods Producer		*Supplier's SG&A Expense*		*Supplier's Asset Redeployability*	
	Yes	No	High	Low	High	Low
Dependent	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.174***	0.085	0.152**	0.082	0.096	0.141*
	(2.61)	(1.26)	(2.14)	(1.29)	(1.20)	(1.88)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,331	1,621	1,467	1,422	1,246	1,188
Adjusted R^2	0.557	0.569	0.599	0.532	0.579	0.587
Year FE	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES

Table 4. Customers' bargaining power

This table presents the results for the cross-sectional analyses of the association between customers' climate risk and supplier's bank loan spread based on the customers' bargaining power. The dependent variable, Ln(Spread), is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. Customer Climate Risk is the sales weighted average climate risk of major customers. In Panel A, columns (1) and (2), the HHI of customers is the Herfindahl Hirschman index of customers' industry sales. In columns (3) and (4), market share of customers is the ratio of a customer's sales to total sales in its industry. In columns (5) and (6), barriers-to-entry in a customer's industry are calculated as weighted average gross value of property, plant, and equipment for firms in an industry, with weights determined by each firm's sales market share. In panel B, columns (1) and (2), the fluidity score captures how competitors are changing the product vocabulary that overlaps with a firm's product descriptions, provided by Hoberg et al. (2014). In columns (3) to (6), the similarity score and TNIC HHI reflects customers' competitiveness, provided by Hoberg and Phillips (2016). For each supplier, we calculate a sales-weighted average of the attribute values above for its major customers. We then spilt our full sample into two sub-samples High or Low based on the sample median of each attribute measures mentioned above. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Customers' Bargaining power						
	(1)	(2)	(3)	(4)	(5)	(6)
	HHI of Customers		*Market Share of Customers*		*Barrier-to-Entry of Customers*	
	High	Low	High	Low	High	Low
Dependent	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.159**	0.098	0.206***	0.092	0.169**	0.101
	(2.41)	(1.26)	(2.61)	(1.63)	(2.54)	(1.62)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,534	1,418	1,548	1,404	1,421	1,525
Adjusted R^2	0.596	0.541	0.578	0.550	0.585	0.570
Year FE	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES
Panel B: Customers' Product market competition						
	(1)	(2)	(3)	(4)	(5)	(6)
	Customers' Product Fluidity		Customers' Product Similarity		Customers' TNICHHI	
VARIABLES	High	Low	High	Low	High	Low
Dependent	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.085	0.251***	0.078	0.144**	0.148**	0.093
	(1.29)	(3.61)	(1.06)	(2.22)	(2.09)	(1.59)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,427	1,484	1,463	1,464	1,365	1,562
Adjusted R^2	0.504	0.619	0.591	0.548	0.547	0.580
Year FE	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES

Table 5: Customers' Climate Risk and Corporate Loan Spread: A DID approach and dynamic effects

This table presents the results of analyses examining the relationship between customers' climate risk and suppliers' bank loan spread. *Ln(Spread)* is the natural logarithm of *Spread*, which is the all-in loan spread obtained from the DealScan database for a given loan facility. Shock$_{i,t-1}$ is a dummy variable that equals one if at least one of the borrower's customers is located in a county hit by a natural disaster in the year prior to the loan issuance, and zero otherwise. *Shock(-1)* equals one if the loan is issued in one year prior to the disaster shock affecting its customers, and zero otherwise. *Shock(0)* equals one if the loan is issued in the same year as the disaster shock affecting its customers, and zero otherwise. *Shock(+1)* equals one if the loan is issued in one year after the disaster shock affecting its customers, and zero otherwise. *Shock(2+)* equals one if the loan is issued in two or more years after the disaster shock affecting its customers, and zero otherwise. Continuous variables are winsorized at the 1% and 99% levels. The definitions of variables included in the regressions are summarized in Appendix A. The *t*-statistics are reported in parentheses, and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent	*Ln(Spread)*	*Ln(Spread)*
$Shock_{i,t-1}$	0.070*	
	(1.84)	
Shock(-1)		-0.005
		(-0.14)
Shock(0)		-0.026
		(-0.66)
Shock(+1)		0.077**
		(2.05)
Shock(2+)		-0.044
		(-1.22)
Controls	YES	YES
Observations	2,952	2,952
Adjusted R^2	0.566	0.554
Year FE	YES	YES
FF48 FE	YES	YES
Loan Purpose FE	YES	YES
Loan Type FE	YES	YES
Cluster Firm	YES	YES

Table 6: Robust Test

This table presents the results for analyses of the association between customers' climate risk and supplier's bank loan spread using alternative measure of customers' climate risk. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *Customer Climate Risk* is the sales weighted average climate risk of major customers. In Column (1), customers' climate risk is measured at the subsidiary level, calculated as a subsidiary-weighted average of natural disasters in the geographic regions of the customers' subsidiaries. In Column (2), customers' climate risk is measured at the establishment-level, using a facility-weighted average of excess climate risk in the counties where customers' factories are located. In Column (3), we exclude observations where the customer and supplier are located in the same county. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Robust Tests	*Customer Climate Risk* (Subsidiary- state level)	*Customer Climate Risk* (Facility-county level)	*Customer Climate Risk* (Exclude suppliers and customers located within the same county)
Dependent	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.224**	0.309**	0.140***
	(2.18)	(2.17)	(2.95)
Controls	YES	YES	YES
Observations	2,952	946	2,653
Adjusted R^2	0.553	0.562	0.552
Year FE	YES	YES	YES
FF48 FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Loan Type FE	YES	YES	YES
Cluster Firm	YES	YES	YES

Table 7: 2SLS: climate risk, trade credit, and liquidity

This table presents the 2SLS results to investigate the relationship between customer's climate risk and the supplier's liquidity. The key endogenous variable, *Change in Trade Credit*, is measured as the change in accounts receivables scaled by sales from year $t-1$ to year t. *Cash Flow*, as a proxy for supplier's liquidity, is defined as the operating cash flow of suppliers in year t. *Customer Climate Risk* is the sales weighted average climate risk of major customers. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Stage	1st Stage	2nd Stage
Dependent	*Change in Trade Credit*	*Cash Flow*
Customer Climate Risk	0.015***	
	(4.26)	
Fitted Change in Trade Credit		-1.676***
		(-4.03)
Ln (Asset)	-0.008***	-0.011**
	(-3.52)	(-1.97)
Leverage	-0.001	-0.011
	(-0.12)	(-0.82)
MTB	0.003*	0.025***
	(1.72)	(6.77)
AGE	0.002	-0.003
	(0.26)	(-0.29)
F statistics	18.146	
Observations	2,785	2,785
Year FE	YES	YES
FF48 FE	YES	YES
Loan Purpose FE	YES	YES
Loan Type FE	YES	YES
Cluster Firm	YES	YES

Table 8: The mediating effect of suppliers' cash flow

This table presents the results on the mediation effect of suppliers' cash flow on the relationship between customer climate risk and cost of debt. *Cash Flow*, as a proxy for supplier's liquidity, is defined as the operating cash flow of suppliers in year of loan issuance. *Customer Climate Risk* is the sales weighted average climate risk of major customers. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent	*Ln(Spread)*	*Cash Flow*	*Ln(Spread)*
Customer Climate Risk	0.121***	-0.018**	0.097**
	(2.64)	(-2.02)	(2.13)
Cash Flow			-0.806***
			(-3.90)
Sobel Test			<0.01
Supplier Climate Risk	0.077*	-0.000	0.062
	(1.65)	(-0.01)	(1.49)
Ln (Asset)	-0.110***	0.011***	-0.095***
	(-6.75)	(5.83)	(-5.79)
Leverage	0.534***	0.011	0.574***
	(7.00)	(0.65)	(7.28)
MTB	-0.135***	0.026***	-0.116***
	(-7.03)	(7.38)	(-6.16)
Tangibility	-0.128	0.077***	-0.101
	(-0.96)	(3.83)	(-0.80)
Zscore	-0.027**	0.018***	-0.024*
	(-2.21)	(7.22)	(-1.86)
Unrated	-0.144***	-0.000	-0.147***
	(-4.27)	(-0.07)	(-4.54)
Customer Leverage	0.008	0.034	0.011
	(0.07)	(1.44)	(0.11)
Customer Profitability	-0.628***	0.090**	-0.498**
	(-2.59)	(1.99)	(-2.18)
Customer Concentration	0.012	0.009	0.056
	(0.14)	(0.59)	(0.64)
Profitability	-0.846***		-0.610***
	(-4.07)		(-2.71)
Ln(Matruity)	0.076***		0.093***
	(3.43)		(4.04)
Performance Pricing	-0.182***		-0.160***
	(-5.66)		(-4.96)
Ln(Loan Size)	-0.104***		-0.112***
	(-6.18)		(-6.38)
Constant	6.938***	-0.127***	6.914***
	(23.31)	(-4.68)	(28.81)
Observations	2,952	2,772	2,772
Adjusted R^2	0.554	0.281	0.567
Year FE	YES	YES	YES
FF48 FE	YES	YES	YES
Loan Purpose FE	YES	NO	YES
Loan Type FE	YES	NO	YES
Cluster Firm	YES	YES	YES

Table 9: Public Attention to Climate Change

This table presents the results for the cross-sectional analyses of the association between customers' climate risk and supplier's bank loan spread based on the climate change attention. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *Customer Climate Risk* is the sales weighted average climate risk of major customers. *WSJ index* is the standardized measure of climate attention index, constructed by Engle et al. (2020), reflecting the level of climate attention in the Wall Street Journal during the month a loan is issued. *Google Index* is based on the raw search traffic data for the term "climate change" on Google between 2004 and 2023, scaled to 100 for the maximum search volume. *Above WSJ and Above Google Index* are indicators for loans issued in months with above median level of climate change attention. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Depenent	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	-0.190	0.062
	(-1.62)	(1.07)
Above WSJ	-0.738*	
	(-1.96)	
Above WSJ×Customer Climate Risk	0.308**	
	(2.40)	
Above Google Index		0.151
		(0.34)
Above Google Index× Customer Climate Risk		0.162*
		(1.85)
Controls	YES	YES
Observations	2,618	2,710
Adjusted R^2	0.554	0.567
Year FE	YES	YES
FF48 FE	YES	YES
Loan Purpose FE	YES	YES
Loan Type FE	YES	YES
Cluster Firm	YES	YES

Table 10: Customer Lending Relationship with lead bank

This table presents the results for the cross-sectional analyses of the association between customers' climate risk and supplier's bank loan spread based on the climate change attention. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *Customer Climate Risk* is the sales weighted average climate risk of major customers. In Column (1), Prior 3 is an indicator variable that equals one if the customer had a loan relationship with the lender within the three years prior to the supplier receiving a loan from the same lender, and zero otherwise. Similarly, in Column (2), Prior 5 is an indicator variable that equals one if the customer had a loan relationship with the lender within the five years prior to the supplier receiving a loan from the same lender, and zero otherwise. Continuous variables are winsorised at 1% and 99%. The definition of variables included in the regressions are summarized in Appendix A. The t-statistics are reported in parentheses and standard errors are clustered at the firm level. The superscripts ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Depenent	*Ln(Spread)*	*Ln(Spread)*
Customer Climate Risk	0.130**	0.126**
	(2.45)	(2.30)
Prior 3	-0.616	
	(-1.03)	
Prior 3×Customer Climate Risk	-0.336***	
	(-3.02)	
Prior 5		-0.287
		(-0.56)
Prior 5×Customer Climate Risk		-0.271***
		(-2.76)
Controls	YES	YES
Observations	2,952	2,952
Adjusted R^2	0.562	0.561
Year FE	YES	YES
FF48 FE	YES	YES
Loan Purpose FE	YES	YES
Loan Type FE	YES	YES
Cluster Firm	YES	YES

Climate Leverage: Major Customer Climate Risk in Syndicated Loans

November 2024

Online Appendix:

Table OA1:Sample Selection Criteria

This table reports the sample selection criteria. The selection process of loan data and customer-supplier data are reported in Panel A and Panel B, respectively. Panel C matches the borrowers that have major customers during the sample period with the fundamental data in Compustat.

Panel A: Syndicated loan data

Selection Process	Number of observations
1. Select all facilities in the DealScan from 2003 to 2022	257,798
2. Merge with link table to identify the borrower's unique GVKEY	103,546

Panel B: Customer-supplier data

Selection Process	Number of observations
1. Supplier firms with customer relationships during 2002-2021 shown in Compustat Segment Customer files	65,377
2. Retain suppliers with over 10% of their sales to major customers	26,902
3. Merge with SHELDUS to identify the climate risk of major customer based on the customer's headquarter location	20,506
4. Retain the sales-weighted climate risk of major customers for each supplier	14,983
5. Merge with SHELDUS to identify the climate risk of supplier based on supplier's headquarter location	12,461

Panel C: Merged sample data

Selection Process	Number of observations
1. Merge the loan data in Panel A with the customer-supplier data in Panel B	4,056
2. Exclude suppliers from utility (SIC code 4900–4999) and financial industries (SIC codes 6000–6999)	3,708
3. Keep suppliers with available loan variables and accounting variables as controls (Unique US suppliers with borrowing: 777)	2,952

Table OA2:Variable Definition

This Appendix presents definitions of variables in the baseline regression model. The loan data is obtained from Thomson Reuters Loan Pricing Corporation (LPC) DealScan database. Climate risk data is from Spital Hazard Events and Losses Database for United States (SHELDUS) maintained by Arizona State University. Control variables at the supplier firm and customer levels are constructed using data from Compustat.

Dependent variable	
Ln (Spread)	The natural logarithm of all-in loan spread drawn for each facility obtained. All-in loan spread drawn is defined as the amount the borrower pays in bps over LIBOR or LIBOR equivalent for each dollar drawn down. Source: DealScan.
Independent variable	
Customer Climate Risk	Sales-weighted average climate risk of customers immediately prior to a year in which obtains the loan facility. Source: SHELUDS.
Control variables	
Supplier Climate Risk	Corporate climate risk. Source: SHELDUS.
Ln (Asset)	The natural logarithm of total asset (at). Source: Compustat.
Leverage	Ratio of long-term debt (dltt) to total asset (at). Source: Compustat.
MTB	Market value of common equity (prcc_f*csho) divided by the book value of equity (ceq). Source: Compustat.
Tangibility	Property, Plant, and equipment (PPENT) divided by total assets (at). Source: Compustat.
Profitability	Operating income (oibdp) divided by total assets (at). Source: Compustat.
Zscore	The modified Altman's (1968) Z-score, which is computed as (1.2 working capital + 1.4 retained earnings + 3.3 EBIT + 0.999 sales) divided by total assets. Source: Compustat.
Unrated	Dummy (=1, if the firm does not have an S&P long-term issuer rating, =0 otherwise). Source: S&P.
Customer Leverage	Sales-weighted average leverage of all major customers. Source: Compustat.
Customer Profitability	Sales-weighted average profitability of all major customers. Source: Compustat.
Customer Concentration	Sales made to all major customers divided by the total sales for a firm. Source: Compustat.
Ln (Maturity)	The natural logarithm of the number of months to maturity of a loan facility. Source: DealScan.
Performance Pricing	Dummy (=1, if the loan contract includes performance pricing provision, =0 otherwise). Source: DealScan.
Ln (Loan Size)	The natural logarithm of the amount of a loan facility. Source: DealScan.
Loan Type	Indicator variables for loan type, including term loan and other loan type. Source: DealScan.
Loan Purpose	Indicator variables for loan purpose, including corporate purposes, debt repayment, working capital, takeover, capital investment, and other purposes. Source: DealScan.

10 Appendix 3

Climate Risk, Liquidity, and Bank Loan Pricing

This appendix presents how climate-related financial risks, particularly the major customer climate risk (ρ), affect supplier liquidity and loan spread. The framework demonstrates how deferred payments induced by climate risks propagate financial instability across the supply chain, increasing the supplier's default probability and influencing loan spreads set by banks. The analysis involves three participants: suppliers who provide input to customers, customers who transform inputs into outputs and make payments to suppliers, and banks who lend to suppliers and set loan spreads based on risk assessments.

As mentioned in Section 2.3, the model timeline spans three periods: at $t = 0$, suppliers deliver inputs; at $t = 1$, payments are due, but may be delayed due to customer financial distress caused by climate-related shocks; and at $t = 2$, deferred payments are settled. At $t = 1$, customer distress driven by climate-related shocks may defer a portion of payments. The percentage of delayed payments, $(1 - X)$, depends on customer climate risk (ρ) and other factors (o):

$$(1 - X) = f(\rho, o),$$

where $\frac{\partial f}{\partial \rho} > 0$, indicating that higher climate risk increases the probability of delayed payments.

The supplier experiences a liquidity shortfall due to deferred payments, expressed as:

$$\Delta L_S = (1 - X) \cdot I \cdot \frac{r_c}{1 + r_c},$$

where I represents the payment for the input provided by the supplier and r_c is the supplier's cost of capital. Substituting $(1 - X) = f(\rho, o)$, the liquidity shortfall becomes:

$$\Delta L_S = f(\rho, o) \cdot I \cdot \frac{r_c}{1 + r_c}.$$

The above equation shows that the supplier's liquidity shortfall increases with higher customer climate risk (ρ). The supplier's probability of default (p) further depends on two key factors: the financial condition of the supplier (θ) and the reduction in liquidity experienced due to deferred payments (ΔL_S). The default probability of the supplier can be presented in the following model:

$$p(\theta) = p_0 + \beta_1 \theta + \psi(\Delta L_S),$$

where p_0 represents the baseline default probability in the absence of any liquidity stress or financial fluctuations. The term $\beta_1 \theta$ reflects the sensitivity of default probability to the supplier's financial condition, with higher values of β_1 indicating that a poorer financial state significantly increases default risk. Finally, $\psi(\Delta L_S)$ captures the impact of liquidity reductions on the supplier's probability of default, where $\frac{\partial \psi}{\partial \Delta L_S} > 0$ implies that an increase in liquidity shortfalls worsens the supplier's financial stability.

By substituting the expression for liquidity reduction, $\Delta L_S = f(\rho, o) \cdot I \cdot \frac{r_c}{1+r_c}$, into the default probability equation, we obtain:

$$p(\theta) = p_0 + \beta_1 \theta + \psi \left(f(\rho, o) \cdot I \cdot \frac{r_c}{1 + r_c} \right).$$

The above equation illustrates how climate risk (ρ), through its impact on deferred payments, directly influences the liquidity shortfall (ΔL_S) and, consequently, the supplier's default probability. Higher major customer climate risk can lead to significant liquidity reductions, which increases the term $\psi(\Delta L_S)$ and amplifies the supplier's financial risk. This mechanism demonstrates how climate risk propagates through supply chain relationships further affects firm's liquidity and default probability.

Following Allen and Gale (2000), Hellmann et al. (2000), and Repullo and Suarez (2004) the *bank's payoff* (Π_b) is a function of loan spread (r), loan amount (L), and default probability (p):

$$\Pi_b = (1 - p(\theta)) \cdot (1 + r) \cdot L - p(\theta) \cdot (1 - \lambda) \cdot L,$$

where λ represents the recovery rate in the event of default and L represents the loan amount provided by the bank to the borrower. To optimize the payoff, the bank adjusts the loan spread r to compensate for increased risk. By setting $\frac{\partial \Pi_b}{\partial r} = 0$, the optimal loan spread is obtained as:

$$r^* = r_0 + \gamma \cdot \frac{\partial p(\theta)}{\partial \rho}.$$

Substituting $p(\theta)$, the partial derivative with respect to ρ is given by:

$$\frac{\partial p(\theta)}{\partial \rho} = \frac{\partial \psi}{\partial \Delta L_S} \cdot \frac{\partial \Delta L_S}{\partial \rho}.$$

Since the liquidity shortfall is defined as $\Delta L_S = f(\rho, o) \cdot I \cdot \frac{r_c}{1+r_c}$, the partial derivative of ΔL_S with respect to ρ becomes:

$$\frac{\partial \Delta L_S}{\partial \rho} = \frac{\partial f}{\partial \rho} \cdot I \cdot \frac{r_c}{1 + r_c}.$$

Substituting this into the expression for $\frac{\partial p(\theta)}{\partial \rho}$, we get:

$$\frac{\partial p(\theta)}{\partial \rho} = \frac{\partial \psi}{\partial \Delta L_S} \cdot \frac{\partial f}{\partial \rho} \cdot I \cdot \frac{r_c}{1 + r_c}.$$

The optimal loan spread can now be written as:

$$r^* = r_0 + \gamma \cdot \frac{\partial \psi}{\partial \Delta L_S} \cdot \frac{\partial f}{\partial \rho} \cdot I \cdot \frac{r_c}{1 + r_c}.$$

In conclusion, borrower liquidity risk, driven by climate risk (ρ), directly influences the bank's loan spread (r^*). As the level of climate risk (ρ) increases, customer payment delays reduce the supplier's liquidity, which in turn increases the Supplier's default probability. This heightened default risk leads the bank to adjust loan spreads upward to reflect the increased risk.