Finance Research Letters 77 (2025) 107111

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Measuring firm-level supply chain risk using a generative large language model☆

Siyu Fan[a,b,*], Yifei Wu[a], Ruochen Yang[a]

[a] *School of Management and Engineering, Nanjing University, China*
[b] *Department of Accountancy, College of Business, City University of Hong Kong, China*

ARTICLE INFO

JEL Codes:
G12
G30
G32

Keywords:
Supply chain risk
Large language models
Generative AI
Site visit

ABSTRACT

Using site visit transcripts from Chinese-listed firms, we propose a generative large language model (LLM)-based approach to quantify firm-level supply chain risks. We validate our measure by showing that it varies intuitively over time and across industries, and it correlates with higher capital costs, greater stock return volatility, and larger inventory reserves. Furthermore, we identify distinct categories of supply chain risks at both the micro and macro levels, finding that supply chain concentration drives micro-level risks, while exposure to overseas markets and macroeconomic conditions drives macro-level risks. Our findings highlight the capability of LLMs to assess supply chain risk.

1. Introduction

Supply chain risk refers to unexpected macro-level or micro-level adverse events or conditions that affect the supply chains, resulting in failures or irregularities at the operational, tactical, or strategic levels (Ho et al., 2015). Assessing and managing supply chain risks has become a key factor in ensuring operational efficiency and financial performance, which is particularly important for Chinese companies, given their significant role in the global value chain. However, measuring firm-level supply chain risks remains a challenge due to the complexity and dynamism of supply chains (Sodhi et al., 2012; Ho et al., 2015), and conventional dictionary-based methods are limited in their ability to fully capture context within corporate disclosures (Wu, 2024), which often leads to measurement errors.

The advent of large language models (LLMs) presents new opportunities to address these methodological limitations. Trained on a large corpus of text data, LLMs possess superior capabilities in text understanding and reasoning. They can perform various natural language tasks, such as text generation, summarization, and classification, even without direct fine-tuning (Dowling and Lucey, 2023; Chen et al., 2023; Kim et al., 2023; Lopez-Lira and Tang, 2023; Cao et al., 2024; Kirtac and Germano, 2024; Ma et al., 2024). In this paper, we propose a generative LLM-based approach to measure firm-level supply chain risk exposure.

The unique dataset from corporate site visits in China offers several advantages for analyzing supply chain risks.[1] Corporate site

☆ This work is supported by the Major Program of National Fund of Philosophy and Social Science of China (No. 19ZDA105). All errors are our own.

* Corresponding author.
E-mail addresses: fansiyu@smail.nju.edu.cn (S. Fan), yifeiwu@smail.nju.edu.cn (Y. Wu), ruochen@smail.nju.edu.cn (R. Yang).

[1] Site visits, as a form of private interaction between investors and firms, are generally either not documented or prohibited from being disclosed by firms in the U.S. and Europe. However, the Shenzhen Stock Exchange requires mandatory public disclosure of these records for listed firms.

https://doi.org/10.1016/j.frl.2025.107111
Received 11 October 2024; Received in revised form 27 November 2024; Accepted 26 February 2025
Available online 27 February 2025
1544-6123/

visits, where investors visit company headquarters or factories and engage in direct discussions with management, serve as private interactions between investors and firms. Unlike scheduled quarterly earnings calls, site visits can be initiated by investors at any time, allowing the transcripts to capture timely information on supply chain risks and unexpected events. Moreover, fund managers and analysts, who possess the expertise to identify potential risks, are the primary participants in these private meetings (Liu et al., 2017; Han et al., 2018). As a result, transcripts from these interactions provide valuable insights into corporate risks that may not be fully revealed in financial reports or other public disclosures.

We employ the GPT-4o mini model to analyze the site visit transcripts. The approach involves several steps. First, we design a prompt that instructs the GPT model to identify and summarize the supply chain risks mentioned in the text and to classify these risks into macro-level and micro-level categories based on the definitions provided in the prompt. Next, we feed each transcript into the GPT model along with the designed prompt, which generate a summary of the identified supply chain risks along with their respective classifications. Finally, we calculate the length of the generated summary relative to the total length of the transcript, which serves as a proxy for our firm-level supply chain risk exposure. A higher ratio suggests a greater focus on risk discussions during the site visit, indicating higher exposure to supply chain risks.

We conduct several validation tests to verify our methodology. First, following Hassan et al. (2019), we examine the face validity of our GPT-based measure by investigating whether it varies intuitively over time and across industries. Second, we explore whether our measure closely correlates with firm-level outcomes or behaviors theoretically related to supply chain risk. Consistent with theoretical predictions, we find that our measure is associated with higher capital costs, greater stock return volatility, and larger inventory reserves, indicating that it indeed captures supply chain risks. We further test whether our GPT-based measure offers incremental predictive power over existing proxies. The results show that even after controlling for the bag-of-words-based proxy, our measure retains significant predictive power for these outcomes. Finally, we subcategorize supply chain risks at the micro and macro levels, exploring their respective determinants. We find that supply chain concentration drives micro-level risks, while exposure to overseas markets and macroeconomic conditions drives macro-level risks.

Our study makes several contributions to the literature. First, we contribute to the supply chain risk management literature by introducing an LLM-based measure of firm-level supply chain risk exposure. Our findings offer new insights into the determinants and consequences of supply chain risks, providing valuable guidance for effective risk management. Second, our work adds to the growing literature employing generative LLMs in accounting and finance. Recent studies have documented the capability of LLMs in sentiment analysis, classification, and information extraction (Chen et al., 2023; Kim et al., 2023; Lopez-Lira and Tang, 2023). Our study extends this line of research by showcasing the application of LLMs in measuring firm-level supply chain risks.

2. Data and methodology

2.1. Data and sample

We obtain site visit transcripts and firm-level financial data from the CSMAR database, as well as stock returns from the Choice financial database. Our sample includes A-share listed firms on the Shenzhen Stock Exchange from 2016 to 2023 with available transcripts. We exclude financial firms, firms under Special Treatment (ST) or Particular Transfer (PT) status, as well as industries with fewer than 10 observations. Continuous variables are winsorized at the 1st and 99th percentiles to mitigate outliers. The final sample consists of 9341 firm-year observations from 2408 unique firms.

2.2. Measuring supply chain risk exposure

We use OpenAI's GPT-4o mini model, a state-of-the-art generative large language model, for its advanced text intelligence and ability to handle large context windows (up to 128 K tokens), enabling us to process full transcripts without losing coherence. Its enhanced tokenizer efficiently handles non-English text, making it suitable for our analysis of Chinese transcripts.

Our analysis begins with preprocessing site visit transcripts, which typically consist of two sections: a management discussion and a Q&A session. To focus on risk-related information, we exclusively extract the Q&A section, as management discussions often contain boilerplate language or promotional content.

Next, we design a prompt instructing the GPT model to identify, summarize, and classify supply chain risks present in the transcripts. A prompt is a set of precise instructions or input given to the language model to generate a specific response. As detailed in Appendix A, our prompt consists of two main components: (1) definitions and classifications of supply chain risks based on the framework of Ho et al. (2015), which categorizes risks into macro-level and micro-level types, and (2) tasks for identifying, summarizing, and categorizing supply chain risk-related information within the transcripts. This prompt design ensures that the model produces accurate, consistent, and interpretable outputs.

Finally, we input each transcript and the designed prompt into the GPT model, which then identifies and summarizes supply chain risks, categorizing them as macro or micro risks. Following Kim et al. (2023), after obtaining the summaries, we calculate the ratio of each summary's length to the total length of the corresponding transcript. This ratio serves as a proxy for supply chain risk exposure, with higher ratios indicating greater exposure. We define three types of supply chain risk exposure measures—*SCRiskSum, SCRiskMicro*, and *SCRiskMacro*—as follows:

$$SCRisk_{it}^{k} = \frac{1}{N_{it}} \sum_{j=1}^{N_{it}} \frac{\text{length}\left(Summary_{ijt}^{k}\right)}{\text{length}(Transcript_{ijt})} \tag{1}$$

where i represents the firm, t represents the year, j represents the jth transcript, and k represents the type of risk exposure measure (*Sum* for overall risk, *Micro* for micro-level risk, and *Macro* for macro-level risk). N_{it} is the number of transcripts for firm i in year t, $\text{length}\left(Summary_{ijt}^{k}\right)$ is the length of the GPT-generated summary, and $\text{length}(Transcript_{ijt})$ is the length of the jth transcript. To facilitate comparison, we standardize all three measures by subtracting the mean and dividing by the standard deviation within each year.

In addition, to compare our GPT-based measures with the bag-of-words-based proxy from Wu (2024), we replicate his approach to construct *SCRiskBow*. This involves counting the co-occurrence of supply chain-related and risk-related words within a 10-word window, scaled by transcript length.

3. Empirical results

3.1. Descriptive statistics

Panel A of Table 1 provides the descriptive statistics for the key variables used in our analysis.

The mean values of *SCRiskSum, SCRiskMicro*, and *SCRiskMacro* are 0.0223, 0.0104, and 0.0038, respectively, indicating that discussions on micro-level risks are more prevalent than those on macro-level risks. Furthermore, the firms in our sample have an average cost of capital of 5.64 % and an average inventory ratio of 12.45 %. These figures are broadly consistent with findings from previous studies on Chinese-listed firms. Panel B presents the industry distribution of supply chain risks. Specifically, the manufacturing sector and the "agriculture, forestry, animal husbandry, and fishery" sector exhibit significantly higher levels of risk exposure. In contrast, service-related industries demonstrate relatively low levels of exposure.[2] Additionally, upstream industries generally face higher risks compared to downstream industries.

3.2. Face validity of supply chain risk exposure

Following Hassan et al. (2019), we examine the face validity of our GPT-based measures by investigating whether they vary intuitively over time and across industries. As shown in Fig. 1A, our measures align with major supply chain disruptions. For example, all measures significantly increased during the China-US trade war, with an even sharper rise during the COVID-19 pandemic. *SCRiskMacro* responded more strongly to macroeconomic shocks like the pandemic, while *SCRiskMicro* fluctuated more steadily. The end of the COVID-19 lockdown in 2022 corresponds to a decline in overall supply chain risk, signaling economic recovery. Fig. 1B shows that manufacturing firms consistently exhibit higher supply chain risk than service firms, particularly during events like the trade war and pandemic. This outcome is intuitive, as manufacturing typically involves more complex logistics and supply chain networks.

Fig. 2A, B, and C present word clouds from the LLM-generated risk summaries. Micro risks are highlighted by terms like "Demand" and "Raw Materials," while macro risks are dominated by terms like "Economy," "Policy," and "Pandemic." These results further validate the face validity of our risk measures.

3.3. Construct validity of supply chain risk exposure

To establish construct validity, we test the relationship between our supply chain risk measure and firm-level outcomes associated with risk. First, we investigate whether our measure effectively captures actual firm risks. According to conventional financial models, an increase in any type of risk, including supply chain risks, is expected to lead to higher volatility in a firm's stock returns (Hassan et al., 2019). As investors and creditors become aware of these risks, they typically demand higher returns to compensate for the increased uncertainty. Second, we assess whether our measure aligns with actions firms typically take to mitigate supply chain risks. The literature on inventory management suggests that firms facing heightened supply chain risks often increase their inventory levels as a buffer to protect against potential disruptions (Olivares and Cachon, 2009). In summary, we expect a positive correlation between our risk measure and these outcomes.

Based on these expectations, we estimate the following model:

$$Outcomes_{i,t} = \alpha + \beta SCRiskSum_{i,t} + \delta \mathbf{X}_{i,t} + \theta_j + \eta_t + \varepsilon_{i,t} \tag{2}$$

where $Outcomes_{i,t}$ represents a firm-level outcome or behavior, such as the cost of capital, stock return volatility, or inventory, $SCRiskSum_{i,t}$ is our GPT-based firm-level supply chain risk exposure, $X_{i,t}$ is a vector of firm-level control variables, θ_j and $\eta_t$capture industry and year fixed effects, respectively. The specific control variables included in $X_{i,t}$ vary depending on the outcome $Y_{i,t}$ being

[2] "Agriculture, forestry, animal husbandry, and fishery" sector may face heightened risk exposure due to their reliance on external factors such as weather conditions, climate change, and global commodity price fluctuations. Supporting this, unreported descriptive results indicate that this sector records the highest mean value of macro-level supply chain risk exposure (*SCRiskMacro*).

Table 1
Descriptive statistics.
Panel A summarizes descriptive statistics for our variables. All variable definitions are provided in Appendix B. Panel B presents the industry distribution of *SCRiskSum* (raw mean values) using the CSRC industry classification.

Panel A Descriptive statistics

VARIABLES	P25	Mean	Median	P75	SD	Obs
SCRiskSum(raw)	0.0019	0.0223	0.0194	0.0339	0.0208	9341
SCRiskMicro(raw)	0.0000	0.0104	0.0066	0.0160	0.0127	9341
SCRiskMacro(raw)	0.0000	0.0038	0.0006	0.0058	0.0058	9341
SCRiskSum	−0.9794	−0.0000	−0.1394	0.5610	1.0000	9341
SCRiskMicro	−0.8252	−0.0000	−0.2998	0.4374	1.0000	9341
SCRiskMacro	−0.6513	0.0000	−0.5479	0.3401	1.0000	9341
WACC(%)	4.8328	5.6415	5.5286	6.3830	1.1829	9338
Volatility	0.3651	0.4750	0.4525	0.5481	0.1702	9339
Inventory	0.0616	0.1245	0.1069	0.1626	0.0948	9241
RawMaterials	0.0125	0.0330	0.0261	0.0450	0.0294	8750
IntermediateGoods	0.0057	0.0255	0.0144	0.0318	0.0318	7398
FinishedGoods	0.0136	0.0451	0.0308	0.0582	0.0497	8827
CusCon	0.1565	0.3292	0.2794	0.4593	0.2185	9295
SupCon	0.1972	0.3310	0.2900	0.4303	0.1820	9310
SCCon	0.2092	0.3289	0.3070	0.4240	0.1565	9324
Overseas	0.0000	0.1692	0.0258	0.2495	0.2606	9341
PMI	49.8917	50.2521	49.9167	50.5417	0.7188	9341
Size	21.4300	22.2523	22.1024	22.9011	1.1354	9341
Lev	0.2353	0.3871	0.3813	0.5251	0.1849	9341
ROA	0.0198	0.0447	0.0440	0.0749	0.0615	9341
Age	16.0000	19.7766	19.0000	23.0000	5.9754	9341
Growth	0.0034	0.1913	0.1315	0.2978	0.3561	9341
MB	0.9932	2.1436	1.6804	2.7306	1.7250	8447
Loss	0.0000	0.0969	0.0000	0.0000	0.2958	9341
PPE	0.0808	0.1853	0.1597	0.2612	0.1348	9341
CFO	0.0145	0.0534	0.0510	0.0911	0.0645	9341
SOE	0.0000	0.2020	0.0000	0.0000	0.4015	9341
Inshold	0.1538	0.3746	0.3601	0.5732	0.2444	9339
Largesthold	0.2064	0.3114	0.2942	0.3949	0.1364	9341
Opinion	1.0000	0.9848	1.0000	1.0000	0.1224	9341
Turnover	0.0208	0.1355	0.0352	0.0626	0.5424	9239

Panel B Industry distribution of supply chain risks

Industry	*SCRiskSum* (raw)	Industry	*SCRiskSum* (raw)
A: Agriculture, Forestry, Animal Husbandry, and Fishery	0.0306	**K:** Real Estate	0.0127
B: Mining	0.0244	**L:** Leasing and Business Services	0.0182
C: Manufacturing	0.0240	**M:** Scientific Research and Technical Services	0.0167
D: Production and Supply of Electricity, Heat, Gas, and Water	0.0253	**N:** Water Conservancy, Environment, and Public Facility Management	0.0191
E: Construction	0.0222	**P:** Education	0.0192
F: Wholesale and Retail Trade	0.0226	**Q:** Health and Social Work	0.0170
G: Transportation, Storage, and Postal Services	0.0221	**R:** Culture, Sports, and Entertainment	0.0110
H: Accommodation and Catering Services	0.0087	**S:** Comprehensive	0.0140
I: Information Transmission, Software, and Information Technology Services	0.0126		

examined, and the definitions of all variables are shown in Appendix B.

Table 2 shows that higher *SCRiskSum* is positively and significantly associated with both the weighted average cost of capital (*WACC*) and stock return volatility, indicating that greater supply chain risk exposure leads to higher financing costs and uncertainty. For the control variables, firm size (*Size*) exhibits a negative correlation with both financing costs and volatility, consistent with prior literature. Leverage (*Lev*) is negatively associated with *WACC* but positively related to stock return volatility, indicating that while higher leverage may reduce financing costs due to tax shields, it also increases financial risk, resulting in greater stock price fluctuations.

Table 3 reveals the relationship between supply chain risk exposure and inventory holdings. Column (1) shows a positive and significant relationship between *SCRiskSum* and the total inventory ratio at the 1 % level. For the control variables, the negative relationship between turnover (*Turnover*) and inventory suggests that firms with faster inventory turnover may need to hold less inventory overall. We further disaggregate the inventory into its components: raw materials, intermediate goods, and finished goods, as reported in firms' annual reports. Columns (3) to (5) show that this effect is primarily driven by raw materials and intermediate goods. These results are consistent with Wu (2024), indicating that the association between supply chain risks and inventory is largely

Table 2
Supply chain risk exposure and firm risk outcomes.
This table presents the results of OLS regressions examining the relationship between GPT-based supply chain risk exposure (*SCRiskSum*) and common proxies for firm risk. The dependent variables are the weighted average cost of capital (*WACC*) in Columns (1) and (3) and stock return volatility (*Volatility*) in Columns (2) and (4). In Columns (3) and (4), *SCRiskBow*, the bag-of-words-based supply chain risk exposure proxy, is included for comparison. All regressions include year- and industry-fixed effects. The t-statistics, based on robust standard errors, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

VARIABLES	(1) *WACC*	(2) *Volatility*	(3) *WACC*	(4) *Volatility*
SCRiskSum	0.026*** (2.58)	0.002** (1.98)	0.029*** (2.73)	0.003** (2.19)
SCRiskBow			−0.052 (−0.91)	−0.007 (−0.98)
Size	−0.053*** (−3.80)	−0.028*** (−19.08)	−0.054*** (−3.80)	−0.028*** (−19.09)
Lev	−1.023*** (−13.37)	0.105*** (11.64)	−1.022*** (−13.35)	0.106*** (11.65)
ROA	−1.106*** (−3.76)	−0.166*** (−5.17)	−1.098*** (−3.73)	−0.165*** (−5.14)
Age	−0.007*** (−3.76)	−0.001*** (−4.22)	−0.007*** (−3.78)	−0.001*** (−4.24)
Growth	0.147*** (4.11)	0.034*** (9.30)	0.147*** (4.11)	0.034*** (9.29)
MB	0.142*** (12.85)	0.026*** (21.19)	0.142*** (12.87)	0.026*** (21.21)
Loss	−0.106** (−2.28)	−0.011* (−1.92)	−0.107** (−2.31)	−0.011* (−1.94)
PPE	−0.114 (−1.19)	−0.007 (−0.60)	−0.115 (−1.21)	−0.007 (−0.61)
CFO	0.222 (1.12)	−0.120*** (−5.09)	0.215 (1.09)	−0.121*** (−5.12)
SOE	−0.061** (−2.15)	−0.012*** (−3.73)	−0.062** (−2.20)	−0.012*** (−3.78)
Inshold	−0.103* (−1.87)	0.000 (0.05)	−0.103* (−1.87)	0.000 (0.05)
Largesthold	−0.244*** (−2.90)	0.006 (0.56)	−0.243*** (−2.90)	0.006 (0.56)
Opinion	−0.003 (−0.05)	−0.019** (−2.01)	−0.003 (−0.04)	−0.019** (−2.00)
Constant	7.220*** (22.73)	1.040*** (30.40)	7.227*** (22.75)	1.041*** (30.39)
Year FE	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Observations	8442	8443	8442	8443
Adj R-squared	0.423	0.380	0.423	0.380

Table 3
Supply chain risk exposure and inventory buffer.
This table presents the results of OLS regressions examining the relationship between supply chain risk exposure and inventory. The key independent variable is *SCRiskSum*, which measures the overall supply chain risk exposure. In Column (2), *SCRiskBow* is included to compare the results of the GPT-based risk exposure proxy with the bag-of-words-based approach. The dependent variable in Columns (1) and (2) is inventory scaled by total assets. In Columns (3)-(5), we subcategorize inventory into raw materials (*RawMaterials*), intermediate goods (*IntermediateGoods*), and finished goods (*FinishedGoods*), respectively, all scaled by total assets. All regressions include year- and industry-fixed effects. The t-statistics, based on robust standard errors, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

VARIABLES	(1) *Inventory*	(2) *Inventory*	(3) *RawMaterials*	(4) *IntermediateGoods*	(5) *FinishedGoods*
SCRiskSum	0.002*** (2.98)	0.002* (1.76)	0.002*** (5.59)	0.001** (2.45)	0.001 (1.50)
SCRiskBow		0.020*** (4.60)			
Size	−0.008*** (−8.66)	−0.008*** (−8.55)	−0.002*** (−7.35)	−0.003*** (−7.41)	−0.002*** (−3.31)
Lev	0.139*** (21.38)	0.139*** (21.33)	0.013*** (6.15)	0.018*** (6.49)	0.041*** (11.77)
ROA	0.166*** (9.54)	0.161*** (9.26)	0.050*** (8.00)	0.023*** (3.08)	0.040*** (4.26)
Age	0.000 (0.95)	0.000 (1.09)	0.000 (0.88)	0.000 (0.99)	0.000 (0.52)
Growth	0.000 (0.17)	0.000 (0.15)	0.001 (1.24)	0.000 (0.40)	−0.001 (−0.85)
PPE	−0.083*** (−11.27)	−0.082*** (−11.21)	0.012*** (4.38)	0.007** (2.48)	−0.031*** (−7.37)
CFO	−0.168*** (−9.45)	−0.165*** (−9.35)	−0.051*** (−8.25)	−0.051*** (−7.18)	−0.017* (−1.72)
Turnover	−0.032*** (−14.67)	−0.032*** (−14.67)	−0.004*** (−12.66)	−0.055*** (−5.38)	−0.010*** (−11.48)
Constant	0.265*** (13.92)	0.260*** (13.65)	0.077*** (11.63)	0.079*** (10.75)	0.070*** (6.99)
Year FE	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes
Observations	9238	9238	8749	7396	8825
Adj R-squared	0.372	0.374	0.256	0.228	0.326

concentrated on supply-side buffers, particularly raw materials and intermediate inputs.

Moreover, our GPT-based measure provides incremental information beyond the bag-of-words-based proxy, retaining significant explanatory power even after controlling for this alternative measure, demonstrating its superiority in capturing firm-level supply chain risks.

To further investigate potential heterogeneity across industries, we focus on manufacturing and service firms and partitioned the sample accordingly. As reported in Table 4, supply chain risks exert a significant impact on manufacturing firms, influencing their cost of capital, stock return volatility, and inventory management strategies. By contrast, no statistically significant relationships are identified for service firms. These results are consistent with the reliance of manufacturing firms on physical supply chains and production processes, rendering them inherently more susceptible to disruptions and uncertainties.

3.4. Determinants of supply chain risk exposure

Risk factors are conditions that contribute to specific types of supply chain risks (Ho et al., 2015). While previous research has identified risk factors, little has been done to quantify their impact. Given the extensive range of theoretically established supply chain risk factors, a comprehensive examination of each is impractical. Therefore, we focus on three potential drivers of supply chain risks: supply chain concentration, exposure to overseas markets, and macroeconomic conditions. These factors are selected due to their quantifiability and their status as key determinants.

To examine the relationship between these factors and supply chain risk, we estimate the following model:

$$SubSCRisk_{i,t} = \alpha + \beta Concentration_{i,t} + \gamma Overseas_{i,t} + \lambda PMI_t + \delta \mathbf{X}_{i,t} + \theta_j + \eta_t + \varepsilon_{i,t} \tag{3}$$

where $SubSCRisk_{i,t}$ is either *SCRiskMacro* or *SCRiskMicro,* $Concentration_{i,t}$ is a set of measures evaluating the firm's supply chain concentration, $Overseas_{i,t}$ is a measure of the firm's exposure to overseas markets, and PMI_t refers to the annual average Purchasing Managers' Index, which is a leading indicator of macroeconomic conditions relevant to supply chains. θ_j and $\eta_t$capture industry and year fixed effects, respectively.

Table 5 shows that supply chain concentration (*SupCon, CusCon, SCCon*) is positively and significantly associated with *SCRiskMicro*, indicating that firms with more concentrated supply chains face higher micro-level risks. However, these concentration measures are not significantly related to *SCRiskMacro*, suggesting that concentration mainly drives micro-level risks. The control variables reveal that larger firms (*Size*) and more profitable firms (*ROA*) are associated with lower *SCRiskMicro*, while higher leverage (*Lev*) increases it. These results highlight the influence of firm characteristics on micro-level supply chain risk.

Table 6 highlights the effects of overseas operations and economic conditions on supply chain risk exposure. Column (3) shows that overseas operations are associated with a significant increase in macro-level supply chain risk, suggesting that firms operating in international markets are more vulnerable to macroeconomic disruptions. The negative and statistically significant coefficient for the *PMI* in Column (4) indicates that economic downturns are likely to further heighten macro-level risks. These findings are consistent with the theoretical framework of Ho et al. (2015). In contrast, these determinants show no significant impact on micro-level risks, confirming these factors primarily affect macro-level risk.

4. Conclusion

By applying a GPT model to a dataset of site visit transcripts from Chinese-listed firms, we construct firm-level measures of supply chain risk exposure. These measures exhibit intuitive variation over time and across industries, demonstrating robust predictive power in explaining key firm-level outcomes such as the cost of capital, stock return volatility, and inventory management strategies. Furthermore, we identify the distinct determinants of macro and micro-level risks, highlighting the roles of supply chain concentration, international exposure, and macroeconomic conditions.

This study offers both theoretical and practical contributions to the fields of supply chain management and financial research. Theoretically, it advances the application of generative LLMs in finance research, demonstrating their potential to analyze complex and unstructured textual data. It also provides a methodological foundation for future research on corporate risks, with potential extensions to domains such as climate risk and political risk exposure. From a practical perspective, our research benefits managers and institutional investors by offering a replicable framework for assessing firm-specific risks that go beyond traditional, generalized risk measures. This approach enables practitioners to conduct timely risk assessments, enhancing their ability to make informed, data-driven decisions.

CRediT authorship contribution statement

Siyu Fan: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

Table 4
Manufacturing and service firms.
This table reports OLS regression results on the relationship between supply chain risk exposure and firm outcomes for two industry subsamples: manufacturing firms (Columns (1)–(3), CSRC code C) and service firms (Columns (4)–(6), including CSRC code H, I, L, and M). All regressions include controls, as well as year- and industry-fixed effects. T-statistics, based on robust standard errors, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

	Manufacturing Firms			Services Firms		
VARIABLES	(1) *WACC*	(2) *Volatility*	(3) *Inventory*	(4) *WACC*	(5) *Volatility*	(6) *Inventory*
SCRiskSum	0.029** (2.48)	0.004*** (2.77)	0.005*** (5.61)	0.016 (0.47)	−0.005 (−1.28)	−0.004 (−1.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6174	6175	6791	1031	1031	1094
Adj R-squared	0.358	0.380	0.244	0.474	0.300	0.277

Table 5
Determinants of micro-level supply chain risk exposure.
This table presents the results of OLS regressions examining the relationship between supply chain concentration measures (*SupCon, CusCon*, and *SCCon*) and supply chain risk exposure, categorized into macro-risks (*SCRiskMacro*) and micro-risks (*SCRiskMicro*). The dependent variable is *SCRiskMicro* in Column (1)-(3) and *SCRiskMacro* in Column (4)-(6). All regressions include year- and industry-fixed effects. The t-statistics, based on robust standard errors, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

VARIABLES	*SCRiskMicro*			*SCRiskMacro*		
	(1)	(2)	(3)	(4)	(5)	(6)
SupCon	0.152*** (2.90)			−0.054 (−1.06)		
CusCon		0.126** (2.04)			−0.064 (−1.05)	
SCCon			0.241*** (3.28)			−0.102 (−1.42)
Size	−0.028** (−2.32)	−0.029** (−2.36)	−0.024** (−2.01)	0.017 (1.40)	0.017 (1.42)	0.016 (1.32)
Lev	0.192** (2.46)	0.200** (2.55)	0.199** (2.55)	−0.014 (−0.18)	−0.027 (−0.37)	−0.022 (−0.29)
ROA	−0.447** (−2.29)	−0.463** (−2.36)	−0.456** (−2.33)	−0.588*** (−2.89)	−0.616*** (−3.02)	−0.594*** (−2.92)
Age	0.001 (0.73)	0.001 (0.59)	0.001 (0.69)	0.001 (0.69)	0.001 (0.58)	0.001 (0.54)
Constant	0.497* (1.95)	0.516** (2.02)	0.384 (1.48)	−0.351 (−1.39)	−0.344 (−1.35)	−0.307 (−1.19)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9294	9309	9323	9294	9309	9323
Adj R-squared	0.045	0.045	0.046	0.047	0.047	0.047

Table 6
Determinants of macro-level supply chain risk exposure.
This table presents the results of OLS regressions examining the effects of overseas operations and economic conditions on supply chain risk exposure. *Overseas* is the percentage of operating revenue generated from overseas markets. *PMI* is the annual average of the monthly Purchasing Managers' Index. The dependent variable is *SCRiskMicro* in Column (1)-(2) and *SCRiskMacro* in Column (3)-(4). All regressions include industry-fixed effects, with year-fixed effects applied where relevant. The t-statistics, based on robust standard errors, are reported in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

VARIABLES	*SCRiskMicro*		*SCRiskMacro*	
	(1)	(2)	(3)	(4)
Overseas	0.058 (1.36)		0.259*** (5.89)	
PMI		0.005 (0.32)		−0.139*** (−9.71)
Size	−0.034*** (−2.87)	−0.032*** (−2.67)	0.014 (1.18)	0.020* (1.66)
Lev	0.187** (2.39)	0.185** (2.37)	−0.030 (−0.40)	−0.000 (−0.00)
ROA	−0.469** (−2.40)	−0.497** (−2.54)	−0.656*** (−3.22)	−0.513** (−2.54)
Age	0.001 (0.48)	0.002 (1.34)	0.001 (0.75)	0.001 (0.77)
Constant	0.685*** (2.78)	0.377 (0.48)	−0.343 (−1.40)	6.543*** (8.59)
Year FE	Yes	No	Yes	No
Ind FE	Yes	Yes	Yes	Yes
Observations	9340	9340	9340	9340
Adj R-squared	0.045	0.042	0.051	0.042

Yifei Wu: Writing – review & editing, Investigation, Visualization. **Ruochen Yang:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

We, the authors, confirm that this manuscript is an original work, and it has not been submitted or published elsewhere. We have disclosed any potential conflicts of interest, and final manuscript was reviewed and approved by all authors. We have adhered to the highest standards of academic integrity and have appropriately acknowledged the contributions of each author based on their respective roles and responsibilities.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Claude in order to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendix A. Model and full prompts for the targeted summaries

In this paper, we use GPT-4o mini, a compact version of the GPT-4o model with exceptional capabilities in both textual intelligence and multimodal reasoning. It was released in July 2024, with knowledge extending up to October 2023. As of July 18, 2024, GPT-4o mini outperformed GPT-4 in chat preferences on the LMSYS Chatbot Arena Leaderboard, achieving an impressive score of 82 % on the

MMLU benchmark.[3]

To extract targeted summaries from the transcripts, we design a comprehensive prompt that defines supply chain risks and outlines instructions for identifying, summarizing, and classifying risk-related information. The model processes each site visit transcript and outputs the results in JSON format. Below are the specific prompts, with the site visit transcript content inserted in the {text} section for GPT model processing.

````
Supply chain risk refers to the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain, leading to operational, tactical, or strategic level failures or irregularities.
Supply chain risks can be divided into two main categories: macro-risks and micro-risks. Specifically:
* Macro Risks: adverse and relatively rare external events or situations that might have a negative impact on companies, such as natural disasters, pandemics, geopolitical conflicts, regulatory changes, economic downturns, and sociocultural tensions.
* Micro Risks: relatively recurrent events originated directly from internal activities of companies and/or relationships within partners in the entire supply chain, categorized into:
1. Demand Risks: Adverse events from downstream partners, such as demand uncertainty, inaccurate forecasts, bullwhip effect, customer dependency, short lead times, demand surge, demand variability, market changes, market competition, etc.
2. Manufacturing Risks: Events affecting a firm's production capacity, quality, or profitability, such as labor disputes, employee accidents, capacity constraints, machine failures, quality issues, inventory risks, production disruptions, technological changes, etc.
3. Supply Risks: Adverse events from upstream partners, such as supply interruptions, supplier dependency, fulfillment errors, rising costs, and failure to meet quality or delivery standards.
4. Infrastructure Risks: Risks related to IT, transportation, or financial systems, such as infrastructure breakdowns, delayed information, cyberattacks, transport disruptions, high transportation costs, port congestion, and issues with accounts receivable/payable.
The text within the following three backticks is a transcript of a management-investor conversation during a site visit for a Chinese-listed company. Based only on the provided text, without using external information or indirect inference, complete the following tasks:
1. Identify and summarize all negative information related to the company's supply chain risks in the "RiskSummary" field.
2. Based on the above summary, classify the identified supply chain risks into "MacroRisks" or/and "MicroRisks" categories. If no risk falls into a category, use "NA."
3. Output the results in JSON format as follows:
{{
"RiskSummary": "Summary of supply chain risks",
"MacroRisks": "Summary of macro supply chain risks",
"MicroRisks": "Summary of micro supply chain risks",}}
4. If no relevant supply chain risks are found, input "NA" in the corresponding fields, for example:
{{
"RiskSummary": "NA",
"MacroRisks": "NA",
"MicroRisks": "NA",}}
Here is the full transcript:
```
{text}
```
````

Appendix B. Variable Descriptions

Variables	Description
Key Variables	
SCRiskSum	Firm-level supply chain risk exposure is calculated as the ratio of the GPT-generated supply chain risk summary length to the total characters in site visit transcripts, averaged across all firm-years and standardized.
SCRiskMicro	Micro-level supply chain risk exposure is calculated as the ratio of the GPT-generated micro-level risk summary length to the total characters in site visit transcripts, averaged across all firm-years and standardized.
SCRiskMacro	Macro-level supply chain risk exposure is calculated as the ratio of the GPT-generated macro-level risk summary length to the total characters in site visit transcripts, averaged across all firm-years and standardized.
WACC	The weighted average cost of capital is calculated as the weighted average of the cost of debt (after tax) and the cost of equity, where the weights are determined by the firm's capital structure.
Volatility	The stock return volatility, calculated as the standard deviation of daily logarithmic returns, is annualized to reflect yearly fluctuations.
Inventory	The ratio of the firm's inventory to total assets.

(*continued on next page*)

[3] https://openai.com/index/gpt-4o-mini-advancing-cost-efficient-intelligence/

(*continued*)

Variables	Description
RawMaterials	The ratio of raw materials to total assets.
IntermediateGoods	The ratio of intermediate goods to total assets.
FinishedGoods	The ratio of finished goods to total assets.
SupCon	The supplier concentration ratio is calculated as the percentage of total annual purchases attributable to the top five suppliers.
CusCon	The customer concentration ratio is calculated as the percentage of total annual sales attributable to the top five customers.
SCCon	(percentage of purchases from top 5 suppliers + percentage of sales to top 5 customers) / 2.
Overseas	The percentage of operating revenue generated from overseas markets is calculated as overseas operating revenue divided by total operating revenue.
PMI	The annual average of the monthly Purchasing Managers' Index released by the National Bureau of Statistics of China.
Control Variables	
Size	Firm size is calculated as the natural logarithm of total assets.
Lev	The leverage ratio is calculated as total liabilities divided by total assets.
ROA	Return on assets is calculated as net income divided by total assets.
Age	Firm age is calculated as the number of years since the initial public offering (IPO).
Growth	Firm growth is calculated as the annual growth rate of operating income.
MB	The market-to-book ratio is calculated as the market value of equity divided by the book value of equity.
Loss	A dummy variable that equals one if the firm reports a net loss in the current year, and zero otherwise.
PPE	The ratio of property, plant, and equipment (PPE) to total assets.
CFO	The ratio of cash flow from operating activities to total assets.
SOE	State ownership is a dummy variable equal to 1 if the ultimate controlling shareholder is the state, and 0 otherwise.
Inshold	The percentage of shares held by institutional investors.
Largesthold	The percentage of shares held by the largest shareholder.
Opinion	The audit opinion is a dummy variable that equals 1 if the firm receives an unqualified opinion and 0 otherwise.
Turnover	The inventory turnover ratio is calculated by dividing the cost of goods sold by the average inventory during the same period.

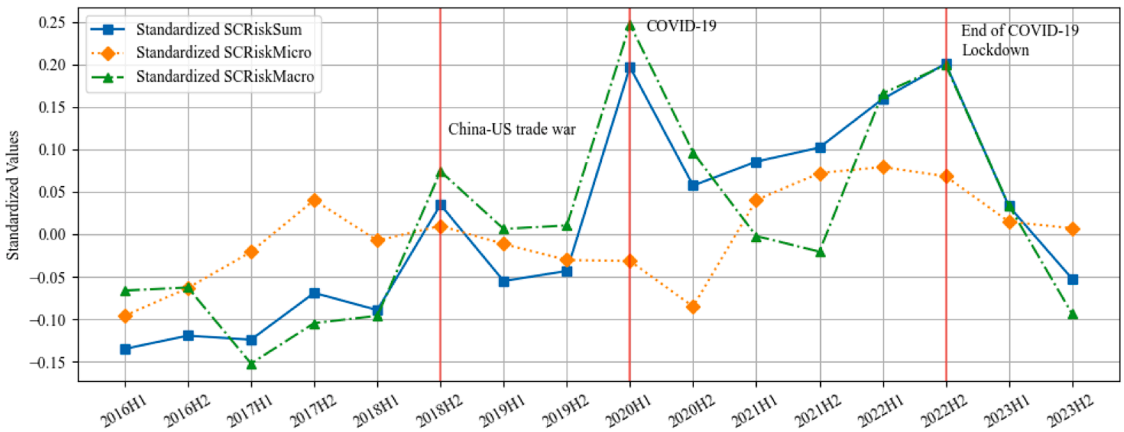

Fig. 1a. Supply Chain Risk Exposure over Time. This figure shows the evolution of average GPT-based supply chain risk exposure for Chinese A-share listed firms on the Shenzhen Stock Exchange from 2016 to 2023.

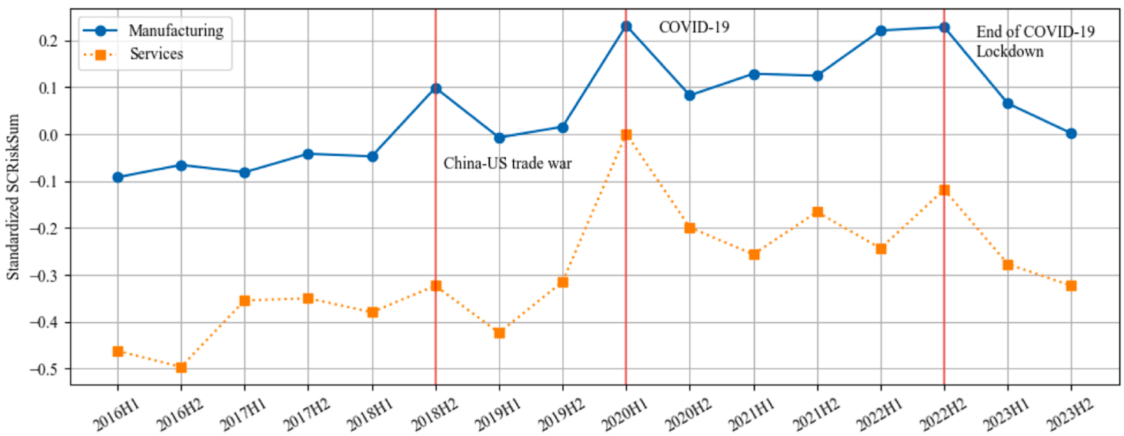

Fig. 1b. Supply Chain Risk Exposure Over Time (Manufacturing vs. Services). This figure shows the industry averages of supply chain risk exposure (*SCRiskSum*) for manufacturing and service sectors among Chinese A-share listed firms from 2016 to 2023. The sector classification is based on the China Securities Regulatory Commission (CSRC) industry code (2012 version). The manufacturing sector is represented by CSRC code

C, while the service sector includes firms in the following industries: Hotel and Catering (H), Information Transmission, Software, and Information Technology Services(I), Leasing and Business Services (L), Scientific Research and Technical Services (M).

Fig. 2a. Word Cloud of *SCRiskSum*. This figure presents the word cloud generated from the LLM-summarized supply chain risk based on site visit transcripts from 2016 to 2023.

Fig. 2b. Word Cloud of *SCRiskMicro*. This figure presents the word cloud generated from the LLM-summarized micro-level supply chain risk based on site visit transcripts from 2016 to 2023.

Fig. 2c. Word Cloud of *SCRiskMacro*. This figure presents the word cloud generated from the LLM-summarized macro-level supply chain risk based on site visit transcripts from 2016 to 2023.

Data availability

Data will be made available on request.

References

Cao, S.S., Jiang, W., Lei, L., Zhou, Q., 2024. Applied AI for finance and accounting: alternative data and opportunities. Pac-basin. Financ. J. 84 (2), 102307. https://doi.org/10.1016/j.pacfin.2024.102307.

Chen, J., Tang, G., Zhou, G., Zhu, W., 2023. ChatGPT, Stock market predictability and links to the macroeconomy. https://doi.org/10.2139/ssrn.4660148.

Dowling, M., Lucey, B., 2023. ChatGPT for (Finance) research: the Bananarama Conjecture. Financ. Res. Lett. 53 (3), 103662. https://doi.org/10.1016/j.frl.2023.103662.

Han, B., Kong, D., Liu, S., 2018. Do analysts gain an informational advantage by visiting listed companies? Contemp. Account. Res. 35 (4), 1843–1867. https://doi.org/10.1111/1911-3846.12363.

Hassan, T.A., Hollander, S., Van Lent, L., Tahoun, A., 2019. Firm-level political risk: measurement and effects. Q. J. Econ. 134 (4), 2135–2202. https://doi.org/10.1093/qje/qjz021.

Ho, W., Zheng, T., Yildiz, H., Talluri, S., 2015. Supply chain risk management: a literature review. Int. J. Prod. Res. 53 (16), 5031–5069. https://doi.org/10.1080/00207543.2015.1030467.

Kim, A.G., Muhn, M., Nikolaev, V.V., 2023. From transcripts to insights: uncovering corporate risks using generative AI. https://doi.org/10.2139/ssrn.4593660.

Kirtac, K., Germano, G., 2024. Sentiment trading with large language models. Financ. Res. Lett. 62 (4), 105227. https://doi.org/10.1016/j.frl.2024.105227.

Liu, S., Dai, Y., Kong, D., 2017. Does it pay to communicate with firms? Evidence from firm site visits of mutual funds. J. Bus. Finan. Account. 44 (5–6), 611–645. https://doi.org/10.1111/jbfa.12232.

Lopez-Lira, A., Tang, Y., 2023. Can ChatGPT forecast stock price movements? Return Predictability and Large Language Models. https://doi.org/10.2139/ssrn.4412788.

Ma, F., Lyu, Z., Li, H., 2024. Can ChatGPT predict Chinese equity premiums? Financ. Res. Lett. 65 (7), 105631. https://doi.org/10.1016/j.frl.2024.105631.

Olivares, M., Cachon, G.P., 2009. Competing retailers and inventory: an empirical investigation of general motors' dealerships in isolated U.S. markets. Manage. Sci. 55 (9), 1586–1604. https://doi.org/10.1287/mnsc.1090.1050.

Sodhi, M.S., Son, B., Tang, C.S., 2012. Researchers' Perspectives on Supply Chain risk management. Prod. Oper. Manag. 21 (1), 1–13. https://doi.org/10.1111/j.1937-5956.2011.01251.x.

Wu, D., 2024. Text-based measure of supply chain risk exposure. Manag. Sci. 70 (7), 4781–4801. https://doi.org/10.1287/mnsc.2023.4927.