Measuring Corporate Risk Using Large Language Model Embeddings: Evidence on Corporate Climate Risk and Supply Chain Restructuring

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Abstract

We propose a novel text-based approach to measuring corporate climate risk that combines large language model (LLM) sentence embeddings with supervised machine learning. We find that this combined approach improves the precision of climate-related sentence classification by 23% relative to predefined keyword methods and by 26% compared to a recent LLM agent-based classifier. Using the resulting corporate risk measure, we further explore how firms react to supplier climate risk. We find that after controlling for firm- and supplier-level non-climate risk, supplier climate risk exposure increases the likelihood of terminating existing suppliers by 5.3% and adding new suppliers by 6.3%. Our analysis further suggests that such restructuring is strategic. First, the restructured supply networks exhibit greater geographic diversity, indicating firms' efforts to mitigate future climate-related disruptions by diversifying supplier locations. Second, firms prioritize adding new suppliers that produce more unique products or occupy more central positions in the supply chain network. We also document that such restructuring is most pronounced for supplier backward-looking climate risk and extreme physical climate risk. Firms with higher operational efficiency and greater product differentiation respond more aggressively to supplier climate risk.

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1 Introduction

Measuring corporate risk is a fundamental task across finance, accounting, and economics. Following Loughran and McDonald (2011), researchers have increasingly turned to disclosure text as a primary data source, using textual analysis to measure political uncertainty (Hassan et al., 2019), cybersecurity threats (Florackis et al., 2022), supply chain disruptions (Ersahin et al., 2023), and climate risk (Sautner et al., 2023). The keyword-based approach, though popular for its simplicity and interpretability, faces significant limitations. Constructing domain-specific dictionaries is costly and time-intensive, and the resulting dictionaries often lack extensibility beyond their narrow target domains. More fundamentally, keyword-based methods suffer from high rates of false positives and negatives due to their inability to capture semantic context. For example, terms like "electric vehicle" and "government India" rank among the top 50 n-grams in major climate-related dictionaries (Sautner et al., 2023), yet they are also expected to appear in contexts unrelated to climate risk.

The recent development of generative AI offers a promising alternative. Large language models can potentially produce more precise and extensible corporate risk measures by leveraging their deep contextual understanding of language. Some recent studies have experimented with using LLM agents directly as classifiers or summarizers to extract risk-related information from corporate disclosures (Kim et al., 2023). Yet this approach introduces new challenges: LLMs lack transparency in their outputs, are prone to hallucination, and produce results that are difficult to reproduce across different models. Passing large-scale firm disclosures to LLM agents for summarization or classification is not only expensive but also potentially unreliable. As a result, to the best of our knowledge, there's no well-accepted LLM agent-based method for measuring corporate risk so far.

In this paper, we propose a hybrid approach that combines LLM sentence embeddings with supervised machine learning to measure corporate risk from firm disclosures. This approach retains the superior contextual understanding of LLMs while ensuring interpretability and reproducibility by following a classic supervised machine learning framework that generates sentence-level risk classification results.

Specifically, we employ OpenAI's text-embedding-ada-002 model to encode each sentence from earnings call transcripts into a 1,536-dimensional vector. These sentence embeddings capture rich semantic and contextual information by leveraging the transformer-based architecture and large-scale pretraining behind ChatGPT. We then combine the LLM embeddings with a Support Vector Machine (SVM) classifier to identify whether each sentence is climate-related and risk-related. Aggregating the sentence-level classifications over 65 million sentences at the firm-quarter level enables us to construct

large-scale measures of both climate and non-climate risk for 3,615 U.S. listed firms on a quarterly basis. Our LLM embedding-based approach mitigates the misclassification concerns inherent in keyword-based methods by leveraging the pre-trained knowledge and deep contextual understanding of LLMs. In the climate-related sentence classification task, our proposed approach achieves an 11.6% improvement in F1-score and a 23.1% improvement in precision compared to the keyword-based approach adapted from Li et al. (2024) and Sautner et al. (2023). Moreover, by incorporating domain knowledge through supervised learning, the proposed method also outperforms classification by state-of-the-art LLM agents—achieving a 15.2% improvement in F1-score and a 25.8% improvement in precision compared to GPT-5 results.

We then use the firm-quarter level corporate risk measures to examine how firms respond to supplier climate risk. Climate risk is one of the most pressing challenges of our time. According to the World Economic Forum, climate-related risk—both physical and regulatory—account for five of the top ten global threats anticipated over the next decade.[1] In modern economies, the production of goods and services relies heavily on a wide range of inputs and interconnected supply chains. Understanding the impact of climate risk within these production interdependencies is therefore crucial. While the direct effects of climate risk exposure are widely documented (e.g., Pankratz et al. (2023); Tran (2023)), it remains unclear whether indirect exposure–through supply chain networks–affects firm performance and drives strategic downstream response.

Moreover, the theoretical prediction of how firms react to supplier climate risk is ex ante ambiguous. Supplier-customer relationships have both competitive and collaborative dimensions, leading to opposing predictions. On the one hand, these relationships are often governed by relational contracts that can be terminated when external conditions—such as climate disruptions—deteriorate (Baker et al., 2002; Klein et al., 1978). Upstream climate shocks can disrupt production, raise input costs, and reduce downstream firm performance, potentially motivating firms to terminate vulnerable supplier relationships or diversify their supply base. This competitive view suggests firms would actively restructure their supply chains in response to supplier climate risk.

On the other hand, supplier-customer relationships are also collaborative. Firms jointly create value for end customers, which incentivizes long-term cooperation and mutual investment (Cannon et al., 2010; Cao and Zhang, 2011; Ganesan, 1994). Restructuring is not costless: switching suppliers—especially those

[1]World Economic Forum. (2024). *Global Risk Report 2024*. Retrieved from `https://www.weforum.org/publications/global-risks-report-2024/`. Bilal and Stock (2025) offers an excellent survey linking macroeconomics and climate change. Beyond its economic consequences, climate risk has also entered the broader discourse on environmental justice. Nobel laureate Amartya Sen, through his capability approach, emphasizes that justice is best served when goods and resources enhance individuals' capabilities to live dignified and socially integrated lives (Sen et al., 1993; Schlosberg, 2007).

providing highly specific inputs—can be time-consuming and expensive (Cohen and Lee, 2020; Barrot and Sauvagnat, 2016). These frictions create "stickiness" in supply chain relationships, where the benefits of continuity may outweigh the costs of potential disruption. This collaborative view suggests firms should maintain existing supplier relationships when suppliers face climate risk. The tension between these two perspectives makes it theoretically ambiguous how firms will respond to upstream climate risk.

By integrating our LLM embedding-based risk measures with firm-level financial, operational, and supply chain data, we provide large-scale empirical evidence to answer this underexamined question. We find that exposure to supplier climate risk significantly reduces downstream firms' sales growth and operating income growth. In response, firms engage in supply chain restructuring through both **supplier re-selection**—terminating existing relationships and adding new suppliers—and **geographic diversification**—expanding the spatial distribution of their supplier base.

Consistent with the competitive view of supplier-customer relationships, firms are significantly more likely to terminate existing suppliers and add new ones when facing upstream climate risk. These restructuring actions are strategic: the resulting supplier networks exhibit greater inter-supplier geographic dispersion and reduced state-level concentration, indicating intentional diversification efforts. We further document that such restructuring is most pronounced for supplier backward-looking climate risk and extreme physical climate risk. However, these responses are moderated by supplier characteristics in ways consistent with the collaborative view. We find that **input-specific suppliers**—those providing highly specialized inputs—and **high-centrality suppliers**—those occupying critical positions within the supply chain network—are less likely to be terminated, even when exposed to climate risk. When adding new suppliers, firms also prefer input-specific and high-centrality suppliers, suggesting strategic efforts to enhance supply network resilience for critical inputs that are difficult to replace. Firm-level characteristics further shape these adaptive strategies. Firms with higher operational efficiency or those producing more unique products respond more aggressively to supplier climate risk.

The contributions of our paper are twofold. First, we introduce a novel approach that combines LLM embeddings with supervised machine learning to measure corporate risk from unstructured text. This method offers a flexible framework that can be extended to other domains, such as measuring corporate AI adoption or innovation intensity. By making our tools and data publicly available, we encourage further research and facilitate broader exploration of climate risk impacts and mitigation strategies[2]. Second, we provide large-scale empirical evidence on how downstream firms restructure their supplier

[2]We plan to open-source our labeled dataset and firm-quarter measures in future versions.

networks in response to upstream climate risk exposure. Our findings highlight that climate risk trigger strategic adaptation behaviors, such as supplier termination, addition, and geographic diversification. We show that these responses are moderated by supplier- and firm-level characteristics. Notably, our results highlight that firms must consider not only the direct effects of climate risk but also the strategic responses of downstream customers, which further underscores the importance of climate resilience. Our findings suggest that firms can reduce the likelihood of downstream termination by increasing product uniqueness and enhancing their supply chain network centrality—an insight that extends the literature on supply chain disruptions and the indirect effects of climate risk.

Our research also offers several practical implications. First, the open-source LLM embedding-based risk measures developed in our study provide executives with a scalable tool to monitor vulnerabilities within their supply chains. Integrating these measures into operational planning enables firms to proactively assess supplier risk exposure and adjust sourcing strategies before disruptions materialize. Second, our empirical findings offer actionable guidance for corporate decision-makers. We identify the conditions under which firms are more likely to terminate or replace suppliers, diversify geographically, or maintain existing relationships while outsourcing to alternative suppliers. These insights are particularly relevant for firms operating in highly interconnected, climate-sensitive sectors. Third, our study provides valuable insights for investors and policymakers by shedding light on how firms respond to climate risk exposure faced by their upstream supplier chain. Overall, our research equips stakeholders with the tools and evidence to better identify, monitor, and respond to supplier climate risk.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data sources, processing procedures, and summary statistics. Section 4 outlines the methodology for constructing the LLM embedding-based risk measure. Section 5 details the empirical strategy. Section 6 presents the main findings on strategic supply chain restructuring in response to supplier climate risk. Finally, Section 7 concludes with a discussion of key insights, managerial and policy implications, and directions for future work.

2 Literature Review

Our research contributes to three streams of literature. First, our study advances the literature on text-based measures of corporate risk. Prior research has leveraged text data to measure various types of risk, such as supply chain disruptions (Ersahin et al., 2023), political uncertainty (Hassan et al., 2019), cybersecurity threats (Florackis et al., 2022), and climate risk (Li et al., 2024; Sautner et al., 2023).

Existing text-based approaches predominantly relied on dictionary-based methods, which use predefined lists of keywords to identify and measure risk exposure from text such as earnings calls and filings. However, these keyword-based approaches often fail to capture the full context of corporate discussions. Misclassification among keyword-based methods is high because the same keywords may be used in different contexts, and predefined static dictionaries can not adapt to evolving risk factors (Loughran and McDonald, 2011). More recent work has recognized these limitations and introduced machine learning–based methods to improve keywords construction and measurement accuracy. For example, Li et al. (2021) apply Word2Vec embeddings to develop evolving keyword lists for analyzing corporate culture, while Kim et al. (2023) use ChatGPT to generate textual summaries from earnings calls and construct risk measures based on the length of AI-generated summary of AI, climate, and political risk.

Building on this stream of literature, we propose a novel LLM-embedding-based framework to construct corporate climate risk measures. Unlike traditional keyword-based that depend on static keyword lists, LLM embeddings allow us to capture nuanced contextual meanings of earnings call text to identify climate and risk discussions. Unlike the generative AI-based approach proposed by Kim et al. (2023), our embeddings-based method is more robust to variations in prompts and LLM models, and it offers greater interpretability and reproducibility. Overall, our approach provides a more precise yet still interpretable measure of firm- and supplier-level climate risk.

Second, this study contributes to the broader literature on the economic impacts of climate risk. A large body of prior research has documented the direct effects of climate risk on firm performance. For example, Ardia et al. (2023) find that rising public concern over climate risk leads to higher green stock valuations. Klusak et al. (2023) show that temperature increases can result in sovereign credit downgrades and higher borrowing costs. Pankratz et al. (2023) demonstrate that extreme heat significantly reduces corporate revenues and operating income. Tran (2023) find that weather variability exacerbates sales volatility in climate-sensitive sectors. These studies primarily focus on direct, firm-level impacts, and largely overlook how climate risk exposure propagates through supply chains and drive downstream strategic reactions. A notable exception is Pankratz and Schiller (2024), which examines how firm-level exposure to heat and flooding affects downstream firm financial performance.

We extend this literature by investigating the indirect impacts of climate risk given supply chain interdependencies. Our study differs from Pankratz and Schiller (2024) in two key ways. First, while their analysis focuses narrowly on extreme heatwaves and floods identified based on firm location, our approach employs a comprehensive text-based measure that captures a broader spectrum of

firm-level climate risk exposures—including both physical and regulatory risk. Second, while their study investigates the impact of extreme weather shocks on downstream firm performance, we shift the focus to the corresponding response, particularly how downstream firms proactively restructure their supply networks in response to supplier climate risk. By highlighting firm adaptation strategies under climate risk, our study offers new insights into how climate risk indirectly affects firms through supplier-customer networks and how firms mitigate these indirect climate risk through proactive supply chain decisions.

Third, we also build on studies examining how external shocks cascade through supply chains. Most existing literature on supply chain disruptions focuses on demand-side shocks (e.g., Acemoglu et al. (2012), Osadchiy et al. (2016), and Kesavan et al. (2016)). More recently, a growing body of research has explored how regional or industrial supply disruptions—including natural disasters (Barrot and Sauvagnat, 2016; Hendricks et al., 2020; Carvalho et al., 2021), COVID-19 lockdowns (Lafrogne-Joussier et al., 2022), geopolitical risk (Leung et al., 2024), and extreme weather (Pankratz and Schiller, 2024)—propagate across supply chains. For example, Barrot and Sauvagnat (2016) show that natural disasters significantly disrupt suppliers, with cascading losses for customers, particularly when suppliers' input specificity is high. Similarly, Carvalho et al. (2021) quantify the ripple effects of the Great East Japan Earthquake on production networks. However, this literature predominantly addresses large-scale supply shocks at the regional or sectoral level.

Unlike most regional or industrial supply shocks, which are typically regarded as temporary and unexpected, climate risk represent a more persistent form of disruption, which can alter managerial expectations about long-term climate and policy uncertainties (Giglio et al., 2021). These characteristics make climate risk fundamentally different from short-term shocks and potentially more consequential for long-term supply chain planning. Whether existing findings from temporary, event-driven disruptions generalize to the slower-moving and diffuse nature of climate risk remains unclear. We contribute to this literature by focusing on supplier climate risk as a firm-level, supply-side disruption and by providing large-scale empirical evidence on how it triggers strategic restructuring by downstream firms.

3 Background and Data

3.1 Earnings Conference Calls

We collect earnings conference call transcripts for publicly listed U.S. firms from the Refinitiv Eikon and Capital IQ databases, covering the period from 2002 to 2023. A typical earnings call begins with

a 30- to 60-minute prepared presentation by senior executives—primarily the CEO and CFO—followed by a 30- to 40-minute Q&A session. During the presentation, executives typically discuss quarterly financial performance and operational highlights. If earnings fall short of expectations, management often provides additional context and outlines plans to address the challenges. In the Q&A session, equity analysts, institutional investors, and business journalists pose follow-up questions. When a company is exposed to climate risk, executives are expected to discuss them during the presentation. Analysts and journalists may also raise climate-related questions during the Q&A session if such risk are considered material to the firm's performance.

Earnings calls offer two major advantages. First, the real-time, conversational format between information producers (managers) and consumers (analysts) mitigates selective disclosure bias. Unlike scripted filings, the Q&A session requires executives to respond spontaneously, reducing their ability to withhold information. In contrast, documents such as 10-Ks and annual reports are carefully curated by legal and investor relations teams. Second, earnings calls often occur every quarter, providing timely insights into firm operations, strategy, and risk exposures, whereas annual or ESG reports often emphasize long-term objectives.

To prepare the corpus, we tokenize each transcript into sentences with a minimum length of 20 words to ensure sufficient semantic context. We also extract firm identifiers (GVKEY, ISIN, CUSIP, and PERMNO) to link transcripts with financial and supply chain datasets. Our final corpus consists of 135,209 earnings call transcripts from U.S.-listed firms. The detailed methodology for constructing the text-based climate risk measures is provided in Section 4.

3.2 Financial and Operational Data

We obtain quarterly firm-level operational and financial data from the Compustat-CRSP merged database. To control for firm innovation intensity, we merge in quarterly U.S. patent data from the United States Patent and Trademark Office (USPTO), following the methodology of Kogan et al. (2017) to identify filled and issued patents for each firm-year. Additionally, to measure product uniqueness and industry competition, we incorporate 10-K-based product similarity and industrial concentration metrics from Hoberg and Phillips (2016).

To capture input specificity, we follow Barrot and Sauvagnat (2016), who suggest that suppliers producing more unique products, operating in industries with higher centrality, and holding more patents are more likely to provide highly specific inputs. We construct three proxies for supplier input specificity:

(1) Product similarity: lower similarity scores indicate more unique product offerings; (2) Industry competition: a higher Herfindahl-Hirschman Index (HHI) implies less competitive (and more specialized) industries; and (3) Patent holdings: a greater number of patents suggests higher technological specificity. A supplier is classified as input-specific if its 10-K–based product similarity lies below the median, its industry HHI lies above the median, or its number of issued patents lies above the median across all suppliers. We hypothesize that firms' responses to supplier climate risk exposure are moderated by input specificity. From a competitive view of supplier–customer relationships, firms are more likely to terminate and replace low-specificity suppliers. In contrast, from a collaborative view, firms are more inclined to maintain relationships with high-specificity suppliers to preserve operational continuity.

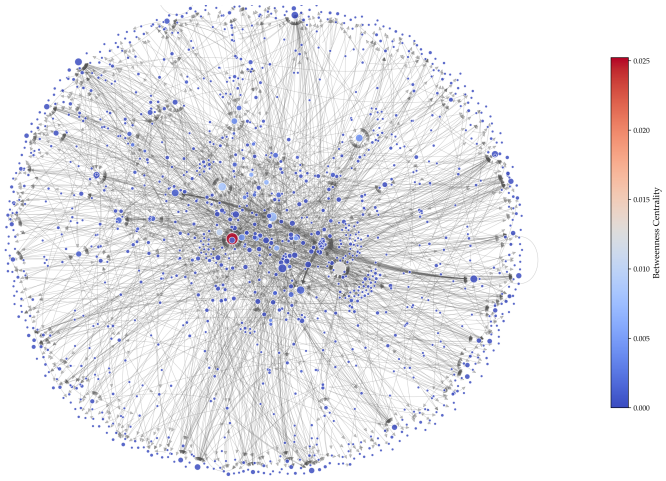
3.3 Supplier-Customer Relationships

We acquire supply chain relationship data from a combination of the FactSet Revere Supply Chain Relationships and the Compustat Segments Customer File. Both datasets are widely used in the literature to identify supplier–customer linkages (See Barrot and Sauvagnat (2016) and Leung and Sun (2021) for examples). The FactSet Revere dataset provides global supplier–customer relationships for U.S.-listed firms, derived from public filings, media sources, B2B transaction data, and verified by in-house analysts. The Compustat Segments Customer File identifies major customer relationships for U.S. public firms based on SEC disclosure requirements, which mandate firms to report any customer accounting for at least 10% of total revenue.

For example, Figure 1 illustrates the supply chain network for the year 2022. As shown, the network exhibits a core–periphery structure, with a small subset of firms maintaining extensive connections to both suppliers and customers. This structural pattern motivates our use of network centrality measures to quantify firms' positions within the supply chain and to examine how these positions moderate downstream restructuring responses to supplier climate risk exposure.

To quantify firm positions within supply chain networks, we construct a directed network $\mathcal{G}_t = (V_t, E_t)$ for each year t, where V_t is the set of firms and E_t is the set of directed customer-supplier links. An edge $(i,j) \in E_t$ indicates that firm i supplies to firm j in year t. We compute three standard centrality measures to assess firm influence and connectivity: degree centrality, betweenness centrality, and closeness centrality, following (Borgatti and Everett, 2006).

Figure 1: Identified Supply Chain Network in 2022



Notes: This network visualization depicts supply chain relationships among 1,283 U.S. publicly listed firms in 2022 (i.e., $\mathcal{G}_{2022}=(V_{2022},E_{2022})$). The network comprises 1,283 nodes (firms, i.e., V_{2022}) and 2,173 edges (supplier-customer links, i.e., E_{2022}). Node size reflects firm degree centrality, with larger circles indicating firms connected to more tier-1 suppliers and customers. Node color represents betweenness centrality, with lighter shades indicating higher values. Arrows denote the direction of supply flow from suppliers to customers. The network structure exhibits a core-periphery pattern with notable heterogeneity in supply chain centrality across firms. Building on this observation, we consider the supply chain centrality of suppliers as a key moderator in analyzing downstream firms' responses to supplier climate risk exposure.

Degree centrality captures a firm's number of direct connections, defined as:

$$C_D(i,t)=\sum_{j\neq i}A_{ij}(t), \tag{1}$$

where $A_{ij}(t)$ is the adjacency matrix of G_t, with $A_{ij}(t)=1$ if firm i supplies to firm j in year t, and 0 otherwise. Firms with high degree centrality maintain extensive direct connections to suppliers and customers.

Betweenness centrality measures the extent to which a firm serves as an intermediary between others, calculated as:

$$C_B(i,t)=\sum_{s\neq i\neq t}\frac{\sigma_{st}(i,t)}{\sigma_{st}(t)}, \tag{2}$$

where $\sigma_{st}(t)$ is the total number of shortest paths between firms s and t, and $\sigma_{st}(i,t)$ is the number passing through firm i. Firms with high betweenness centrality are key bridges that facilitate connections across the supply chain.

Closeness centrality reflects how quickly a firm can interact with others in the network, defined as:

$$C_C(i,t)=\frac{1}{\sum_{j\neq i}d(i,j,t)}, \tag{3}$$

where $d(i,j,t)$ is the shortest path distance between firms i and j in G_t. A firm with high closeness centrality can rapidly access multiple firms.

To illustrate how different centrality measures capture strategic positions in the supply chain, Appendix Figure A.1 presents firms with the highest (a) degree, (b) betweenness, and (c) closeness centrality. A

firm with high degree centrality maintains many direct connections with tier-1 suppliers and customers, indicating broad network participation. A firm with high betweenness centrality connects fewer direct partners, but those partners themselves have high connectivity, positioning the firm as a critical bridge linking otherwise unconnected parts of the network. In contrast, a firm with high closeness centrality connects to moderately central partners and can reach others in the network through short paths.

We hypothesize that firms' responses to supplier climate risk exposure are also moderated by supplier centrality. Specifically, downstream firms are more likely to retain high-centrality suppliers and adopt a collaborative perspective when these suppliers face climate risk due to their strategic importance in the network. Furthermore, we hypothesize that when firms restructure their supplier networks, they are more likely to add new suppliers with greater centrality to strengthen future resilience and maintain fast connections with the broader production network.

3.4 Summary Statistics

Following common practice in the literature (Sautner et al., 2023; Leung and Sun, 2021; Li et al., 2024), we exclude financial institutions and insurance companies (SIC codes 6000–6500 and 6700–6800) when constructing our panel. To mitigate the influence of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Our final dataset comprises a firm-quarter-level panel of 3,615 unique U.S.-listed firms covering 88 quarters from 2002 to 2023. Table 1 presents the summary statistics of our major variables.

4 LLM Embedding-Based Measures of Corporate Risk

Measuring corporate risk is challenging due to their evolving and multifaceted nature. Traditional location-based methods often fail to capture heterogeneity in risk intensity across firms. As a result, recent research has proposed text-based approaches, particularly those relying on keyword matching. While keyword-based methods are widely used, they suffer from several limitations. First, risk factors, such as climate-risk-related terminology, evolve fast. It is difficult to develop a comprehensive and accurate keyword list that is effective over time. Second, risk-related terms—such as those related to energy or natural resources in the climate risk context—can also appear in unrelated settings, leading to systematic misclassification of risk exposure. Moreover, most existing risk keyword lists are domain-specific: constructing a comprehensive list that captures a broad range of corporate risk is

Table 1: Summary Statistics

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Panel A: Corporate Risk Measures								
Climate Risk	134,306	0.239	0.666	0.000	0.000	0.000	0.000	14.583
Suppliers' Average Climate Risk	100,849	0.187	0.441	0.000	0.000	0.000	0.192	9.605
$\mathbb{1}$(Climate Risk)	134,306	0.223	0.417	0.000	0.000	0.000	0.000	1.000
$\mathbb{1}$(Suppliers Climate Risk)	100,849	0.409	0.492	0.000	0.000	0.000	1.000	1.000
Non-Climate Risk	134,306	4.932	3.808	0.000	2.165	3.987	6.716	43.182
Suppliers' Average Non-Climate Risk	100,849	0.049	0.029	0.000	0.029	0.043	0.062	0.335
Forward-Looking Climate Risk	134,306	0.001	0.003	0.000	0.000	0.000	0.000	0.757
Backward-Looking Climate Risk	134,306	0.002	0.012	0.000	0.000	0.000	0.000	3.544
Extreme Physical Climate Risk	134,306	0.001	0.012	0.000	0.000	0.000	0.000	3.942
Mild Physical Climate Risk	134,306	0.001	0.005	0.000	0.000	0.000	0.000	0.574
Regulatory Climate Risk	134,306	0.000	0.001	0.000	0.000	0.000	0.000	0.098
Panel B: Supply Chain Measures								
Log(Variance Between-Supplier Distance + 1)	120,914	6.542	6.852	0.000	0.000	0.000	13.976	16.302
Supplier State Concentration Index	123,747	0.575	0.346	0.046	0.250	0.500	1.000	1.000
$\mathbb{1}$(Suppliers Termination)	123,931	0.413	0.492	0.000	0.000	0.000	1.000	1.000
$\mathbb{1}$(Suppliers Addition)	123,931	0.546	0.498	0.000	0.000	1.000	1.000	1.000
Number of Suppliers	118,592	6.658	13.462	1.000	1.000	3.000	6.000	230.000
Panel C: Firm Characteristics								
TNIC3 HHI	237,345	0.304	0.282	0.015	0.096	0.191	0.422	1.000
Inventory Turnover	181,050	7.387	87.544	0.041	0.753	1.351	3.236	10788.000
Debt/Assets	248,376	0.237	0.264	0.000	0.021	0.190	0.363	14.306
CAPEX/Assets	255,468	0.029	0.046	0.000	0.005	0.014	0.033	2.013
R&D/Assets	139,385	0.036	0.100	0.000	0.004	0.018	0.043	20.834
Asset Tangibility	255,815	0.249	0.242	0.000	0.063	0.157	0.366	0.996
Sales Growth	249,814	0.234	1.091	-1.000	-0.048	0.063	0.212	10.000
Operating Income Growth	253,974	0.002	1.967	-10.000	-0.290	0.033	0.313	10.000

Notes: This table presents summary statistics for our sample from 2002 to 2023. Panel A reports climate risk measures derived from earnings call transcripts. Panel B presents supply chain characteristics including geographic dispersion, concentration, and relationship dynamics. Panel C shows firm characteristics including product market competition, inventory management, financial structure, investment, and growth metrics. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table 1 presents the definitions and data sources of our main variables.

highly impractical, as it would require identifying and validating an enormous number of terms. The diversity, contextual nuance, and ongoing evolution of corporate risk across firms and industries make it infeasible to develop an exhaustive, universally applicable keyword framework.

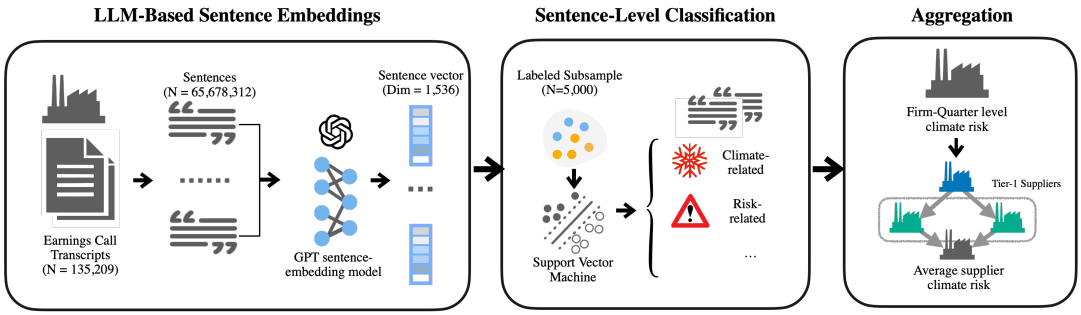
To overcome these limitations, we use LLM-based sentence embeddings to analyze earnings call transcripts and identify firm- and supplier-level climate risk as well as non-climate risk. LLMs offer two advantages over traditional keyword-based approaches. First, they capture sentence meaning in context, which helps separate truly risk-related discussion from generic mentions (e.g., energy or natural resources) that would otherwise create false positives. Second, they reduce reliance on a fixed, hand-built vocabulary, since the embedding space naturally groups similar phrasing and can handle new or shifting terminology without constant dictionary updates. This combination makes LLM embeddings a more reliable and scalable foundation for detecting risk discussions in corporate disclosures.

Note that we do not rely on LLM agents directly, because recent work has raised concerns about

their reproducibility and reliability. First, LLM outputs can vary across providers, model versions, and even small changes in prompt design, making results hard to replicate across studies (de Kok, 2025). Second, LLMs can hallucinate—producing content that is incorrect or not verifiable—which can introduce measurement error when risk measures are built from generated text (Gui and Toubia, 2023). Together, these issues suggest that risk measures derived directly from LLM-generated outputs may lack transparency, reliability, and replicability.

To address these concerns while still benefiting from LLMs' language understanding, we adopt a hybrid approach. Instead of using LLMs to generate or summarize text, we use LLM sentence embeddings to map each sentence into a structured numerical representation, and then feed these embeddings into a supervised classifier trained on labeled subsamples. This setup yields sentence-level classifications that are transparent and empirically validated, while avoiding dependence on prompt engineering or generative outputs. The embeddings help capture context and leverage pre-trained language knowledge, and the supervised step lets us inject domain expertise and maintain consistent measurement. Our climate risk measure is therefore straightforward and interpretable: the proportion of sentences in an earnings call that discuss climate-related risk. Figure 2 summarizes the workflow for constructing our text-based corporate risk measures.

Figure 2: Research Pipeline for LLM-Derived Climate Risk Measures



Notes: This plot illustrates out pipeline for constructing firm- and supplier-level climate and non-climate risk measures using LLM embeddings. We begin with sentence-level tokenization of earnings call transcripts. Each sentence is embedded using OpenAI's text-embedding-ada-002 model to obtain 1,536-dimensional vectors that capture semantic context. Supervised classifiers are then trained to identify climate-related and risk-related sentences. The sentence-level classifications are aggregated to produce quarterly firm-level climate risk and non-climate risk measures, which are further integrated with supplier networks to measure supplier climate risks.

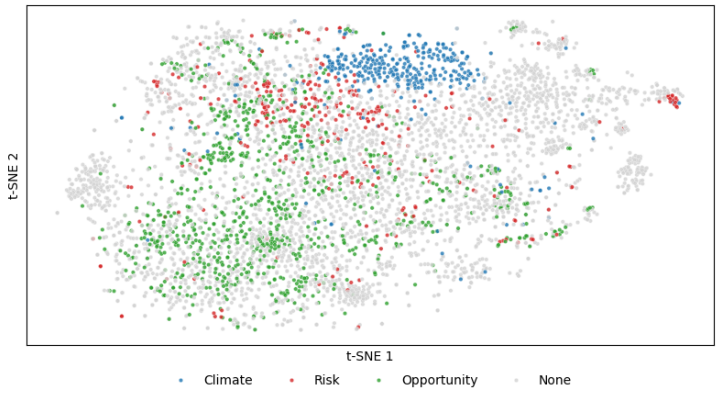
4.1 Measure Construction with LLM Embeddings

We begin by tokenizing each earnings call transcript into sentences with a minimum length of 20 words.[3] We then generate 1,536-dimensional sentence embeddings using OpenAI's text-embedding-ada-002

[3]The final corpus includes 65,678,312 sentences.

model.[4] LLMs such as OpenAI's GPT series excel at capturing semantic meaning and contextual relationships (Brown et al., 2020). By leveraging pre-trained language knowledge, LLM embeddings enable accurate classification while mitigating sensitivity to specific model versions or prompt designs. We use these embeddings as input features in a supervised learning framework to classify each sentence along two target dimensions—climate-related and risk-related—and one benchmark dimension—opportunity-related—to show that our approach can extend beyond risk measurement. At the firm-quarter level, we then aggregate sentence-level predictions into intensity measures by calculating the proportion of relevant sentences in each transcript.

Figure 3: t-SNE Visualization of LLM Embedding Space



Notes: This figure shows a t-SNE projection of the LLM embedding space. Each point represents a labeled sentence from earnings call transcripts, colored by sentence labels.

To build the labeled training set, we randomly sampled 5,000 sentences and had them independently annotated by two trained research assistants. We used an iterative process to ensure label quality. We first wrote detailed labeling guidelines with clear definitions and examples, trained the annotators, and then conducted labeling in rounds of 500 sentences. After each round, we ran quality checks. If the two annotators agreed, we accepted the label; if they disagreed, a third domain expert reviewed the sentence and assigned the final label.

To show that LLM embeddings capture label-relevant meaning, we use t-SNE to project the 1,536-dimensional sentence embeddings into two dimensions. Figure 3 shows clear clustering by label: sentences with the same labels tend to lie close to each other in the projected space. This pattern suggests that the LLM embedding space indeed organizes sentences in a way that aligns with our interested topics, which is exactly what our supervised classifier can exploit for scalable and consistent sentence-level classification.

Using this labeled dataset, we trained several supervised classification models, using the LLM

[4]For more details on the embedding model, see https://platform.openai.com/docs/guides/embeddings.

embeddings as input features and binary labels for each classification dimension as outputs. The labeled data was split into a 70% training set and a 30% test set, and we evaluated model performance using 10-fold cross-validation. We compared the performance of various classifiers, including Support Vector Machines (SVM), logistic regression, XGBoost, and random forest models. Among these, the SVM classifier achieved the highest performance, with an average prediction accuracy of approximately 95.1% (see Table 2). Given its robustness, we selected the SVM model for the main analysis.

Table 2: Performance Metrics of Supervised Classification Models

		LLM Agent-Based		**LLM Embedding-Based**				
Measure	**Metric**	**GPT-4o-mini**	**GPT-5-nano**	**Logistic Regression**	**XGBoost**	**Random Forest**	**SVM**	**Neural Network**
Climate	F1	0.792	0.816	0.913	0.896	0.854	0.940	**0.941**
	Accuracy	0.937	0.946	0.979	0.977	0.972	**0.987**	0.986
Risk	F1	0.731	0.687	0.793	0.791	0.738	**0.844**	0.830
	Accuracy	0.876	0.836	0.914	0.931	0.930	**0.948**	0.941
Opportunity	F1	0.692	0.604	0.819	0.791	0.720	**0.866**	0.844
	Accuracy	0.749	0.644	0.873	0.878	0.860	**0.919**	0.901
Average	F1	0.738	0.702	0.842	0.826	0.771	**0.883**	0.872
	Accuracy	0.854	0.809	0.922	0.929	0.921	**0.951**	0.943

Notes: The table presents the test performance metrics of LLM agent-based models (GPT-4o-mini, GPT-5-nano) and LLM embedding-based supervised classification models (Logistic Regression, XGBoost, Random Forest, SVM, Neural Network) for three measures: Climate, Risk, and Opportunity. All results are based on the test set (N=1,500). The best-performing model for each metric is highlighted in bold.

Using the sentence-level classification results, we construct firm–quarter-level measures by calculating the proportion of relevant sentences in each dimension relative to the total number of sentences in a given earnings call transcript. For each sentence s of firm i in quarter t, the firm-quarter level measures are defined as follows:

$$\text{Climate Risk}_{it} = \frac{1}{|S_{it}|} \sum_{s=1}^{|S_{it}|} \text{Climate}_{ist} \times \text{Risk}_{ist} \tag{4}$$

$$\text{Non-Climate Risk}_{it} = \frac{1}{|S_{it}|} \sum_{s=1}^{|S_{it}|} (1 - \text{Climate}_{ist}) \times \text{Risk}_{ist} \tag{5}$$

where $|S_{it}|$ denotes the total number of sentences in firm i's earnings call in quarter t.

We interpret these text-based indicators as firm–quarter-level intensities for the corresponding dimensions. Climate Risk_{it} reflects a firm's exposure to climate-related challenges, including both physical risk (e.g., natural disasters) and regulatory risk (e.g., policy changes). Non-Climate Risk_{it} captures firm-level exposure to non-climate risk such as financial volatility, geopolitical uncertainty, or supply chain disruptions.

To construct a supplier-level climate risk measure, we integrate Climate Risk_{it} values with supply chain linkages obtained from the combined FactSet Revere and Compustat Segments Customer File.

Specifically, we define a dummy variable, $\mathbb{1}(\text{Suppliers Climate Risk})_{it}$ as follows:

$$\mathbb{1}(\text{Suppliers Climate Risk})_{it} = \begin{cases} 1 & \text{if any supplier } j \text{ of firm } i \text{ in quarter } t \\ & \text{has Climate Risk}_{jt} > 0, \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

where Climate Risk_{jt} represents the climate risk measure for supplier j in quarter t. Similarly, we also construct a dummy variable, $\mathbb{1}(\text{Climate Risk})_{it}$, indicating whether the focal firm itself is exposed to any climate risk in a given quarter. Table 3 reports year-level summary statistics for our LLM embedding-based measures from 2002 to 2023.

Table 3: Year-Level Summary Statistics of LLM-Derived Measures

Year	Number of Transcripts	Climate Risk (%)		Suppliers' Climate Risk (%)		𝟙(Climate Risk) (Dummy)		𝟙(Suppliers Climate Risk) (Dummy)		Non-Climate Risk (%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2002	1,467	0.193	0.532	0.085	0.285	0.217	0.412	0.168	0.375	5.245	3.402
2003	3,141	0.330	0.775	0.205	0.493	0.298	0.458	0.432	0.495	5.013	3.333
2004	3,657	0.207	0.565	0.139	0.341	0.227	0.419	0.379	0.485	3.960	2.713
2005	3,970	0.414	0.924	0.299	0.708	0.330	0.470	0.475	0.499	4.479	3.215
2006	4,357	0.314	0.766	0.248	0.571	0.282	0.450	0.410	0.492	4.340	3.088
2007	4,783	0.308	0.784	0.212	0.461	0.275	0.447	0.396	0.489	4.664	3.481
2008	5,206	0.248	0.680	0.196	0.534	0.246	0.431	0.378	0.485	6.087	4.315
2009	5,250	0.191	0.548	0.165	0.449	0.210	0.407	0.367	0.482	7.831	5.133
2010	5,452	0.230	0.629	0.160	0.367	0.228	0.420	0.377	0.485	4.955	3.423
2011	5,790	0.324	0.743	0.247	0.453	0.305	0.460	0.501	0.500	4.826	3.395
2012	5,819	0.255	0.655	0.192	0.369	0.257	0.437	0.479	0.500	4.701	3.362
2013	5,703	0.248	0.625	0.181	0.346	0.247	0.432	0.445	0.497	4.559	3.278
2014	6,303	0.403	0.898	0.319	0.622	0.307	0.462	0.493	0.500	4.124	3.044
2015	6,560	0.212	0.582	0.132	0.290	0.217	0.413	0.386	0.487	4.753	3.730
2016	6,669	0.190	0.547	0.129	0.341	0.198	0.399	0.363	0.481	4.680	3.585
2017	7,490	0.322	0.832	0.218	0.462	0.251	0.433	0.435	0.496	4.014	3.067
2018	8,165	0.223	0.605	0.160	0.329	0.219	0.414	0.441	0.497	3.702	2.939
2019	6,316	0.249	0.696	0.154	0.373	0.215	0.411	0.380	0.485	4.308	3.511
2020	9,168	0.156	0.555	0.110	0.270	0.166	0.372	0.391	0.488	6.387	4.623
2021	9,735	0.205	0.621	0.172	0.489	0.186	0.389	0.317	0.465	4.758	3.790
2022	10,252	0.134	0.463	0.118	0.324	0.142	0.349	0.238	0.426	5.546	4.206
2023	9,956	0.169	0.590	0.226	0.549	0.148	0.355	0.235	0.425	5.143	4.129
Overall	**135,209**	**0.239**	**0.666**	**0.187**	**0.441**	**0.224**	**0.417**	**0.409**	**0.492**	**4.932**	**3.808**

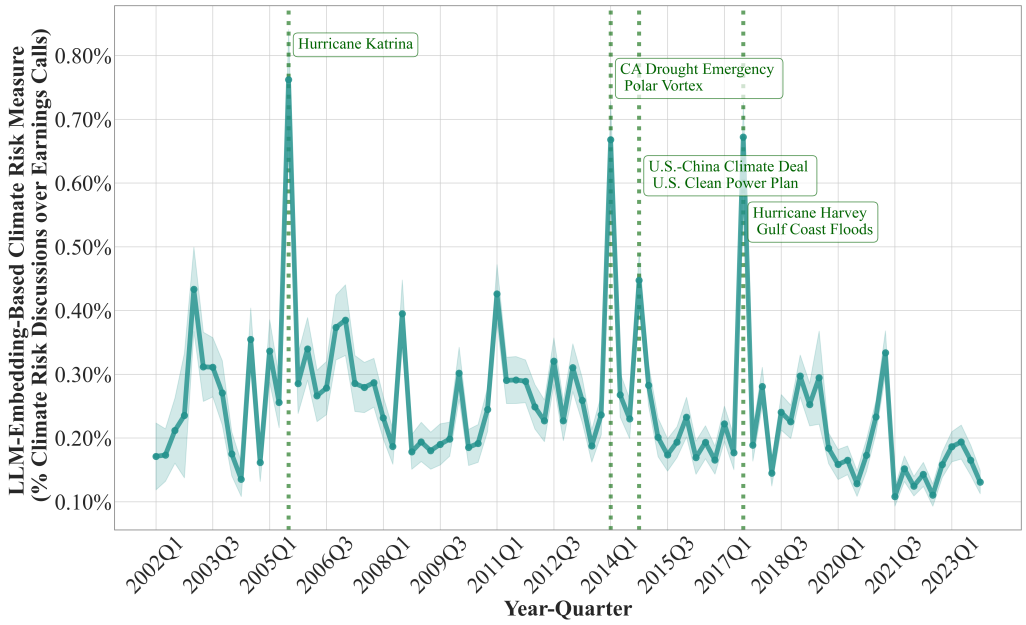
Notes: This table reports yearly averages of our transcript-based measures from 2002 to 2023. For each measure, we report the mean and standard deviation (SD). The Climate Risk and Suppliers' Climate Risk columns capture the intensity of climate risk discussions in firms' and their suppliers' earnings calls. The dummy variables indicate whether climate risk mentions exceed a threshold. Non-Climate Risk captures the intensity of general (non-climate) risk discussions. All values except Number of Transcripts are expressed as percentages. The last row reports the overall average across the full sample period.

4.2 Validations

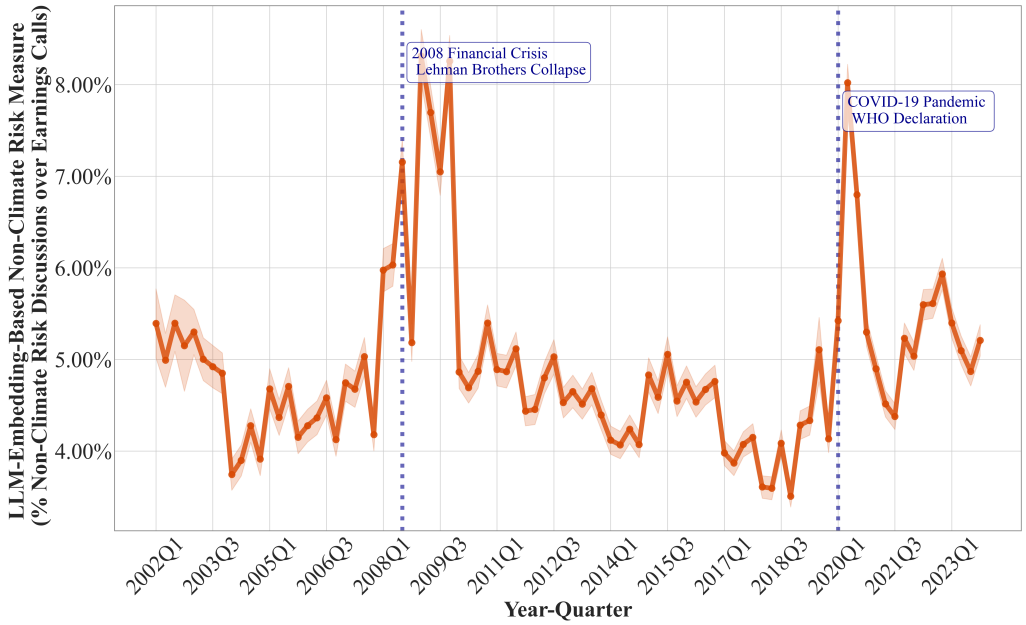
We validate our constructed LLM embedding-based measures using two complementary approaches. First, we examine whether the aggregate temporal trends of our firm-level measures align with real-world events and expected risk dynamics. Specifically, we aggregate the LLM embedding-based measures to the year-quarter level and plot their evolution from 2002 to 2023. As shown in Figure 4, the climate risk measure (Panel A) exhibits noticeable spikes following major climate-related events—such as Hurricane Katrina (2005Q3), the U.S.-China Climate Deal (2014Q4), and Hurricane Harvey (2017Q3)—demonstrating

its sensitivity to exogenous climate shocks. Panel B illustrates that the non-climate risk measures also reflect meaningful temporal variation, including increases during the global financial crisis (2008–2009) and the COVID-19 pandemic (2020).

Figure 4: Temporal Trends of Climate Risk and Non-Climate Risk Measures



(a) Climate Risk Measure over Time



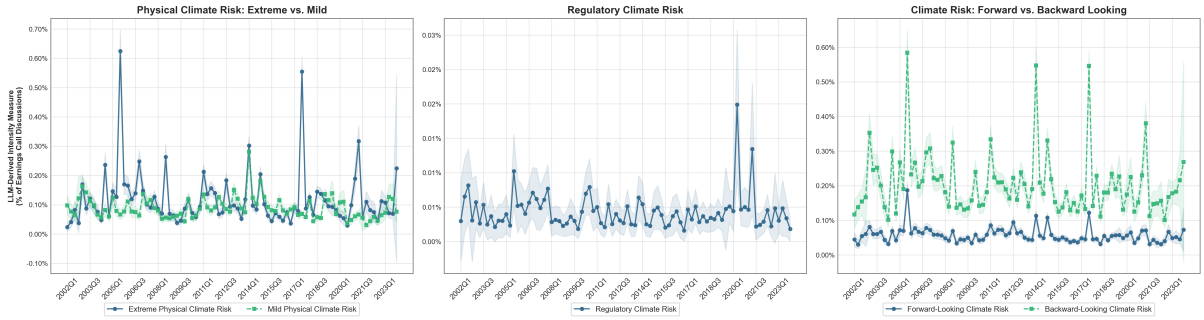
(b) Non-Climate Risk Measures over Time

Notes: This figure presents quarterly trends in climate and non-climate risk measures for U.S. publicly listed firms from 2002 to 2023. Panel A shows the climate risk measure with notable climate events annotated. Panel B shows the non-climate risk measure with major risk events annotated. Shaded regions represent 95% confidence intervals.

Moreover, given the climate-risk-related sentences identified in the first step, we further apply GPT-5

nano to classify each sentence by (i) orientation (forward- vs. backward-looking) and (ii) climate risk type (extreme physical, mild physical, and regulatory). Table 4 provides representative excerpts for each category. Figure 5 plots quarterly trends across orientations and risk types. Overall, most climate risk discussion is backward-looking and concentrated in physical climate risk. We see sharp spikes in extreme physical climate risk but not mild physical climate risk during quarters that coincide with major natural disasters.

Figure 5: Temporal Trends in Climate Risk Exposure by Type and Orientation



Notes: This figure shows quarterly time series of climate risk exposure from 2002 to 2023. The left panel compares extreme versus mild physical climate risks. The middle panel shows regulatory climate risk. The right panel contrasts forward-looking versus backward-looking climate risk discussions. Lines represent quarterly mean exposure rates. Shaded areas indicate 95% confidence intervals.

Second, we evaluate the classification accuracy of our LLM embedding-based model against traditional keyword-based methods using our labeled test set. The LLM embedding-based classifier refers to the SVM trained on sentence-level embeddings generated by OpenAI's text-embedding-ada-002 model. The keyword-based approach relies on a dictionary of 9,731 climate-related terms compiled from two recent studies (Li et al., 2024; Sautner et al., 2023), classifying a sentence as climate-related if it contains any of these predefined keywords. As reported in Table 5, though the LLM agent-based methods perform even worse than the keywords-based method, our proposed LLM embedding-based classifier achieves an 11.6% higher F1-score compared to the keyword approach, primarily driven by a 23.1% improvement in precision. Precision—the proportion of correctly identified positive cases—is especially critical in risk classification to avoid overestimating exposure. The keyword-based method exhibits a relatively high false positive rate, yielding a low precision score of 0.784.

The comparison results underscore a key limitation of the keyword-based approach—its susceptibility to a high false positive rate. This is consistent with the known drawback of keyword-matching methods, which often misclassify sentences due to their inability to capture contextual meaning. As a result, keyword-based measures systematically overestimate the intensity of climate-related concerns, particularly in industries where many of the predefined terms (e.g., those referencing energy or natural resources) are commonly used but not necessarily climate-relevant. In contrast, the LLM embedding-based classifier

Table 4: Excerpts of Earnings Call Climate Risk Discussions

Category	Company	Year	Quarter	Example
Panel A: Climate Risk Orientation				
Forward-Looking	Land Securities Group	2020	2	"Long after the COVID-19 crisis has passed, climate change will still be the defining challenge over the next 2 decades."
	PAO NOVATEK	2020	3	"Climate change is the defining issue of this generation. The oil and gas industry are at the forefront of this debate, and we must ensure that our collective efforts remain focused."
	Coal India Limited	2020	3	"Once rainfalls takes place – if there is heavy rainfall in September, October, November, then the demand will get reduced."
Backward-Looking	DTE Energy Company	2021	2	"This was $114 million higher than the first quarter of 2020 primarily due to new rate implementation and colder weather in 2021."
	Westlake Corporation	2021	1	"As the effects of the hurricanes limited our production and sales volumes for both ethylene and polyethylene, our fourth quarter 2020 operating income of $22 million decreased $27 million from the fourth quarter 2019."
	Imperial Oil Limited	2022	1	"Unplanned downtime, coupled with extreme cold weather presented challenges for these operations in December as detailed in the statement issued by the operator, Suncor, earlier in January."
Panel B: Climate Risk Type				
Extreme Physical	Sanghi Industries	2020	1	"While the plant is ready to operate, because of the heavy downfall, the mines were flooded and we were not able to extract the material."
	Gujarat Pipavav Port	2022	2	"The 11% corresponds basically to the drop also about 10% in container volumes that's directly attributed to the cyclone."
	Odfjell SE	2021	2	"When it comes to the Texas freeze, we have said that around USD 2 million negatively impacted our time-charter earnings in this quarter."
Mild Physical	AgroFresh Solutions	2020	3	"Disruptions related to weather and crop size in Latin America and Australia negatively impacted our SmartFresh revenue for the first half, which decreased 9%."
	LSB Industries	2020	1	"It's been a little slow going. You've had a lot of wet weather particularly in certain regions of the Western corn belt, but we've also seen a lot of wet weather in the Eastern corn belt."
	TreeHouse Foods	2013	2	"The crops were a little bit late in the Southeast and the cool weather has delayed some of the plantings and we have had some storms in the upper Midwest that could have a bit of an impact on the cucumber crop."
Regulatory	Exxaro Resources Limited	2022	3	"Worsened by the subsequent European energy crisis. With winter approaching, European governments have implemented unprecedented measures to ensure adequate energy supplies, such as thermal coal in the event that Russian gas supply seizes."
	Emerson Electric	2016	1	"Climate Technologies underlying sales declined 10% as global air conditioning sales decreased driven by higher US residential demand in the prior year resulting from regulatory changes."
	Watts Water Technologies	2017	3	"Our HVAC business was affected by a slowdown in demand associated with a directive to use more energy efficient products in Italy."

Notes: This table presents representative examples of identified climate risk discussions. Panel A shows examples categorized by temporal orientation: forward-looking (anticipatory discussion of future climate impacts) and backward-looking (retrospective discussion of realized climate impacts). Panel B shows examples categorized by risk type: extreme physical (catastrophic events like hurricanes, floods, wildfires), mild physical (gradual weather variations affecting operations), and regulatory (climate-related policy and compliance matters).

demonstrates significantly higher precision, enabling a more nuanced and context-aware identification of climate-related content. We conclude that our LLM embedding-based measure offers a more accurate and reliable assessment of climate risk intensity, effectively capturing multifaceted risk factors with higher precision than benchmark keyword-based methods.

Table 5: Performance Metrics Comparison Between Keyword-Based and LLM-Based Classifiers

Model	**F1-Score**	**Precision**	**Recall**	**Accuracy**
Keywords-based	0.842	0.784	0.944	0.952
LLM agent-based (GPT-5-nano)	0.816	0.767	0.897	0.946
LLM embedding-based (SVM)	**0.940**	**0.965**	**0.918**	**0.987**
Improvement vs. Keywords-based:				
LLM agent-based	(−3.1%)	(−2.2%)	(−5.0%)	(−0.6%)
LLM embedding-based	(+11.6%)	(+23.1%)	(−2.8%)	(+3.7%)
Improvement vs. LLM agent-based:				
LLM embedding-based	(+15.2%)	(+25.8%)	(+2.3%)	(+4.3%)

Notes: This table compares the performance of keyword-based classifiers, LLM agent-based classifiers (GPT-5-nano), and LLM embedding-based classifiers (SVM with embeddings) for climate-related sentence classification. Note that the accuracy of all models is high because the climate class is highly imbalanced. F1-Score provides more informative metric for model comparison.

5 Empirical Strategy

Our empirical strategy exploits variation in supplier-level climate risk exposure as a plausibly exogenous shock to identify its causal effects on downstream firm performance and supply chain restructuring. Specifically, we test whether upstream climate risk events lead to adverse performance outcomes and prompt strategic adjustments in the downstream firm's supplier network. The key treatment variable is an indicator, $\mathbb{1}(\text{Suppliers Climate Risk})_{it}$, which equals one if at least one supplier of firm i is exposed to climate risk in quarter t, and zero otherwise.

We employ a two-way fixed effects (TWFE) regression framework, which is consistent with existing literature on supply chain propagation of natural disasters and extreme weather (Barrot and Sauvagnat, 2016; Pankratz and Schiller, 2024). Our baseline specification is given by:

$$\begin{aligned} Y_{i,t} = \boldsymbol{\alpha}' \boldsymbol{X_{i,t-4}} + \beta_1 \mathbb{1}(\text{Suppliers Climate Risk})_{i,(t-4,t)} \\ + \beta_2 \mathbb{1}(\text{Climate Risk})_{i,(t-4,t)} + \gamma_i + \delta_t + \epsilon_{it}, \end{aligned} \tag{7}$$

where $Y_{i,t}$ represents the outcome of interest for firm i in quarter t. The primary treatment variable is $\mathbb{1}(\text{Suppliers Climate Risk})_{i,(t-4,t)}$, a binary indicator equal to one if at least one supplier of firm i was exposed to climate risk within the previous four quarters, and zero otherwise. To isolate the impact of upstream climate risk exposure, we also control for the firm's own direct exposure to climate risk using the indicator $\mathbb{1}(\text{Climate Risk})_{i,(t-4,t)}$, which captures whether firm i experienced any climate-related risk during the same period.

The control vector $X_{i,t-4}$ includes firm-specific time-variant controls: number of suppliers, capturing

supply network size; text-based network industry concentration index derived by Hoberg and Phillips (2016), measuring industrial competition; inventory turnover ratio, measuring firm operational efficiency; debt-to-asset ratio, measuring financial leverage; capital expenditure-to-asset ratio, measuring physical investment intensity; R&D intensity, capturing innovation efforts; and asset tangibility, measuring physical capital dependence and potential vulnerability to disruptions. All control variables are measured at $t-4$ to avoid simultaneity bias. In some specifications, we further expand $X_{i,t-4}$ to include firm-level non-climate risk.

Our outcome vector $Y_{i,t}$ includes three categories of dependent variables. First, we examine downstream firm performance, measured by the four-quarter percentage growth in sales, Sales Growth$_{i,(t-4,t)}$ and operating income, Operating Income Growth$_{i,(t-4,t)}$. Including these firm performance dependent variables helps capture the downstream consequences of supplier climate risk exposure, offering insight into why firms are motivated to actively restructure their supply networks in response. The corresponding empirical results are presented in Section 6.1.

Second, we assess supply chain restructuring through three indicators: $\mathbb{1}(\text{Suppliers Termination})_t$, a binary variable equal to one if firm i terminates at least one existing supplier relationship in quarter t; $\mathbb{1}(\text{Suppliers Addition})_t$, equal to one if firm i adds at least one new supplier during quarter t; and ΔN Suppliers$_{(t,t-4)}$, the net change in the number of suppliers over the four quarters from $t-4$ to t. These variables capture active re-selection of suppliers in response to upstream climate risk.

Third, we investigate geo-diversification of the supply base, using three widely adopted metrics in the supply chain literature (Chu et al., 2019; Bray et al., 2019): the logarithm of the mean customer–supplier distance, indicating the average geographic proximity of suppliers; the logarithm of the variance in supplier locations, capturing geographic dispersion using supplier physical locations; and supplier state concentration, which reflects spatial clustering of suppliers at the U.S. state level. These variables further examine how downstream firms allocate the geographic locations of their restructured supplier networks. The corresponding empirical results on restructuring and geo-diversification are presented in Section 6.2.

To address potential endogeneity concern, we incorporate a comprehensive set of fixed effects. Firm fixed effects (γ_i) control for time-invariant characteristics, such as industry positioning, corporate governance structures, and persistent risk preferences. Year-quarter fixed effects (δ_t) absorb macroeconomic shocks, global market dynamics, and temporal trends affecting all firms within the same period. In extended specifications, we further include industry-year fixed effects to account for sector-specific shocks over time, ensuring that the estimated effects are not confounded by industry-wide developments.

Another identification concern is the potential confounding between supplier and focal firm risk exposures. To address this, we explicitly control for the firm's own climate and non-climate risk exposures, measured from contemporaneous earnings call transcripts. This ensures that the estimated effects of supplier climate risk are not conflated with direct climate-related or non-climate risk faced by the focal firm itself.

To further explore the dynamics of supply chain restructuring, we extend model (7) to a distributed lag model:

$$Y_{i,t} = \boldsymbol{\alpha}' \boldsymbol{X_{i,t-4}} + \sum_{k=0}^{4} \beta_k \mathbb{1}(\text{Suppliers Climate Risk})_{i,t-k} \tag{8}$$
$$+ \theta \mathbb{1}(\text{Climate Risk})_{i,(t-4,t)} + \gamma_i + \delta_t + \epsilon_{it},$$

where $\mathbb{1}(\text{Climate Risk})_{i,t-k}$ and $\mathbb{1}(\text{Suppliers Climate Risk})_{i,t-k}$ indicate whether firm i itself or its suppliers, respectively, were exposed to climate risk in quarter $t-k$, over the past five quarters ($k=0,1,...,4$). This specification allows us to estimate how quickly firms react to climate risk and how these effects dynamically evolve.

To provide deeper insights into the heterogeneity of firms' supply chain restructuring responses, we further decompose two of our primary dependent variables—supplier termination and supplier addition—based on key supplier characteristics. Specifically, we categorize terminated and added suppliers according to their climate risk exposure and their positions along two strategic dimensions: input specificity and supply chain centrality. This decomposition allows us to assess, first, whether supplier re-selection is indeed driven by the supplier climate risk, and second, whether firms strategically restructure supplier relationships—for example, by treating critical suppliers with high input specificity and centrality differently. The results of this decomposition analysis are presented in Section 6.3.

6 Empirical Findings

6.1 Supplier Climate Risk and Firm Performance

We first examine whether or not supplier climate risk affect downstream firm performance in terms of sales and operational income growth. This analysis helps justify why downstream firms may be motivated to proactively respond to such risk. We build on the methodologies of Barrot and Sauvagnat (2016) and Pankratz and Schiller (2024) to examine the effects of both direct and supplier climate risk exposure on firm sales growth and operational income growth.

Table 6 presents results from the year-level aggregated analysis. Columns (1) through (3) sequentially

introduce firm-level controls, non-climate risk controls, and industry-year fixed effects. Across all specifications, we find that supplier climate risk exposure has a significantly negative impact on both sales growth and operational income growth, while direct (self)climate risk exposure exhibits a significant negative impact on sales growth but not operational income growth. Specifically, after controlling for both direct climate risk and non-climate risk exposures, if one of the focal company's suppliers is exposed to climate risk in a given four-quarter period, the corresponding sales growth decreases by approximately 3.0%, which is comparable to the impact of direct climate risk exposure on the firm itself (3.2%). Moreover, supplier climate risk exposure leads to a 6.8% decline in operational income growth.

These results are consistent with the evidence from Barrot and Sauvagnat (2016) and Pankratz and Schiller (2024). We find evidence that climate risk not only directly impact firm performance but also cascade through supply chains. Furthermore, compared to direct climate risk exposure, upstream exposure leads to more significant disruptions in production processes and cost structures, underscoring the operational vulnerabilities created by upstream risk.

Table 6: Direct and Propagation Impacts of Climate Risk Exposure on Firm Performance

	Panel A: Sales Growth			**Panel B: Operational Income Growth**		
	Sales Growth$_{i,(t-4,t)}$			Operational Income Growth$_{i,(t-4,t)}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$	-0.032^{**}	-0.032^{**}	-0.030^{**}	-0.077^{**}	-0.077^{**}	-0.068^{*}
	(0.014)	(0.014)	(0.014)	(0.035)	(0.035)	(0.035)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	-0.037^{***}	-0.035^{***}	-0.032^{**}	-0.046	-0.044	-0.044
	(0.013)	(0.013)	(0.013)	(0.029)	(0.030)	(0.030)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes
Observations	19,364	19,364	19,364	19,291	19,291	19,291
Adjusted R^2	0.352	0.353	0.374	0.095	0.095	0.100

Notes: This table presents two-way fixed effects regression results examining the direct impact and propagation of climate risk exposure through supply chains. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level. Panel A reports results for sales growth rate, while Panel B presents results for operational income growth rate, both measured over a five-quarter period $(t-4,t)$. The key independent variables are $\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$, an indicator variable equal to one if any supplier of the focal firm was exposed to climate risks during the four-quarter period $(t-4,t)$, and $\mathbb{1}$(Climate Risk)$_{(t-4,t)}$, an indicator variable equal to one if the focal firm itself was exposed to climate risks during the same period. All models include firm-specific time-variant controls: number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (2) and (5) also control for text-based non-climate corporate risks at $t-4$. Models (3) and (6) present the full specification with industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2 Supplier Climate Risk and Supply Chain Restructuring

Given the impact of supplier climate risk over firm performance, a natural follow-up question is, do firms proactively restructure their supply chains in response to such upstream risk? We explore this question by analyzing whether firms respond by terminating existing supplier relationships, adding new suppliers, and adjusting the geographic configuration of their supply networks.

Supply chains are governed by relational contracts that can be terminated or renegotiated when conditions change (Baker et al., 2002; Klein et al., 1978). Since supplier climate risk exposure negatively impacts downstream firms' sales and operating income, we anticipate that firms may adapt their supply networks to mitigate climate risk exposure and enhance resilience through two primary mechanisms: **supplier re-selection** (Section 6.2.1) and **geographic diversification** (Section 6.2.2).

6.2.1 Supplier Re-Selection

Customer firms often wield strong bargaining power in supply chains. Prior research shows that dominant buyers impose stricter trade credit terms, enforce annual cost-reduction requirements, and shift inventory risk onto suppliers to minimize their own exposure to uncertainty (Baker et al., 2002; Klein et al., 1978). When climate risk disrupt supply chains, these power asymmetries may intensify, prompting firms to reconstruct their supplier relationships. In such cases, firms may terminate relationships with suppliers vulnerable to climate risk and prioritize partnerships with more resilient, adaptive suppliers.

This competitive view of supply chain relationships highlights supplier re-selection as a strategic, proactive response to mitigate future disruptions and maintain operational stability. Motivated by this competitive view of supplier-customer relationships, we examine whether supplier climate risk increase the likelihood of downstream firms terminating existing supplier relationships and adding new ones.

Table 7 presents the year-level aggregated estimates of supplier termination and addition. We find that supplier climate risk exposure significantly increases the probability that firms restructure their supplier base: the likelihood of terminating at least one supplier rises by 5.3%, and the probability of adding new suppliers increases by 6.3%. In contrast, firms' own climate risk exposure does not yield statistically significant effects on supplier restructuring, suggesting that firms respond more strongly to upstream than to self-experienced risk. Furthermore, the decomposition results suggest that the restructuring response is mainly driven by suppliers' backward-looking and extreme physical climate risk exposure, whereas suppliers' regulatory climate risk shows little association with restructuring outcomes.

Table 7: Impact of Supplier Climate Risks on Downstream Supply Chain Restructuring

	Panel A: Supplier Termination			**Panel B: Supplier Addition**			**Panel C: Net Change in Suppliers**		
	$\mathbb{1}(\text{Suppliers Termination})_t$			$\mathbb{1}(\text{Suppliers Addition})_t$			$\Delta\text{N Suppliers}_{(t,t-4)}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{1}(\text{Suppliers Climate Risk})_{(t-4,t)}$	0.050***	0.050***	0.053***	0.064***	0.064***	0.063***	−0.301**	−0.300**	−0.290**
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.117)	(0.117)	(0.116)
$\mathbb{1}(\text{Climate Risk})_{(t-4,t)}$	0.023*	0.023*	0.020	−0.026**	−0.026**	−0.028**	0.067	0.078	−0.015
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.142)	(0.142)	(0.140)
Decomposition by Climate Risk Orientation:									
$\mathbb{1}(\text{Suppliers Forward-Looking Climate Risk})_{(t-4,t)}$	0.033**	0.034**	0.030**	0.038***	0.040***	0.032**	−0.191*	−0.168	−0.238**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.111)	(0.109)	(0.109)
$\mathbb{1}(\text{Suppliers Backward-Looking Climate Risk})_{(t-4,t)}$	0.047***	0.049***	0.052***	0.055***	0.059***	0.056***	−0.281**	−0.250**	−0.255**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.119)	(0.116)	(0.117)
Decomposition by Climate Risk Type:									
$\mathbb{1}(\text{Suppliers Extreme Physical Climate Risk})_{(t-4,t)}$	0.050***	0.050***	0.041***	0.064***	0.066***	0.064***	−0.295**	−0.268*	−0.262*
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.148)	(0.144)	(0.142)
$\mathbb{1}(\text{Suppliers Mild Physical Climate Risk})_{(t-4,t)}$	0.020	0.021	0.030**	0.030*	0.031*	0.023	0.110	0.120	0.080
	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.015)	(0.157)	(0.155)	(0.162)
$\mathbb{1}(\text{Suppliers Regulatory Climate Risk})_{(t-4,t)}$	−0.007	−0.007	−0.013	0.011	0.011	0.009	0.250	0.242	0.162
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.270)	(0.270)	(0.256)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	19,319	19,319	19,319	19,319	19,319	19,319	19,319	19,319	19,319
Adjusted R^2	0.396	0.397	0.413	0.387	0.388	0.409	0.370	0.370	0.407

Notes: This table presents two-way fixed effects regression results examining firms' supply chain restructuring responses to supplier climate risk exposure. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level. Panel A reports results for supplier termination, Panel B for supplier addition, and Panel C for net change in the number of suppliers. The main independent variable is $\mathbb{1}(\text{Suppliers Climate Risk})_{(t-4,t)}$, an indicator variable equal to one if any supplier of the focal firm was exposed to climate risks during the four-quarter period $(t-4,t)$. We decompose supplier climate risk exposure by orientation (forward-looking vs. backward-looking) and by type (extreme physical, mild physical, and regulatory). $\mathbb{1}(\text{Climate Risk})_{(t-4,t)}$ is an indicator variable equal to one if the focal firm itself was exposed to climate risks during the same period. All models include firm-specific time-variant controls: number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (2), (5), and (8) also control for text-based non-climate corporate risks at $t-4$. Models (3), (6), and (9) present the full specification with industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

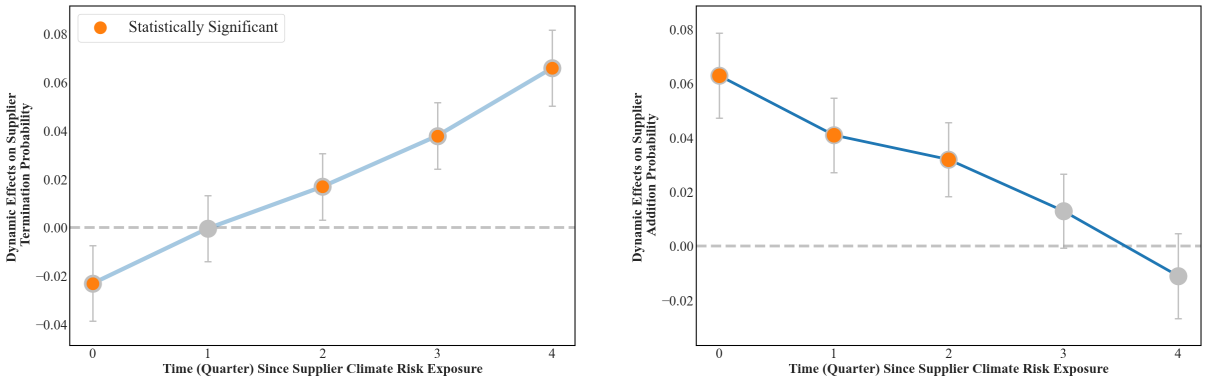
Figure 6 and Table 8 report the dynamic effects of supplier climate risk exposure on supplier termination and addition decisions over the five quarters following exposure. These dynamics offer deeper insights into the timing of re-selection. First, we observe a clear temporal divergence: the effect on supplier termination grows stronger over time, whereas the effect on supplier addition is immediate but diminishes and becomes statistically insignificant after three quarters.

Interestingly, we observe an initial negative effect of supplier climate risk on the probability of termination. This counterintuitive result may reflect manufacturing lead times. Because batch production is common in many industries, customer firms often place orders months in advance. When climate events disrupt a supplier's production, customer firms may already be committed to ongoing orders that are in process, making immediate termination infeasible. Instead, they must wait out the disruption, delaying any restructuring until future procurement cycles. This lag highlights the operational frictions

that shape firms' ability to respond to upstream climate risk in real time.

Taken together, these results suggest that firms do respond strategically to upstream climate risk by actively restructuring their supplier networks. The significant increases in both supplier termination and addition probabilities point to deliberate re-selection efforts rather than passive adjustments. Moreover, the dynamic patterns reveal that firms face operational frictions—such as manufacturing lead times—that delay termination but allow more immediate additions. These findings reinforce the view that firms leverage supplier re-selection as a proactive supplier climate risk responding strategy. The next section builds on this by investigating whether such restructuring is accompanied by changes in the geographic configuration of firms' supplier networks.

Figure 6: Dynamic Effects of Supplier Climate Risk on Supplier Re-selection



(a) Dynamic Effects on Supplier Termination Probability

(b) Dynamic Effects on Supplier Addition Probability

Notes: This figure presents the dynamic effects of supplier climate risk exposure on downstream firms' probability of (a) terminating existing suppliers and (b) adding new suppliers over the subsequent four quarters. Each point represents the estimated effect for a given quarter since exposure, with 95% confidence intervals. Orange points indicate statistically significant effects at the 5% level. The detailed regression results are presented in Table 8.

Table 8: Dynamic Impact of Supplier Climate Risks on Downstream Supply Chain Restructuring

	Dependent Variables								
	$\mathbb{1}$**(Suppliers Termination)**$_t$			$\mathbb{1}$**(Suppliers Addition)**$_t$			Δ**N Suppliers**$_{(t,t-4)}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{1}$(Suppliers Climate Risk)	-0.019^{**}	-0.019^{**}	-0.023^{***}	0.069^{***}	0.069^{***}	0.063^{***}	0.534^{***}	0.532^{***}	0.452^{***}
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.091)	(0.091)	(0.091)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-1}$	0.003	0.003	-0.0003	0.045^{***}	0.045^{***}	0.041^{***}	0.288^{***}	0.287^{***}	0.218^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.077)	(0.077)	(0.079)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-2}$	0.018^{**}	0.018^{**}	0.017^{**}	0.034^{***}	0.034^{***}	0.032^{***}	0.010	0.010	-0.029
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.057)	(0.057)	(0.058)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-3}$	0.038^{***}	0.038^{***}	0.038^{***}	0.013^{*}	0.013^{*}	0.013^{*}	-0.201^{***}	-0.200^{***}	-0.205^{***}
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.061)	(0.061)	(0.062)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-4}$	0.066^{***}	0.066^{***}	0.066^{***}	-0.011	-0.011	-0.011	-0.620^{***}	-0.619^{***}	-0.585^{***}
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.077)	(0.077)	(0.077)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	0.022^{*}	0.022^{*}	0.020	-0.027^{**}	-0.027^{**}	-0.029^{**}	0.065	0.075	-0.014
	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.141)	(0.142)	(0.140)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	19,319	19,319	19,319	19,319	19,319	19,319	19,319	19,319	19,319
Adjusted R^2	0.399	0.399	0.416	0.390	0.390	0.411	0.373	0.373	0.409

Notes: This table presents fixed effects regression results examining firms' supply chain restructuring responses to climate risk exposure. All specifications include firm and year-quarter fixed effects with standard errors clustered at the firm level, reported in parentheses. The dependent variables are: Columns (1)-(3) indicator for supplier termination; Columns (4)-(6) indicator for supplier addition; and Columns (7)-(9) net change in number of suppliers. The key independent variables are indicators for firms with climate-exposed suppliers at different time lags, and an indicator for firms directly exposed to climate risk. Firm-level controls include number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (3), (6), and (9) also control for text-based non-climate corporate risks at $t-4$. Models (3), (6), and (9) include additional industry-year fixed effects and control variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2.2 Geo-Diversification

Beyond terminating and replacing individual suppliers, firms may adapt to climate risk by restructuring the geographic composition of their supplier networks. One key aspect of this strategy involves modifying supplier-customer distances and increasing spatial dispersion among suppliers. A geographically diversified supplier base allows firms to hedge against region-specific climate shocks by spreading risk across a broader set of locations. Because climate disruptions, such as floods, wildfires, or extreme heat, are often regionally concentrated, maintaining a more dispersed supplier network provides firms with operational flexibility to shift sourcing away from affected areas.

This strategy aligns with two theoretical perspectives. First, the resource-based view posits that access to a more diverse and flexible resource base strengthens a firm's ability to adapt to uncertainty. By expanding supplier networks beyond specific regions, firms enhance their capacity to absorb shocks and respond effectively to supply chain disruptions. Second, portfolio selection theory suggests that diversification reduces exposure to firm-specific risk, thereby lowering cash-flow volatility and enhancing financial resilience. A broader supplier base ensures that firms are not overly reliant on any single supplier, reducing the likelihood of operational bottlenecks when climate-related disruptions occur.

In addition to geographic diversification of the supplier base, increasing the average distance between suppliers and customers may further enhance supply chain resilience. By distributing sourcing across multiple regions, firms reduce the likelihood that localized disruptions evolve into system-wide operational breakdowns. This strategic adjustment underscores the value of proactive supply chain restructuring in the face of rising climate risk.

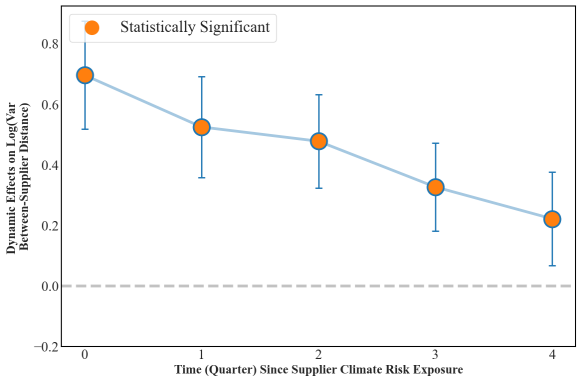
To test this empirically, we examine whether firms facing supplier climate risk actively diversify their supplier networks along geographic locations, in line with the predictions of the resource-based view and portfolio selection theory. Table 9 shows that firms exposed to upstream climate risk are significantly more likely to replace terminated suppliers with new ones located in more geographically dispersed locations and across a broader set of states in one year after the supplier climate risk exposure. Moreover, the decomposition results suggest that this diversification response is stronger when suppliers' climate risk are backward-looking and physical (both extreme and mild), while suppliers' regulatory climate risk shows limited association with downstream geographic diversification. The dynamic analysis points to a similar pattern (see Figure 7 and Table 10).

Table 9: Impact of Supplier Climate Risk Exposure on Downstream Geographic Diversification

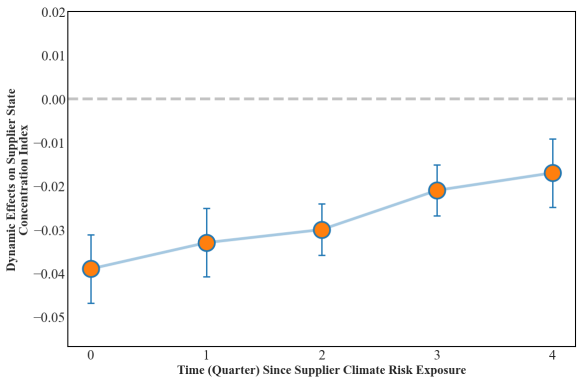
	Panel A: Variance Between-Supplier Distance			**Panel B: Supplier State Concentration**		
	Log(Variance Between-Supplier Distance $+1)_t$			Concentration Index_t		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\text{Suppliers Climate Risk})_{(t-4,t)}$	1.413***	1.413***	1.422***	−0.074***	−0.074***	−0.075***
	(0.189)	(0.189)	(0.189)	(0.008)	(0.008)	(0.008)
$\mathbb{1}(\text{Climate Risk})_{(t-4,t)}$	−0.239*	−0.246*	−0.179	0.003	0.004	0.003
	(0.140)	(0.140)	(0.140)	(0.006)	(0.006)	(0.006)
Decomposition by Climate Risk Orientation:						
$\mathbb{1}(\text{Suppliers Forward-Looking Climate Risk})_{(t-4,t)}$	0.687***	0.718***	0.689***	−0.033***	−0.034***	−0.033***
	(0.147)	(0.148)	(0.141)	(0.007)	(0.007)	(0.006)
$\mathbb{1}(\text{Suppliers Backward-Looking Climate Risk})_{(t-4,t)}$	1.075***	1.113***	1.120***	−0.060***	−0.060***	−0.060***
	(0.174)	(0.175)	(0.179)	(0.007)	(0.007)	(0.007)
Decomposition by Climate Risk Type:						
$\mathbb{1}(\text{Suppliers Extreme Physical Climate Risk})_{(t-4,t)}$	0.886***	0.900***	0.947***	−0.056***	−0.056***	−0.055***
	(0.167)	(0.168)	(0.167)	(0.007)	(0.007)	(0.007)
$\mathbb{1}(\text{Suppliers Mild Physical Climate Risk})_{(t-4,t)}$	0.636***	0.659***	0.551***	−0.036***	−0.036***	−0.035***
	(0.166)	(0.165)	(0.150)	(0.007)	(0.007)	(0.007)
$\mathbb{1}(\text{Suppliers Regulatory Climate Risk})_{(t-4,t)}$	0.047	0.049	0.052	−0.014*	−0.014*	−0.013
	(0.189)	(0.188)	(0.193)	(0.008)	(0.008)	(0.008)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes
Observations	18,381	18,381	18,381	19,316	19,316	19,316
Adjusted R^2	0.658	0.659	0.673	0.719	0.720	0.729

Notes: This table presents two-way fixed effects regression results examining firms' geographic diversification responses to climate risk exposure. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level. Panel A reports results for log variance in supplier distance, capturing geographic dispersion using supplier physical locations. Panel B presents results for supplier state concentration index (Herfindahl-Hirschman Index for share of suppliers distribution over U.S. states), reflecting spatial clustering of suppliers. The main independent variable is $\mathbb{1}(\text{Suppliers Climate Risk})_{(t-4,t)}$, an indicator variable equal to one if any supplier of the focal firm was exposed to climate risks during the four-quarter period $(t-4,t)$. We decompose supplier climate risk exposure by orientation (forward-looking vs. backward-looking) and by type (extreme physical, mild physical, and regulatory). $\mathbb{1}(\text{Climate Risk})_{(t-4,t)}$ is an indicator variable equal to one if the focal firm itself was exposed to climate risks during the same period. All models include firm-specific time-variant controls: number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (2) and (5) also control for text-based non-climate corporate risks at $t-4$. Models (3) and (6) present the full specification with industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 7: Dynamic Effects of Supplier Climate Risk on Geo-Diversification



(a) Dynamic Effects on Log Variance of Supplier Distance



(b) Dynamic Effects on Supplier State Concentration Index

Notes: This figure presents the dynamic effects of supplier climate risk exposure on downstream firms' supplier geo-diversification. Panel (a) shows the effect on the log variance of supplier distances, capturing geographic dispersion. Panel (b) presents the effect on the supplier state concentration index, measuring geographic clustering. Each point represents the estimated effect for a given quarter since exposure, with 95% confidence intervals. Orange points indicate statistical significance at the 5% level. Detailed regression results are reported in Table 10.

Table 10: Dynamic Impact of Supplier Climate Risk Exposure on Downstream Geographic Diversification

	Dependent Variables								
	Log(Avg Customer-Supplier Distance +1)$_t$			**Log(Variance Between-Supplier Distance +1)$_t$**			**Supplier State Concentration Index$_t$**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbb{1}$(Suppliers Climate Risk)	0.037***	0.037**	0.041***	0.689***	0.692***	0.696***	−0.040***	−0.040***	−0.039***
	(0.014)	(0.014)	(0.014)	(0.095)	(0.095)	(0.091)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-1}$	0.022*	0.022*	0.026**	0.533***	0.534***	0.525***	−0.033***	−0.033***	−0.033***
	(0.012)	(0.012)	(0.012)	(0.086)	(0.086)	(0.085)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-2}$	0.016	0.016	0.019*	0.469***	0.469***	0.478***	−0.029***	−0.029***	−0.030***
	(0.011)	(0.011)	(0.011)	(0.080)	(0.079)	(0.079)	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-3}$	0.009	0.009	0.013	0.313***	0.312***	0.327***	−0.020***	−0.020***	−0.021***
	(0.010)	(0.010)	(0.010)	(0.075)	(0.075)	(0.074)	(0.003)	(0.003)	(0.003)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-4}$	0.015	0.015	0.020*	0.214***	0.213***	0.222***	−0.017***	−0.017***	−0.017***
	(0.012)	(0.012)	(0.011)	(0.082)	(0.081)	(0.079)	(0.004)	(0.004)	(0.004)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	0.027	0.027	0.031	−0.242*	−0.249*	−0.183	0.004	0.004	0.003
	(0.022)	(0.022)	(0.023)	(0.140)	(0.140)	(0.140)	(0.006)	(0.006)	(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	19,128	19,128	19,128	18,381	18,381	18,381	19,316	19,316	19,316
Adjusted R^2	0.581	0.581	0.593	0.659	0.659	0.674	0.721	0.721	0.731

Notes: This table presents fixed effects regression results examining firms' geographic diversification responses to climate risk exposure. All specifications include firm and year-quarter fixed effects with standard errors clustered at the firm level, reported in parentheses. The dependent variables are: Columns (1)-(3) log mean supplier distance; Columns (4)-(6) log variance between supplier distance; and Columns (7)-(9) supplier state HHI. The key independent variables are indicators for firms with climate-exposed suppliers at different time lags, and an indicator for firms directly exposed to climate risk. Firm-level controls include number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (2), (5), and (8) control for text-based non-climate corporate risks at $t-4$. Models (3), (6), and (9) include additional industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

In summary, Sections 6.2.1 and 6.2.2 provide strong empirical evidence that firms strategically restructure their supply chains in response to supplier climate risk—by terminating vulnerable suppliers, adding new ones, and increasing the geographic dispersion of their sourcing networks. The dynamic patterns reveal that supplier addition tends to occur more immediately, while supplier termination and geographic diversification unfold more gradually, reflecting the longer lead times and coordination efforts needed to establish new supplier relationships across regions. Over time, geographic diversification emerges as a critical adaptation strategy, enabling firms to buffer against region-specific climate shocks and enhance long-term supply chain resilience.

6.3 Decomposing Supply Chain Restructuring

We further conduct a decomposition analysis to assess whether firms' supply chain restructuring decisions—specifically supplier termination and addition—are influenced by key supplier characteristics, including climate risk exposure, input specificity, and network centrality. This decomposing analysis serves two primary purposes.

First, it allows us to differentiate strategic restructuring from routine supplier turnover that occurs as part of normal business operations. By isolating the role of climate risk, we assess whether observed changes in supplier networks reflect targeted responses to climate risk rather than standard procurement adjustments.

Second, it allows us to evaluate whether firms respond heterogeneously based on the strategic importance of suppliers. Specifically, we examine whether firms are more likely to retain suppliers that provide highly specialized inputs or hold central positions in the supply network. These distinctions offer insight into how firms prioritize supplier relationships when managing climate-induced risk and reveal how supply networks adapt under environmental stress.

Table 11 presents model-free evidence of asymmetries in how downstream firms respond to supplier climate risk exposure. Panel A decomposes supplier termination and addition decisions based on whether the affected suppliers were exposed to climate risk during the quarter. For supplier termination, we find that firms do terminate both climate-exposed and non-exposed suppliers. However, among firms that terminated at least one supplier, 89.7% dropped suppliers that had been exposed to climate risk—suggesting that climate exposure is a key factor influencing termination decisions. This pattern is consistent with our earlier finding that supplier climate risk negatively affect downstream firm performance, prompting firms to adapt by reassessing their supplier relationships. For supplier addition,

the evidence is even more striking: 100% of the newly added suppliers had not been exposed to climate risk in the prior four quarters. This suggests that downstream firms not only respond to past disruptions but also proactively screen for climate resilience when expanding or restructuring their supplier networks.

Table 11: Decomposition of Supplier Terminations and Additions

Variable	Termination mean (%)	Addition mean (%)	N (Termination)	N (Addition)
Panel A: Decomposition by Supplier Climate Risk				
Climate risk exposure	44.5	0.0	29,059	20,565
No climate risk exposure	89.7	100.0	29,059	20,565
Panel B: Decomposition by Supplier Input Specificity				
Non-specific (High TNIC similarity)	100.0	76.4	51,123	33,662
Non-specific (Low TNIC HHI)	100.0	75.4	51,123	33,662
Non-specific (Low patents)	100.0	79.1	51,123	33,662
Specific (High TNIC HHI)	0.0	67.2	51,123	33,662
Specific (High patents)	0.0	61.8	51,123	33,662
Specific (Low TNIC similarity)	0.0	65.5	51,123	33,662
Panel C: Decomposition by Supplier Centrality				
Non-central (Low Closeness Centrality)	100.0	73.3	51,123	33,662
Non-central (Low Betweeness Centrality)	100.0	73.8	51,123	33,662
Non-central (Low Degree Centrality)	100.0	65.8	51,123	33,662
Central (High Closeness Centrality)	0.0	70.0	51,123	33,662
Central (High Betweeness Centrality)	0.0	69.1	51,123	33,662
Central (High Degree Centrality)	0.0	76.9	51,123	33,662

Notes: This table reports means (in %) computed only among quarters with at least one supplier termination or addition, respectively. N reports non-missing counts per column.

An intriguing question arises here: why are some suppliers that were not exposed to climate risk also terminated? We argue that this pattern is driven by supplier strategic importance and power within the supply chain network. When deciding whether to terminate a supplier, firms consider not only the supplier's past climate risk exposure but also their input specificity and network centrality. As shown in Panels B and C, our data reveal no cases in which firms terminated suppliers that provided irreplaceable inputs or occupied highly central positions in the supply chain. In contrast, suppliers that are less specific or less central—even if not exposed to climate risk—are more likely to be removed during restructuring. This vulnerability is due to their lack of power in the supply chain and their relatively passive position, making them more vulnerable to termination when downstream firms restructure their supply networks.

To move beyond descriptive patterns, we next conduct a more systematic stratified analysis to test whether supplier characteristics—climate risk exposure, input specificity, and network centrality—significantly shape termination and addition decisions.

6.3.1 Climate Risk Exposure

We first examine whether the earlier findings on supply network restructuring are driven by climate risk concerns or merely reflect standard procurement adjustments. To do so, we decompose the supplier

termination decision into two subgroups: terminations of suppliers that were exposed to climate risk during the quarter suppliers that were not.

Table 12 reports the results of this stratified panel regression. We find that the significant termination effects reported in Section 6.2.1 are primarily driven by terminations of suppliers that had been exposed to climate risk. In contrast, we do not observe statistically significant relationships between supplier climate risk exposure and the termination of suppliers that were not exposed. These findings confirm that the observed restructuring behavior is indeed a targeted response to supplier climate risk, rather than a reflection of routine or contemporaneous supply chain adjustments.

Table 12: Impact of Climate Risk Exposure on Supplier Termination Decisions

	Panel A: Termination of Climate-Exposed Suppliers			**Panel B: Termination of Non-Exposed Suppliers**		
	$\mathbb{1}$(Suppliers Termination: Climate Risk)$_t$			$\mathbb{1}$(Suppliers Termination: Non-Climate Risk)$_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Suppliers Climate Risk)$_t$	−0.060***	−0.060***	−0.051***	0.008	0.008	0.006
	(0.015)	(0.015)	(0.014)	(0.007)	(0.007)	(0.006)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-1}$	−0.047***	−0.047***	−0.044***	0.009	0.009	0.009
	(0.012)	(0.012)	(0.012)	(0.007)	(0.007)	(0.006)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-2}$	−0.008	−0.008	−0.013	−0.002	−0.002	−0.0004
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-3}$	−0.0002	−0.0002	−0.007	−0.002	−0.002	−0.001
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)	(0.006)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-4}$	0.036***	0.036***	0.026**	−0.009	−0.009	−0.006
	(0.011)	(0.011)	(0.011)	(0.006)	(0.006)	(0.006)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	0.001	0.001	−0.0001	−0.001	−0.002	−0.002
	(0.020)	(0.020)	(0.020)	(0.010)	(0.010)	(0.009)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	No	Yes	Yes	No	Yes	Yes
Industry-Year FE	No	No	Yes	No	No	Yes
Observations	8,102	8,102	8,102	8,102	8,102	8,102
Adjusted R^2	0.291	0.291	0.337	0.409	0.409	0.452

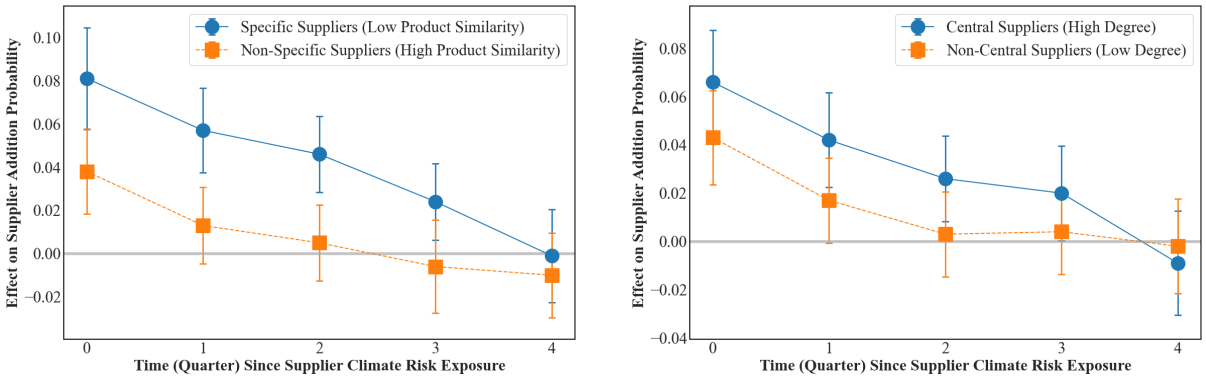
Notes: This table presents two-way fixed effects regression results examining how climate risk exposure affects firms' decisions to terminate supplier relationships. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level. Panel A reports results for termination of at least one climate-risk exposed supplier at time period t. Panel B presents results for termination of at least one supplier without climate risk exposure at time period t. The key independent variables are indicators for firms with climate-exposed suppliers ($\mathbb{1}$(Suppliers Climate Risk)) at different time lags, and $\mathbb{1}$(Climate Risk)$_{(t-4,t)}$, an indicator for firms directly exposed to climate risk. All models include firm-specific time-variant controls: number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. Models (2) and (5) also control for text-based non-climate corporate risks at $t-4$. Models (3) and (6) present the full specification with industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.3.2 Input Specificity and Supply Chain Centrality

We next conduct a second decomposition analysis to examine whether firms respond heterogeneously based on the strategic importance of their suppliers. We propose that power asymmetries in buyer–supplier relationships play a critical role in shaping supply chain restructuring decisions. Smaller suppliers often depend heavily on a few key customers for revenue, making them especially vulnerable during times

of disruption. To secure and retain these relationships, such suppliers typically invest in firm-specific assets—such as customized product development, irreversible R&D, and dedicated production capacity. These relationship-specific investments are costly and difficult to repurpose, thereby limiting the suppliers' flexibility in the face of external shocks. Consequently, supplier characteristics—particularly input specificity and supply chain centrality—are likely to influence how downstream firms restructure their networks in response to climate risk.

Figure 8: Dynamic Effects of Supplier Climate Risk on Adding Suppliers: Decomposed by Input Specificity and Centrality



(a) Dynamic Effects on Adding Specific vs. Non-Specific Suppliers

(b) Dynamic Effects on Adding Central vs. Non-Central Suppliers

Notes: This figure presents the dynamic effects of supplier climate risk exposure on downstream firms' supplier addition decisions, stratified by input specificity and network centrality. Panel (a) compares the effects on adding specific (low product similarity) versus non-specific (high product similarity) suppliers. Panel (b) compares the effects on adding central (high degree centrality) versus non-central (low degree centrality) suppliers. Each point represents the estimated effect for a given quarter since exposure, with 95% confidence intervals. Blue and orange markers correspond to different supplier categories. Detailed regression results, including those using alternative proxies for specificity and centrality, are reported in Tables 13 and 14.

Figure 8 presents the dynamic effects of supplier climate risk exposure on firms' likelihood of adding suppliers with different characteristics. Panel (a) shows that downstream firms are significantly more likely to add **specific** suppliers—those offering low product similarity—than non-specific ones. Similarly, Panel (b) shows a clear preference for **central** suppliers with higher degree centrality in the supply network. These patterns suggest that supplier addition decisions are not random but strategically targeted. In line with our earlier discussion on power asymmetries in buyer–supplier relationships, these results highlight that firms proactively rebuild their supplier networks by selecting more strategically valuable partners—those whose inputs are harder to substitute and who hold influential positions in the supply chain. This reinforces our interpretation that supply chain restructuring in response to climate risk is a strategically selective process, shaped by both risk mitigation need and the strategic importance of suppliers.

Table 13: Impact of Supplier Climate Risk on Supplier Addition: Decomposed by Input Specificity

	Dependent Variables											
	$\mathbb{1}$ (Suppliers Addition) (Low TNIC Similarity)$_t$		**$\mathbb{1}$ (Non-Specific Addition) (Low TNIC Similarity)$_t$**		**$\mathbb{1}$ (Suppliers Addition) (High TNIC HHI)$_t$**		**$\mathbb{1}$ (Non-Specific Addition) (High TNIC HHI)$_t$**		**$\mathbb{1}$ (Suppliers Addition) (High Patents)$_t$**		**$\mathbb{1}$ (Non-Specific Addition) (High Patents)$_t$**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}$(Suppliers Climate Risk)	0.083***	0.081***	0.038***	0.038***	0.078***	0.078***	0.050***	0.049***	0.058***	0.059***	0.059***	0.056***
	(0.012)	(0.012)	(0.011)	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-1}$	0.059***	0.057***	0.019**	0.013	0.048***	0.047***	0.034***	0.027***	0.030***	0.031***	0.039***	0.032***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-2}$	0.047***	0.046***	0.006	0.005	0.040***	0.040***	0.008	0.005	0.022**	0.022***	0.022**	0.019*
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-3}$	0.021**	0.024**	−0.003	−0.006	0.025***	0.026***	−0.004	−0.009	−0.004	−0.003	0.017*	0.013
	(0.010)	(0.009)	(0.010)	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-4}$	−0.002	−0.001	−0.009	−0.010	0.002	0.003	−0.019*	−0.022**	−0.020*	−0.023**	0.004	0.003
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	−0.039**	−0.040**	−0.029*	−0.036**	−0.033*	−0.033*	−0.023	−0.027*	−0.020	−0.024	−0.028*	−0.029*
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588
Adjusted R^2	0.413	0.446	0.406	0.435	0.398	0.428	0.412	0.438	0.377	0.403	0.435	0.461

Notes: This table presents two-way fixed effects regression results examining how climate risk exposure affects firms' decisions to add suppliers with different input specificity characteristics. The dependent variables are indicators for adding: (1)–(2) specific suppliers with lower-than-median product similarity (TNICSIM); (3)–(4) non-specific suppliers with higher-than-median product similarity; (5)–(6) specific suppliers with higher-than-median industrial concentration (TNICHHI); (7)–(8) non-specific suppliers with lower-than-median industrial concentration; (9)–(10) specific suppliers with higher-than-median patent counts; (11)–(12) non-specific suppliers with lower-than-median patent counts. Even-numbered columns include industry-year fixed effects. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level and reported in parentheses. Firm-level controls include number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14: Impact of Supplier Climate Risk on Supplier Addition: Decomposed by Network Centrality

	Dependent Variables											
	$\mathbb{1}$ (Specific Supplier Addition) (High Degree Centrality)$_t$		**$\mathbb{1}$ (Non-Specific Addition) (High Degree Centrality)$_t$**		**$\mathbb{1}$ (Specific Supplier Addition) (High Betweenness)$_t$**		**$\mathbb{1}$ (Non-Specific Addition) (High Betweenness)$_t$**		**$\mathbb{1}$ (Specific Supplier Addition) (High Closeness)$_t$**		**$\mathbb{1}$ (Non-Specific Addition) (High Closeness)$_t$**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}$(Suppliers Climate Risk)	0.067***	0.066***	0.044***	0.043***	0.067***	0.064***	0.049***	0.049***	0.071***	0.067***	0.048***	0.048***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-1}$	0.046***	0.042***	0.023**	0.017*	0.046***	0.040***	0.034***	0.032***	0.045***	0.039***	0.030***	0.028***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-2}$	0.028***	0.026***	0.020**	0.018**	0.032***	0.026***	0.014	0.015*	0.037***	0.033***	0.011	0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-3}$	0.006	0.007	0.004	0.003	0.008	0.003	0.003	0.003	0.007	0.002	0.013	0.013
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$\mathbb{1}$(Suppliers Climate Risk)$_{t-4}$	−0.006	−0.009	−0.004	−0.002	−0.005	−0.011	−0.004	−0.003	−0.005	−0.013	0.001	0.003
	(0.012)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	−0.030*	−0.033**	−0.032*	−0.029*	0.007	0.0004	−0.044**	−0.040**	−0.008	−0.016	−0.044***	−0.041**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-Climate Risk	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588	11,588
Adjusted R^2	0.390	0.419	0.422	0.449	0.385	0.414	0.438	0.463	0.397	0.426	0.427	0.454

Notes: This table presents two-way fixed effects regression results examining how climate risk exposure affects firms' decisions to add suppliers with different network centrality characteristics. The dependent variables are indicators for adding: (1)-(2) central suppliers with higher-than-median degree centrality; (3)-(4) non-central suppliers with lower-than-median degree centrality; (5)-(6) central suppliers with higher-than-median betweenness centrality; (7)-(8) non-central suppliers with lower-than-median betweenness centrality; (9)-(10) central suppliers with higher-than-median closeness centrality; (11)-(12) non-central suppliers with lower-than-median closeness centrality. Even-numbered columns include industry-year fixed effects. All specifications include firm and year-quarter fixed effects, with standard errors clustered at the firm level and reported in parentheses. Firm-level controls include number of suppliers, text-based network industry concentration index, inventory turnover ratio, debt-to-asset ratio, capital expenditure-to-asset ratio, R&D intensity, and asset tangibility. All control variables are measured at $t-4$ to avoid simultaneity bias. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.4 Cross-Sectional Analysis

While supplier-level characteristics such as climate risk exposure, input specificity, and network centrality play a central role in shaping firms' restructuring decisions, these responses are also likely influenced by firm-level capabilities and positioning. Theories such as the resource-based view suggest that firms with greater operational efficiency are better equipped to reconfigure their supply chains in response to external shocks. Similarly, firms with more differentiated products may have stronger incentives to secure resilient and specialized inputs. Building on this perspective, we next examine whether firms' responses to supplier climate risk vary systematically across key firm-level dimensions—namely, inventory turnover and product similarity.

Tables 15 and 16 present the results on the heterogeneous effects of firm-level operational efficiency (proxied by inventory turnover) and product similarity (proxied by a 10-K-based product similarity measure). Across both firm characteristics, we observe stronger and more significant restructuring responses—termination, addition, and geographic diversification—among firms with higher operational efficiency or lower product similarity. High-efficiency firms (measured by high inventory turnover) are more likely to proactively terminate and replace suppliers and diversify their sourcing locations in response to climate risk. Likewise, firms with less substitutable products (low TNIC SIM) exhibit more aggressive sully chain restructuring, likely because they face greater potential losses from supply disruptions and possess more bargaining power within the supply chain to adapt quickly.

Together, these results suggest that firms' supply chain adaptation is not only a function of external risk and supplier attributes but also of internal capabilities and competitive positioning. Firms that are better equipped operationally or that offer more differentiated products are more likely to adopt forward-looking, strategic approaches to mitigate climate risk through selective restructuring and diversification. These findings reinforce the importance of incorporating firm heterogeneity when evaluating organizational resilience and provide empirical support for the resource-based and portfolio selection perspectives introduced at the beginning of this section.

Table 15: Impact of Climate Risk Exposure on Supply Chain Restructuring: The Role of Operational Efficiency

Panel A: Supplier Termination, Addition, and Net Change

	Low Operational Efficiency (Low Inventory Turnover)					**High Operational Efficiency (High Inventory Turnover)**				
	Supplier Termination		**Supplier Addition**		**Net Change**	**Supplier Termination**		**Supplier Addition**		**Net Change**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$	0.040**	0.040**	0.045**	0.041**	−0.208	0.062**	0.065**	0.100***	0.111***	−0.432*
	(0.019)	(0.019)	(0.019)	(0.019)	(0.133)	(0.029)	(0.028)	(0.027)	(0.026)	(0.241)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	0.032**	0.029*	−0.038**	−0.046***	−0.013	0.013	0.007	−0.006	0.001	0.058
	(0.016)	(0.015)	(0.016)	(0.016)	(0.152)	(0.020)	(0.020)	(0.020)	(0.018)	(0.268)
Non-Climate Risk$_{(t-4)}$		0.344*		0.081	−2.467		−0.309		−0.078	−0.981
		(0.187)		(0.181)	(1.980)		(0.234)		(0.233)	(3.822)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes
Observations	11,824	11,824	11,824	11,824	11,824	7,492	7,492	7,492	7,492	7,492
Adjusted R^2	0.421	0.440	0.394	0.423	0.351	0.411	0.445	0.416	0.453	0.478

Panel B: Geographic Diversification of Supply Chains

	Low Operational Efficiency (Low Inventory Turnover)				**High Operational Efficiency (High Inventory Turnover)**			
	Log Variance of Between Supplier Dist.		**Supplier State HHI**		**Log Variance of Between Supplier Dist.**		**Supplier State HHI**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$	1.410***	1.364***	−0.068***	−0.065***	1.464***	1.567***	−0.077***	−0.075***
	(0.228)	(0.225)	(0.010)	(0.010)	(0.324)	(0.318)	(0.012)	(0.012)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	−0.400**	−0.384**	0.009	0.011	−0.084	−0.022	−0.001	−0.002
	(0.183)	(0.187)	(0.007)	(0.007)	(0.195)	(0.187)	(0.009)	(0.008)
Non-Climate Risk$_{(t-4)}$		1.853		−0.181**		0.651		−0.084
		(1.881)		(0.086)		(2.530)		(0.114)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,345	11,345	11,823	11,823	7,032	7,032	7,490	7,490
Adjusted R^2	0.685	0.708	0.744	0.759	0.653	0.675	0.719	0.734

Notes: This table presents two-way fixed effects regression results examining firms' supply chain responses to climate risk exposure, with the sample split by sample median of inventory turnover (low vs. high). All specifications include firm and year-quarter fixed effects with standard errors clustered at the firm level, reported in parentheses. Panel A shows results for supplier termination, supplier addition, and net change in suppliers. Panel B presents results for various measures of geographic diversification. The key independent variables are $\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$, an indicator for firms with climate-exposed suppliers, and $\mathbb{1}$(Climate Risk)$_{(t-4,t)}$, an indicator for firms directly exposed to climate risk. Firm-level controls include number of suppliers, product market competition (measured by TNIC3 HHI), debt-to-assets ratio, capital expenditure (scaled by assets), R&D intensity (scaled by assets), and asset tangibility. Even-numbered columns include industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 16: Impact of Climate Risk Exposure on Supply Chain Restructuring: The Role of Product Similarity

Panel A: Supplier Termination, Addition, and Net Change

	Low Product Similarity (Low THIC SIM)					**High Product Similarity (High THIC SIM)**				
	Supplier Termination		**Supplier Addition**		**Net Change**	**Supplier Termination**		**Supplier Addition**		**Net Change**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$	0.052**	0.054**	0.059***	0.060***	−0.403***	0.032*	0.033*	0.041**	0.045**	0.266**
	(0.021)	(0.021)	(0.023)	(0.022)	(0.154)	(0.018)	(0.018)	(0.018)	(0.017)	(0.127)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	0.011	0.015	−0.015	−0.011	−0.159	0.019	0.008	−0.026	−0.033**	0.259
	(0.016)	(0.016)	(0.016)	(0.016)	(0.182)	(0.019)	(0.018)	(0.016)	(0.016)	(0.162)
Non-Climate Risk$_{(t-4)}$	0.185	0.148	−0.074	0.006	−3.371	0.019	0.015	0.088	0.225	0.082
	(0.200)	(0.199)	(0.185)	(0.183)	(2.349)	(0.240)	(0.241)	(0.220)	(0.217)	(1.632)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes
Observations	10,781	10,781	10,781	10,781	10,781	11,816	11,816	11,816	11,816	11,816
Adjusted R^2	0.419	0.444	0.410	0.445	0.461	0.431	0.456	0.417	0.441	0.375

Panel B: Geographic Diversification of Supply Chains

	Low Product Similarity (Low THIC SIM)				**High Product Similarity (High THIC SIM)**			
	Log Variance of Between Supplier Dist.		**Supplier State HHI**		**Log Variance of Between Supplier Dist.**		**Supplier State HHI**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$	1.692***	1.651***	−0.087***	−0.084***	1.205***	1.269***	−0.066***	−0.065***
	(0.303)	(0.298)	(0.013)	(0.012)	(0.217)	(0.219)	(0.010)	(0.009)
$\mathbb{1}$(Climate Risk)$_{(t-4,t)}$	−0.200	−0.136	−0.001	−0.005	0.026	−0.005	−0.003	−0.001
	(0.168)	(0.169)	(0.008)	(0.008)	(0.203)	(0.204)	(0.008)	(0.008)
Non-Climate Risk$_{(t-4)}$	1.301	2.536	−0.163*	−0.218**	2.320	1.683	−0.187*	−0.172*
	(1.901)	(1.839)	(0.098)	(0.091)	(2.677)	(2.606)	(0.100)	(0.098)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	10,243	10,243	10,779	10,779	11,381	11,381	11,815	11,815
Adjusted R^2	0.674	0.699	0.724	0.742	0.680	0.690	0.736	0.744

Notes: This table presents two-way fixed effects regression results examining firms' supply chain responses to climate risk exposure, with the sample split by sample median of text-based product similarity (measured by TNIC SIM). TNIC similarity scores are computed using textual analysis of product descriptions in 10-K filings. Low TNIC SIM indicates less product similarity compared to the full market, while high TNIC SIM indicates greater product similarity. All specifications include firm and year-quarter fixed effects with standard errors clustered at the firm level, reported in parentheses. Panel A shows results for supplier termination, supplier addition, and net change in suppliers. Panel B presents results for geographic diversification measures, focusing on the log variance of between-supplier distance (a measure of dispersion in supplier locations) and supplier state HHI (a measure of geographic concentration). The key independent variables are $\mathbb{1}$(Suppliers Climate Risk)$_{(t-4,t)}$, an indicator for firms with climate-exposed suppliers, and $\mathbb{1}$(Climate Risk)$_{(t-4,t)}$, an indicator for firms directly exposed to climate risk. Firm-level controls include number of suppliers, product market competition (measured by TNIC HHI), debt-to-assets ratio, capital expenditure (scaled by assets), R&D intensity (scaled by assets), and asset tangibility. Even-numbered columns include industry-year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

7 Discussion

This study examines how to quantify firm- and supplier-level multifaceted climate risk and how firms respond to upstream supplier climate risk. We develop a novel, high-frequency text-based measure of climate risk exposure—constructed using LLM embeddings and corporate earnings call transcripts—to track climate-related risk at both the firm and supplier levels. This approach moves beyond traditional region- or event-specific shock frameworks and enables real-time measurement of how firms experience and respond to supplier climate risk given the interconnected production network.

Using this novel climate risk measurement, we find that when suppliers are exposed to climate risk, downstream firms experience significant declines in both sales and operating income. In response, firms actively restructure their supply chains by terminating some existing suppliers, adding new ones, and diversifying supplier locations. These adjustments are strategic. Firms are more likely to terminate suppliers that provide general-purpose inputs, while retaining those that supply highly specific inputs or occupy central positions within the supply network. Similarly, when adding new suppliers, firms tend to favor those that offer more unique products or hold structurally central positions in the network. Our findings also underscore the importance of firm-level internal capabilities, both supply-side and demand-side, in shaping supply chain responses. Specifically, we document that restructuring behavior varies systematically with firm characteristics: firms with greater supply-side flexibilities (greater operational efficiency) and those with greater demand-side flexibilities (offering more differentiated products) respond more aggressively to supplier climate risk. Together, these results suggest that supplier-level input specificity and centrality, as well as firm-level operational efficiency and product uniqueness jointly moderate how firms adapt to upstream climate shocks.

Overall, our study makes two key contributions. Methodologically, we develop and validate a novel LLM embedding-based approach to quantifying firm-level climate risk exposure. By combining high-dimensional LLM sentence embeddings with supervised machine learning, our method delivers more accurate and precise classifications than traditional keyword-matching approaches, while retaining greater interpretability and reproducibility than direct applications of generative LLM outputs. The framework is flexible and can be readily extended to measure other economically and managerially important constructs in corporate disclosures, such as AI adoption or innovation intensity.

Substantively, we provide empirical evidence that firms respond to upstream, indirect climate risk by strategically restructuring their supplier networks. These responses are shaped not only by supplier characteristics—such as input specificity and network centrality—but also by firm-level factors, including opera-

tional efficiency and product uniqueness. Our findings suggest that whether a firm adopts a competitive or collaborative view toward managing upstream climate risk depends on the interplay between these supplier and firm attributes. Together, these insights deepen our understanding of indirect impact of supplier climate risk and highlight the strategic responses firms undertake to mitigate indirect climate risk exposures.

Our results also carry important practical implications for managers, investors, and policymakers. For managers, our climate risk measures offer a valuable tool to identify vulnerable supplier relationships and proactively plan supply chain adjustments. Beyond managing their own direct exposures, firms should also anticipate potential downstream strategic responses—for instance, if a firm is exposed to climate risk, it may face a higher likelihood of being terminated by downstream customers. To reduce this risk, firms can invest in input specificity and network centrality, which increase their strategic value and encourage downstream partners to adopt a collaborative rather than competitive response during climate-related disruptions. For investors, our measures provide a new tool to evaluate a firm's supply chain resilience and responsiveness to external shocks. For policymakers, our findings point to the importance of developing disclosure standards and risk mitigation frameworks that consider not only firm-level direct exposures but also the broader network of supply chain interdependencies. As climate risk continue to intensify, understanding how such risk propagate through supply chains—and how firms respond—will be essential for fostering more adaptive and resilient economic systems.

Despite these contributions, our study has several limitations that we aim to address in future work. First, our analysis is limited to U.S.-listed firms due to data constraints in our supply chain dataset. Since in real life, firms can restructure their supply networks globally, our focus on U.S. domestic supplier networks may underestimate the extent of restructuring. Besides, this data limitation may also lead to an undercount of supplier climate risk exposure, as many foreign suppliers potentially facing climate risk fall outside our data scope.

Second, there remains a concern on selective disclosure of climate risk. While our measure is based on earnings call transcripts, which offer high-frequency, real-time insights and are arguably less subject to strategic manipulation than formal filings such as 10-K or 8-K reports, disclosure bias may still persist. A natural extension would be to construct a combined measure that integrates information from earnings calls, 10-Ks, and 8-Ks. Such a multi-sourced approach would help mitigate selective disclosure concerns and enhance the robustness of our climate risk measurement.

Lastly, we acknowledge the possibility of spillover effects across suppliers. That is, if peer suppliers observe climate risk faced by others and respond strategically, our estimates may partially conflate

supplier climate risk exposure with peer supplier strategic adjustments. To account for this, future work will include empirical tests for spillovers and incorporate peer-supplier-level controls to disentangle potential spillover effects.

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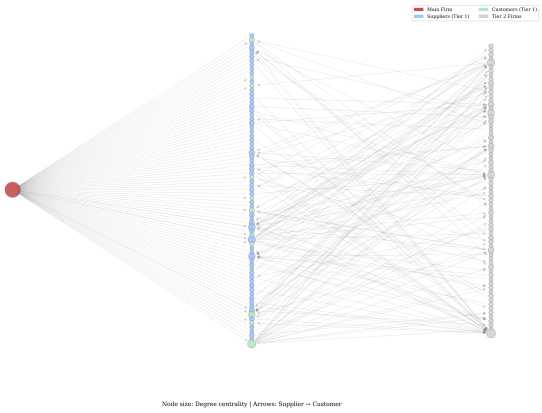
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Appendix

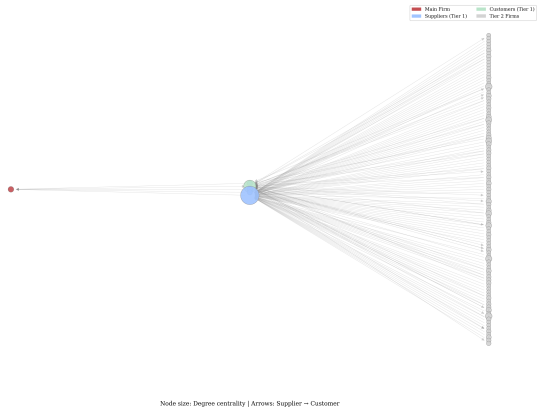
Table A.1: Variable Definitions and Data Sources

Variable	Description	Source
Panel A: LLM-Derived Measures		
Climate Risk	Percentage of sentences in firm earnings call transcripts that mention climate-related risks (e.g., extreme weather, regulatory changes).	Refinitiv Eikon, Capital IQ
Non-Climate Risk	Percentage of transcript sentences discussing firm-specific risks not related to climate, such as economic, political, or operational risks.	Refinitiv Eikon, Capital IQ
Supplier Climate Risk	Binary indicator equal to one if any upstream supplier of the firm discusses climate risks in its own earnings call in the same quarter.	Refinitiv Eikon, Capital IQ, Compustat
Panel B: Firm Financial and Operational Variables		
R&D / Assets	Research and development expenditures scaled by total assets, capturing firm innovation intensity.	CRSP-Compustat
CAPEX / Assets	Capital expenditures divided by total assets, reflecting investment in long-term assets.	CRSP-Compustat
ROA	Return on assets, calculated as net income divided by total assets, measuring profitability.	CRSP-Compustat
Leverage	Ratio of total debt to total assets, capturing financial risk.	CRSP-Compustat
Cash / Assets	Cash and short-term investments scaled by total assets, indicating liquidity.	CRSP-Compustat
TNIC3 HHI	Herfindahl-Hirschman Index based on text-based network industry classification, measuring industry concentration.	(Hoberg and Phillips, 2016)
TNIC3 SIM	Average textual similarity of a firm's 10-K product descriptions to those of other firms, indicating product uniqueness.	(Hoberg and Phillips, 2016)
Panel C: Supply Chain Relationships		
Number of Suppliers	Total number of unique suppliers linked to a firm in a given quarter.	Factset, Compustat Segments
Supplier Termination	Binary indicator equal to one if the firm drops at least one supplier compared to the previous quarter.	Factset, Compustat Segments
Supplier Addition	Binary indicator equal to one if the firm adds at least one new supplier not seen in the prior quarter.	Factset, Compustat Segments
Mean Supplier Distance	Logarithm of the average geographic distance (in kilometers) between the firm and its active suppliers.	Factset, Compustat Segments
Variance in Supplier Distance	Logarithm of the variance in geographic distances between the firm and its suppliers, capturing spatial dispersion.	Factset, Compustat Segments
Inventory Turnover	Ratio of cost of goods sold to average inventory, indicating efficiency in inventory management.	Compustat

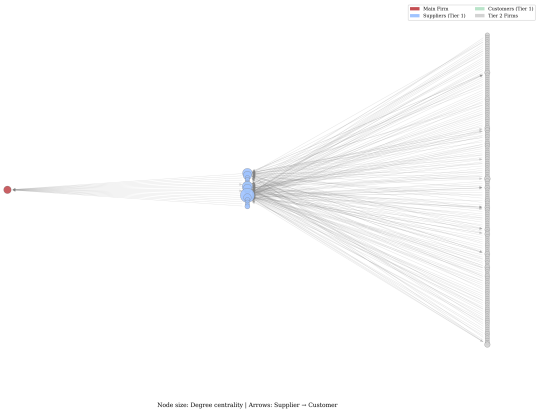
Figure A.1: In-Sample Examples of Firms with the Highest Centrality in the Supply Chain Network



(a) Example Firm with the Highest Degree Centrality



(b) Example Firm with the Highest Betweenness Centrality



(c) Example Firm with the Highest Closeness Centrality

Notes: This figure presents examples of firms with high centrality measures in the 2-tier supply chain network of U.S. publicly listed firms. Panel (a) shows a firm with the highest degree centrality, directly linked to the most suppliers and customers. Panel (b) highlights a firm with the highest betweenness centrality, playing a key intermediary role in supply chain connectivity. Panel (c) illustrates a firm with the highest closeness centrality, indicating its strategic position for quick information or material flow. Node size represents degree centrality, while node color reflects firm types (main firm, suppliers, or customers). Arrows indicate the direction of supply flow from suppliers to customers.

Table A.2: Misclassification Cases of Keywords-Based Approach

Type	**Excerpts in Earnings Call**	**True Label (Climate)**	**Keyword-Based Classification**	**Matched Bigrams**
Panel A: False Positives				
False Positive	I think the competition is finding it extremely difficult to compete across the leading edge of the technology of the product, which drives the different performance parameters in terms of electrical efficiency being one, beam quality, the tremendous scale we have on manufacturing, the service and support we have around the world, the application laboratories that support that service and sales, the investment that's gone into that.	False	True	electrical efficiency
	And one of the big bills was a $50 billion program in the state of Washington for Sound Transit. And Sound Transit, obviously, is their major transit program in the Puget Sound.	False	True	transit program
	We expect increased public demand to provide long-sought balance to the ever competitive local construction market we serve. On April 6, the legislature in California approved the passage of SB 1, the Road Repair and Accountability Act of 2017.	False	True	accountability act
	And last Friday, Governor Brown signed it. The bill will raise $52.4 billion over the next 10 years to fix roads, improve maintenance, add capacity, improve local transit and help to move goods to market.	False	True	governor brown
	Energy was the largest vertical contributor followed by chemicals. Looking at our 10 largest transactions in the quarter, there was, again, a mix of engineering and manufacturing supply chain transactions.	False	True	vertical contributor
	We've also been giving a great deal of thought about other levels of hydrogen, how to provide hydrogen from electrolyzers and reformers to more large-scale liquid plants and how we could partner with experts in those areas.	False	True	provide hydrogen
Panel B: False Negatives				
False Negative	Now where did it end up? It ended up at $52 billion over 10 years. It ended up with a host of funding mechanisms through gas taxes, diesel taxes, zero emission vehicle taxes, transportation improvement fees, diesel sales tax, all those things.	True	False	NA
	I'm especially pleased by our results this quarter in light of the heatwave that we experienced across Europe during the month of June, which had retailers stocking ice cream over savory frozen.	True	False	NA
	So overall, globally, demand for corn is strong and I think there's an expectation here that we'll have a decent, a pretty good demand if the weatherman cooperates.	True	False	NA

Continued on next page

Table A.2 continued

Type	Excerpts in Earnings Call	True Label (Climate)	Keyword-Based Classification	Matched Bigrams
	All that being said, very granularly, there's a couple more payroll days in the fourth quarter than there are in the third quarter because of the calendar, and, you know, as we've said a couple times before, as it gets a little bit colder outside, it gets a little more expensive for us in some of our locations.	True	False	NA
	And we have extreme winters, we have mild winters, this was one that was mild. I would say on average within a tolerable range in terms of we didn't have any real upsets this year and the plants ran continually well.	True	False	NA
	We continue here to closely monitor working capital and we will further reduce payment terms in 2004. In Europe, the extreme drought conditions led to a declining fungicide market, limiting growth potential for our fungicide portfolio.	True	False	NA

Notes: This table presents examples of misclassification issues in the keywords-based approach for identifying climate discussions in earnings call transcripts. False positives represent sentences incorrectly classified as climate-related, while false negatives represent true climate-related discussions missed by the keywords-based method. Matched bigrams highlight specific terms that led to incorrect classifications for false positives.