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

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June 2025

Abstract

We document that customer's exposure to physical climate risk leads to unfavorable syndicated loan pricing for their suppliers. This finding is explained by a simple theoretical model and supported by empirical evidence, highlighting a novel liquidity-risk channel: customers with higher climate risk exposure delay payments by using more trade credit, thereby reducing suppliers' cash flow. This form of liquidity risk, in turn, raises suppliers' borrowing costs, especially when suppliers cannot easily switch to other customers or with lower bargaining power. We further find that customers' own liquidity conditions and prior lending relationships with suppliers' lead banks moderate the main effect. Beyond these immediate liquidity strains, suppliers also experience persistent sales declines following disasters affecting their customers.

JEL Classification: G32; M14; K12
Keywords: Climate Risk, Syndicated Loan, Supply Chain

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1 Introduction

As global climate conditions become increasingly volatile, with more frequent and extreme weather events such as heatwaves, floods, and wildfires, firms along the supply chain are experiencing operational instability (Barrot and Sauvagnat, 2016; Carvalho et al., 2021).[1] For example, "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).

Climate disaster shocks cause liquidity shortfalls, raising concerns about financial system stability.[2] For this reason, 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 (European Central Bank, 2021; Federal Reserve, 2024). Commercial banks are increasingly factoring the effects of climate disasters into credit risk assessments,[3] with recent empirical studies document that banks are pricing climate-related physical risks into their lending decisions (Schüwer et al., 2019; Javadi et al., 2023; Huang et al., 2022; Correa et al., 2022). While academic literature has so far focused on banks' corporate clients' direct climate risks, the understanding of whether and how banks perceive the propagation of climate risk through borrowers' supply chains has remained under-explored, despite some interest from regulators.[4] To fill this gap, we specifically focus on the upstream spillover of climate risk along the supply chain, investigating

[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). 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]Companies facing natural disasters are often forced to change their corporate strategies. For instance, Duong and Huynh (2025) find that firms are 35.77% more likely to seek equity funding after facing extreme weather events. Additionally, there is a 13.84% increase in their likelihood of borrowing from banks and a 40.98% rise in seeking funds from supply chain partners.

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

[4]For example, Basel Committee on Banking Supervision (2024) suggests that "A comprehensive assessment would also include modeling 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."

how climate risk faced by downstream customers affects the cost of bank loans of their upstream suppliers. [5]

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.[6] Seminal studies highlight the importance of supplier-customer relationships and how they can affect capital structure decisions (Titman, 1984). Recent contributions show that customer's 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). Moreover, bankruptcy risk and adverse credit 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). Despite growing interest in the role played by customers in affecting suppliers' cost of debt, and given that climate risk is a key risk factor in bank lending decisions, we are the first to bridge these two strands of literature.

We argue that natural disasters experienced by customers—a primary source of physical climate risk—act as a form of (indirect) liquidity shock to suppliers: they disrupt the customers' operations, causing delays in payments to their suppliers and straining their suppliers' liquidity. Such liquidity shocks, cascading through the supply chain, ultimately affect suppliers' creditworthiness.[7] Banks respond by raising suppliers' borrowing cost to account for the higher probability of default. We formalize this mechanism in a simple theoretical framework integrating supply chain liquidity dynamics, borrowers' liquidity risk and default probability in a bank payoff model. Our arguments are supported by prior empirical evidence indicating that severe weather events impose a significant cash-flow shock on firms, and banks charge borrowers higher interest rates to allow for disaster-related liquidity risk (Brown et al., 2021). Liquidity risk also propagates

[5] Throughout the paper, we use the terms "supplier" and "borrower" interchangeably.

[6] 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).

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

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 US firms that are identified as suppliers within the supply chain. We begin by constructing a de-trended measure of individual major customer's exposure to local natural disasters.[8] We then aggregate suppliers' exposure to climate risk from their multiple major customers (or Customer Climate Risk, CCR) by using a sales-weighted average approach. Our main analysis is based on a sample consisting of 2,952 loan-year observations from 777 unique borrowers identified as suppliers over 2003–2022. We find that banks charge 3.3% higher loan spreads on suppliers whose major customers face a one-standard-deviation increase in climate risk, which supports our prediction that lenders adjust interest rates to account for the propagation of climate risk along the supply chain.

We conduct a battery of robustness tests. First, to mitigate endogeneity concerns and also capture potential dynamic effects, instead of using the de-trended continuous measure of CCR, we employ a Difference-in-Differences (DiD) approach and treat each natural disaster occurring at customer's location as exogenous shock to liquidity along the supply chain. We find that the impact of such disasters is evident in suppliers' loans issued within one year after the shock, but dissipates thereafter. These results align with prior studies suggesting that natural 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). We also employ alternative measures of climate risk to validate our main findings, such as using more granular measures of firms' climate risk exposure at the subsidiary and establishment levels based on the factory locations obtained from the TRI (Toxics Release Inventory) database. To avoid confounding effects of customer climate risk and the borrower's own climate risk in nearby areas, we use an alternative sample that excludes observations where the borrowers and their customers are

[8]We focus on the borrowing costs of syndicated loans, one of the most important sources of external finance for firms, accounting for more than half of the total debt raised in the U.S. (Chava et al., 2009; Allen et al., 2013). We measure excess disaster exposure by eliminating the long-term trends of disaster patterns which are correlated with stable time and spatial characteristics.

located in the same county. In addition, we add bank fixed effects and state fixed effects in our regression models to account for time-invariant characteristics at the bank and state levels.

We carry out several cross-sectional tests to explore heterogeneity in our results, based on the nature of customer-supplier relationships. We find that the effect on borrowers' cost of debt is more pronounced when borrowers face higher switching costs in the supply chain relationship, proxied by durable goods production, low asset redeployability, or high selling, general and administrative expenses (SG&A). Similarly, the impact is more evident when borrowers' customers possess significant bargaining power, measured by customers' market shares and by whether customers operate in industries with lower competition and with higher entry barriers. These findings align with prior studies suggesting that switching costs 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.

Next, we dig deeper into the influential mechanism, i.e., higher loan spreads are set to compensate for the increased liquidity risk induced by borrowers' CCR. First, using a Two-Stage Least Squares (2SLS) regression framework, we find that CCR increases the use of trade credit by customers, thereby reducing borrowers' cash flow. Second, we conduct a mediation analysis and provide evidence consistent with a cash-flow channel: CCR indirectly affects borrowers' cost of debt because of a negative impact on borrowers' cash flow. In addition, we find a long-lasting adverse effect of CCR on borrowers' fundamental performance. Specifically, higher CCR leads to a persistent decline in borrowers' sales over the next five years. This finding provides additional insights into the channels through which lenders anticipate fundamental deterioration of borrowers and, in turn, increase loan costs.

We extend our baseline results with additional tests. First, we examine whether customer liquidity constraints amplify the impact of CCR on suppliers' borrowing costs. When liquidity-constrained customers face temporary shocks, they demand more trade credit (Cunat, 2007; Shenoy and Williams, 2017), thereby increasing borrowers' liquidity risk and raising their cost of debt. Using proxies such as excess cash holdings, Altman (1968)'s Z-score, and the Kaplan-Zingales index, our results support the conjecture. Second, non-pricing terms such as collateral and covenants might compensate lenders for credit risk stemming from CCR, as these contractual terms help reduce lenders' exposure by limiting borrowers' risk-shifting behaviour (Campello and Gao, 2017; Cen et al., 2017; Huang et al., 2022). We find that the adverse effect of CCR on loan spreads is significantly attenuated for loans that include collateral or covenants. Third, prior studies show that interfirm ownership networks reduce information asymmetry and improve lenders' ability to assess borrower creditworthiness (Gao et al., 2022). We expand on this by exploring whether lenders' interactions with a borrower's supply-chain network similarly offer informational advantages that lower loan spreads in our climate risk setting. We find that the adverse impact of CCR on borrowers' cost of debt is weaker when lead banks have prior lending relationships with the borrower's major customers. This suggests that such relationships provide banks with better insight into potential liquidity risk spillovers from borrower's customers, thereby reducing the premium banks require. Additionally, we find that public awareness of climate risk, proxied by media attention, influences the effect of CCR on borrowers' cost of debt, confirming that our results are driven by climate risk rather than confounding events (Hirshleifer et al., 2011; Huynh and Xia, 2023).

Our study contributes to several strands of literature. First, we significantly advance the banking literature on climate-related risks. As climate change becomes more severe and its negative impact on economic dynamics is more evident, lenders are incorporating climate-related factors into their default risk assessments. While prior research primarily focuses on the direct impact of climate risk on borrowers (Huang et al., 2022; Correa et al., 2022; Huang et al., 2024), we address a critical gap by showing how lenders incorporate indirect climate risk spillovers from borrowers' supply chain networks into the loan pricing decisions. Our findings on the increased borrowing costs of suppliers following their customers' disaster shocks underscores the broader implications of climate risk for financial institutions and highlights the need to incorporate indirect exposures arising from interfirm relationships.

Second, we bridge the fields of climate finance and supply chain literature. Prior studies have explored how climate risk affects a firm's performance, financing costs, and capital structure (Huang et al., 2022; Huynh et al., 2020; Zhang et al., 2018; Ginglinger and Moreau, 2023; Pankratz et al., 2023). Our research extends this by demonstrating how physical climate risk is transmitted to supply chain partners through liquidity and trade credit channels. Our findings also complement supply chain research that emphasizes how customer concentration (Dhaliwal et al., 2016; Campello and Gao, 2017), and specific customer characteristics—including 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 supplier loan terms. Overall, our exploration deepens the understanding of financial interdependencies within supply chains and highlights the extensive economic consequences of climate risk that extend beyond individual corporate boundaries, a critical aspect largely neglected in prior climate risk literature.

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. Section 4 presents the main empirical findings, followed by the channel analysis in Section 5 and the extended analysis in Section 6. Section 7 concludes.

2 Institutional background and Conceptual Framework

2.1 Institutional Responses to Climate Risks in Banking

Central banks and regulatory agencies are increasingly aware of the potential impacts of both physical and transition risks associated with climate change on lenders and the broader real economy.[9] To assess the resilience of the banking system, supervisory agencies have increasingly implemented climate risk stress tests. These exercises not only identify vulnerabilities but also mitigate information asymmetries, enabling banks to better understand borrowers' exposure to climate risks. For example, the Federal Reserve's 2023 Climate Scenario Analysis (CSA) exercise (Federal Reserve, 2024) emphasized that, beyond direct portfolio impacts, participants should consider indirect effects on local economies, infrastructure, pricing, and supply chains. This finding demonstrates the need for a comprehensive approach, one that integrates detailed supply chain analysis, to effectively address the systemic nature of climate risk.

Regulatory bodies have recently strengthened climate risk management requirements through new guidelines. The Interagency Principles for Climate-Related Financial Risk Management (October 2023) provide a structured framework for large financial institutions to manage both physical and transition risks, with a particular focus on supply chain vulnerabilities. Similarly, the Federal Reserve Supervisory Letter SR 23-9 (October 2023) requires robust measures to mitigate physical climate risks, including disruptions to supply networks. Furthermore, the Basel Committee on Banking Supervision's exploration of climate-specific capital buffers and scenario-based stress tests (Basel Committee on Banking Supervision, 2024), along with the Network for Greening the Financial System (NGFS) scenario portal, encourages banks to adopt granular, forward-looking risk assessments. Such a forward-looking perspective is critical because climate risk increasingly influences loan pricing and overall financial stability.

2.2 Literature Review

Recent research highlights how extreme climate events reshape corporate financial strategies because of the impact of physical climate risk 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

[9] Physical risk relates to extreme climate events such as droughts and floods, while transition risk arises from borrowers' lack of preparedness for decarbonization, which can trigger significant shifts in asset and liability valuations.

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 implementing 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, firms' exposure to physical climate risk is likely to correlate positively with the cost of external financing. Holders 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 by imposing stricter loan conditions (Huang et al., 2022; Correa et al., 2022).[10]

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 requires suppliers to make specific investments (Titman, 1984; Banerjee et al., 2008), resulting in significant reliance on the customers' operations 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 higher interest rates 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.

[10]Although we focus on a channel based on rational responses of bank managers to CCR, irrational factors, such as salience bias, might also play a role (Correa et al., 2022; Huynh and Xia, 2023; Huang et al., 2024).

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 returns on borrowers' 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: $t = 0, 1, 2$, where the first period begins at $t = 0$ and the second period at $t = 1$. 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 is I for *Supplier* and aI for *Customer*, where $a > 1$. For simplicity, we assume that there is a homogeneous good or, equivalently, that outputs are expressed in a numeraire (Ersahin et al., 2024). Therefore, the profits of *Supplier* and *Customer*, i.e., net of input costs, are I and $aI - I$, respectively.[11]

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*.

[11]This setting is based on Ersahin et al. (2024)'s model with three firms: Firm 2, Firm 1, and Firm 0. In their framework, the output at each stage of production is I, Ia, and Ia^2, with corresponding profits of I, $I(a-1)$ and $aI(a-1)$. We simplify this structure by removing Firm 0. The remaining two firms are the Supplier and Customer, respectively.

We consider a case in which *Customer* is affected by a natural disaster shock that occurs in the first period, 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 $t = 2$. 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 a positive correlation between climate risk and the likelihood of a liquidity shock for *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 *Supplier* at $t = 1$ is $XI + (1 - X)\frac{I}{1+r_c}$, where r_c represents *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 is: $I - \left(XI + (1 - X)\frac{I}{1+r_c}\right) = (1 - X)I\frac{r_c}{1+r_c}$. That is, *Supplier* allows *Customer* to delay the payment for part or all of the input purchased, I, providing trade credit at a cost below *Customer*'s cost of debt. Given that $(1 - X) = f(\rho, o)$, the above equation can be written as: $f(\rho, o)I\frac{r_c}{1+r_c}$, where $\frac{\partial f}{\partial \rho} > 0$. This indicates that the value of this subsidy depends on *Customer*'s exposure to climate risk ρ. When ρ increases, the likelihood of delayed payment rises, leading to an increasing liquidity that *Supplier* extends to *Customer*.

Firms with higher default risk tend to pay higher loan spreads (Valta, 2012). Since *Customer*'s climate risk reduces *Supplier*'s liquidity and increases cash flow risk, it further increases *Supplier*'s default risk. In the Online Appendix (Appendix B), we further explain why banks increase loan spreads in response to *Supplier*'s liquidity reduction. This leads to the first empirical implication of our theoretical framework.

Implication 1: Higher CCR is associated with higher borrowing costs for bank loans to *Supplier*.

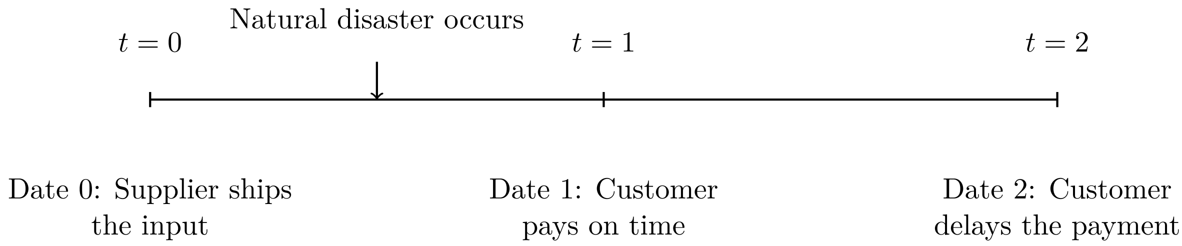

Figure 1: Timeline

2.3.2 Supplier Switching Costs

In the discussion above, we have assumed 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, certain factors would provide *Supplier* with strong incentives to retain *Customer* to avoid the significant costs associated with terminating the relationship.

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 XI as partial payment, while the remaining $(1 - X)\frac{I}{1+r_c}$ is deferred to $t = 2$ as trade credit. This deferred payment represents a liquidity reduction for *Supplier*. However, *Supplier* can avoid the liquidity reduction by switching to another *Customer* at $t = 1$. In fact, suppliers have an advantage in liquidating inputs in case of default by their customers, given that they have distribution channels to re-sell inputs (Maksimovic and Frank, 2005). Switching to another customer entails a cost, K. If *Customer* fails to pay on time, *Supplier* retrieves the input associated with the unpaid portion $(1 - X)I$ and resells it to other customers on the market. Thus, *Supplier* switches when *Customer* has experienced a liquidity shock if: $(1 - X)\frac{I}{1+r_c} < (1 - X)I - K$, that is, if:

$K < (1-X)I\frac{r_c}{1+r_c}$. This can be further simplified as: $K < f(\rho, o)I\frac{r_c}{1+r_c}$

This implies that when *Customer*'s climate risk ρ increases, *Supplier*'s response depends on their switching costs. If *Supplier*'s switching costs are low, they may replace *Customer* to avoid the liquidity reduction caused by *Customer*'s climate risk. In this case, the expected payoff for the *Supplier* at $t = 1$ is: $XI + (1-X)I - K$. Conversely, if *Supplier*'s switching costs are high, *Supplier* is more likely to absorb the liquidity reduction rather than switch customers, amplifying the negative impact of *Customer*'s climate risk on *Supplier*'s liquidity. As a result, *Supplier* faces higher default risk, prompting lenders to raise interest rates on *Supplier*'s loans. These considerations lead to the second implication of our theoretical framework.

Implication 2: If *Supplier* faces high switching costs, the effect of CCR on *Supplier*'s cost of debt will be more pronounced.

2.3.3 Customer Bargaining Power

Customers' bargaining power also plays a crucial role. An imbalance in bargaining power between suppliers and customers can significantly influence the contractual terms agreed upon by the counterparties. 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).[12]

Building on these considerations, we predict that customers with greater bargaining power are more likely to negotiate payment extensions. In this case, *Supplier* may receive a partial payment at $t = 1$ and the rest of the payment will occur at a later period. To capture this, we introduce $\beta \geq 1$, where a larger value for β represents a larger *Customer*'s bargaining power. Specifically, the expected payoff at $t = 1$ for *Supplier* is: $XI + (1-X)\frac{I}{(1+r_c)^\beta}$. Consequently, *Supplier*'s expected payment reduction can be expressed as: $I - \left(XI + (1-X)\frac{I}{(1+r_c)^\beta}\right)$, which is simplified as: $(1-X)I\left(1 - \frac{1}{(1+r_c)^\beta}\right)$. This can be further presented as: $f(\rho, o)I\left(1 - \frac{1}{(1+r_c)^\beta}\right)$.

[12] 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*).

In addition, we predict that when *Customer* has greater bargaining power, *Customer* may negotiate a larger proportion of the payment due to be deferred. To simplify the framework, we use the same parameter β as above to reflect *Customer's* bargaining power in this respect. At $t = 1$, *Customer* pays $\frac{1}{\beta}XI$, where $0 < \frac{1}{\beta} \leq 1$. A larger β indicates greater *Customer*'s bargaining power because *Customer* reduces the payment occurring at $t = 1$ relative to payments in later periods. The remaining amount, $I(1 - \frac{1}{\beta}X)$, represents trade credit. Thus, the expected payment at $t = 1$ for *Supplier* is: $\frac{1}{\beta}XI + \frac{\left(1-\frac{1}{\beta}X\right)I}{1+r_c}$. Consequently, *Supplier*'s expected payment reduction can be expressed as:$I - \left(\frac{1}{\beta}XI + \frac{\left(1-\frac{1}{\beta}X\right)I}{1+r_c}\right)$. This can be simplified as:$Ir_c\frac{\left(1-\frac{1}{\beta}X\right)}{1+r_c}$.

Therefore, under conditions of high *Customer*'s climate risk, ρ, if *Customer*'s bargaining power β is also high, they can demand even longer payment periods and more trade credit at $t = 1$. This leads to a greater expected payment reduction for *Supplier* at $t = 1$. As a result, *Supplier* faces higher default risk, prompting lenders to increase the interest rates on loans to *Supplier*. These considerations lead to the third implication of our theoretical framework.

Implication 3: If *Customer* has higher bargaining power, the effect of CCR on *Supplier*'s cost of debt will be more pronounced.

3 Sample and Research Design

3.1 Sample Construction

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

We collect customer-supplier relationship data for the period from 2002 to 2021 from Compustat's Segment Customer File.[13] 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 Cohen and Frazzini (2008), we match customers to their corresponding unique identifiers (GVKEY) in Compustat and only keep those listed on a stock exchange.[14] We retain only those 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 are gathered from Spatial 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 loan-level data with supplier-customer data. After excluding borrowers from utility and financial industries, we retain 2,952 loan facility observations for borrowers identified as suppliers. This final dataset includes detailed loan characteristics, borrower and customer characteristics, as well as climate risk exposure for both borrowers and customers. In the Online Appendix, Table OA1 summarizes the sample selection criteria and the corresponding number of remaining observations.

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

[14]Some suppliers may voluntarily report customers representing less than 10% of their sales.

3.2 Variable Definition

3.2.1 Major customers' climate risk

The variable of interest in our study is the physical climate risk of major customers (CCR). First, following Huynh et al. (2020), we measure firm-specific climate risk based on the exposure to extreme climate events within the county where the firm's headquarters is located. The rationale for this measurement is twofold: first, firms frequently hit by natural disasters experience significant disruption in their production processes and are more susceptible to the adverse effects of climate change (Dessaint and Matray, 2017; Hong et al., 2019; Brown et al., 2021; Pankratz et al., 2023); second, prior studies indicate that firms typically conduct their operations 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 county-level natural disaster data from SHELDUS. This database provides detailed information on the type of disaster, the Federal Information Processing Standards (FIPS) codes 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 that led to Presidential Disaster Declaration by Federal Emergency Management Agency (FEMA) and caused damage exceeding 1 billion dollars (adjusted for inflation).[15] 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. We classify a county as affected if it is hit by natural disaster causing damages exceeding 1 billion dollars.

[15] 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. The natural disasters names reported in the two databases are consistent.

Given that natural disasters may correlate with stable time and spatial characteristics, which could harm their 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 shocks based on historical norms. Specifically, we identify the excess disaster exposure 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 a 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 obtain 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 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 remains within the normal historical range and thus is not highlighted.

We use the county location of a firm's historical headquarters to determine the extent to which a firm is affected by unexpected severe disaster shocks.[16] 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. To account for cases where a supplier has more than one major customer, we employ a sales-weighted average method to

[16]We rely on the historical location data of firms' headquarters extracted from 10-K filings, as firms may have relocated their headquarters during our sample period (Barrot and Sauvagnat, 2016). We thank Bill McDonald for sharing the historical location data (https://sraf.nd.edu/data/augmented-10-x-header-data/)

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:[17]

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

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. The supplier's overall exposure to customers' climate risk (CCR) is then calculated as:

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

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

Figure 2 shows the excess frequency of climate disasters for each U.S. counties during 2002-2021 relative to the 1990s. The map reveals that many counties are more frequently hit than in the past, especially those located along the southeast and the Atlantic coast hit by hurricanes and tropical storms, and west coast hit by wildfires.

< INSERT FIGURE 2 HERE >

3.2.2 Control variables

In our baseline regression, we consider a range of control variables that could affect a firms' borrowing costs (Graham et al., 2008; Bharath et al., 2011; Kim et al., 2015; Campello and Gao, 2017). First, we control for the borrower's own climate risk (*Borrower Climate Risk*), as higher climate risk exposure for the borrower can directly lead to increased loan spreads

[17]For example, suppose a supplier has two major customers, A and B, with sales to them amounting to \$10 million and \$40 million, respectively. The supplier's total sales are \$100 million. 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 $\left(\frac{40}{100}\right) / \left(\frac{10}{100} + \frac{40}{100}\right) = 0.8$.

(Javadi and Masum, 2021; Huang et al., 2022). We also control for the borrower's fundamental characteristics, including firm size (*Ln(Asset)*), long-term debt to total asset ratio (*Leverage*), the ratio of market value of assets to the book value of assets (*MTB*), the ratio of tangible assets to total assets (*Tangibility*), the ratio of operating income to total assets (*Profitability*), the modified Altman (1968)'s Z score (*Zscore*), and whether the firm lacks an S&P long-term issuer rating (*Unrated*), which aligns with prior bank contracting literature (Campello and Gao, 2017; Huang et al., 2022). Second, given the focus of our study on supply chain, we also control for customer-level characteristics that could influence the borrower's 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 customers (*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 for 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*), the natural logarithm of loan size (*Ln(Loan Size)*) and a dummy variable for loan type (*Term Loan*). For instance, Graham et al. (2008) show that lenders demand a liquidity premium for long-term debt, which results in higher loan spreads. Huang et al. (2022) suggest that lenders charge lower spreads for larger loan facilities and loans that include performance pricing provisions. To mitigate the impact of outliers, all continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. In the Online Appendix, Table OA2 provides a detailed description of all variables used in our analysis.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for climate risk, borrower and customers characteristics, and loan terms. *CCR* 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 *CCR* is 0.098, capturing the average excess disaster exposure faced by the customers of the borrowing firm (i.e., the supplier). The mean of *Borrower Climate Risk* is 0.128, capturing the average excess disaster exposure of the borrowers themselves. Figure **??** shows industry-level excess disaster exposure for both borrowers and their customers, based on the Fama-French 12-industry classification. With respect to the borrowers' 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 values are comparable to those reported in previous studies (e.g., Campello and Gao, 2017; Huang et al., 2022). Regarding customer characteristics, the mean (median) of customer leverage ratio (*Customer Leverage*) and profitability (*Customer Profitability*) are 0.22 (0.20) and 0.14 (0.14), respectively. Additionally, the average level of customer concentration (*Customer Concentration*) is 0.28, implying that, on average, borrowers derive 28% of their sales from their major customers. This value closely aligns with the findings of Campello and Gao (2017), which reports that firms attributed approximately 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 257 (225) basis points and 50 (60) months. These values are consistent with those reported in the existing 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 customers' climate risk on a borrower's cost of debt, we specify the following regression model:

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

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 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* (*CCR*) is the sales-weighted average climate risk of the supplier's (i.e., borrower's) major customers. *Borrower 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 industry (based on Fama-French 48 industry classification) and year fixed effects, which account for time-invariant differences across industries, and time-varying changes that occur over the years, respectively. Loan purpose fixed effects (*Loan Purpose FE*) are also included to control for the specific purpose behind the loans. All models in our analysis are estimated using heteroskedasticity-robust standard errors clustered at the borrower level (Carvalho et al., 2023).

4 Empirical Results

4.1 Baseline Results

Table 2 reports the results of the baseline regression model. We begin by running the regression using only CCR, and sequentially add different covariates to better assess the impact of CCR on loan spreads. The effect remains positive and statistically significant, demonstrating a robust contagion effect of CCR on suppliers' cost of debt along the supply chain. The economic magnitude is sizeable: for example, in the full model shown in column (5), a one-standard-deviation increase in CCR increases loan spreads by about 3.3% (i.e., 0.121×0.272). The average loan spread of the sample firms is 257 basis points, so the 3.3% increase implies an increase of 8.48 basis points in loan spreads (i.e., $257 \times 3.3\%$).[18] The findings support that bankers incorporate major customers' climate risk when pricing loans to suppliers (borrowers), which highlights the role of climate risk along the supply chain as a key factor in borrowers' credit risk evaluations. This evidence further complements prior studies that emphasize firms' own climate risk in determining their cost of capital (Chava, 2014; 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 (*Borrower Climate Risk*) also has a significantly positive impact on the loan spreads, consistent with prior findings (Chava, 2014; Huang et al., 2022; Correa et al., 2022). As shown in columns (2) and (4), the effects of *Customer Climate Risk* (CCR) and *Borrower Climate Risk* are statistically and economically comparable, underscoring the material impact of climate risk across the supply chain. For instance, in column (5), a one-standard-deviation increase in a firm's own climate risk is associated with an increase of approximately 6.31 basis points in the loan spreads.[19] As for other control variables, the empirical results are largely consistent with the findings in the existing literature (e.g., Graham et al. (2008)). 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

[18] Given that the mean sample loan size is \$549 million and the average loan's time to maturity is around four years, a one-standard-deviation increase in CCR results in average \$1.86 million (= \$549 million $\times$ 0.000848 $\times$ 4) interest expense increase.

[19] The decline in the coefficient magnitude of *Borrower Climate Risk* in column (5) compared with column (2) and (4) might be attributed to the inclusion of detailed loan characteristics. For example, a firm's own climate risk may prompt lenders to adopt performance pricing provisions more frequently (Huang et al., 2022). An increased use of such provisions could allow lenders to better manage risk through contractual flexibility, thereby mitigating the direct impact of climate risk on loan spreads.

customers can obtain bank loans with lower loan spreads. Additionally, loan characteristics such as maturity,[20] size, and performance pricing have significant effects on loan spreads, aligning with findings from previous studies. Overall, our results confirm that banks perceive climate risk of borrowers' major customers as a significant determinant of their credit risk.

< INSERT TABLE 2 HERE >

4.2 Robustness Check

4.2.1 DID approach

In our baseline regression, we employ a continuous measure of "abnormal" climate risk. In other words, we consider climate risk beyond historical trends. One potential concern with this approach is that such a continuous de-trended index may capture broader trends unrelated to climate risk. For this reason, 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 Difference-in-Differences framework to compare the loans of firms whose customers experienced disaster-related disruptions with 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. [21]

[20] The results keep consistent when we replace loan maturity with firm-level debt maturity constructed from Compustat (Byun et al., 2021).

[21] We also add borrower fixed effects to control for firm-level heterogeneity. The estimated coefficient on the shock variable remains positive, but insignificant.

Panel A of Table 3 reports the results. As shown in columns (1) and (2), the coefficient on the *Shock* dummy is positive and statistically significant at the 10% level in both specifications, suggesting that banks raise loan spreads for borrowers in the year following a natural disaster affecting their customers, consistent with our baseline findings. The coefficient estimate also indicates that following a natural disaster affecting customers, banks raise the loan spread for borrowers by approximately 6.04 basis points.

< INSERT TABLE 3 HERE >

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 assumption, we include 8 *Shock* dummies capturing different time periods: *Shock(-5)*, *Shock(-4)*, *Shock(-3)*, *Shock(-2)*, *Shock(-1)*, *Shock(0)*, *Shock(+1)*, and *Shock(2+)*. Specifically, *Shock(-5)*, *Shock(-4)*, *Shock(-3)*, *Shock(-2)*, and *Shock(-1)* equal one if the loan was issued five, four, three, two, or one year prior to the disaster shock, respectively, and zero otherwise. Similarly, *Shock(0)* equals one if the loan was issued in the same year as the disaster shock affecting its customers, and zero otherwise. *Shock(+1)* and *Shock(2+)* equal one if the loan was issued one or two years after the disaster shock, respectively, and zero otherwise.

Figure 3 illustrates the coefficients and 95% confidence intervals for these dummy variables, which compare the changes in borrowers' loan spreads across different years surrounding a disaster shock affecting borrowers' major customers. It is evident that during five years prior to the disaster shock affecting major customers, the estimates are small and statistically insignificant, confirming that there are no pre-existing trends in the borrowers' increasing cost of debt before their major customers experience a natural disaster. The results also show that the coefficient on *Shock(+1)* is positive 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. This implies that the impact of disaster shocks decays quickly, in line 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 the Difference-in-Differences (DiD) approach provide evidence that the borrowers' cost of debt increases only in the year following a natural disaster affecting their customers, but not before. This result highlights a positive relation between CCR and the supplier's cost of debt, further supporting the robustness of our main findings.

< INSERT FIGURE 3 HERE >

4.2.2 Alternative measures and model specifications

In our current setting, we follow prior studies and use a firm's headquarters location to determine its exposure to climate risk (Barrot and Sauvagnat, 2016; Ersahin et al., 2024).[22] However, a firm' plants and establishments are not always located in the same county as its headquarters. Thus, our estimates of climate risk might be biased due to measurement error. To alleviate this issue, we employ more granular measures of customers' climate risk exposure at the subsidiary and establishment level.

For subsidiary-level exposure, we follow Huang et al. (2022) and use the number of climate-related disasters in the geographic regions where a firm's subsidiaries are located. First, leveraging information from the SHELDUS database, we aggregate the number of natural disasters that occurred each year in each state.[23] Then, we compute a subsidiary-weighted average number of natural disasters and use it as an index of a firm's climate risk.[24] For establishment-level

[22]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.

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

[24]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 $(1/4\times7+3/4\times5) = 5.5$. After scaling this value by 100, the firm's climate risk for that year is 0.055.

exposure, we follow Hsu et al. (2018) and use the U.S. Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database to identify the locations of a firm's factories. [25] Following the approach proposed by Xiong and Png (2019), we match the TRI database with Compustat data to link facilities to their corresponding parent firms. Then, we calculate the abnormal climate risk for each county where a firm's facilities are located. Finally, we compute a facility-weighted average climate risk to indicate the firm's climate risk.

For each supplier, we calculate the sales-weighted average of the subsidiary-level and establishment-level climate risk exposures of its customers to estimate the supplier's overall exposure to CCR. The results in columns (1) and (2) of panel B in Table 3 correspond to the subsidiary-level and establishment-level approaches. The coefficients on customers' climate risk are positive and statistically significant in both models, indicating an adverse impact of customers' climate risk on corporate loan spreads.

In our baseline regression model, we control for the borrower's own climate risk to account for the possibility that natural disasters may simultaneously affect both borrowers and their customers in a supply chain link. As an additional robustness 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 along the supply chain. Our results, shown in column (3) of Panel B in Table 3, remain consistent.

Prior studies show that differences in banks' lending decisions can arise from their time-invariant characteristics (e.g., Campello and Gao, 2017; Javadi and Masum, 2021; Ge et al., 2024). For instance, some banks may be able to better assess firms' credit quality or to more closely monitor firms. These banks might offer a lower loan spread to borrowers exposed to higher CCR. In addition, we control for unobserved heterogeneity arising from time-invariant

[25] 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).

factors at the state level where the borrowers are headquartered. Therefore, we add bank fixed effects and state fixed effects in our baseline regression models. The results presented in Panel C of Table 3 remain robust to both additional specifications.

< INSERT TABLE 3 HERE >

4.3 Cross-sectional heterogeneity: Supplier's Switching Costs and Customers' Bargaining Power

The average effect of CCR on the cost of debt could vary cross-sectionally. The propensity of a firm to switch from customers affected by natural disasters to alternative customers should be lower if switching costs are high. In such cases, the negative effect of CCR on a supplier's cost of debt is likely to be stronger when it is hard for suppliers to find alternative customers. In addition, extensive research on supply chain supports the view 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 make 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, the supplier develops ties with customers, and it becomes costly to find alternative uses for its products, making it more vulnerable to customers' climate shocks. Therefore, we expect that CCR should be more significantly positively related to the borrowing cost of the firms acting as suppliers when the cost of substituting a customer is high.

To measure borrowers' switching costs in the supply chain relationships, we rely on three different proxies. 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). Moreover, we also consider the asset redeployability metric constructed by Kim and Kung (2017). Suppliers with assets that can easily be redeployed are less vulnerable to being "held up" by their customers. We identify whether a firm operates in durable industry, defined by three-digit SIC codes 245, 250-259, 283, 301, and 324-399. As a second proxy, we consider selling, general and administrative (SG&A) expenses to capture a supplier's relationship-specific investments. Based on these variables, we create three sets of subsamples, one comprising firms with high switching costs and one with firms with low switching costs. We then run our baseline regressions (see Table 2) again on each of the six subsamples.

The subsample results are presented in Table 4. In columns (1) and (2), firms are assigned to the Yes (No) group if the firms operate in a durable (non-durable) goods industry. Similarly, in columns (3) to (6), firms are assigned to the high (low) group if the value of SG&A or asset redeployability lies above (below) the sample median. The baseline results indicate that the positive impact of CCR on borrowers' cost of debt is larger and statistically significant only when they ,as the suppliers, operate in durable goods industry, incur higher SG&A expenses, or exhibit higher asset redeployability, as shown in columns (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 supply chain relationships.

< INSERT TABLE 4 HERE >

In addition to analyzing supplier-specific heterogeneity, we explore whether customer bargaining power moderates the impact of CCR on borrowers' cost of debt, as proposed in Implication 3. Bargaining power between suppliers and customers can significantly influence suppliers' contractual terms and financial performance. When facing powerful customers, suppliers may be compelled to grant 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 favorable contract terms demanded by powerful customers can exacerbate the supplier's cash flow risks, which in turn increase their default risk. Thus, we expect the increase in the cost of bank loans to be stronger for borrowers with less bargaining power relative to their customers.

We construct three measures of customers' bargaining power from the perspective of market dynamics. First, customers operating in less competitive markets have stronger bargaining power Campello and Gao (2017). We measure market competition using Herfindahl Hirschman index (HHI) of customers' industry sales and customer's product market fluidity as developed by Hoberg et al. (2014), in which a high HHI or a low fluidity value indicates lower market competition.[26] Second, prior research suggests that customers with a higher market share have greater bargaining power, which enables them to negotiate more favorable 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 the 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 strengthens their bargaining power relative to suppliers (Hui et al., 2012). For suppliers with multiple customers, we calculate the weighted-average value of these variables above to capture the overall bargaining power of their customer base. We then partition our full sample into two subsamples, High or Low, based on the sample median of each attribute measure mentioned above.

The subsample results are shown in Table 5. The positive relationship between CCR and cost of loans is more pronounced for the group of customers with lower market competition, higher market share, and those in the high barriers-to-entry industries. The findings are consistent with the conjecture in Implication 3, suggesting 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 5 HERE >

[26] Our results keep consistent when using product market similarity (Hoberg and Phillips, 2016).

5 Channel Analysis

5.1 2SLS: The impact of customers' climate risk on borrower's liquidity

Our findings so far consistently demonstrate that CCR elevates supplier's borrowing costs. Building on our theoretical model, we propose that CCR leads to an increase in the trade credit extended by suppliers, which consequently increases suppliers' liquidity risk. As a result, banks charge higher interest rates to compensate for the increased liquidity risk when suppliers borrow. To test this hypothesis, we employ a Two-Stage Least Squares approach to analyze the relationships among CCR, trade credit usage, and borrower's liquidity.

Suppliers tend to extend more trade credit to customers affected by natural disasters (e.g., Ersahin et al., 2024). We thus use CCR in year $t-1$ as an instrumental variable for the endogenous variable, i.e., the deviation of trade credit in year t from its average over years $t-1$ and $t-2$. 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 borrowers' trade credit on CCR, controlling for various supplier-level and customer-level determinants of trade credit that are commonly used in prior studies (e.g., Shenoy and Williams, 2017; Ersahin et al., 2024; Lian, 2017). The exclusion restriction underlying our identification strategy is that customers' climate risk is exogenous and only influences the borrower's liquidity through its effect on the usage of trade credit of borrowers who are suppliers. In the second stage, we regress borrowers' liquidity, proxied by cash flow from operation scaled by total assets, on the predicted value of changes in trade credit from the first-stage regression. We use cash flow as a proxy for the borrower's liquidity, defined as the operating cash flow of borrowers in year t. Formally, we estimated the following system of equations:

$$Change\ in\ Trade\ Credit_t = \beta_1 CCR_{t-1} + \sum_{k=2}^{n} \beta_i Controls_{t-1} + Fixed\ Effects + \nu \tag{6}$$

$$CashFlow_t = \alpha_1 Change\ in\ \widehat{trade}\ credit_t + \sum_{k=2}^{n} \alpha_i Controls_{t-1} + Fixed\ Effects + u \tag{7}$$

Table 6 presents the results of the 2SLS estimation. Column 1 reports the first-stage regression. The coefficient on CCR is positive and statistically significant at 1% level, suggesting that

CCR can significantly increase the usage of trade credit provided by borrowers as suppliers. To mitigate weak instrument concerns, *CCR* must be a sufficiently strong predictor of borrowers' trade credit. The Cragg-Donald F-statistic on *CCR*—shown in Column 1—is approximately 17, exceeding the threshold of 16 suggested by Stock and Yogo (2002). Therefore, our results are unlikely to be affected by weak-instrument bias, and CCR is a strong predictor of changes in trade credit. We then use the fitted value of *Change in Trade Credit* in the first stage as a regressor in the second stage, where the borrowers' cash flow (*Cash Flow*) is the dependent variable. The coefficient of *Fitted Change in Trade Credit* in Column 2 is negative and statistically significant, indicating that *Cash Flow* declines after natural disaster shocks because suppliers extend more trade credit to customers. Moreover, the Anderson–Rubin test is significant at the 5% level, confirming that the trade credit coefficient is statistically significant even under weak-instrument robust inference. Overall, our 2SLS results support our proposed underlying mechanism: CCR propagates through the supply chain via the use of trade credit, ultimately reducing borrowers' liquidity.

< INSERT TABLE 6 HERE >

5.2 Mediation effect

Building on our 2SLS findings, we further investigate whether the negative impact of CCR on suppliers' cash flow results in higher loan costs for suppliers. However, we do not use a 2SLS approach because suppliers' liquidity risk might not be exclusively driving the observed relationship between CCR and their cost of debt. To establish whether liquidity is the main driver of the relation between suppliers' loan costs and CCR, we conduct a mediation analysis following the framework of Baron and Kenny (1986), recently employed in the finance literature (e.g., Rahaman et al. (2020); Azevedo et al. (2024)).

To claim that a mediation effect occurs, three conditions must be met. First, the independent variable—*CCR*—should correlate with the main dependent variable *Ln(Spread)*. Second, *CCR* should also correlate with the mediator variable—*Cash Flow*, which acts as a proxy for liquidity. Third, in a regression where *Ln(Spread)* is the dependent variable and both *CCR*) and *(Cash Flow)* are the independent variables: the coefficient on the mediator—*Cash Flow*—should be statistically significant; and the significance of the independent variable—*CCR*– should decrease, relative to the first regression. If this is the case, then *Cash Flow* is considered to play a mediating role between *Ln(Spread)* and *CCR*. To examine the significance of the mediating effect (if any), we follow Krull and MacKinnon (2001) and employ the Sobel (1982) test.

Table 7 presents the results of the mediation analysis. Column 1 reports the results of the first-stage analysis, which corresponds to the baseline regression model, indicating a statistically significant positive relation between *Ln(Spread)* and *CCR*. Column 2 reports the second stage of the analysis, where the dependent variable is *Cash Flow*. The coefficient on *CCR* is negative and statistically significant This result aligns with our theoretical predictions and satisfies the second condition for mediation analysis.

In Column 3, we include both *CCR* and *Cash Flow* as explanatory variables in a regression on *Ln(Spread)*. The results reveal a negative and statistically significant relationship between *Cash Flow* and *Ln(Spread)*, consistent with the expectation that reduced cash flow increases borrowing costs. Notably, while the coefficient on *CCR* remains positive and statistically significant related to *Ln(Spread)*, its magnitude decreases from 0.121 in Column 1 to 0.089 in Column 3. This reduction captures the mediation effect: controlling for cash flow accounts for part of the impact of CCR on loan spreads. Specifically, the total effect of *CCR* on *Ln(Spread)* is 0.121 (Column 1), while the direct effect, after accounting for a mediation (indirect) effect of *Cash Flow*, is 0.089 (Column 3). The mediation effect, calculated as the difference between the total effect and the direct effect, is 0.032 (i.e., 0.121-0.089). Thus, after controlling for the variable *Cash Flow*, the total effect of *CCR* declines by approximately 26% (0.032/0.121*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 borrower's liquidity serves as a key channel through which CCR impacts bank loan spreads.

< INSERT TABLE 7 HERE >

5.3 The long-term impact of customers' climate risk on borrowers

The aforementioned discussions highlight the short-term spillover impact of customers' climate risk on supliers' liquidity risk, thus elevating their borrowing costs. However, does customers' climate risk exert a long-lasting influence on supplier' operations, a factor that lenders might consider when pricing loans for suppliers? This perspective might offer an additional explanation for the increased cost of debt, as our mediation analysis in the above section indicates that suppliers' short-term liquidity shortfalls due to customers' climate risk capture only a portion of the observed increase in debt financing costs. In the long term, natural disasters can severely disrupt customers' production activities, reducing their ability to fulfill existing commitments to suppliers and potentially reducing the demand for future orders from suppliers. Prior studies also highlight that financial distress among key customers can deteriorate suppliers' ability to generate future earnings potential, which in turn increases supplier default risk (Houston et al., 2016; Campello and Gao, 2017; Files and Gurun, 2018). Therefore, we conjecture that customers' climate risk would have a sustained impact on suppliers' fundamental operations, particularly their sales, and that banks will incorporate these expected fundamental changes into their loan pricing decisions.

We examine the suppliers' sales to their major customers over the subsequent five years, where sales are measured as the ratio of sales to major customers relative to total assets. Table 8 presents the results. Panel A reports the impact of CCR in year $t-1$ on supplier sales from year t to $t+5$. The consistently significant negative coefficients in columns (1), (2), (4), and (5) indicate a notable decline in supplier sales to major customers following an increase in customers' climate risk. Furthermore, using a dummy variable to denote whether a major customer was affected by a natural disaster as an alternative measure of customers' climate risk, Panel B also reveals a significant and persistent decrease in supplier sales in the following years. Collectively, our findings provide additional evidence on the mechanism through which natural disaster shocks to the supply chain spill over into the lending market, that is, the expected long-lasting impact of customer climate risk on borrowers' fundamental performance would be an additional rationale for the increased borrowing costs.

< INSERT TABLE 8 HERE >

6 Extended Analysis

6.1 Customers' liquidity constraints

In addition to analyzing supply chain heterogeneity, we explore whether customer liquidity constraints moderate the impact of CCR on borrowers' cost of debt. Under the implied equity stake hypothesis proposed by Petersen and Rajan (1997), suppliers hold an implied equity stake in their customers, as a portion of the supplier's value is tied to the future liquidity of its customers. Consequently, suppliers tend to extend more trade credit to liquidity-constrained customers to protect the value of this implied equity stake. This hypothesis has been empirically validated in Cunat (2007) and Shenoy and Williams (2017). These studies demonstrate that trade credit links function as a liquidity transfer mechanism, reallocating liquidity from suppliers to financially distressed customers through delayed repayment—especially when customers experience temporary liquidity shocks. Therefore, we expect that when a customer faces liquidity constraints, a higher CCR exposure will further increase the customer's trade credit demand, thereby increasing liquidity risk for suppliers. As a result, banks are likely to charge higher interest rates on suppliers as compensation for the extra-risk incurred.

We employ three proxies for customers' liquidity constraints. The first measure is excess cash holdings (Opler et al., 1999). Specifically, we follow Gao and Mohamed (2018) and calculate the difference between the actual cash ratio and the predicted cash ratio, where the latter is estimated using a pooled OLS regression with year dummies. Following Shenoy and Williams (2017), we consider two additional measures: Altman (1968)'s Z-score of financial distress and the Kaplan-Zingales index for financial constraints (Kaplan and Zingales, 1997). For suppliers with multiple customers, we calculate the (sales-weighted) average value of the variables above to capture the overall liquidity constraints of their customer base. We then partition our full sample into two subsamples, "High" or "Low", based on whether an observation falls below or above the sample median of each proxy.

Table 9 reports the results of these tests. The coefficient on *CCR* is positive and statistically significant for high values of *KZ index* and for low values of *Z-score*, and *Excess Cash*. This finding aligns with the view that low levels of cash holdings and high levels of default risk amplify the positive and statistically significant impact of CCR on loan costs. Our findings also align with the evidence presented by Garcia-Appendini and Montoriol-Garriga (2013); Shenoy and Williams (2017).

< INSERT TABLE 9 HERE >

6.2 Non-pricing terms

Our previous analysis shows that banks perceive customers' climate risk as a relevant risk factor and incorporate it into their loan pricing decisions. However, a loan contract consists of two critical components: the price of the loan (i.e. loan spread) and the non-pricing terms (e.g., collateral, covenants), which are widely recognized as important terms that lenders use to mitigate borrowers' risk-shifting incentives (Rajan and Winton, 1995; Cen et al., 2016; Campello and Gao, 2017; Huang et al., 2022). Rajan and Winton (1995) show that banks use collateral requirements as an effective monitoring tool, especially when their payoffs are sensitive to borrower's financial health. Furthermore, the presence of covenants improve ex post supervision of creditworthiness changes resulting from customers' climate risk (Huang et al., 2022). Non-pricing loan terms, particularly covenants, serve as mechanisms to mitigate information asymmetry between borrowers and lenders. Although such provisions do not directly eliminate underlying climate-related risks, they enhance the lender's ability to monitor borrower behavior and enforce compliance. This enhanced monitoring capacity, in turn, diminish the extent to which lenders must rely on pricing mechanisms to compensate for unobservable or unmanaged climate-related risks.

We conduct cross-sectional tests by splitting the sample into two groups based on whether the loan contract includes non-pricing terms or not. Results are presented in Table 10. The coefficients on CCR are significantly positive only in the subsample without collateral or covenants but statistically insignificant when such non-pricing terms are present, indicating that banks tend to price in the climate risk of the borrower's customer through loan spreads when such risks are not mitigated by collateral or other covenants.

< INSERT TABLE 10 HERE >

6.3 Customers' lending relationships with lead banks

In this section, we investigate whether lenders' prior lending relationships with borrowers' major customers mitigate the impact of customers' climate risk on borrowers' cost of debt. As outlined in our hypothesis, customers highly exposed to natural disasters may face unfavorable changes in liquidity constraints and therefore need to negotiate longer payment terms with their suppliers. Consequently, the supplier may be forced to accept unexpected delays in payments and bear greater liquidity risk. In this situation, banks face uncertainty regarding the realized value of outstanding receivables and the extent of suppliers' exposure to negative cash flow shocks. However, repeated interactions with major customers allow banks to acquire more private information about borrowers' customers and their fundamentals (e.g., operating performance, financial conditions, creditworthiness, costs of capital, payment practices, resilience to negative shocks) at a lower marginal cost than would be possible without an existing lending relationship (Bharath et al., 2007; Gong and Luo, 2018; Hasan et al., 2020). Such private supply chain information enables lenders to better evaluate borrowers' risks exposed to their customers and reduce errors and biases caused by information asymmetry in their credit assessments (Gong and Luo, 2018; Hasan et al., 2020). Therefore, we conjecture that prior lending relationships with a borrower's major customers may provide lenders with deeper insights into borrowers' exposure to customers' climate risk.

To test this hypothesis, we conduct subsample analyses based on the prior lending relationships between major customers and the lender. The results are reported in Table 11. Specifically, in columns (1) and (2), borrowers are split based on whether their major customers had a loan relationship with the same lender of the borrower within the five years prior to the borrower's loan from that lender. We find that the effect of customer climate risk on the borrower's cost of debt is weaker in the subsamples where major customers have a prior lending relationship with the lender. This finding highlights the informational role of prior lending relationships, which help reduce potential biases in evaluating borrower's credit risk arising from supply chain spillovers. Our findings remain consistent when we do not restrict the duration of the lending relationship between borrowers' lenders and their customers, as shown in columns (3) and (4).

< INSERT TABLE 11 HERE >

6.4 Additional Analysis

In this section, we conduct two additional analyses to extend the scope of our study. First, we examine whether the effect of CCR on suppliers' cost of debt is stronger during periods of heightened public attention to climate change. Prior studies show that the intensity of investors' reaction to natural disasters is particularly acute in periods of higher public attention to climate change (Hirshleifer et al., 2011; Gustafson et al., 2023), suggesting that lenders may behave similarly. Using the WSJ Climate Change News Index (Engle et al., 2020) and Google search trends as proxies, we find that the effect of CCR on loan spreads is more pronounced when public attention is high (Appendix Table OA3).

We further examine whether a firm's own climate risk influences its cost of debt, as documented in prior studies (Correa et al., 2022; Huang et al., 2022). Moreover, we explore potential heterogeneous effects, depending on whether the borrowers are suppliers or customers. The results, reported in Appendix Table OA4, show that a firm's own climate risk has a significant impact on its cost of debt only when the borrowers are suppliers, but not when they are customers. One possible explanation is that suppliers may be more vulnerable to physical climate risk due to factors such as their size and other industry characteristics.[27] Moreover, major customers can transmit temporary liquidity shocks to suppliers through trade credit given their relatively stronger bargaining power. In this context, trade credit serves as an alternative source of funding for customers, reducing their reliance on external banking financing (Cunat, 2007; Shenoy and Williams, 2017). As a result, bank lenders may perceive customers – particularly larger firms with stronger bargaining power – as having greater financial flexibility and access to alternative funding sources, mitigating the direct impact of climate risk on firm's liquidity. In contrast, suppliers may be viewed as more vulnerable to climate-related disruptions, resulting in lenders adjusting borrowing costs accordingly. When both subsamples are pooled together, we find that the overall impact of climate risk on firms' cost of debt is significantly positive, aligning with prior studies (Correa et al., 2022; Huang et al., 2022).

7 Conclusions

Natural disasters disrupt business operations, affecting warehouses and manufacturing facilities, prompting firms to adjust funding strategies by seeking more external financing—such as bank loans, equity, and supply chain credit—while reducing reliance on internal and informal sources. This growing dependence on external funding highlights the critical role of supply chain dynamics in managing climate risk. When customers face climate-related disruptions, their ability to make

[27] In our sample, customers' firms size (approximaltely 72 billions) is significantly larger than the suppliers' firm size on average (approximately 3 billions), consistent with prior studies (Cen et al., 2017).According to the United Nations Environment Programme Finance Initiative, suppliers in manufacturing and agricultural industries face significant exposure to physical climate risk.

timely payments declines, straining suppliers' cash flows. Consequently, supply chain resilience becomes essential, as disruptions may cause significant financial challenges that affect multiple companies, amplifying the broader economic impact of climate shocks.

In this paper, we have examined whether the climate risk of major customers is associated with suppliers' cost of bank loans. We have found 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 borrowers' loan price terms is more pronounced when borrowers face higher switching costs or their customers have greater bargaining power. Our main results remain robust when we adopt alternative measures of customers' climate risk, apply a generalized Difference-in-Differences (DiD) approach, and test alternative model specifications with different sets of fixed effects. We also find that the increase in spreads for borrowers is driven by the increased liquidity risk they face due to their exposures to CCR. These results are consistent with the testable predictions of a simple theoretical model introduced in this paper.

In addition to these main results, we have also shown—via mediation analysis—that CCR have a significant and positive impact on suppliers' loan spreads through increased liquidity risk. Thus, our study is the first to demonstrate that CCR increases a borrower's liquidity risk, which in turn raises the cost of debt. This implies that banks are aware of the potential cash flow disruption related to climate risk and how this increases their own liquidity risk.

These results bear important policy implications. As climate risk continues to evolve, both corporate finance strategies and regulatory frameworks must advance in tandem. A comprehensive approach that integrates detailed supply chain analyses, forward-looking climate scenarios, and strengthened supervisory measures would enhance the firms' resilience and, in turn, financial stability. Reinforcing regulatory intervention in this context is likely to improve financial stability and promote a more sustainable allocation of capital, ensuring that businesses and financial institutions can effectively navigate the growing challenges of climate change.

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Figure 2: County Average Excess Exposures

This figure shows the average county-level excess exposure to climate risk, measured as the excess frequency of climate disasters in U.S. counties during 2002–2021 relative to the 1990s. The exposures are based on disaster records in the SHELDUS database for hurricanes/tropical storms, floods, and wildfires.

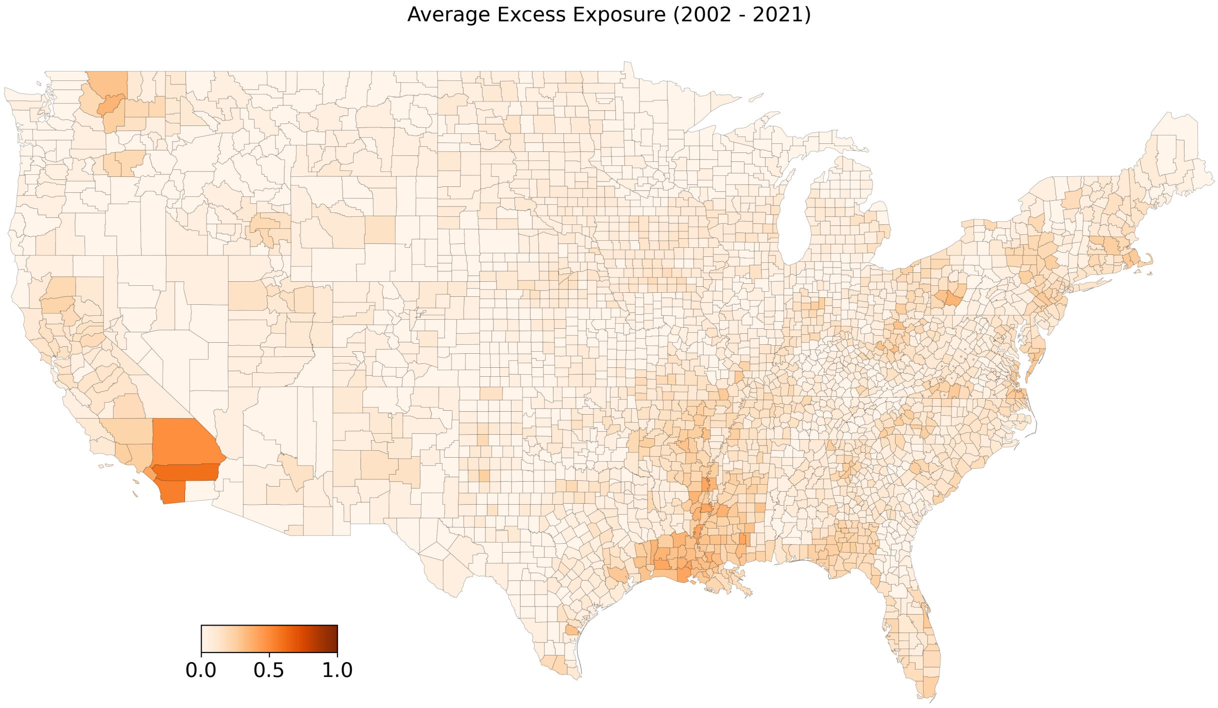
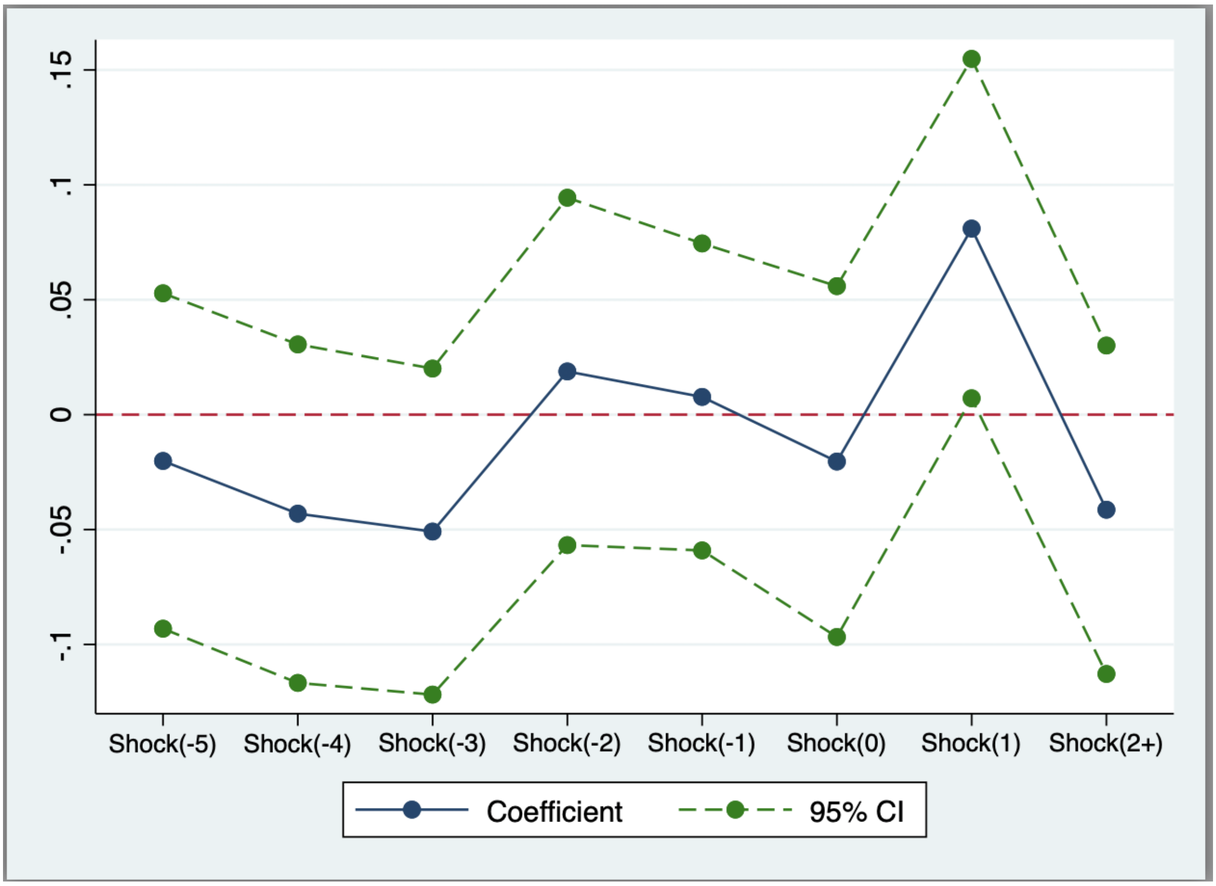


Figure 3: Dynamic DID effects

This figure presents the difference-in-differences estimates of the impact of customer climate disasters on borrowers' loan spread over time. *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(-5)* equals one if the loan was issued five years prior to the disaster shock affecting at least one of its customers, and zero otherwise.*Shock(-4)* equals one if the loan was issued four years prior to the disaster shock affecting at least one of its customers, and zero otherwise. Shock(-3) equals one if the loan was issued three years prior to the disaster shock affecting its customers, and zero otherwise. *Shock(-2)* equals one if the loan was issued in two years prior to the disaster shock affecting at least one of its customers, and zero otherwise. *Shock(-1)* equals one if the loan was issued one year prior to the disaster shock affecting at least one of its customers, and zero otherwise. *Shock(0)* equals one if the loan was issued in the same year as the disaster shock affecting at least one of its customers, and zero otherwise. *Shock(+1)* equals one if the loan was issued one year after the disaster shock affecting at least one of its customers, and zero otherwise. *Shock(2+)* equals one if the loan was issued two or more years after the disaster shock affecting at least one of its customers, and zero otherwise. The solid blue line represents the estimated coefficients for each period, while the dashed green line shows the corresponding 95% confidence interval. Continuous variables are winsorized at the 1% and 99% levels. The definition of variables included in the regressions are summarized in Table OA2. The standard errors are clustered at the firm level.



Tables

Table 1: Summary Statistics

Variable	N	Mean	Std.dev	P25	P50	P75
Firm climate risk variable						
CCR	2,952	0.098	0.272	0	0	0
Borrower Climate Risk	2,952	0.128	0.319	0	0	0
Borrowing firm characteristics						
Ln (Asset)	2,952	7.249	1.719	6.068	7.319	8.415
Leverage	2,952	0.25	0.207	0.08	0.226	0.372
MTB	2,952	1.778	0.88	1.203	1.535	2.068
Tangibility	2,952	0.26	0.228	0.096	0.184	0.344
Profitability	2,952	0.122	0.091	0.086	0.126	0.169
Zscore	2,952	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	2,952	0.222	0.124	0.135	0.207	0.288
Customer Profitability	2,952	0.136	0.061	0.087	0.139	0.169
Customer Concentration	2,952	0.276	0.185	0.14	0.21	0.348
Loan facility characteristics						
Spread	2,952	256.774	179.933	135.000	225 .000	325.000
Ln(Spread)	2,952	5.303	0.752	4.905	5.416	5.784
Maturity	2,952	49.908	21.608	36.000	60.000	60.000
Ln(Maturity)	2,952	3.761	0.626	3.584	4.094	4.094
Performance Pricing	2,952	0.403	0.491	0	0	1
Loan Size	2,952	549.402	1546.019	55.000	200.000	500.000
Ln(Loan Size)	2,952	5.12	1.607	4.007	5.298	6.215
Term Loan	2,952	0.376	0.484	0	0	1

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. *CCR* is the sales-weighted average climate risk from the borrower's major customers. *Borrower Climate Risk* is the borrower's own climate risk. The climate risks of both borrowers and their major customers are determined by the unexpected natural disaster shocks in the counties where their headquarters are located. Loan characteristics are measured in year t, while the characteristics of borrowers and their customers are measured in year $t-1$. The definition of variables included in the regressions are summarized in Table OA2. Continuous variables are winsorized at 1% and 99%.

Table 2: Customers' Climate Risk and Corporate Loan Spread

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*	*Ln(Spread)*
CCR	0.107*	0.110**	0.116*	0.112**	0.121***
	(1.79)	(2.18)	(1.91)	(2.23)	(2.64)
Borrower 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(Maturity)					0.076***
					(3.43)
Performance Pricing					-0.182***
					(-5.66)
Ln(Loan Size)					-0.104***
					(-6.18)
Term Loan					0.282***
					(12.61)
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	0.230	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
Cluster Firm	YES	YES	YES	YES	YES

The table presents the results of regression analyses examining the impact of customers' climate risk on firms' cost of debt. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility in year t. *CCR* is the sales-weighted average climate risk from the borrower's major customers in year $t-1$. Continuous variables are winsorized at the 1% and 99% levels. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 3: Customers' Climate Risk and Corporate Loan Spread: A DID approach and alternative measures

Panel A: DID approach			
Dep. Var. = *Ln(Spread)*	(1)	(2)	
$Shock_{i,t-1}$	0.083*	0.070*	
	(1.76)	(1.84)	
Controls	NO	YES	
Observations	2,952	2,952	
Adjusted R^2	0.230	0.566	
Year FE	YES	YES	
FF48 FE	YES	YES	
Loan Purpose FE	YES	YES	
Cluster Firm	YES	YES	
Panel B: Alternative Measure of Customers' Climate Risk			
Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)
	CCR (Subsidiary-state level)	*CCR* (Facility-county level)	*CCR* (Exclude suppliers and customers located within the same county)
CCR	0.224**	0.274*	0.140***
	(2.18)	(1.87)	(2.95)
Controls	YES	YES	YES
Observations	2,952	1,121	2,653
Adjusted R^2	0.553	0.553	0.552
Year FE	YES	YES	YES
FF48 FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Cluster Firm	YES	YES	YES
Panel C: Incorporate different fixed effect			
Dep. Var. = *Ln(Spread)*	(1)	(2)	
	Adding Bank Fixed Effect	*Adding State Fixed Effect*	
CCR	0.078*	0.119***	
	(1.82)	(2.58)	
Controls	YES	YES	
Observations	2,952	2,952	
Adjusted R^2	0.608	0.562	
Year FE	YES	YES	
FF48 FE	YES	YES	
State FE	NO	YES	
Bank FE	YES	NO	
Loan Purpose FE	YES	YES	
Cluster Firm	YES	YES	

This table presents the results of regression analyses examining the impact of customers' climate risk on firms' cost of debt. *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. In panel A, $\text{Shock}_{i,t-1}$ 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. In Column (1) of panel B, CCR 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) of panel B, CCR 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) of Panel B, we exclude observations where the borrowers and their major customers are located in the same county. Column (1) and (2) in Panel C report robust regressions results which additionally include bank fixed effects and state fixed effects in the model, respectively. Continuous variables are winsorized at the 1% and 99% levels. The definitions of variables included in the regressions are summarized in Table OA2. 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.

Table 4: Borrower's Switching Cost in Supply Chain

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)	(5)	(6)
	Supplier is a Durable Goods Producer		*Supplier's SG&A Expense*		*Supplier's Asset Redeployability*	
	Yes	No	High	Low	High	Low
CCR	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
Cluster Firm	YES	YES	YES	YES	YES	YES

This table presents the results of cross-sectional analyses that examine the impact of major customers' climate risk on firms' cost of debt considering firms' switching costs in the supply-chain relationship. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. In columns (1) and (2), the sample is split into two sub-samples based on whether borrowers are durable goods producers or not. Firms are classified as durable goods producers if they operate in industries with SIC codes 245, 250-259, 283, 301, or 324-399. In columns (3) and (4), the sample is split into two sub-samples based on the median value of borrowers' SG&A in the sample. SG&A is calculated as the ratio of the firm's selling, general and administrative expenses to total assets. In columns (5) and (6), the sample is split into two sub-samples based on the median value of borrowers' asset redeployability in the sample. Asset redeployability is calculated based on Kim and Kung (2017). Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 5: Customers' Bargaining Power in Supply Chain

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI of Customers		*Product Fluidity*		*Market Share of Customers*		*Barrier-to-Entry*	
	High	Low	High	Low	High	Low	High	Low
CCR	0.159**	0.098	0.085	0.251***	0.206***	0.092	0.169**	0.101
	(2.41)	(1.26)	(1.29)	(3.61)	(2.61)	(1.63)	(2.54)	(1.62)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,534	1,418	1,427	1,484	1,548	1,404	1,421	1,525
Adjusted R^2	0.596	0.541	0.504	0.619	0.578	0.550	0.585	0.570
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the results of cross-sectional analyses that examine the impact of customers' climate risk on firms' cost of debt considering customers' bargaining power in the supply-chain relationship. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. HHI of customers is the Herfindahl Hirschman index of customers' industry sales. Customers' Product Fluidity score captures how competitors are changing the product vocabulary that overlaps with a firm's product descriptions, provided by Hoberg et al. (2014). Market share of customers is the ratio of a customer's sales to total sales in its industry. 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. For each borrower, we calculate a sales-weighted average value of each proxy for its major customers. We split our sample into two sub-samples based on the sample median of each proxy mentioned above. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 6: 2SLS: climate risk, trade credit, and liquidity

	(1)	(2)
	1st Stage	2nd Stage
Dep. Var. =	*Change in Trade Credit*	*Cash Flow*
CCR	0.015**	
	(2.45)	
Fitted Change in Trade Credit		-1.623**
		(-2.05)
Controls	YES	YES
Cragg-Donald F-statistic	16.846	
Anderson-Rubin Wald F-statistic	6.08**	
Observations	2,796	2,796
Year FE	YES	YES
FF48 FE	YES	YES
Cluster Firm	YES	YES

This table presents the results of 2SLS investigating the relationship between CCR and the borrower's liquidity. The key endogenous variable, *Change in Trade Credit*, is measured as the deviation of firm's accounts receivables scaled by sales in year t from its average over years $t-1$ and $t-2$. *Cash Flow*, as a proxy for the borrower's liquidity, is defined as the operating cash flow scaled by total assets of suppliers in year t. *CCR* is the sales-weighted average climate risk from the borrower's major customers in year $t-1$. Consistent with prior studies (e.g., Shenoy and Williams, 2017; Ersahin et al., 2024; Lian, 2024), control variables include both customers' and suppliers' asset (logarithm of total assets), firm age (logarithm of a firm's age since IPO year), leverage (long-term debt over total assets), MTB (market value of common equity over the book value of equity), Tangbibility (tangible assets to total assets) and HHI (Herfindahl Hirschman index (HHI) of industry sales. Customer concentration (the ratio of sales to major customers to suppliers' total sales) and supplier's own climate risk are also included. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 7: The mediating effect of borrowers' cash flow

Dep. Var.	*Ln(Spread)*	*Cash Flow*	*Ln(Spread)*
CCR	0.121***	-0.014*	0.089**
	(2.64)	(-1.73)	(2.00)
Cash Flow			-1.130***
			(-6.21)
Sobel Test			<0.01
Borrower Climate Risk	0.077*	0.004	0.061
	(1.65)	(0.56)	(1.44)
Ln(Asset)	-0.110***	0.009***	-0.093***
	(-6.75)	(5.53)	(-5.52)
Leverage	0.534***	-0.024	0.567***
	(7.00)	(-1.51)	(7.26)
MTB	-0.135***	0.010***	-0.110***
	(-7.03)	(2.89)	(-5.87)
Tangibility	-0.128	0.053***	-0.138
	(-0.96)	(3.13)	(-1.13)
Profitability	-0.846***	0.464***	-0.566**
	(-4.07)	(10.48)	(-2.52)
Zscore	-0.027**	0.001	-0.025**
	(-2.21)	(0.43)	(-1.98)
Unrated	-0.144***	-0.002	-0.145***
	(-4.27)	(-0.39)	(-4.37)
Customer Leverage	0.008	0.033	0.041
	(0.07)	(1.61)	(0.39)
Customer Profitability	-0.628***	0.041	-0.550**
	(-2.59)	(1.08)	(-2.40)
Customer Concentration	0.012	0.018	0.075
	(0.14)	(1.33)	(0.85)
Ln(Matruity)	0.076***		0.098***
	(3.43)		(4.09)
Performance Pricing	-0.182***		-0.155***
	(-5.66)		(-4.77)
Ln(Loan Size)	-0.104***		-0.112***
	(-6.18)		(-6.21)
Term Loan	0.282***		0.249***
	(12.61)		(11.30)
Constant	6.938***	-0.111***	6.904***
	(23.31)	(-4.88)	(28.22)
Observations	2,952	2,703	2,703
Adjusted R^2	0.554	0.382	0.575
Year FE	YES	YES	YES
FF48 FE	YES	YES	YES
Loan Purpose FE	YES	NO	YES
Cluster Firm	YES	YES	YES

This table presents the results on the mediation effect of borrower's cash flow on the relationship between CCR and borrower's cost of debt. *Cash Flow*, as a proxy for borrower's liquidity, is defined as the operating cash flow scaled by total assets of suppliers in year of loan issuance. *CCR* is the sales-weighted average climate risk from the borrower's major customers. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 8: The impact of customers' climate risk on sales

Panel A: Customer climate risk exposure						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. =	$Sale_t$	$Sale_{t+1}$	$Sale_{t+2}$	$Sale_{t+3}$	$Sale_{t+4}$	$Sale_{t+5}$
CCR	-0.035**	-0.040*	-0.029	-0.041*	-0.038*	-0.032
	(-2.06)	(-1.80)	(-1.28)	(-1.80)	(-1.76)	(-1.21)
Controls	YES	YES	YES	YES	YES	YES
Observations	2,359	2,042	1,823	1,532	1,414	1,261
Adjusted R^2	0.443	0.432	0.443	0.455	0.451	0.441
Year FE	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES
Panel B: Customer hit by natural disasters						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. =	$Sale_t$	$Sale_{t+1}$	$Sale_{t+2}$	$Sale_{t+3}$	$Sale_{t+4}$	$Sale_{t+5}$
$Shock_{t-1}$	-0.036**	-0.040**	-0.031*	-0.041**	-0.040**	-0.037**
	(-2.54)	(-2.31)	(-1.70)	(-2.33)	(-2.47)	(-1.98)
Controls	YES	YES	YES	YES	YES	YES
Observations	2,359	2,042	1,823	1,532	1,414	1,261
Adjusted R^2	0.444	0.434	0.444	0.456	0.452	0.443
Year FE	YES	YES	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES	YES	YES

This table presents the results from a set of tests examining whether customers' climate risk affects suppliers' sales. $Sale_t$, $Sale_{t+1}$, $Sale_{t+2}$, $Sale_{t+3}$, $Sale_{t+4}$, and $Sale_{t+5}$ represent the ratio of sales to major customers from year t to year $t+5$, scaled by the supplier's total assets. In Panel A, *CCR* is the sales-weighted average climate risk of the borrower's major customers in year $t-1$. In Panel B, $Shock_{t-1}$ is a dummy variable indicating whether a major customer was affected by a natural disaster in year $t-1$.Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 9: Customers' liquidity constraints

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)	(5)	(6)
	KZ index of Customers		*Z score of Customers*		*Excess Cash of Customers*	
	High	Low	High	Low	High	Low
CCR	0.193**	0.092	0.117	0.173**	0.090	0.212***
	(2.50)	(1.45)	(1.42)	(2.14)	(1.33)	(2.93)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,446	1,506	1,342	1,282	1,310	1,352
Adjusted R^2	0.594	0.539	0.614	0.502	0.579	0.583
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
Cluster Firm	YES	YES	YES	YES	YES	YES

This table presents the results of cross-sectional analyses that examine the impact of customers' climate risk on firms' cost of debt considering customers' liquidity constraints. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. We use Kaplan-Zingales index, Z score, and excess cash flows as the proxies for the firm's liquidity constraints. For each borrower, we calculate a sales-weighted average value of each proxy for its major customers. We split our full sample into two sub-samples based on the sample median of each proxy mentioned above. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 10: Loan Non-Pricing Terms

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)
	Whether the loan is collaterized		*Whether the loan has covenants*	
	Yes	No	Yes	No
CCR	-0.109	0.222***	0.038	0.157**
	(-1.53)	(4.33)	(0.67)	(2.41)
Controls	YES	YES	YES	YES
Observations	1,096	1,856	1,713	1,239
Adjusted R^2	0.419	0.617	0.584	0.580
Year FE	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES

This table presents the results of cross-sectional analyses examining the impact of customers' climate risk on firms' cost of debt considering loan's non-pricing terms. The dependent variable, Ln(Spread), is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. In columns (1) and (2), the sample is split based on whether the loan is is secured by a collateral requirement or not. In columns (3) and (4), the sample is split into two groups: loans with covenants (including either general or financial covenants) and loans without covenants. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table 11: Customer Lending Relationship with Borrower's Lead Banks

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)
	Prior 5 years		*Prior*	
	Yes	No	Yes	No
CCR	-0.054	0.114**	0.014	0.158**
	(-0.68)	(2.06)	(0.23)	(2.52)
Controls	YES	YES	YES	YES
Observations	766	2,186	1,171	1,781
Adjusted R^2	0.549	0.567	0.584	0.580
Year FE	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES

This table presents the results of cross-sectional analyses that examine the impact of customers' climate risk on firms' cost of debt considering customer lending relationships. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. In columns (1) and (2), the sample is split based on whether the customer had a loan relationship with the same lender of the borrower within the five years prior to the borrower's loan from that lender. In columns (3) and (4), the sample is split based on whether the customer had a loan relationship with the same lender of the borrower prior to the borrower receiving a loan from the same lender. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

A Online Appendix

Table OA1: Sample Selection Criteria

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. Suppliers 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

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.

Table OA2: Variables' Definitions

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 (CCR)	Sales-weighted average climate risk of customers immediately prior to a year in which obtains the loan facility. Source: SHELUDS.
Control variables	
Borrower Climate Risk	Borrower's own 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 (1968)'s 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.
Term Loan	Dummy (=1, if the type of loan contract is a term loan, =0 otherwise). Source: DealScan.
Loan Purpose	Indicator variables for loan purpose, including corporate purposes, debt repayment, working capital, takeover, capital investment, and other purposes. Source: DealScan.

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 borrower and their customer levels are constructed using data from Compustat.

Table OA3: Public Attention to Climate Change

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)	(4)
	WSJ Index		*Google Trend*	
	High	Low	High	Low
CCR	0.124**	0.024	0.136**	0.089
	(2.11)	(0.22)	(2.26)	(1.55)
Controls	YES	YES	YES	YES
Observations	2,062	556	975	1,710
Adjusted R^2	0.563	0.591	0.534	0.573
Year FE	YES	YES	YES	YES
FF48 FE	YES	YES	YES	YES
Loan Purpose FE	YES	YES	YES	YES
Cluster Firm	YES	YES	YES	YES

This table presents the results of cross-sectional analyses that examine the impact of customers' climate risk on firms' cost of debt considering public attention to climate change. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. *CCR* is the sales-weighted average climate risk from the borrower's major customers. In columns (1) and (2), *WSJ index* is the standardized monthly climate attention index constructed by Engle et al. (2020), measured in the month prior to loan issuance. In columns (3) and (4), *Google Index* is based on the raw monthly search traffic data for the term "climate change" on Google between 2004 and 2023, scaled to 100 for the maximum search volume, and also measured in the months prior to the loan issuance. We split our full sample into two sub-samples based on the sample median of these two proxies in the month prior to the loan issuance. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

Table OA4: The Impact of Firm's Climate Risk on the Cost of Debt: Variations Across Suppliers Sample and Customers Sample

Dep. Var. = *Ln(Spread)*	(1)	(2)	(3)
	Supplier Sample + Customer Sample	*Supplier Sample*	*Customer Sample*
Borrower Climate Risk	0.072**	0.098**	0.041
	(2.01)	(2.11)	(0.75)
Ln (Asset)	-0.123***	-0.110***	-0.158***
	(-11.18)	(-7.14)	(-7.91)
Leverage	0.605***	0.481***	0.664***
	(9.27)	(6.95)	(5.34)
MTB	-0.113***	-0.103***	-0.153***
	(-6.04)	(-5.49)	(-4.40)
Tangibility	-0.077	0.013	-0.231
	(-0.80)	(0.12)	(-1.56)
Profitability	-1.011***	-0.681***	-1.132***
	(-5.00)	(-3.51)	(-3.05)
Zscore	-0.051***	-0.045***	-0.062**
	(-4.09)	(-3.84)	(-2.29)
Unrated	-0.128***	-0.088***	-0.153***
	(-4.58)	(-2.60)	(-3.89)
Ln(Maturity)	0.112***	0.059**	0.127***
	(6.33)	(2.39)	(5.26)
Performance Pricing	-0.131***	-0.229***	-0.068*
	(-5.18)	(-7.77)	(-1.87)
Ln(Loan Size)	-0.116***	-0.060***	-0.156***
	(-9.04)	(-4.38)	(-8.31)
Constant	6.551***	6.654***	6.848***
	(31.48)	(23.62)	(27.64)
Observations	5,479	2,838	2,641
Adjusted R^2	0.552	0.481	0.572
Year FE	YES	YES	YES
FF48 FE	YES	YES	YES
Loan Purpose FE	YES	YES	YES
Cluster Firm	YES	YES	YES

This table presents the results of regressions examining the relationship between a firm's own climate risk and its cost of debt considering the heterogeneity in borrower roles as either suppliers and customers in the supply chain relationship. The dependent variable, *Ln(Spread)*, is the natural logarithm of the all-in loan spread obtained from DealScan for a given loan facility. The key independent variable, *Borrower Climate Risk*, measures the borrower's own exposure to climate-related disasters. Columns (1), (2), and (3) present results using three distinct samples: (1) both suppliers and customers, (2) suppliers only, and (3) customers only, respectively. Continuous variables are winsorized at 1% and 99%. The definition of variables included in the regressions are summarized in Table OA2. 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.

B Climate Risk, Liquidity, and Bank Loan Pricing

This appendix presents how climate-related financial risks, particularly the major CCR (ρ), affect supplier liquidity and loan spread. The framework demonstrates how deferred payments induced by climate risk 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 CCR (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 customers' climate risk, or CCR (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 CCR 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 spreads 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 spreads (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.