Supply Chain Risk Measurement and Resilience: Insights from Large Language Models*

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Abstract

Identifying supply chain risks and enhancing resilience have become crucial aspects of strategic decision-making for companies. In this paper, we introduce a novel index to quantify firm-level supply chain risks (SCR) by leveraging a cutting-edge natural language processing technique—zero-shot prompting of large language models (LLMs)—applied to corporate annual and quarterly reports. We validate this index through multiple methods, including comparisons with baseline measures and human-labeled data, visualizing and interpreting supply chain risks over time and across industries, analyzing the index's sensitivity to events like trade wars, and demonstrating a strong positive correlation between the supply chain risks of suppliers and customers. We then identify key strategies firms use to manage high supply chain risks—hiring specialists with expertise in supply chain management. Our findings show that the acquisition of such human capital enhances supply chain resilience through geographic diversification and multi-sourcing of suppliers, while also reducing the need for large inventory buffers when facing significant supply chain risks.

Keywords: supply chain risks; human capital acquisition; NLP; zero-shot prompting; large language models

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Building resilient American supply chains will necessitate enhancing domestic manufacturing capacity, supporting America's competitive edge in research and development, encouraging innovation, reinforcing critical infrastructure, and creating well-paying jobs.

— Executive Order on White House Council on Supply Chain Resilience, June 14, 2024

1 Introduction

In recent years, businesses have faced growing susceptibility to disruptions in their supply chains, which can significantly threaten their operational stability. Events such as global pandemic (e.g., COVID-19), geopolitical tensions (e.g., U.S.-China trade war and Ukraine war), and climate change (e.g., natural disasters such as Hurricane Katrina) have heightened these risks, attracting considerable attention from researchers, practitioners, and policymakers. Consequently, accurately assessing supply chain risks and enhancing resilience have become critical aspects of corporate strategy for production and operations.

Accurate risk assessment is essential for formulating strategies to prevent or mitigate potential disruptions. However, this process typically requires detailed information that companies hold but is not commonly accessible to the public. To accurately assess risks, we have developed a firm-level index of supply chain risks by analyzing their annual and quarterly reports, specifically SEC 10-K and 10-Q filings from the EDGAR database. Our methodology primarily employs zero-shot prompting of large language models (LLMs). Our dataset, which spans from 2001 to 2022, comprises over 436,000 reports from 14,270 unique firms. Given the extensive size of our dataset, direct application of an advanced LLM to all texts is impractical, leading us to adopt a two-step approach.

First, following the established approach in risk-related literature, we filter sentences related to risks using dictionary-based approach with the dictionary provided by Hassan et al. (2019). Second, we prompt large language models (LLMs) in a zero-shot manner to determine whether the topic of each sentence pertains to supply chain risks. Recent advancements in

Natural Language Processing (NLP) and LLMs, such as OpenAI's GPT, Google's BERT and Flan-T5, and Facebook's BART (Devlin et al., 2018; Brown et al., 2020; Chung et al., 2022; Lewis et al., 2020), have revolutionized the automatic extraction of information from textual data (Brown et al., 2020). These models, trained on vast datasets, excel at understanding human language, discerning context, identifying sentiment, and extracting key themes from unstructured text.

In this paper, we primarily leverage Google's Flan-T5 model as a sub-optimal yet efficient alternative to more advanced models like ChatGPT for processing firms' financial reports, due to the high cost of using closed-source, cutting-edge models on large-scale textual data.[1] After generating labels with Flan-T5, we aggregate the number of sentences related to supply chain risks at the firm-quarter level, using the number of words in each sentence as a weight. To conduct placebo tests, we also construct a non-supply-chain risk (Non-SCR) index by aggregating the number of sentences containing risk-related terms that are not associated with supply chain risks, applying the same weighting method.

To validate our approach using the Flan-T5 model, we compare it to the traditional word dictionary method on a small set of manually labeled data. Our approach outperforms the baseline across all metrics. To further justify the selection of Flan-T5, we compare it with GPT-4 and demonstrate that it is an effective and cost-efficient substitute for fee-based LLMs in our context. We also validate the firm-level supply chain risk (SCR) index by examining its responsiveness to the U.S.–China trade war and analyzing the correlation between firms' SCR and that of their suppliers. We find a significant increase in a firm's SCR index when facing a higher negative impact from the trade war. As expected, there is a strong correlation between a firm's SCR index and those of its suppliers and customers, while the non-supply-chain risks (Non-SCR) of suppliers and customers show no correlation with the firm's SCR index. These results suggest that our measure effectively captures firm-level supply chain risks rather than other types of risks.

[1]Note that, for small-scale textual analyses, such as examining skill information in job postings in Section 2.1.2, we still use ChatGPT.

With the SCR index in hand, we delve into the characteristics of firms that correlate with higher SCR and the strategies they employ to manage these risks. Our findings indicate that firms in manufacturing sectors, those with larger size or market value, and those with a higher Tobin's Q are generally more susceptible to supply chain risks. Consistent with predictions, a higher SCR is positively linked to a larger inventory of stock, encompassing raw materials, work in progress, and finished goods. Additionally, companies facing elevated SCR tend to hold more cash and increase their accounts payable.

We then examine the strategies firms adopt to counteract heightened supply chain risks and bolster resilience. A Deloitte survey of 600 executives reveals that three-quarters of responding companies prioritize supply chain resilience, with key improvement enablers including dual and multi-sourcing, enhanced demand planning and forecasting, and increased collaboration with supply chain partners (Deloitte, 2022).[2] These strategies underscore the need for specialists skilled in supply chain management.

Using job posting data from Lightcast, we observe that firms facing higher supply chain risks in the previous quarter tend to seek more personnel with supply chain management skills. This pattern is not mirrored in job postings for other skillsets such as finance, healthcare, or design. To ensure that our job posting data specifically reflects responses to supply chain risks, we construct an index for non-supply-chain risks using the same textual data and employ this non-SCR index in a placebo test. The results indicate that the demand for supply chain management skills does not fluctuate with higher non-SCR.

Dual and multi-sourcing are recognized as the most critical practice for enhancing supply chain resilience, according to the Deloitte survey (Deloitte, 2022). We then explore the role of hiring supply chain specialists in developing a diversified supplier network. By measuring firms' stock of specialists based on their recruitment demand over the last 4, 8, or 12 quarters, we find that a larger stock of supply chain specialists helps to reduce geographical

[2]A similar survey by the McKinsey Global Institute (MGI) among over 100 supply chain managers across various industries reports that 90% of respondents intend to further enhance resilience, with nearly three-quarters planning to increase spending on resilience initiatives (MGI, 2022).

concentration and expand the supplier base.

As previously mentioned, firms often maintain substantial inventories and cash in response to higher SCR, which can be inefficient and costly. Employing a specialized supply chain team skilled in demand and supply forecasting can potentially reduce the reliance on buffer stocks and lower costs. Our findings align with this hypothesis: companies with a larger stock of such specialists are better equipped to manage supply chain risks, mitigating the need for inventory or cash buffers when facing elevated supply chain risks.

Our paper contributes to the extensive body of literature that seeks to comprehend and quantify various variables of interest encountered by corporations (i.e., the supply chain risks in our context) through the analysis of textual data, e.g., disclosures in financial reports and conference calls. Researchers have utilized these textual data to develop metrics for firm-specific idiosyncratic risks (Handley and Li, 2020), trade-policy risks (Benguria et al., 2022; Caldara et al., 2020), Brexit risks (Campello et al., 2020), climate change (Sautner et al., 2023; Li et al., 2024), cybersecurity (Florackis et al., 2023), among others. It is a nontrivial task to quantify the variable of interest from large-scale unstructured textual data (Bao and Datta, 2014). Manual analysis becomes impractical at scale, prompting finance and social science researchers to adopt automated text analysis techniques (Lazer et al., 2009). The conventional approach to textual data classification involves the creation of a keyword set by domain experts, followed by categorizing textual data based on the constructed dictionary (Bao and Datta, 2014). Examples include financial sentiment dictionary (Loughran and McDonald, 2016), risk dictionary (Hassan et al., 2019), climate change bigrams (Sautner et al., 2023), etc. The method is straightforward and effective, requiring minimal computational resources. However, it may not capture all semantic details and could be subject to the biases of the experts who construct the dictionary. For tasks that require clear keyword boundaries and limited contextual understanding, dictionary methods are highly effective. To capture semantic nuances, the literature has increasingly adopted supervised machine learning (SML), which involves manually labeling a set of documents to train a supervised

classifier, such as deep learning models. Despite offering greater accuracy, SML's performance heavily depends on the availability of high-quality labeled datasets (Zhang et al., 2022). Recent advancements in large language models (LLMs) provide new opportunities for automated text analysis, allowing for the extraction of more nuanced insights without the need for labeled data.

Our work builds on these recent advancements in processing textual data and is closely related to recent studies by Wu (2023) and Ersahin et al. (2024), both of which construct firm-level supply chain risk using conference call data, with Wu (2023) employing machine learning to develop a supply chain lexicon and Ersahin et al. (2024) creating a dictionary by comparing terminology from supply chain and financial accounting textbooks. Going beyond these dictionary-based approaches, our paper contributes a novel approach by harnessing the latest advancements in large language models (LLMs), demonstrating an improvement in supply chain risk construction. We employ zero-shot prompting with LLMs, which does not require dictionary and labeled data, thus bypassing the limitations associated with dictionary-based and SML approaches. This method allows us to analyze a vast array of textual data efficiently and effectively, providing a more nuanced and comprehensive assessment of supply chain risks.

Our study also contributes to the nascent literature that applies AI-powered large language models (LLMs) to risk measurement. LLMs, particularly through techniques like zero-shot prompting, offer a powerful new tool for understanding language with subtlety, though their integration into academic research is still in its early stages (Kim et al., 2023; Li et al., 2023; Jha et al., 2024; Kim et al., 2024). Our approach integrates the traditional dictionary method with advanced, open-source LLMs, offering an efficient and cost-effective solution for analyzing extensive textual data.

Finally, our paper contributes to the literature on the impacts of risks and firms' responses in managing such risks (Bloom, 2007; Gulen and Ion, 2015; Kumar et al., 2023; Campello and Kankanhalli, 2024). Ersahin et al. (2024) provides evidence that companies are more inclined

to pursue vertical mergers and acquisitions when confronted with heightened supply chain risk. Our research complements this by examining the role of human capital acquisition as a strategic response to increased supply chain risks and offering preliminary evidence of the benefits of such an approach. In the vein of our investigation, several studies have explored the importance of human capital in managing risks across various contexts. For example, Bana et al. (2022) finds that firms increase hiring in both cybersecurity and public relations following a data breach. Shu et al. (2024) discover that Chinese companies hit hard by the trade war tend to hire executives with European backgrounds and marketing skills. Schneider et al. (2023) demonstrate that banks invest in human capital to manage risk in the wake of the global financial crisis and the introduction of stress testing.

The rest of the paper proceeds as follows. Section 2 describes our data sources and methodology used to quantify firm-level supply chain risks. Section 3 presents the validation tests for our approach. Section 4 examines firms' strategies for enhancing supply chain resilience through human capital management. Section 5 concludes.

2 Data and Measurement Construction

2.1 Data

In this part, we introduce the data sources used in our study: SEC Edgar filings, Lightcast job posting data, and supply chain network data from Factset Revere. These datasets form the foundation for our analysis of supply chain risks and firms' responses to these risks.

2.1.1 SEC Edgar Filings

To measure supply chain risks, we use the text of SEC 10-K and 10-Q filings available in the EDGAR database.[3] All publicly traded firms in the U.S. are mandated to submit

[3]EDGAR is created by the US Security and Exchange Commission (SEC) as a database to provide free public access to information about public companies. It aims to improve the accessibility and efficiency of corporate filings while also improving the fairness and effectiveness of the securities markets. EDGAR

these annual and quarterly reports to the U.S. Security and Exchange Commission (SEC). In each document, the firm discusses a series of descriptions on firm business, risk factors, financial information, management's discussions, etc. Although standardized in terms of format, the SEC EDGAR filings are reflective of current business policies and conditions, making them a reliable source for understanding firm-specific dynamics. We use a publicly available repository of SEC/EDGAR files from The Notre Dame Software Repository for Accounting and Finance website (Loughran and McDonald, 2016). This is a cleaned version by removing irrelevant characters from the original SEC filings. To tailor these documents to fit our research needs, we further removed page numbers and tables, focusing on text content only. Our analysis covers a period of over two decades, from 2001 to 2022, and includes 601,933 reports from 17,595 unique firms.

To ensure the relevance of our data, we limited our dataset to companies that are also listed in the Compustat database. By merging SEC reports with the Compustat dataset using the Central Index Key (CIK), we successfully matched 436,362 reports from 14,270 firms. Then, we employed the Natural Language Toolkit (NLTK) library to segment each document into sentences, discarding those with fewer than ten words to eliminate headings, table entries, and content lists, which generally provide minimal informative value. After applying these filtering steps, we compiled a corpus 361 million sentences from 14,270 firms and form the basis for our analysis of supply chain risks.

2.1.2 Lightcast Job Demand

We rely on job demand data from Lightcast (formerly known as Burning Glass Technologies) to identify firm-level supply chain related human capital acquisition. Lightcast, as one of the leading vendors of labor market analytics, claims to cover the near-universe of job postings in the U.S. It scans more than 40,000 online platforms and tracks over 200 million online job vacancies. Each job posting is parsed and de-duplicated with detailed

contains millions of companies and individual filings, and includes a public company's various financial information and business operations in filings required by SEC, such as 10-Ks and 10-Qs filings.

information on job title, employer name, industry code, occupation code, location, and more importantly, the skills required for the job. The skill requirements are mapped to a detailed taxonomy with 3 hierarchical levels including skills, skill clusters, and skill cluster families. In detail, there are approximately 16,000 skills nested within 658 skill clusters which are further nested within 28 skill cluster families.

Job-level skill requirements data has been used to track the diffusion of technology and human capital. As supply chain related tasks require highly specialized human capital, Lightcast database serves as a desirable candidate to construct firm-level acquisition of supply chain skills. We extract information regarding firm's investment in and adoption of supply chain skills, and propose a skill-based measure of supply chain skill demand at the firm level. To this end, we first assess whether a given set of job taxonomy elements (i.e., skill, skill cluster, and skill cluster family) is pertinent to supply chain. The underlying idea is applying zero-shot prompting of GPT-4 to classify whether a set of job taxonomy elements is related to supply chain (Chung et al., 2022). This method identifies 841 unique supply chain skill sets, allowing us to compute the supply chain (SC) skill investment by

$$\text{SC Skill Investment}_{it} = \frac{\sum_k \frac{1}{\text{Number of skills required}_{itk}} \cdot \mathbb{1}\{\text{SC skill required}\}_{itk}}{N_{it}},$$

where i, t and k index firm, time (year-quarter), and job posting, respectively. N_{it} is the total number of job postings for firm i in its quarter t. For job posting k in a specific quarter, $\text{Number of skills required}_{itk}$ is the total number of required skills and $\mathbb{1}\{\text{SC skill required}\}_{itk}$ indicates whether any of the required skills is related to supply chain. Specifically, if a posting requires multiple skills, its weight will be reduced accordingly. For example, if a posting requires three skills and one of them is related to supply chain, we will assign a weight of 1/3. Last, for the sake of robustness and to conduct placebo tests, we apply the same classification method to differentiate between finance, healthcare and design skills.

To bridge the Lightcast data with Compustat records, we use a fuzzy name and address

matching approach following Bai et al. (2021). This method takes into account discrepancies in naming conventions between parent companies and their subsidiaries, significantly enhancing the match rate. As a result, we matched more than 4,000 unique firms (from BGT firm name to GVKEY) spanning from 2010 to 2022.

2.1.3 Supply Chain Networks

To analyze the spread of supply chain risks across supply chain networks, we use the FactSet Revere database to gather information on firms' production networks. FactSet Revere compiles data from various public sources, including annual and quarterly reports, investor presentations, company websites, and press releases, providing one of the most comprehensive datasets on firm-level supplier-customer relationships. The data spans from January 2003, when the database was established, to 2022, aligning with the timeframe of our supply chain risk index. It includes the start and end dates of each supplier-customer relationship, which we use to create a quarterly dataset. A relationship is considered active in a given quarter if its duration overlaps with that quarter.

We merge the FactSet Revere data with Compustat North America quarterly data using the Committee on Uniform Securities Identification Procedures (CUSIP) code to obtain firms' financial indices. We then merge this with our supply chain risk index using the Central Index Key (CIK) at the quarterly level. Financial firms (NAICS code 52) are excluded from our analysis. Over this period, we have 653,540 firm-supplier quarterly relationships matched to the supply chain risk index, covering 4,101 firms with 114,183 firm-quarter observations.

2.2 Measuring Supply Chain Risks

To quantify supply chain risks from annual and quarterly reports, we employ large language models (LLMs) to analyze the semantic content of sentences for indications of supply chain risks. However, the high computational cost of LLMs makes it impractical to directly process all 361 million sentences in our sample with a LLM. To address this, we break it

down into two tasks: identifying whether a piece of text pertains to risks (task T1) and supply chain (task T2).

Task T1 deals with the identification of risks. Expressions of risks typically revolves around specific keywords and a well-developed dictionary exists in the literature (Hassan et al., 2019). For this task, we adhere to the literature and employ the aforementioned dictionary to sift through the text for sentences relevant to risks.[4] Specifically, the dictionary of risks includes 138 words that signify risks (for instance, "threat" and "unsure"). A sentence is classified as relevant to risks if it contains any of these keywords. Upon completing task T1, there remains a total of 26.8 million sentences that are indicative of risks.

Task T2 pertains to the recognition of text related to supply chains, which is a considerably more diverse and multifaceted subject. It incorporates terms across a broad spectrum of areas, from sourcing and raw materials to logistics (Wu, 2023). To the best of our knowledge, Wu is the first to propose a supply chain dictionary using a NLP technique known as word embedding (Mikolov et al., 2013). However, such a dictionary-based approach completely ignores the semantic of sentences, which is crucial given the complex nature of supply chains. For instance, the sentence "additional risks are present related to our pipeline that traverses areas in Florida where karst conditions exist" (first example in Table 2) may not be identified as relevant to supply chains using dictionary methods as it does not include any words of the supply chain dictionary, despite its clear relevance once the sentence is semantically interpreted.

To take into account the semantic information, recent literature refers to the supervised machine learning (SML) approach. However, the performance of SML hinges heavily on the availability of moderately large and high-quality labeled datasets (Zhang et al., 2022). In addition, it may suffer from the biases embedded in the labeled datasets. In this research, we explore a hitherto untapped approach—zero-shot prompting of LLMs (Liu et al., 2023). This NLP method designs task-specific prompts to adapt pre-trained LLMs to a specific

[4]The decision to not implement a zero-shot prompting approach as in task T2 is due to the considerable computational resources required by such large language model-based methodologies.

task, without requiring additional training or labeled datasets. An intuitive example to understand such an approach is directly asking ChatGPT whether a sentence is related to supply chain or not. An ideal case would be processing all 26.8 million sentences from task T1 using a cutting-edge LLM like ChatGPT. However, due to the limited availability of ChatGPT (or other fee-based cutting-edge LLMs) to process huge amounts of sentences, we chose to use Google's FLAN-T5 model instead (Chung et al., 2022). FLAN-T5 is a state-of-the-art language model in the T5 (Text-to-Text Transfer Transformer) family, designed for various NLP tasks. It distinguishes itself by being trained in a "zero-shot" or "few-shot" learning setting, meaning it can understand and execute tasks with no or just a few examples. As larger models are usually associated with better performance, we use the one with a vast number of parameters (i.e., Flan-T5-XXL[5]). This model serves as an efficient approximation of the more advanced, fee-based LLMs. We will validate the performance of the Flan-T5-XXL model in our setting in Section 3. In our context, to judge whether a sentence pertains to supply chain, we compose a specific prompt for this task, as shown in Table 1, and input it into the Flan-T5-XXL model. A sentence is classified as "related" if the model generates "yes", and "unrelated" otherwise.

[Insert Table 1 here]

We use two real-world examples to demonstrate the superiority of our proposed approach over the dictionary method. Table 2 presents positive and negative sentences w.r.t. supply chain relevance. For the first sentence, both human evaluation and our proposed approach classify it as pertaining to supply chain as it highlights a specific risk associated with the pipeline, a physical infrastructure that is crucial to the supply chain network. Yet, it does not contain any explicit supply chain terminology. In such a scenario, the dictionary method fails to correctly identify its relevance, due to its inability to grasp the semantic essence of the sentence. In the second sentence, human evaluation and our model both categorize it as

[5]https://huggingface.co/google/flan-t5-xxl

unrelated to the supply chain. Yet, the dictionary-based approach categorizes it as related to the supply chain because "operator" and "prospect" are listed in the supply chain dictionary.

[Insert Table 2 here]

Leveraging dictionary methods for task T1 and LLM prompt engineering for task T2, we devised an index of supply chain risks (SCR) at the firm-quarter level, from the quarterly report in the SEC Edgar filings (as introduced Section 2.1.1). Specifically, in task T1, we first filter out sentences that are irrelevant to risks. As a results, the quarterly report of each firm contains on average 609 sentences (SD=548.2, MIN=0, MAX=23, 819) pertaining to risks. Then, for each sentence, task T2 assesses its relevance to supply chain. Last, for each firm, the quarterly index is defined as the proportion of words related to SCR in the quarterly report. This is calculated as the ratio of words in SCR-relevant sentences to the total word count:

$$\text{SCR}_{it} = \frac{\sum_{j=1}^{n} \mathbb{1}\{\text{SCR-related}\}_{itj} * \text{NW}_{itj}}{\text{NW}_{it}}, \tag{1}$$

where i, t, and j index firm, quarter, and sentence in each quarterly report, respectively. NW_{it} indicates the word count of quarterly report for firm i in its quarter t. For sentence j in the quarterly report, NW_{itj} is the number of words and $\mathbb{1}\{\text{SCR-related}\}_{itj}$ refers to its relevance to SCR, which equals to 1 if the sentence is related to SCR, and 0 otherwise. The average SCR index is 0.8%, indicating that, on average, words related to SCR account for 0.8% of the total words in a report.

To conduct placebo tests, we define a similar index, called Non-SCR, which focuses on the sentences that are related to risks yet irrelevant to supply chain. Formally, the Non-SCR index is defined as:

$$\text{Non-SCR}_{it} = \frac{\sum_{j=1}^{n} \mathbb{1}\{\text{Risk-related, SC-unrelated}\}_{itj} * \text{NW}_{itj}}{\text{NW}_{it}}, \tag{2}$$

where $\mathbb{1}\{\text{Risk-related, SC-unrelated}\}_{itj}$ equals to 1 if the sentence talks about risks yet is

irrelevant to supply chain, and 0 otherwise. NW_{it} and NW_{itj} are similarly defined as in the definition of SCR.

2.3 Summary Statistics

Thus far, we have introduced the data sources used in our research and harnessed the power of LLMs to quantify the supply chain risks at the firm-quarter level. Table 3 presents the summary statistics of the SCR indices, firm level control variables, and job posting data. All variables are at quarterly frequency and have been winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. The SCR (Wu) index replicates the dictionary-based approach described by Wu (2023) where the dictionary was extracted using word embedding techniques. Inventory/Asset represents the ratio of inventory to total assets. Tobin's Q is defined as the market value of common stock plus total assets, minus the book value of common equity, all scaled by total assets (Younge and Marx, 2012). Size is the logarithm of total assets. ROA (return on assets) is defined as net income divided by total assets. Supply chain skill-related job (ratio) is the proportion of job postings requiring supply chain-related skills scaled by the total number of job postings. Hiring in the past four quarters is measured as the logarithm of the postings requiring supply chain skills during that period, as defined in Section 2.1.2.

[Insert Table 3 here]

3 Validation Tests of Measure

Similar to the literature (Wu, 2023), we economically validate the constructed measure using a multi-pronged approach, including comparing with baselines and human-labeled data, visualizing and interpreting supply chain risks over time and across industries, analyzing the sensitivity of our index to trade war, and showing the positive correlation of suppliers' and customers' supply chain risks.

3.1 Comparison with Baselines and Human-Labeled Data

To validate the performance of our proposed approach, i.e., zero-shot prompting using Flan-T5, we manually labeled a small set of sentences and treat this manually-labeled dataset as ground truth to compare our approach with dictionary method (Wu, 2023). Specifically, we randomly sampled 1,500 sentences from all risk-related sentences obtained in task T1 and two raters with necessary domain knowledge dedicatedly labeled them. The consistency rate is 92.3%, which means that two raters agreed with each other on 92.3% of the sentences. The Cohen's kappa score between the labels is 62.32%, suggesting moderate level of agreement (McHugh, 2012). In cases of inconsistent annotations, two raters reach a consensus through discussion.[6] Using the above human-labeled data, we benchmark the proposed approach against the dictionary method (Wu, 2023),[7] across several metrics including F1 score, ROC AUC, accuracy, precision, and recall.[8] As displayed in Table 4, our proposed approach significantly outperforms the dictionary method across all metrics.

To further assess whether Flan-T5-XXL stands as a strong candidate against leading closed-source large language models (e.g. ChatGPT), we conducted a comparative analysis with GPT-4. We used the same prompt for both models (see Table 1) to label the previously sampled 1,500 sentences. The consistency rate is 94% and F1 score is 61.86%, suggesting superior performance given that this is an extremely imbalanced classification task. Although Flan-T5 is an open-source model, it acts as an efficient approximation of the more advanced, fee-based large language models.

[Insert Table 4 here]

[6]Note that, our data is extremely imbalanced—of all risk-related sentences, only approximately 6% of the sentences pertain to supply chain. We argue that a Cohen's kappa score of 62.32% is an acceptable value in our case.

[7]The original code and dictionary are not publicly accessible. Thus, we replicate the method based on the descriptions provided in the paper. All elements remain the same except that the 75,000 annual reports used to train word embedding model are randomly sampled from the period between 2001 and 2021 while they were drawn from the period between 1994 and 2009.

[8]For imbalanced data, metrics such as accuracy, precision, and recall may not provide much insight (Wei et al., 2022). They are reported here for reference.

It is important to note that, in our comparison, the F1 scores are not as high as those found in some traditional tasks like sentiment analysis (Medhat et al., 2014), due to a few reasons: 1) Unlike many artificially balanced datasets, we employ random sampling from the original context, preserving the inherent imbalance and increasing the practical interpretation and implication; 2) The task of identifying sentences related to supply chain is more challenging given the diverse and multifaceted nature of supply chain language. Last, we would like to emphasize that despite the moderate performance of the proposed approach, which may potentially lead to an underestimation of the significance level in our empirical study, our findings presented in Section 4 retain their statistical significance.

3.2 Supply Chain Risks Over Time and Across Industries

To demonstrate the validity of our constructed index, we visualized the quarterly supply chain risks across industries from 2001 to 2022 in Figure 1. We marked the major events likely to influence supply chain dynamics. The average supply chain risks across all industries is 0.8%, indicating that, on average, sentences about supply chain issues comprise 0.8% of the total words in the report.

To enhance our understanding of how supply chain risks varies across industries, we refer Wu (2023) to classify firms into the manufacturing and services sectors based on the North American Industry Classification System (NAICS) 2-digit codes. Firms within the manufacturing sector are identified by NAICS 2-digit codes 31, 32, and 33. Meanwhile, the service sector encompasses firms with NAICS 2-digit codes 51, 52, 53, 54, 55, and 56. Our findings reveal that the manufacturing sector exhibits a higher average supply chain risks of 1.17%, compared to 0.24% in the services industry. This difference is expected due to the manufacturing sector's higher reliance on global resources. Notably, the index for the manufacturing industry reached a peak of 1.92% in the last quarter of 2022, which suggests that, on average, statements regarding supply chain risks accounted for 1.92% of the report's content during that period. The responsive surge following the supply chain disruptions

(especially trade war and COVID-19) clearly suggests the validity of the constructed index, even after we applied a moving average to eliminate seasonal fluctuations. Moreover, the decrease in index after China joined the WTO reflects the resolution of supply chain risks, which our measure also captures.

[Insert Figure 1 here]

3.3 The Supply Chain Risks after the Trade War

In this subsection, we validate our index by investigating whether firms that were hit harder by the trade war faced a larger increase in the supply chain risks index. On March 22, 2018, the Trump administration unexpectedly issued a presidential memorandum proposing a tariff increase on Chinese imports. The US-China trade war is the largest trade conflict, leading to tariff increases on about 350 billion of Chinese goods. The trade war roughly has five rounds, resulting in the average tariff increasing from 3.1% in 2017 to 21.0% in 2020. Table A1 in the Appendix shows the number of products (measured by Harmonized System (HS) Codes), the value of imports of these covered products, and the tariff increase in each round.

The US-China trade war had destructive effects on US firms' production networks, creating a lot of uncertainty and risks for firms, as shown in Figure 1, especially for firms in industries that were hit harder by the trade war. To further validate our index, we investigate whether firms that were hit harder by the trade war faced a larger increase in the supply chain risks index. We construct two indices about the trade war shock to provide a comprehensive analysis of how the trade war influences supply chain risks across different companies. The first index aggregates the product-level tariff to the industry level (measured by the first 4 digits of NAICS code) using the import value of each product before the trade

war as weights. The detailed construction process is shown in the following formula:

$$\text{Tariff increase}_{jt} = \sum_{p \in E_j} \left[\frac{X_{jp}}{\sum_{s \in E_j} X_{js}} \cdot \triangle \tau_{pt} \right]$$

where τ_{pt} indexes tariff in year t for product p; X_{jp} indexes the average Chinese import value from 2013 to 2017 for product p in industry j; E_j represents all the products imported from China in industry j.

The second index uses companies' stock market reactions in the four-day window around March 22, 2018, the most significant date in the US-China trade war (Huang et al., 2023). Specifically, we define a dummy variable *Large trade war shock*, which equals to 1 if the firm's raw stock market return in this window is negative.[9] This index could capture the stock market's expectations about how badly the firm would be affected by the trade war and has some advantages as a trade shock measure (Greenland et al., 2022; Shu et al., 2024).

[Insert Table 5 here]

Table 5 presents the results. The first three columns employ our first index of trade war shock. Column (1) shows the effect of tariff increases on SCR without any controls or fixed effects. Unsurprisingly, firms in the industries that had a larger increase in tariff faced a higher supply chain risks. The results are robust no matter whether we add industry fixed effects to control for industry-level invariant characteristics, year-by-quarter time fixed effects to control for aggregate time-varying fluctuations or firm-level control variables or add firm-level time-variant controls (including firm size, ROA, Tobin's Q, and leverage). These results imply that our SCR index captures the right information.

The last three columns in Table 5 present the difference-in-differences result taking firms with negative stock market returns as the treatment group (hit harder by the trade war shock). On average, firms in the treatment experienced a 0.112 standard deviations increase

[9]The results are similar but slightly weaker if we define the dummy variable as equal to 1 for those whose raw stock market returns is this window are below the median.

in SCR compared to those hit less hard.[10] These results suggest that our supply chain risk index successfully captures the large impacts of the trade war on disrupting firms' supplier network, resulting in a higher level of SCR.

3.4 Positive Correlation of Suppliers' and Customers' Supply Chain Risks

We further validate our measure by examining the spread of supply chain risks between suppliers and customers. Since firms are linked to each other in the production networks, if suppliers in the upstream or customers in the downstream face higher SCR, it may transfer to firms themselves. Therefore, we investigate the correlation between firms' own SCR and their suppliers' and customers' SCR as another validation test. We aggregate the SCR indices of all the suppliers (customers) of a given firm in each quarter to the firm level to construct suppliers' (customers') SCR.[11]

[Insert Table 6 here]

Table 6 presents the results. The first three columns show a strong and robust correlation between suppliers' SCR and firms' own SCR, no matter whether we add the firm, time fixed effects, or control for firms' size and performance. When the suppliers' SCR is higher, firms' own SCR will also go up. Similarly, when the firm's customers' SCR is at a high level, it also correlates with a high level of the firm's own SCR, as is shown in column (4) to (6). These results suggest that our index indeed captures risks about the supply chain, otherwise, it should not have such a strong correlation for the supplier-customer pairs. As a placebo test, in the following six columns, we replace suppliers' SCR with Non-SCR index. The construction of Non-SCR is presented in Equation 2. The results show that firms' SCR is

[10] We confine our sample to the period from 2013 to 2022, as we aim to offer a comprehensive and balanced timeframe before and after the trade war shock.

[11] Since in the Factset dataset information about the sales between firms is mostly missing, we do not use weight in such aggregation process.

not correlated with either the suppliers' or customers' non-supply-chain-related risk index, which strengthens our results and suggests that our SCR index indeed captures the risks along the supply chain rather than any random or aggregate risks. Instead of aggregating the SCR of all suppliers and customers to the firm level, Table A3 in the appendix conducts analyses at the supplier-customer relationship level and finds similar positive correlations between firms' own SCR and SCR of their suppliers or customers.

3.5 Variance Decomposition of Supply Chain Risks

In this subsection, we decompose the variance of supply chain risks (SCR) to investigate the contribution of diverse factors to SCR. Our analysis encompasses the SCR index that tracks 14,270 firms across 367 industries (NAICS 4-digit), spanning from 2001 to 2022. This dataset comprises 436,362 observations.

[Insert Table 7 here]

Table 7 presents the variance decomposition of SCR, examining the extent to which different factors contribute to SCR. Economy-wide shocks, as captured by time-fixed effects, have a minimal impact on SCR, explaining approximately 2.5 percent of the variance. This suggests that broader economic trends play a limited role in SCR fluctuations. In contrast, four-digit NAICS industry fixed effects can explain 22.3 percent of SCR, suggest industry-level shock can explain a quite large proportion of SCR. After adding both time and industry-fixed effects, the R-squred increases to 24.8 percent. Thus our measure captures aggregate and sectoral fluctuations while leaves substantial residual variation (75.2 percent) for identification.

4 Building Resilient Supply Chains

In this section, we analyze what strategies firms take, how firms build resilient supply chains, and whether it works in the face of higher SCR. We start by investigating the cor-

relation between SCR and a firm's characteristics. Following this, we examine the impact of SCR on firms' inventory, trade credit, and cash holdings. Finally, we explore how firms can actively manage supply chain risks, focusing on the acquisition of human capital with supply chain management skills and evaluating the effectiveness of these strategies.

4.1 Supply Chain Risks and Firm Characteristics

This section explores the variation of SCR across firms with different characteristics. Specifically, we regress the firm-level SCR on a set of firm characteristics commonly related to risk exposure, including (1) a dummy variable indicating whether firms belong to manufacturing, (2) whether firms belong to service, (3) the one-quarter-lagged SCR, (4) firm size, (5) market value, (6) the value of property asset, and (7) Tobin's Q.

[Insert Table 8 here]

Consistent with expectation, the regression results show that overall the manufacturing sector has higher SCR, while service sector has lower SCR compared to the rest of sectors. It is noteworthy that SCR is highly persistent as the correlation between the current SCR and one-quarter-lagged SCR is quite high, as shown in column (3). This strong correlation suggests that supply chain uncertainties are likely to remain stable over time and persist from one quarter to the next. Interestingly, larger firms, as measured by the value of assets, market value, and property assets, tend to have higher SCR indices as indicated in column (4) to (6). This trend might be attributed to the fact that larger companies typically manage more complex supply chains, spanning numerous countries and involving a vast network of suppliers. This complexity makes them more vulnerable to supply chain uncertainties. Furthermore, the analysis also uncovers a negative correlation between SCR and Tobin's Q as shown in column (7), indicating that an increase in the market's valuation of a firm's assets relative to their replacement cost correlates with higher supply chain risks. A higher Tobin's Q may indicate that investors expect strong future performance. In such cases, firms

may be under pressure to meet high expectations, which can amplify vulnerabilities in their supply chain (Bloom, 2009). This finding highlights the potential impact of supply chain risks on investor perception and firm valuation.

4.2 Firm-level Responses: Inventory and Cash Holding

In this subsection, we refer Wu (2023) to examine how the SCR index correlates with actions that firms typically undertake in response to supply chain risks. Intuitively, if the SCR index indeed captures supply chain risks well, it should be correlated with typical operational "buffers," such as inventory, cash holding, etc (Lins et al., 2010). From the large literature on inventory management, we know that higher supply chain risks lead to higher inventory buffer, including raw material and intermediate goods (Wu, 2023). To compare our findings with existing literature, we use the following identification to quantify the effect:

$$Y_{ijt} = \alpha + \beta \cdot SCR_{ij,t-1} + \gamma \cdot \mathbf{X}_{ijt} + \delta_j + \delta_t + \epsilon_{ijt}$$

where Y_{ijt} represents multiple variables of interest, including inventory, cash holding, trade credit. $SCR_{ij,t-1}$ denotes the supply chain risks faced by the firm in the previous quarter. $\mathbf{X}$ is a set of control variables, including firm size (logarithm of total assets), return on assets (ROA), Tobin's Q, and leverage. δ_j represents the NAICS 4-digit industry fixed effect used to control the influence of industry-specific attributes on the estimation. δ_t represents the year by quarterly fixed effects used to control the influence of macro shocks on the estimation.

The results of our analysis are presented in table 9. Consistent with theoretical predictions, column (1) demonstrate a robust positive correlation between supply chain risks, as measured by the SCR index, and inventory levels. Specifically, a one standard deviation increase in the SCR index from the previous quarter results in a 0.602% rise in inventory as a percentage of total assets. To explore further, we decompose total inventory into three distinct categories: (1) Raw Material, (2) Work in Progress, and (3) Finished Goods. Our

analysis reveals that the SCR index is significantly correlated with all three types of inventory. These results show the influence of supply chain risks across different stages of the production cycle.

[Insert Table 9 here]

After that, we investigate the correlation between the SCR and cash holding. Consistent with previous findings, column (5) shows a strong and positive correlation between cash holding and the SCR from the previous quarter. This suggests that firms facing higher supply chain risks increase their cash buffer to hedge against the risk. Similarly, we find that SCR is positively related to accounts payable, consistent with the finding that firms purchase more inventories in the face of higher supply chain risk. We do not see a significant relation between SCR and accounts receivable.

As a placebo test, we employ Non-SCR index constructed in Equation 2 as our key explanatory variable. Intuitively, firms' inventory should not be correlated with Non-SCR, while cash holding and trade credits may correlate with it. Results in Table 10 confirm the predictions. Columns (1)-(4) show that firms' inventory variables are actually negatively correlated with Non-SCR instead of being positively correlated as shown in Table 9. This may be due to that firms reduce production and investment in the face of higher risks which then decreases the inventory level. Similar as responses to supply chain risk, firms also increase cash holding and accounts payable to hedge again higher non-supply chain risks from the previous quarter.

[Insert Table 10 here]

4.3 Enhancing Supply Chains Resilience: Human Capital Acquisition

This section studies how SCR influences firms' recruitment decisions. Intuitively, as firms are more vulnerable to (supply chain) shocks when facing supply chain risks, they

might hire more people to ensure continuity of operations, maintain supplier relationships, manage risks and crisis, and control cost. Thus we expect that supply chain risks is positively correlated with firms' hiring strategy in specialists with supply chain management skills. To examine this relationship, we first plot a non-parametric bin scatter of supply chain skill investment relative to supply chain risks as in Figure 2,[12] where each circle represents the mean supply chain risks within bins optimally selected following (Cattaneo et al., 2024) and firm characteristics and time (year-quarter) and indsutry (2-digit NAICS) FEs are controlled for. The plot shows a clear positive relationship which confirms our hypothesis.

[Insert Figure 2 here]

We employ the following identification strategy to quantify the impact:

$$JobRatio_{ijt} = \alpha + \beta \cdot SCR_{ij,t-1} + \gamma \cdot \mathbf{X}_{ijt} + \delta_j + \delta_t + \epsilon_{ijt}$$

where $JobRatio_{ijt}$ is the ratio of posting requiring a certain skill to all job postings made by by the firm i in industry j during the quarter t. We weight the supply chain postings based on the number of skills required in each posting. A job posting requiring more skills is assigned a lower weight for each skill category. $SCR_{ij,t-1}$ denotes the supply chain risks faced by the firm in the previous quarter. $\mathbf{X}$ is a set of control variables, including firm size (logarithm of total assets), return on assets (ROA), Tobin's Q, and leverage. δ_j represents the NAICS 4-digit industry fixed effect used to control the influence of industry-specific attributes on the estimation. δ_t represents the year by quarterly fixed effects used to control the influence of macro shocks on the estimation.

[Insert Table 11 here]

Column (1) in Table 11 shows the results of the influence of SCR on firms' job postings that require supply chain-related skills. Consistent with results in Figure 2, column (1)

[12]We also document a rising demand for supply chain expertise over the sample period.

shows that demand for supply chain skills increases by 0.1% with one standard deviation increase in SCR. This indicates firms experiencing higher level of supply chain risks hire more human capital specialized in managing these challenges. Columns (2) to (4) show the results of placebo tests, confirming that the rise in SCR specifically increases the demand for supply chain-related jobs rather than for jobs requiring other specialized skills. Specifically, we demonstrate SCR's increase does not significantly affect job postings in either Finance, Healthcare or Design sectors. This result aligns with our findings and suggests that the increase in SCR primarily pushes up the demand for employees with supply chain-related skills rather than other specialized skills.

To further rule out the possibility that the hirings with supply chain skills were driven by aggregate level of risks or other types of risks rather than supply chain risks, in column (5) to (8) of Table 11, we replace SCR with an index that indicates the risks not related to supply chains (non-SCR) using the same textual data. We find that firms' hiring with supply chain management skills do not positively respond to other types of risks (non-SCR). Firms' hiring in other types of skills (finance, healthcare, and design) is not positively related to non-SCR, either. These results suggest that firms demand more human capital with a specialization in supply chain management when firms face higher supply chain risks.

Following this, we delve deep into whether firms' hiring decisions could help them build a more resilient supply chain and then operate more efficiently. According to the survey by Deloitte (2022), the most important practice in enhancing supply chain resilience firms have taken is to have dual and multi-sourcing and geographic diversification of suppliers, while all of these require specialists with supply chain management skills to coordinate and build. Hence, we first investigate whether the stock of human capital specializing in supply chain management helps companies connect to more suppliers and reduce geographic concentration.

Table 12 presents the results. We use the number of a firm's job postings in the past 4 quarters that require skills related to supply chain management as the proxy for a firm's stock

of human capital in supply chain management. Tables A4 and A5 in the Appendix consider alternative measures of such stock using the number of job postings in the past 8 and 12 quarters and find similar results. The first three columns focus on the impacts of such stocks on the number of suppliers, showing that when the stock of human capital with supply chain skill increases by 1%, the number of suppliers will increase by 0.073%. This effect is significant after controlling for the effects of time, industry, and firms' characteristics. In the last three columns, We focus on the impacts of such human capital stock on the geographic concentration of firms' suppliers measured by the Herfindahl-Hirschman Index (HHI) of a firm's suppliers across countries. The results demonstrate that having a large stock of human capital in supply chain management significantly reduces supplier concentration across countries. These two sets of results suggest firms' strategy in hiring more talents specializing in supply chain management indeed helps firms enhance supply chain resilience.

[Insert Table 12 here]

Given that occupying a large stock of human capital in supply chain management strengthens the resilience of the supply chain network, firms may not need to hold a large stock of inventory and cash as a buffer even in the face of higher SCR, as holding such buffer is usually inefficient and costly. To test such effects, in Table 13, we interact the SCR with firms' stock of talents in supply chain management. Consistent with results in Table 9, we find that firms increase inventory and cash holding when SCR is high. However, for those with a larger stock of such human capital, the incentive of holding inventory buffers is lower, as the coefficient of the interaction is significantly negative. When we decompose inventory into different types: raw material, work in progress, and finished goods, we find the effect mainly concentrates on finished goods. Similarly, the incentive of holding more cash holding is also lower when firms have a larger stock of human capital in supply chain management. Column (6) further demonstrates that firms with a larger stock of such human capital tend to have higher accounts payable, which may be caused by the increased bargaining power with their suppliers. Furthermore, we conduct robustness checks in Tables A6 and A7 of

the Appendix using the number of job postings in the past 8 and 12 quarters and find similar effects. These results suggest that firms' strategy of hiring more talents with skills in supply chain management helps firms operate more efficiently.

[Insert Table 13 here]

5 Conclusion

This paper constructs a firm-level index to measure supply chain risks by analyzing firms' annual and quarterly reports, primarily using zero-shot prompting of large language models (LLMs). We validate our index through several methods, including comparisons with baselines and human-labeled data, visualizing and interpreting supply chain risks over time and across industries, analyzing the index's sensitivity to trade wars, and demonstrating a strong positive correlation between the supply chain risks of suppliers and customers.

We then examine how firms respond to increased supply chain risks. Our findings show that firms tend to hire more specialists in supply chain management when their supply chain risks rise. This strategy enhances supply chain resilience, as a larger stock of human capital in supply chain management leads to a greater number of suppliers and reduces the geographic concentration of those suppliers. Additionally, having a more substantial pool of such specialists improves operational efficiency by lowering the need to maintain larger buffers of inventory and cash, even in the face of heightened supply chain risks.

In the future, researchers could further validate the zero-shot prompting approach by: (1) examining its robustness across different large language models (e.g., BERT, Flan-T5, BART), and (2) comparing it with other existing methods (e.g., dictionary-based methods and supervised machine learning) and alternative measures in terms of their responsiveness to external shocks. Additionally, researchers could explore the implications of supply chain risks by linking the proposed index to more dependent variables, such as stock market returns, to provide more actionable insights for the supply chain management community.

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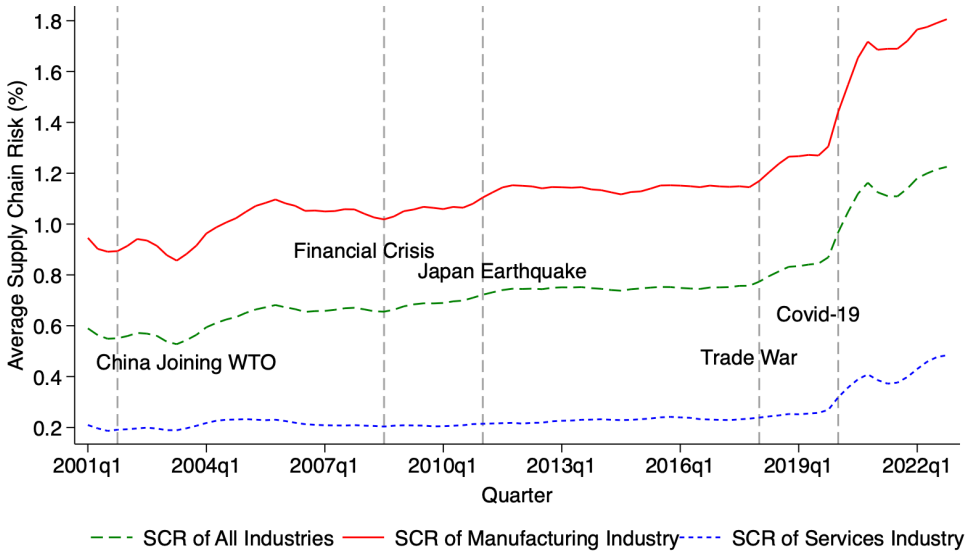
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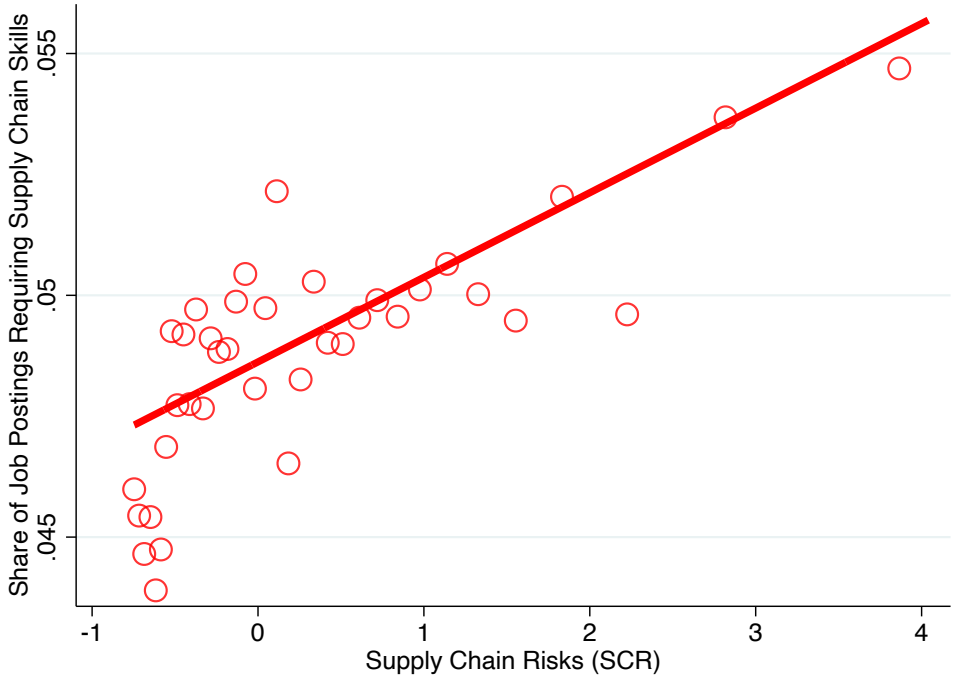
Figures

Figure 1: Average Supply Chain Risks



Note: This figure shows the average quarterly supply chain risk (SCR) across various industries from 2001 to 2022. The quarterly average SCR is calculated using an equally weighted moving average, incorporating the current quarter and the previous three quarters. The green line shows the average SCR across all industries. The red line indicates the average SCR for manufacturing firms with 2-digit NAICS industry codes 31, 32, and 33. The blue line represents the average SCR for service sector firms with 2-digit NAICS codes 51, 52, 53, 54, 55, and 56.

Figure 2: Supply Chain Risk and Supply Chain Skill Acquisition



Note: This figure shows the relationship between supply chain risks and firms' investment (share of job postings) in supply chain skills. Each circle on the graph represents the average investment in supply chain skills measured by following Cattaneo et al. (2024)

Tables

Table 1: Prompt to Classify Whether a Sentence is Related to Supply Chain

You are an expert at classifying whether a sentence in financial report relates to supply chain. Your job is to classify the provided sentence into one of the following labels: yes, no. You will return the answer with just one element: "the correct label" Now I want you to label the following example: Example: {sentence to classify} Label:

Table 2: Positive and Negative Sentences w.r.t. Supply Chain Relevance

	Ground Truth	Proposed	Baseline
Additional risks are present related to our pipeline that traverses areas in Florida where karst conditions exist	1	1	0
Our insurance may not protect us against operating risks, including an operator of a prospect in which we participate failing to maintain or obtain adequate insurance	0	0	1

Note: The label refers to whether the sentence is relevant to supply chain. The first column presents human-labeled results, the second column shows results generated by our proposed method, and the third column displays results from a dictionary-based method.

Table 3: Summary Statistics

	N	Mean	p50	p10	p90	SD
SCR	436,362	0.008	0.003	0.000	0.022	0.011
SCR (standardized)	436,362	0.017	-0.428	-0.661	1.368	1.008
Non-SCR	436,362	0.100	0.092	0.046	0.165	0.048
Non-SCR (standardized)	436,362	0.000	-0.163	-1.120	1.354	0.991
SCR (Wu)	436,362	0.019	-0.265	-0.869	1.369	1.005
Inventory/Asset	436,362	8.510	1.497	0.000	26.629	13.156
Raw Materials/Assset	236,211	2.580	0.000	0.000	8.328	4.927
Intermediate Goods/Asset	234,615	1.237	0.000	0.000	4.077	2.910
Finished Goods/Asset	237,001	3.953	0.000	0.000	12.165	7.747
Cash/Asset	436,313	21.059	9.649	0.955	63.550	25.511
Account Payable/Asset	432,887	24.467	6.386	0.942	73.237	64.122
Account Receivable/Asset	314,861	12.744	9.055	0.000	29.344	14.175
Tobin's Q	436,362	6.863	1.473	0.937	6.069	29.143
Leverage	410,216	0.445	0.178	0.000	0.669	1.346
Size	436,362	5.545	5.905	1.676	8.983	2.926
ROA	436,362	-0.091	0.006	-0.160	0.042	0.464
From the Ligthcast Dataset:						
Supply chain skills related job (ratio)	101,463	0.033	0.014	0.000	0.087	0.050
Design skills related job (ratio)	101,463	0.063	0.035	0.000	0.161	0.091
Finance skills related job (ratio)	101,463	0.038	0.004	0.000	0.093	0.105
Healthcare skills related job (ratio)	101,463	0.012	0.004	0.000	0.029	0.031
Hiring in the past 4 quarters	109,811	1.621	0.892	0.000	4.450	1.855
Hiring in the past 8 quarters	99,072	2.088	1.474	0.000	5.180	2.070
Hiring in the past 12 quarters	88,312	2.421	1.900	0.000	5.635	2.187

Note: This table presents a summary of key indicators related to supply chain risks, inventory levels, cash holdings, trade credits, and control variables. It also includes the ratio of skill categories in firms' job postings. The data covers 14,270 unique firms over the period from 2001 to 2022.

Table 4: Performance of Proposed Approach vs. Baseline

	Accuracy	Precision	Recall	F1 Score	ROC AUC
Proposed approach	93.80	75.53	53.19	61.72	75.60
Baseline (Wu, 2023)	90.70	51.11	24.47	33.09	61.02

Notes: Accuracy represents the percentage of correct predictions made by the model. Precision measures the proportion of correct positive predictions (true positives) out of all positive predictions, including both true positives and false positives. Recall, also known as the true positive rate, refers to the proportion of actual positives correctly identified by the model. The F1 score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. The ROC AUC (Receiver Operating Characteristic - Area Under the Curve) quantifies the area under the ROC curve, which plots the true positive rate against the false positive rate at various thresholds. A higher ROC AUC value indicates better model performance.

Table 5: Trade War and Supply Chain Risks

	(1)	(2)	(3)	(4)	(5)	(6)
	Supply Chain Risk					
Tariff increase at the industry level	3.660***	1.190***	1.168***			
	(0.152)	(0.228)	(0.223)			
Large trade war shock x post trade war				0.123***	0.129***	0.112***
				(0.029)	(0.028)	(0.031)
Large trade war shock				0.024	0.071**	0.037
				(0.036)	(0.034)	(0.036)
Log (total assets)			0.072***			0.046***
			(0.007)			(0.008)
ROA			0.013			0.269***
			(0.012)			(0.093)
Tobin's Q			0.001***			0.003
			(0.000)			(0.002)
Leverage			-0.005			-0.051
			(0.003)			(0.042)
Observations	159,509	159,508	143,957	93,753	93,753	85,873
Adjusted R-squared	0.049	0.204	0.228	0.018	0.238	0.228
Industry FE	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes
Sample	2013q1-2022q4					

Note: This table presents the relationship between trade wars and supply chain risk. The first three columns show the correlation between tariff increases and supply chain risk. The last three columns show how firms' supply chain risks vary with trade war shock. The large trade war shock is a dummy variable, equal to 1 for firms with negative stock market returns within a four-day window surrounding the trade war event. Industry fixed effects are applied at the NAICS 4-digit level. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Correlation between Suppliers' and Customers' SCR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Supply Chain Risk											
Suppliers' SCR	0.142***	0.023***	0.026***									
	(0.011)	(0.008)	(0.008)									
Customers' SCR				0.194***	0.057***	0.058***						
				(0.011)	(0.009)	(0.010)						
Suppliers' Non-SCR							0.008	-0.001	0.002			
							(0.009)	(0.008)	(0.008)			
Customers' Non-SCR										-0.002	-0.015*	-0.013
										(0.009)	(0.008)	(0.008)
Log (total assets)			0.026***			0.035***			0.025***			0.034***
			(0.007)			(0.007)			(0.007)			(0.007)
ROA			0.629***			0.441***			0.634***			0.436***
			(0.161)			(0.150)			(0.161)			(0.149)
Tobin's Q			0.014**			0.011**			0.015***			0.011**
			(0.006)			(0.005)			(0.006)			(0.005)
Leverage			-0.137***			-0.204***			-0.139***			-0.209***
			(0.037)			(0.038)			(0.037)			(0.038)
Observations	114,183	114,183	107,937	119,587	119,585	111,432	116,229	114,183	107,937	119,587	119,585	111,432
Adjusted R-squared	0.019	0.223	0.223	0.037	0.224	0.216	0.000	0.222	0.223	0.000	0.222	0.214
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sample	2003q1-2022q4											

Note: The first six columns show the spread of supply chain risk (SCR) between suppliers and customers, specifically examining whether suppliers' SCR influences a firm's SCR. The last six columns provide results from placebo tests using a Non-SCR index, which evaluate whether risks from suppliers, unrelated to supply chain issues (Non-SCR), influence the firm's SCR. The supplier's SCR is calculated as the average SCR of all the firm's suppliers. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Variance Decomposition of Supply Chain Risks

VARIABLES	R-squared
Time FE	2.5%
Industry FE (4-digit NAICS)	22.3%
Industry FE (4-digit NAICS) x Time FE	24.8%
Number of industries	367
Number of firms	14,270
Number of observations	436,362
Sample period	2001q1-2022q4

Note: The table displays a variance decomposition analysis of supply chain risk (SCR), detailing the R-squared values for each individual fixed effect across different levels.

Table 8: Supply Chain Risks and Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Supply Chain Risk						
Manufacturing	0.584***						
	(0.017)						
Services		-0.724***					
		(0.013)					
L.SCR (standardized)			0.670***				
			(0.005)				
Log (total assets)				0.062***			
				(0.002)			
Log (market value)					0.062***		
					(0.003)		
Log (property asset)						0.064***	
						(0.003)	
Tobin's Q							-0.003***
							(0.000)
Observations	436,362	436,362	414,221	436,362	436,362	230,844	436,362
Adjusted R-squared	0.106	0.148	0.578	0.272	0.269	0.245	0.254
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4

Notes: The table shows the variation of supply chain risks across firms with different characteristics. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Supply Chain Risks and Firms' Inventory and Cash Holdings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inventory	Raw Material	Work in Progress	Finished Goods	Cash Holding	Payable	Receivable
L.SCR (standardized)	0.602***	0.156***	0.115***	0.387***	0.883***	0.459***	0.060
	(0.079)	(0.047)	(0.028)	(0.061)	(0.136)	(0.160)	(0.076)
Log (total assets)	-0.440***	-0.270***	-0.032**	-0.135***	-1.751***	-1.394***	-0.028
	(0.044)	(0.025)	(0.014)	(0.028)	(0.081)	(0.150)	(0.053)
ROA	1.755***	0.787***	0.309***	0.588***	-1.200***	-54.870***	2.591***
	(0.180)	(0.073)	(0.033)	(0.087)	(0.432)	(2.740)	(0.190)
Tobin's Q	-0.011***	-0.004***	-0.001**	-0.003***	0.047***	0.169***	-0.005**
	(0.002)	(0.001)	(0.000)	(0.001)	(0.006)	(0.029)	(0.002)
Leverage	0.185***	0.027	0.007	0.033	-2.255***	19.382***	0.228***
	(0.061)	(0.026)	(0.010)	(0.030)	(0.165)	(1.137)	(0.072)
Observations	389,198	210,822	209,300	211,570	389,162	386,847	285,219
Adjusted R-squared	0.500	0.340	0.307	0.507	0.380	0.680	0.317
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4

Notes: The table shows how firms response to supply chain risks. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Non-Supply Chain Risks and Firms' Inventory and Cash Holdings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inventory	Raw Material	Work in Progress	Finished Goods	Cash Holding	Payable	Receivable
Non-SCR (standardized)	-0.499***	-0.246***	-0.090***	-0.333***	2.382***	0.419*	-0.155
	(0.069)	(0.040)	(0.026)	(0.052)	(0.154)	(0.248)	(0.108)
Log (total assets)	-0.371***	-0.246***	-0.019	-0.090***	-1.854***	-1.394***	-0.014
	(0.044)	(0.025)	(0.014)	(0.028)	(0.081)	(0.152)	(0.052)
ROA	1.723***	0.774***	0.304***	0.572***	-0.974**	-54.824***	2.581***
	(0.179)	(0.073)	(0.033)	(0.087)	(0.429)	(2.740)	(0.190)
Tobin's Q	-0.011***	-0.004***	-0.001**	-0.003***	0.046***	0.169***	-0.004**
	(0.002)	(0.001)	(0.000)	(0.001)	(0.006)	(0.029)	(0.002)
Leverage	0.179***	0.025	0.006	0.028	-2.251***	19.381***	0.227***
	(0.060)	(0.026)	(0.010)	(0.030)	(0.164)	(1.137)	(0.072)
Observations	389,198	210,822	209,300	211,570	389,162	386,847	285,219
Adjusted R-squared	0.499	0.341	0.306	0.506	0.385	0.680	0.317
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4	01q1-22q4

Notes: The table presents a placebo test, examining firms' responses to risks not related to supply chain issues. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: SCR and Firms' Hirings with Different Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Share of Job Postings Requiring Specific Skills							
	Supply Chain	Finance	Healthcare	Design	Supply Chain	Finance	Healthcare	Design
L.SCR (standardized)	0.001**	0.000	-0.002**	-0.000				
	(0.000)	(0.000)	(0.001)	(0.000)				
L.Non-SCR (standardized)					-0.001***	0.000	-0.002*	0.000
					(0.000)	(0.001)	(0.001)	(0.000)
Log (total assets)	0.000*	-0.002***	0.000	-0.000	0.001**	-0.002***	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
ROA	-0.000	0.014	-0.005	-0.000	-0.000	0.015	-0.007	0.000
	(0.000)	(0.010)	(0.016)	(0.004)	(0.000)	(0.010)	(0.016)	(0.004)
Tobin's Q	-0.001***	-0.001**	-0.001	0.000	-0.001***	-0.001**	-0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Leverage	0.001	0.004	0.010**	-0.003***	0.001	0.004	0.010**	-0.003***
	(0.002)	(0.003)	(0.005)	(0.001)	(0.002)	(0.003)	(0.005)	(0.001)
Observations	89,704	89,704	89,704	89,704	89,704	89,704	89,704	89,704
Adjusted R-squared	0.276	0.239	0.429	0.083	0.276	0.239	0.429	0.083
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	2010q1-2022q4							

Notes: The table shows the impact of supply chain risks on firms' hiring decisions across various skill categories. The columns display the ratio of job postings requiring specific skills. For job postings listing multiple skills, each skill is weighted inversely by the total number of skills listed. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Hiring on Suppliers Diversification

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Number of Total Suppliers			Supplier HHI by Country		
Log (hiring in the past 4 quarters)	0.274***	0.257***	0.073***	-0.036***	-0.036***	-0.005**
	(0.012)	(0.013)	(0.011)	(0.002)	(0.003)	(0.002)
Log (total assets)			0.399***			-0.064***
			(0.013)			(0.003)
ROA			-1.838***			0.225***
			(0.242)			(0.066)
Tobin's Q			0.032***			-0.003
			(0.009)			(0.002)
Leverage			-0.056			-0.032*
			(0.069)			(0.017)
Observations	75,701	75,700	70,588	75,701	75,700	70,588
Adjusted R-squared	0.174	0.394	0.574	0.057	0.274	0.366
Industry FE	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes
Sample	2010q1-2022q4					

Note: This table shows how hiring supply chain specialists influences firms' supplier diversification. The Herfindahl-Hirschman Index (HHI) measures supplier concentration by summing the squared market shares of a firm's suppliers across various countries. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Effect of Hiring on Firms' Operations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inventory	Raw Material	Work in Progress	Finished Goods	Cash Holding	Accounts Payable	Accounts Receivable
SCR (standardized) x log(the number of hirings with SC skills in the past 4 quarters)	-0.151***	0.009	-0.014	-0.144***	-0.182**	0.093*	0.001
	(0.053)	(0.031)	(0.018)	(0.042)	(0.078)	(0.056)	(0.052)
SCR (standardized)	0.684***	0.145*	0.112**	0.443***	1.116***	-0.274*	-0.176
	(0.152)	(0.087)	(0.057)	(0.122)	(0.284)	(0.165)	(0.158)
Log (hiring in the past 4 quarters)	0.268***	0.113***	0.026	0.218***	-0.471***	0.437***	0.346***
	(0.087)	(0.044)	(0.030)	(0.076)	(0.123)	(0.112)	(0.105)
Observations	97,259	61,670	61,277	62,784	99,457	98,845	81,422
R-squared	0.661	0.482	0.399	0.671	0.538	0.868	0.487
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	2010q1-2022q4						

Note: The table shows the impact of hiring supply chain specialists on firms' operations. The logarithm of firms' hiring data over the past four quarters is used to assess this effect, with additional data over eight and twelve quarters provided in the appendix. The number of hires is weighted by the number of skills required in the job postings. A job posting that requires multiple skills is weighted inversely by the number of skills mentioned in section 2.1.2. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1: Timeline of Trade War

Date enacted	Products (HS-10)	2017 imports ($ billion)	Tariff increase (%)
July 6, 2018	1629	340	25
August 23, 2018	401	160	25
September 24, 2018	8664	2000	10
May 10, 2019	8664	2000	15
September 1, 2019	5597	1120	15

Note: The table presents the number of products categorized by Harmonized System codes, the value of imports for these products, and the tariff increases implemented during each round of the US-China trade war.

Table A2: Trade War and Supply Chain Risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Supply Chain Risk (Wu)					
Tariff increase at the industry level	2.161***	0.443***	0.397***			
	(0.135)	(0.132)	(0.135)			
Large trade war shock x post trade war			0.042***	0.099***	0.104***	0.089***
			(0.004)	(0.031)	(0.031)	(0.033)
Large trade war shock			0.045***	0.039	-0.044	-0.061
			(0.013)	(0.041)	(0.042)	(0.045)
Log (total assets)			0.000*			0.019**
			(0.000)			(0.008)
ROA			-0.008**			0.460***
			(0.004)			(0.110)
Tobin's Q	159,509	159,508	143,957			0.009***
	0.018	0.142	0.153			(0.003)
Leverage			-0.005			-0.103***
			(0.003)			(0.034)
Observations	159,509	159,508	143,957	93,753	93,753	85,873
Adjusted R-squared	0.049	0.204	0.228	0.008	0.181	0.172
Industry FE	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes
Sample	2013q1-2022q4					

Note: This table presents the relationship between trade wars and supply chain risk, using the dictionary-based index constructed following Wu (2023). The first three columns show the correlation between tariff increases and supply chain risk. The last three columns show how firms' supply chain risks vary with trade war shock. The large trade war shock is a dummy variable, equal to 1 for firms with negative stock market returns within a four-day window surrounding the trade war event. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Correlation between Suppliers' and Customers' SCR

	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(5)	(6)	(4)	(5)	(6)
	Supply Chain Risk											
Suppliers' SCR	0.087***	0.010**	0.011***									
	(0.007)	(0.004)	(0.004)									
Custom' SCR				0.099***	0.021***	0.023***						
				(0.010)	(0.004)	(0.004)						
Suppliers' Non-SCR							0.021***	-0.001	0.000			
							(0.008)	(0.004)	(0.004)			
Custom' Non-SCR										-0.005	-0.011***	-0.010***
										(0.011)	(0.003)	(0.003)
Log (total assets)			0.023			0.028***			0.022			0.028***
			(0.022)			(0.009)			(0.022)			(0.009)
ROA			-0.350			-0.028			-0.352			-0.025
			(0.860)			(0.267)			(0.860)			(0.267)
Tobin's Q			0.073			0.016*			0.073			0.016*
			(0.046)			(0.009)			(0.047)			(0.009)
Leverage			0.005			-0.147**			0.004			-0.147**
			(0.089)			(0.063)			(0.089)			(0.063)
Observations	653,540	653,540	627,815	674,123	674,122	619,440	653,540	653,540	627,815	674,123	674,122	619,440
Adjusted R-squared	0.008	0.241	0.247	0.010	0.351	0.339	0.009	0.241	0.247	0.000	0.351	0.338
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
YEAR BY QUARTER FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sample	2003q1-2022q4											

Note: The first six columns show the spread of supply chain risk (SCR) between suppliers and customers, specifically examining whether suppliers' SCR influences a firm's SCR. The last six columns provide results from placebo tests using a Non-SCR index, which evaluate whether risks from suppliers, unrelated to supply chain issues (Non-SCR), influence the firm's SCR. The analysis is conducted at the individual supplier-customer pair level, rather than at an aggregate level. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Hiring on Suppliers Diversification

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Number of Total Suppliers			Supplier HHI by Country		
Log (hiring in the past 8 quarters)	0.256***	0.242***	0.064***	-0.034***	-0.035***	-0.005**
	(0.011)	(0.012)	(0.010)	(0.002)	(0.002)	(0.002)
Log (total assets)			0.406***			-0.066***
			(0.013)			(0.003)
ROA			-1.820***			0.230***
			(0.251)			(0.067)
Tobin's Q			0.034***			-0.003
			(0.009)			(0.002)
Leverage			-0.048			-0.035**
			(0.071)			(0.017)
Observations	69,912	69,910	65,166	69,912	69,910	65,166
Adjusted R-squared	0.180	0.402	0.581	0.063	0.284	0.378
Industry FE	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes
Sample	2010q1-2022q4					

Note: This table shows how hiring supply chain specialists influences firms' supplier diversification. The Herfindahl-Hirschman Index (HHI) measures supplier concentration by summing the squared market shares of a firm's suppliers across various countries. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Hiring on Suppliers Diversification

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Number of Total Suppliers			Supplier HHI by Country		
Log (hiring in the past 12 quarters)	0.250***	0.237***	0.061***	-0.034***	-0.035***	-0.005**
	(0.011)	(0.012)	(0.010)	(0.002)	(0.002)	(0.002)
Log (total assets)			0.413***			-0.068***
			(0.013)			(0.003)
ROA			-1.846***			0.245***
			(0.258)			(0.069)
Tobin's Q			0.037***			-0.003
			(0.009)			(0.002)
Leverage			-0.053			-0.034*
			(0.072)			(0.018)
Observations	63,802	63,801	59,459	63,802	63,801	59,459
Adjusted R-squared	0.185	0.411	0.591	0.069	0.293	0.392
Industry FE	No	Yes	Yes	No	Yes	Yes
Year by quarter FE	No	Yes	Yes	No	Yes	Yes
Sample	2010q1-2022q4					

Note: This table shows how hiring supply chain specialists influences firms' supplier diversification. The Herfindahl-Hirschman Index (HHI) measures supplier concentration by summing the squared market shares of a firm's suppliers across various countries. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effect of Hiring on Firms' Operations (Using hiring in the past 8 quarters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inventory	Raw Material	Work in Progress	Finished Goods	Cash Holding	Accounts Payable	Accounts Receivable
SCR (standardized) x log(the number of hirings with SC skills in the past 8 quarters)	-0.128***	0.011	-0.008	-0.129***	-0.183**	0.104**	0.008
	(0.050)	(0.029)	(0.017)	(0.040)	(0.074)	(0.053)	(0.049)
SCR (standardized)	0.700***	0.145*	0.101*	0.473***	1.195***	-0.355*	-0.184
	(0.165)	(0.087)	(0.061)	(0.133)	(0.310)	(0.181)	(0.171)
Log (hiring in the past 8 quarters)	0.256***	0.140	0.030	0.209***	-0.457***	0.391***	0.354***
	(0.081)	(0.095)	(0.028)	(0.071)	(0.119)	(0.106)	(0.101)
Observations	87,786	55,658	55,301	56,657	89,782	89,240	73,447
R-squared	0.665	0.485	0.397	0.670	0.541	0.870	0.492
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	2010q1-2022q4						

Note: The table shows the impact of hiring supply chain specialists on firms' operations. The logarithm of firms' hiring data over the past four quarters is used to assess this effect, with additional data over eight and twelve quarters provided in the appendix. The number of hires is weighted by the number of skills required in the job postings. A job posting that requires multiple skills is weighted inversely by the number of skills mentioned in section 2.1.2. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effect of Hiring on Firms' Operations (Using hiring in the past 12 quarters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inventory	Raw Material	Work in Progress	Finished Goods	Cash Holding	Accounts Payable	Accounts Receivable
SCR (standardized) x log(the number of hirings with SC skills in the past 12 quarters)	-0.113**	0.011	-0.006	-0.115***	-0.174**	0.002	0.112**
	(0.048)	(0.028)	(0.017)	(0.039)	(0.073)	(0.006)	(0.051)
SCR (standardized)	0.703***	0.145	0.098	0.466***	1.198***	0.041*	-0.431**
	(0.173)	(0.099)	(0.064)	(0.140)	(0.329)	(0.023)	(0.194)
Log (hiring in the past 12 quarters)	0.244***	0.105**	0.031	0.195***	-0.448***	-0.021**	0.367***
	(0.080)	(0.042)	(0.028)	(0.069)	(0.119)	(0.011)	(0.105)
Observations	78,295	49,538	49,273	50,505	80,109	70,935	79,635
R-squared	0.669	0.928	0.395	0.670	0.540	0.751	0.872
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	2010q1-2022q4						

Note: The table shows the impact of hiring supply chain specialists on firms' operations. The logarithm of firms' hiring data over the past four quarters is used to assess this effect, with additional data over eight and twelve quarters provided in the appendix. The number of hires is weighted by the number of skills required in the job postings. A job posting that requires multiple skills is weighted inversely by the number of skills mentioned in section 2.1.2. The sample ranges from 2010, when the Lightcast dataset begins, to 2022. Industry fixed effects are applied at the NAICS 4-digit level. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.