

Article

Generative AI Application, Risk Governance Transformation, and Corporate Supply Chain Disruption Risk Exposure

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Abstract

Against the backdrop of frequent global shocks and increasingly complex supply chain networks, supply chain disruption risk exposure has become a major challenge affecting firms' operational stability and sustainable competitive advantage. Meanwhile, generative artificial intelligence is being increasingly embedded in business operations and has demonstrated strong application potential in information processing, risk identification, and decision support. Based on data from Chinese A-share listed firms from 2017 to 2024 and using text measures based on Management Discussion and Analysis (MD&A) disclosures of Generative AI application and supply chain disruption risk exposure, this study examines the relationship between Generative AI application and corporate supply chain disruption risk exposure, and further explores the channels through which this relationship may operate from the perspective of risk governance transformation. The results show that Generative AI application is significantly associated with lower corporate supply chain disruption risk exposure, and this relationship remains robust across a series of robustness checks and supplementary endogeneity analyses. Channel analyses suggest that this relationship may be related to firms' risk governance transformation, mainly reflected in enhanced risk identification capability, improved resource allocation capability, and strengthened collaborative response capability. Heterogeneity analyses show that this association is more pronounced among firms facing higher environmental uncertainty, manufacturing firms, and firms located in cities with lower entrepreneurial vitality. This study provides text-based firm-level evidence for understanding the relationship between Generative AI application and supply chain risk governance, and offers managerial implications for firms seeking to promote scenario-based Generative AI application and enhance supply chain resilience and risk governance capability.

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1. Introduction

Against the backdrop of deepening globalization and increasingly complex supply chain networks, firms have become progressively more dependent on coordination across regions, organizations, and operational stages, making supply chain disruption risk an

increasingly important threat to operational stability and sustainable competitive advantage. In recent years, external shocks such as trade frictions, geopolitical conflicts, public health crises, and extreme weather events have occurred with growing frequency, rendering modern supply chain systems—characterized by low inventories, just-in-time delivery, and global sourcing—more vulnerable to disruption propagation and even network-level cascading failures [1]. Once an abnormality arises in a single link, the shock may rapidly spread across procurement, production, logistics, and sales, eventually escalating into a systemic disruption. Supply chain disruptions not only directly lead to production stoppages, delivery delays, and rising costs, but may also trigger revenue volatility, cash flow pressure, and damaged customer relationships, thereby undermining firms' market performance and long-term development capacity [2]. At the same time, industry monitoring data indicate that disruption shocks at the firm level are still intensifying. Resilinc reports that global supply chain disruptions increased by 38% year on year in 2024, with the impact concentrated particularly in key industries such as life sciences, healthcare, general manufacturing, high technology, and automotive. A survey conducted by Maersk among more than 2000 European clients further shows that 76% of firms experienced supply chain disruptions in the past 12 months, and 22% encountered more than 20 disruption events. These observations suggest that supply chain disruption risk is no longer merely a short-term operational disturbance at the firm level; rather, it has become closely associated with the stable functioning of critical industrial chains and broader industrial security, which makes it all the more urgent and strategically important to investigate how such risk can be mitigated.

Meanwhile, Generative AI is rapidly penetrating key supply chain functions, including demand forecasting, planning, procurement coordination, inventory management, logistics scheduling, customer service, and risk control [3]. Unlike traditional digital technologies, which primarily perform data processing, process automation, and localized analytical tasks, Generative AI, powered by large models and natural language interaction capabilities, can process both structured and unstructured information and generate explanations, judgments, and response options in complex contexts. In practice, such technologies have already begun to enter corporate supply chain risk management. For example, AMD has deployed the GenAI Supply Chain Troubleshooter to address complex issues related to order commitments, product allocation, and supply shortages. According to official disclosures, the tool has reduced problem-solving time and costs by 90%, saved approximately 3120 labor hours annually, and enabled the firm to respond more rapidly to supply chain disruptions. Walmart, in turn, has applied self-healing inventory and agentic AI to demand forecasting, inventory redirection, and out-of-stock response, with self-healing inventory alone reportedly generating savings of more than USD 55 million. These cases suggest that the role of Generative AI is not limited to improving the operational efficiency of individual business functions; more fundamentally, it is reshaping how firms acquire information, interpret risks, make decisions, and organize responses. Existing studies on the scenario-based application of digital technologies further indicate that firm-level technology adoption can be characterized through business processes, operational data, and key performance indicators, and that technologies such as text recognition can transform unstructured business information into processable managerial data [4,5]. This provides a practical basis for this study to identify Generative AI application from firms' textual information and to examine its role in the context of supply chain risk governance.

From the perspective of risk governance, the formation of supply chain disruption risk does not stem solely from execution failures at individual operational nodes; rather, it is closely related to whether firms can promptly identify risk signals, interpret risk contexts, integrate internal and external knowledge, and promote coordinated responses

across multiple actors [6,7]. Traditional risk governance relies heavily on managerial experience, interdepartmental information transmission, and coordination among upstream and downstream supply chain actors, and is therefore often constrained by fragmented information, high interpretation costs, and delayed responses [8]. In highly uncertain environments in particular, risk signals such as supplier abnormalities, logistics delays, policy changes, market fluctuations, and quality problems are typically dispersed across different systems, texts, and organizational actors, making it difficult for firms to quickly complete the entire process from problem detection to action implementation. By contrast, Generative AI can integrate multi-source heterogeneous information, strengthen semantic understanding and contextual interpretation, generate executable alternative solutions, and facilitate the rapid transmission of knowledge within organizations and among supply chain actors. As a result, it may reshape the way knowledge is produced and coordination is organized in corporate risk governance. Therefore, the relationship between Generative AI application and corporate supply chain disruption risk exposure should not be understood merely as the result of improved local operational efficiency, but should instead be examined within the framework of risk governance transformation.

Against this backdrop, this study takes Chinese A-share listed firms from 2017 to 2024 as the research sample to systematically examine the relationship between Generative AI application and corporate supply chain disruption risk exposure, while further exploring its potential channels and heterogeneous associations from the perspective of risk governance transformation. We argue that Generative AI does not function merely as an auxiliary technological tool embedded in existing processes; rather, it may be associated with a deeper transformation in the way firms govern risk. Specifically, Generative AI can help strengthen firms' capabilities for risk identification and contextual interpretation, improve the efficiency of resource allocation and dynamic adjustment, and enhance collaborative response and supply-demand matching. These governance-related changes provide possible channels through which Generative AI application is associated with supply chain disruption risk exposure.

Compared with the existing literature, the marginal contributions of this study are threefold. First, in terms of research perspective, this study incorporates Generative AI application into the analytical framework of corporate supply chain disruption risk exposure and examines its relationship with supply chain risk governance from the perspective of risk governance transformation, thereby extending the intersection between digital technology research and supply chain risk governance research. Second, in terms of research content, this study not only examines the association between Generative AI application and corporate supply chain disruption risk exposure, but also provides channel evidence across three dimensions: risk identification capability, resource allocation capability, and collaborative response capability. This deepens the understanding of how Generative AI application may be related to supply chain risk governance. Third, in terms of research extension, this study further examines heterogeneous associations across firms facing different levels of environmental uncertainty, industries with different production organization modes, and regions with different levels of entrepreneurial vitality, thereby identifying the boundary conditions of this relationship and offering practical implications for firms seeking to promote the scenario-based application of Generative AI and enhance supply chain resilience and risk governance capability.

2. Literature Review

2.1. Research on Supply Chain Disruption Risk

Supply chain disruption risk generally refers to the possibility that upstream suppliers or other supply-chain-related actors, when exposed to internal or external shocks, fail to fulfill their supply obligations on time, in sufficient quantity, or at the required quality,

thereby interrupting the normal functioning of the supply chain and causing losses to firm operations [9–11]. Compared with general business risk, supply chain disruption risk is typically characterized by suddenness, uncertainty, complexity, and transmissibility. Localized disturbances may propagate progressively through multi-tier supply chain networks, generate chain amplification effects, and ultimately undermine the operational stability of focal firms [11,12].

In terms of risk consequences, supply chain disruptions not only impair the continuity of firms' production and operations, but also exert persistent impacts on firms' market performance and network-related actors. Hendricks and Singhal (2005) find that firms experiencing supply chain disruptions suffer an average decline of 33–40% in stock returns over the subsequent three years [2]. Carvalho et al. (2021) further show that the associated economic losses may diffuse through production networks to affiliated firms that are not directly affected by the initial shock [13]. Meanwhile, disruptions that remain unresolved over a prolonged period may erode trust among supply chain members, intensify the fragility of cooperative relationships, and continuously deplete the resilience reserves of the supply chain system [12,14].

Regarding mitigation pathways, the existing literature can be broadly classified into three categories. The first emphasizes strategic prevention, advocating approaches such as supplier diversification and resilient network design to reduce the likelihood of disruption occurrence [15]. The second highlights operational buffering, proposing measures such as inventory optimization, backup supplier agreements, and flexible capacity building to absorb unexpected shocks [10,16]. The third stresses governance coordination, arguing that contractual constraints, shared goals, and cultural alignment help enhance the effectiveness of joint responses among supply chain members [17,18]. Overall, the extant literature has systematically documented the formation characteristics, economic consequences, and mitigation pathways of supply chain disruption risk. However, existing discussions remain focused primarily on traditional supply chain management tools and governance mechanisms, while relatively limited attention has been paid to how emerging digital technologies, particularly Generative AI, may be associated with supply chain disruption risk exposure by transforming firms' risk governance processes.

2.2. Research on Generative AI

Generative AI is generally defined as a class of artificial intelligence technologies that can learn from existing data and generate new content, new solutions, or new pathways, with outputs including text, images, and code. Unlike traditional AI, which primarily relies on existing data for prediction, classification, or decision support, Generative AI places greater emphasis on proactive content generation, semantic understanding, and adaptive problem-solving capabilities [19–21]. From a technical perspective, Generative AI is built upon large-scale pre-trained models, which acquire transferable general capabilities through self-supervised learning on massive corpora and can be rapidly adapted to different tasks through prompting, few-shot learning, and lightweight fine-tuning. In this way, Generative AI reduces the marginal costs of information acquisition, knowledge recombination, and content production within organizations [21–23].

From the perspective of enterprise application, the organizational value of Generative AI does not arise solely from its content generation capability itself, but from whether it can be integrated with firms' business processes, information processing activities, and organizational decision-making processes, and further transformed into managerial capabilities such as information processing, knowledge recombination, decision support, and organizational collaboration. Existing studies show that Generative AI can improve firm productivity and operational efficiency by enhancing information processing efficiency,

assisting complex decision-making, and optimizing task execution [22,23]. It can also promote organizational innovation, business model renewal, and digital transformation by facilitating knowledge recombination, idea generation, and problem solving [24–26]. Furthermore, Generative AI may reshape internal information flows, knowledge production, and modes of collaboration within organizations, thereby exerting a deeper influence on corporate governance processes [22,23].

From a measurement perspective, the application of digital technologies within firms typically needs to be identified and evaluated through business processes, operational data, and firm-level indicators. Existing studies suggest that corporate digital transformation and technology application can be evaluated using indicators derived from textual disclosures, operational processes, and firm-level digital inputs or outputs [4,27]. Related studies on AI-enabled text recognition and information extraction further show that unstructured business information can be transformed into processable operational data in organizational and industrial scenarios [5,28]. These studies provide an important reference for this study to characterize Generative AI application at the firm level and to examine its role in the context of supply chain risk governance.

At the same time, the organizational implications of Generative AI are not determined solely by technological performance, but are also shaped by contextual factors such as data governance, organizational absorptive capacity, and managerial decision-making processes. Related studies on the governance risks of Generative AI and on differences in perceptions between owners and managers in corporate financial management suggest that whether digital technologies can be transformed into stable risk governance capabilities needs to be understood within specific organizational contexts [29–31].

2.3. Literature Review Summary

In summary, the existing literature has systematically documented the formation characteristics, economic consequences, and traditional mitigation pathways of supply chain disruption risk, while also examining the organizational implications of Generative AI from the perspectives of efficiency enhancement, innovation promotion, and organizational transformation. However, there remains a clear disconnect between these two streams of research. Supply chain disruption risk is inherently systemic, transmissible, and amplifying. Under conditions of uncertainty, it often propagates through multi-tier networks and is compounded by distorted supply-demand information, coordination frictions across actors, and delayed responses [12,32]. In this context, Generative AI, with its ability to integrate multi-source data and unstructured information, as well as its functions in explanation generation, contextual judgment, and collaborative communication support, has the potential to transform how firms identify and respond to supply chain shocks [19,21].

However, firm-level empirical evidence directly examining the relationship between Generative AI application and supply chain disruption risk exposure remains relatively scarce. Existing studies on Generative AI still focus primarily on general outcome variables such as productivity, innovation, knowledge creation, and sustainable performance [22,23,33,34], while comparatively limited attention has been paid to contexts involving risk governance, supply chain resilience, and crisis response. Rigorous empirical evidence on outcome variables such as supply chain resilience, crisis response capability, and supply chain disruption risk exposure is still at an early stage, and no consistent conclusion has yet emerged regarding the direction or magnitude of these associations across different contexts [35,36]. Meanwhile, existing studies also suggest that the organizational implications of Generative AI may not be stable or uniform, and that its role needs to be examined in specific managerial contexts [29,30]. To address these gaps, this study focuses

on the relationship between Generative AI application and corporate supply chain disruption risk exposure and further explores its potential channels and heterogeneous associations from the perspective of risk governance transformation, with the aim of providing new firm-level empirical evidence for understanding the role of Generative AI in supply chain risk governance.

3. Theoretical Analysis and Research Hypotheses

3.1. *Generative AI and Supply Chain Disruption Risk*

The key to governing supply chain disruption risk lies in whether firms can promptly identify risk signals dispersed across suppliers, logistics, production, inventory, customer demand, and the external environment, and further transform these signals into actionable risk judgments and response actions [6–8]. Accordingly, this study defines “risk governance transformation” as the systematic adjustment of firms’ processes of risk information acquisition, risk interpretation, resource scheduling, and organizational coordination through Generative AI, thereby shifting supply chain risk governance from experience-driven and ex post responses toward data integration, contextual interpretation, dynamic response, and cross-actor collaboration.

From the perspectives of the resource-based view and dynamic capability theory, data, algorithms, and organizational knowledge do not automatically translate into risk governance capabilities. Only when firms can transform them into risk judgments, resource allocation, and coordinated actions can they become an important capability basis for coping with supply chain disruption shocks [37–39]. Generative AI emphasizes natural language interaction, content generation, semantic understanding, and contextualized problem solving, and can transform unstructured texts, business data, and organizational knowledge into understandable explanations, judgments, and alternative solutions [20,22,40]. In the context of supply chain risk governance, Generative AI helps integrate multi-source information, such as supplier communications, logistics information, market changes, policy documents, and internal business records. It can thereby enhance firms’ capabilities for identifying risk signals, explaining the causes of risks, and generating response plans, ultimately reducing information processing costs and organizational communication costs [30,41].

Furthermore, supply chain disruption risk is characterized by network propagation, as localized disturbances may be further amplified through upstream and downstream transaction relationships and fulfillment arrangements. By improving the interpretability of risk information and the efficiency of response plan generation, Generative AI helps internal departments and external supply chain partners form more consistent responses around shared risk judgments, thereby helping reduce risk diffusion caused by information asymmetry and delayed responses. Of course, the risk governance effect of Generative AI is not unconditional. The effects of emerging supply chain technologies and AI automation depend on specific organizational contexts, behavioral conditions, and governance arrangements. If firms focus excessively on the general benefits of technology while neglecting data quality, human oversight, and organizational complementarities, the application effects may fall short of expectations and may even amplify erroneous judgments or coordination frictions [42–44]. Therefore, this study does not regard Generative AI as an automatic substitute for managerial judgment, but rather as an assistive and augmentative tool embedded in firms’ risk governance processes. Overall, under the basic conditions of data governance, human oversight, and organizational coordination, Generative AI application may be associated with lower supply chain disruption risk exposure by improving risk information processing, response plan generation, and collaborative communication capabilities. Based on the above analysis, this study proposes the following hypothesis:

H1: *A higher level of Generative AI application is associated with lower corporate supply chain disruption risk exposure.*

3.2. Channel Hypotheses

Based on the preceding analysis, the risk governance transformation driven by Generative AI is not merely an efficiency improvement in a single operational function, but rather a continuous process involving identification, response, and coordination. Specifically, risk identification capability corresponds to risk sensing and risk interpretation, emphasizing whether firms can capture risk signals from multi-source information, including suppliers, logistics, market demand, policy environments, and internal operations, and further form actionable risk judgments. Resource allocation capability corresponds to risk response, emphasizing whether firms can promptly adjust key resources such as inventory, procurement, production, logistics, and funds based on identified risks. Collaborative response capability corresponds to risk coordination, emphasizing whether firms can align information, plans, and actions across internal functional departments and external supply chain partners. Accordingly, risk identification provides the informational basis for resource adjustment, resource allocation provides operational support for risk response, and collaborative response further reduces risk transmission and amplification caused by inconsistent actions within supply chain networks.

First, Generative AI application may be associated with lower supply chain disruption risk exposure by enhancing firms' risk identification capability. Because supply chain risk signals are multi-sourced, dispersed, and context-dependent, firms need to transform such signals into actionable risk judgments and response actions through effective information processing and organizational coordination [6–8,11]. Traditional risk identification relies more heavily on manual screening and ex post analysis, and is therefore easily constrained by information delays, data fragmentation, and information silos across departments, which may lead to insufficient risk perception or biased judgments [8,11]. Generative AI can integrate, understand, and interpret both structured and unstructured information, transforming fragmented information into more context-specific risk alerts and action cues. In doing so, it improves the timeliness with which firms identify supplier abnormalities, logistics delays, demand fluctuations, and policy changes. At the same time, Generative AI also helps improve the efficiency of internal risk information transmission and external knowledge absorption, enabling risk information to enter managerial decision-making processes more quickly. As a result, firms can detect potential disturbances earlier and take mitigation measures, thereby reducing the likelihood that localized risks evolve into supply chain disruptions. Therefore, this study proposes Hypothesis H2a:

H2a: *Generative AI application is associated with lower corporate supply chain disruption risk exposure through enhanced risk identification capability.*

Second, Generative AI application may be associated with lower supply chain disruption risk exposure by optimizing firms' resource allocation capability. When firms face supply chain disturbances, whether they can promptly adjust inventory, procurement, production, logistics, and financial arrangements directly affects whether localized risks further translate into operational consequences such as production stoppages, delivery delays, and rising costs [11]. Under traditional management models, resource allocation is often constrained by insufficient information processing, poor information sharing, and inadequate interdepartmental coordination, which weakens firms' response speed and recovery capability in the face of supply chain shocks. Generative AI can integrate multi-dimensional information on orders, inventory, supply, transportation, funds, and market

demand, helping firms identify bottlenecks and generate multiple resource adjustment plans. This enables firms to achieve a more reasonable dynamic balance between operational efficiency and supply chain resilience. On the one hand, it helps firms dynamically adjust inventory, procurement, and production plans in response to demand changes and supply disturbances, thereby reducing inventory backlogs and stockout risks. On the other hand, it also helps improve the efficiency of working capital allocation, allowing firms to deploy operational resources more flexibly when facing unexpected disruptions [23,45]. Accordingly, Generative AI can strengthen firms' resource scheduling and operational recovery capabilities under disruption scenarios, thereby helping lower supply chain disruption risk exposure. Therefore, this study proposes Hypothesis H2b:

H2b: *Generative AI application is associated with lower corporate supply chain disruption risk exposure through optimized resource allocation capability.*

Finally, Generative AI application may be associated with lower supply chain disruption risk exposure by strengthening firms' collaborative response capability. Supply chain disruption risk is characterized by network propagation: localized supplier abnormalities, transportation delays, demand shocks, or production interruptions may spread through upstream and downstream transaction relationships and material flows within the supply chain network, further affecting overall supply chain resilience and operational performance [11,13,46]. Therefore, supply chain risk governance requires not only aligned actions among internal departments such as procurement, production, sales, logistics, and finance, but also improved supply-demand matching and stronger supplier substitution and adjustment capabilities within the external supply chain network. Studies from the perspectives of supply chain digital integration and multi-agent collaborative decision-making suggest that operational collaboration, knowledge collaboration, and multi-node goal coordination help enhance supply chain resilience and recovery capability under disruption scenarios such as demand shocks, node failures, and transportation delays [47,48]. This indicates that collaborative response capability is an important link connecting internal risk governance with supply chain network resilience. Generative AI can integrate information from multiple links, including orders, inventory, supplier fulfillment, logistics status, and market demand, and transform complex risk information into coordination plans that are easier to share and implement through contextual interpretation and plan generation. On the one hand, it helps firms identify demand changes and supply disturbances more promptly, promoting dynamic matching among production plans, inventory arrangements, order fulfillment, and market demand, thereby reducing supply-demand mismatch. On the other hand, it also helps firms identify potential supplier risks, evaluate alternative sources of supply, and optimize supplier portfolios, thereby improving supply chain diversification and external substitution flexibility. As supply-demand matching and supply chain diversification improve, firms are more likely to achieve internal action coordination and external resource substitution when facing localized disturbances, which in turn may help lower supply chain disruption risk exposure. Therefore, this study proposes Hypothesis H2c:

H2c: *Generative AI application is associated with lower corporate supply chain disruption risk exposure through strengthened collaborative response capability.*

Based on the above theoretical analysis, the transmission channels are summarized in Figure 1.

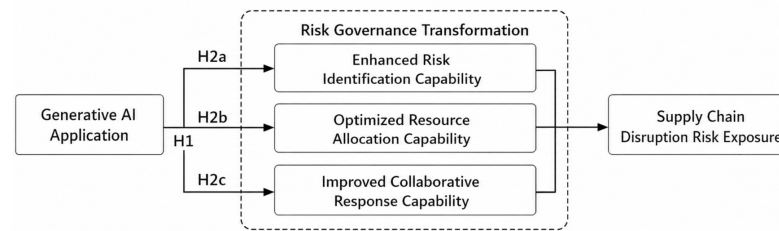


Figure 1. Transmission Channel Diagram.

4. Research Design

4.1. Data Sources and Sample Selection

This study takes Chinese A-share listed firms from 2017 to 2024 as the initial research sample. To ensure data quality, the sample is screened according to the following criteria: (1) firms in the financial industry are excluded; (2) firms designated as ST, *ST, or PT in a given year are excluded; (3) observations with severe missing values for key variables are excluded; and (4) all continuous variables are winsorized at the 1st and 99th percentiles. Firm-level data are obtained primarily from listed firms' annual reports and the CSMAR, Wind, and CNRDS databases.

4.2. Variable Specification

4.2.1. Explanatory Variable

Generative AI application (GenAI). Drawing on prior studies that construct firm-level technology application measures from annual report texts, and considering the technical characteristics of Generative AI and the disclosure context of Chinese listed firms' annual reports, this study constructs a text measure of firms' Generative AI application based on the Management Discussion and Analysis (MD&A) sections of listed firms' annual reports. Given that Generative AI differs substantially from broad artificial intelligence in terms of technological connotation and application mode, this study adopts an externally defined strict dictionary approach to measure Generative AI. Unlike broad artificial intelligence, which mainly focuses on prediction, classification, recognition, and automated decision-making, Generative AI places greater emphasis on large-model-based content generation, semantic understanding, knowledge recombination, multi-modal generation, and contextualized problem solving. Therefore, in constructing the keyword system, this study retains terms that are directly related to the core concepts, key technologies, functional applications, and representative models and platforms of Generative AI, while excluding terms that are more closely associated with broad artificial intelligence, traditional deep learning models, or technical frameworks. This helps improve the accuracy of the measure in identifying Generative-AI-specific application and disclosure. Specifically, this study constructs a Generative AI keyword dictionary from four dimensions: core concept terms, key technology terms, functional application terms, and representative model and platform terms, as reported in Appendix Table A1.

Based on the above keyword system, this study identifies and matches Generative-AI-related keywords in firms' annual MD&A texts and counts their total frequency of occurrence. To avoid double counting caused by nested terms, this study adopts a longest-match-first non-overlapping matching method. For example, when the term "ChatGPT" appears in the text, it is identified only as the keyword "ChatGPT" and is not additionally counted as "GPT"; when the term "Pangu large model" appears in the text, it is identified only as the keyword "Pangu large model" and is not additionally counted as "large model." Finally, the total annual frequency of Generative-AI-related keywords is increased by one and then transformed using the natural logarithm to obtain the firm-level

Generative AI application measure, GenAI. A higher value of this measure indicates a higher level of textual disclosure related to Generative AI application, technological layout, and scenario-based deployment in the firm's business strategy and operational processes.

In addition, to present the distributional characteristics of the GenAI measure, this study further reports the annual distribution of zero and positive GenAI observations during the sample period, as shown in Figure 2. The results indicate that the proportion of positive GenAI observations was relatively low from 2017 to 2021, but increased markedly after 2022, while the proportion of zero observations declined correspondingly. This trend is consistent with the rapid diffusion of Generative AI in recent years, suggesting that the GenAI measure constructed in this study can reasonably reflect the temporal variation in firms' Generative-AI-related disclosures.

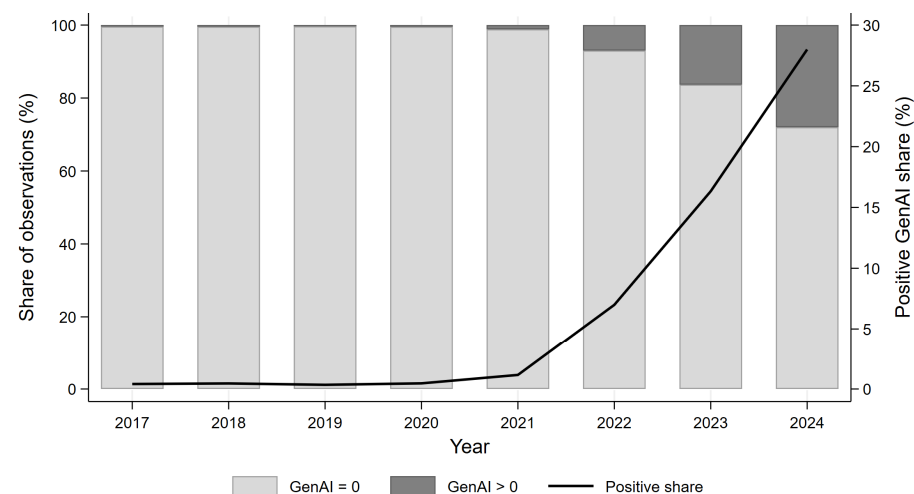


Figure 2. Annual Distribution of GenAI Observations.

4.2.2. Dependent Variable

Supply chain disruption risk exposure (SCDRisk). Drawing on the literature on text-based risk measurement and supply chain disruption risk [49–52], this study constructs a firm-year text measure of disclosed supply chain disruption risk exposure based on the MD&A sections of listed firms' annual reports. Specifically, we first preprocess the MD&A texts by removing non-Chinese characters and standardizing the text format. We then use the jieba package (version 0.42.1) for Chinese word segmentation and retain non-empty tokens to construct the basic corpus for subsequent word vector training. Second, by considering the context of supply chain disruption risk and drawing on prior studies, we construct a seed-word set containing 20 keywords as the initial basis for expanding the risk dictionary, as reported in Table 1.

Table 1. Seed Words for Supply Chain Disruption Risk Exposure.

Seed Word	Seed Word	Seed Word	Seed Word
Supply chain	Supply and demand	Raw materials	Stockpiling
Supplier	Upstream	Price increase	Reserves
Supply	Downstream	Production cutback	Failure
Procurement	Cost	Shortage	Operational risk
Disruption	Work stoppage	Freight cost	Transport capacity

Based on the full-sample MD&A texts, this study trains the Continuous Bag-of-Words (CBOW) model of Word2Vec using the gensim package (version 4.3.2). This model

predicts a target word from its surrounding context words, thereby learning semantic similarities among words and providing a basis for expanding candidate terms related to supply chain disruption risk. We set the word vector dimension to 100, the window size to 5, and the minimum word frequency to 5, and use a fixed random seed to improve the reproducibility of the results. During the dictionary expansion process, we extract similar words for each category of seed words and construct candidate dictionaries based on semantic similarity thresholds. Specifically, we construct three supply chain disruption risk dictionaries with similarity thresholds of 0.5, 0.6, and 0.7, respectively, and use the strict dictionary with a similarity threshold of 0.7 to construct the baseline SCDRisk measure. After obtaining the candidate dictionaries, we further conduct manual screening of the candidate terms in light of the supply chain disruption risk context. Terms with overly broad meanings, terms that cannot directly capture supply chain disruption risk, and terms mainly used in general business descriptions are excluded. This process ultimately yields the baseline supply chain disruption risk dictionary, as reported in Table 2.

Table 2. Baseline Dictionary for Supply Chain Disruption Risk Exposure (Similarity Threshold = 0.7).

Keyword	Keyword	Keyword	Keyword
Disruption	Supply disruption	Supply suspension	Supply shortage
Work stoppage	Production shutdown	Production restriction	Production cutback
Output curtailment	Shortage	Tight supply	Scarcity
Raw-material shortage	Raw and auxiliary material shortage	Transport capacity shortage	Cargo-space shortage
Logistics disruption	Transportation disruption	Freight cost pressure	Delivery delay
Supplier suspension	Supplier shutdown	Supplier default	Supplier risk
Single-point failure	System failure	Network failure	Operational disruption
Supply-demand imbalance	Supply-demand mismatch	Upstream disruption	Downstream disruption

Finally, this study counts the frequency of keywords in the final dictionary appearing in each firm's annual MD&A text and uses the ratio of this frequency to the total number of words in the text to measure firm-year disclosed exposure to supply chain disruption risk. To facilitate the interpretation of regression coefficients, this ratio is multiplied by 100 to obtain the firm-year supply chain disruption risk exposure measure, SCDRisk. A higher value of this measure indicates a higher level of supply chain disruption risk exposure disclosed by the firm in the MD&A section of its annual report. Accordingly, SCDRisk should be interpreted as a text-based measure of disclosed supply chain disruption risk exposure or managerial discussion of such risk, rather than as a direct measure of realized disruption events.

4.2.3. Control Variables

To mitigate potential omitted variable bias, this study includes control variables from several dimensions, including firms' financial conditions, growth capacity, governance structure, and basic characteristics. Specifically, financial conditions may affect firms' resource base and buffering capacity for coping with supply chain shocks, and may also influence their ability to apply digital technologies. Therefore, this study controls for return on equity (Roe), current ratio (Liquid), leverage ratio (Lev), and cash flow ratio (Cash-flow). Firms' growth and size characteristics reflect both operational expansion pressure and resource endowments, and may also affect supply chain complexity and technology application capability. Accordingly, this study controls for revenue growth (Growth), firm size (Size), and listing age (Listage). Corporate governance structure may affect firms' risk identification, decision-making efficiency, and resource allocation capability, and may also influence managers' willingness and ability to promote Generative AI application.

Therefore, this study further controls for state ownership (Soe), independent director ratio (IndDirectorRatio), managerial ownership (Mngmhldn), separation of control rights and cash-flow rights (Separation), and the shareholding ratio of the largest shareholder (Top1). Together, these variables provide a comprehensive characterization of firms' operating conditions, governance features, and resource bases, thereby reducing the influence of firm heterogeneity on the estimation results. The definitions and measurements of all variables are reported in Table 3.

Table 3. Definitions and Measurement of Main Variables.

Variable Type	Variable Name	Variable	Variable Definition
Dependent variable	Supply chain disruption risk exposure	SCDRisk	Frequency of supply-chain-disruption-related dictionary words in MD&A text divided by total MD&A words, multiplied by 100
Explanatory variable	Generative AI application	GenAI	Natural logarithm of one plus the total frequency of generative-AI-related keywords in the MD&A text
Control variables	Return on equity	Roe	Net profit divided by average shareholders' equity
	Current ratio	Liquid	Current assets divided by current liabilities
	Leverage	Lev	Total liabilities divided by total assets
	Revenue growth	Growth	Growth rate of operating revenue
	Cash flow ratio	Cashflow	Net cash flow from operating activities divided by total assets
	Listing age	Listage	Natural logarithm of current year minus listing year plus one
	State ownership	Soe	Equals 1 if the firm is state-controlled, and 0 otherwise
	Independent director ratio	IndDirectorRatio	Number of independent directors divided by total board size
	Managerial ownership	Mngmhldn	Shares held by directors, supervisors, and senior executives divided by total shares outstanding
	Firm size	Size	Natural logarithm of total assets
Control variables	Separation of control and ownership	Separation	Difference between control rights and cash-flow rights of the ultimate controller
	Largest shareholder ownership	Top1	Shares held by the largest shareholder divided by total shares outstanding

4.3. Validity Tests of Text-Based Measures

4.3.1. Validity Test of the Generative AI Measure

To examine whether the GenAI measure can reasonably reflect firms' Generative-AI-related application and disclosure, this study further conducts validity analyses from four aspects: dictionary boundaries, annual trends, manual verification, and external filing information.

First, regarding dictionary boundaries and annual trends, this study constructs the GenAI measure using an externally defined strict dictionary approach rather than automatic semantic expansion based on annual report corpora, so as to avoid mistakenly incorporating broad artificial intelligence or general digital technology terms into the Generative AI dictionary. The main GenAI dictionary has been described above and is reported in Appendix Table A1. To further distinguish Generative-AI-related application and disclosure from general artificial intelligence or digitalization-related expressions, this study constructs two auxiliary text-based measures, BroadAI and PostGenAI. Specifically, BroadAI captures general artificial intelligence and digital technology expressions, such as machine learning, deep learning, natural language processing, knowledge graphs, cloud computing, and the Internet of Things. PostGenAI captures more representative Generative AI models, platforms, and application terms that emerged after the release of ChatGPT. The complete keyword lists for the two measures are reported in Appendix

Tables A2 and A3, respectively. Figure 3 reports the annual trends in the positive-observation shares of BroadAI, GenAI, and PostGenAI. The results show that BroadAI already exhibits a relatively high positive-observation share in the early years of the sample period, whereas GenAI and PostGenAI remain at relatively low levels before 2021 and increase rapidly after 2022, especially in 2023 and 2024. This trend is consistent with the real-world acceleration of Generative AI diffusion after the release of ChatGPT, suggesting that the GenAI measure can reasonably distinguish Generative-AI-related disclosures from general artificial intelligence expressions.

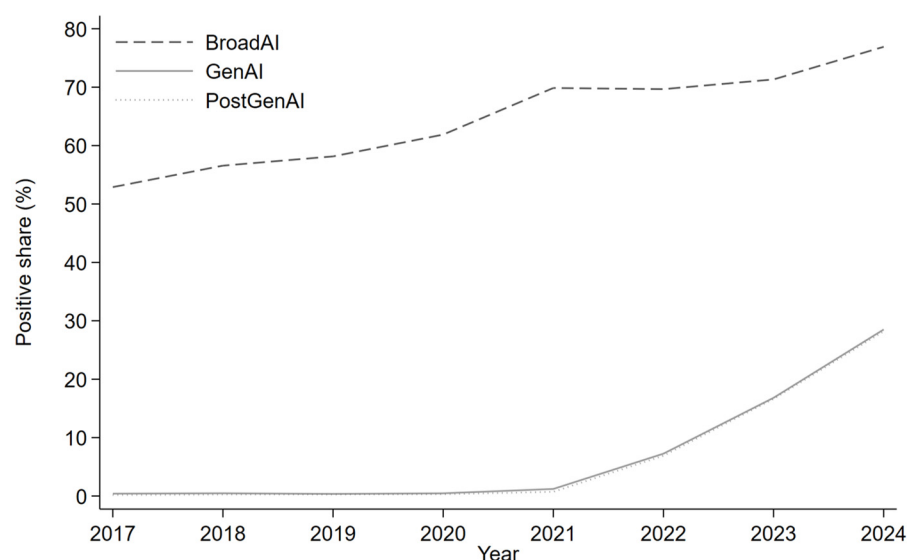


Figure 3. Annual Share of Firms Mentioning BroadAI, GenAI, and PostGenAI.

Second, this study conducts manual verification of the GenAI measure. Specifically, we randomly select 50 firm-year observations from the sample with positive GenAI values, read the sentences containing the keywords as well as their surrounding contexts one by one, and classify them into three categories: directly relevant, indirectly relevant, and misidentified. As shown in Table 4, 37 observations are directly relevant, accounting for 74%; 12 observations are indirectly relevant, accounting for 24%; and only 1 observation is misidentified, accounting for 2%. Directly relevant observations mainly refer to cases in which firms explicitly disclose Generative AI application, product development, technological deployment, or application scenarios closely related to their core businesses. Indirectly relevant observations mainly involve industry trends, policy backgrounds, upstream and downstream demand, or technological diffusion related to Generative AI. These results indicate that the GenAI measure constructed in this study has a low rate of clear misidentification and demonstrates good textual identification validity.

Table 4. Manual Verification Results of the GenAI Measure.

Classification Type	Observations	Percentage
Directly relevant	37	74%
Indirectly relevant	12	24%
Misidentified	1	2%
Total	50	100%

Finally, this study conducts an external validity test using the generative AI service filing and application function registration information released by the Cyberspace Administration of China. Unlike general textual disclosures, filing or registration information

usually corresponds to specific models, services, application functions, or online deployment scenarios, and can therefore reflect, to some extent, firms' practical foundations in Generative AI model development, service deployment, application launch, and compliant provision. Therefore, if the GenAI measure constructed in this study has good identification capability, firms with filing or registration records should exhibit higher GenAI levels. Based on this logic, this study collects publicly disclosed lists of generative AI service filings and application function registrations, matches the filing or registration entities with the names of A-share listed firms, and constructs the GenAI_Filing_ever indicator. This indicator equals 1 if a listed firm appears in the generative AI model filing or application function registration lists, and 0 otherwise. Figure 4 shows that the complementary cumulative distribution curve of GenAI for firms with filing or registration records lies overall above that of firms without such records. Mean comparison tests also show that firms with filing or registration records have significantly higher GenAI levels. These results suggest that the GenAI measure constructed in this study does not merely capture general trend-based disclosures, but can reasonably reflect firms' practical foundations in Generative AI model deployment, service filing, or application implementation.

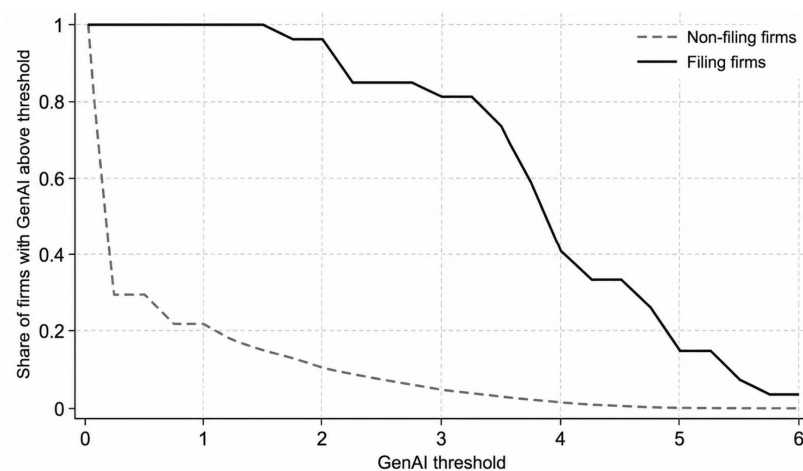


Figure 4. GenAI Distribution by Filing Status.

4.3.2. Validity Test of the Supply Chain Disruption Risk Measure

To further examine the textual identification validity of the SCDRisk measure, this study conducts manual verification using a subset of firm-year observations. Specifically, we randomly select 30 firm-year observations from the high-SCDRisk sample and 30 firm-year observations from the low-SCDRisk sample. We then read the sentences containing the keywords and their surrounding contexts one by one, and judge whether the relevant expressions involve supply chain disruption risk, supply shortages, logistics disruptions, raw material constraints, production stoppages or restrictions, supplier abnormalities, delivery delays, or uncertainty in upstream and downstream fulfillment. The manual verification results show that, among the 30 high-SCDRisk observations, 27 observations involve discussions related to supply chain disruption risk or supply chain disturbances, accounting for 90.0%. Among the 30 low-SCDRisk observations, 28 observations show no obvious expressions related to supply chain disruption risk, accounting for 93.3%. These results indicate that the SCDRisk measure constructed in this study can reasonably distinguish disclosed supply chain disruption risk exposure from general business descriptions in firms' annual reports.

Second, following prior validation logic for text-based supply chain risk exposure measures, this study further examines the relationship between SCDRisk and firms' stock

return volatility [51]. If SCDRisk effectively captures firms' exposure to supply chain disruption risk, firms with higher SCDRisk should face greater market-perceived uncertainty and exhibit higher stock return volatility. Figure 5 presents firms' average stock return volatility across SCDRisk quintiles. The results show that average stock return volatility generally increases as the SCDRisk quintile rises, suggesting that the SCDRisk measure constructed in this study can, to some extent, capture firm-level risk exposure and market-perceived uncertainty. The manual verification and external correlation test jointly indicate that the SCDRisk measure has good validity as a text-based measure of disclosed supply chain disruption risk exposure.

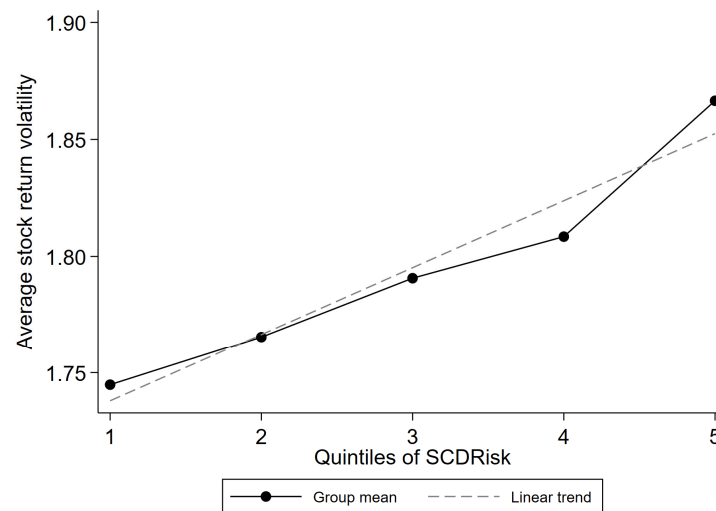


Figure 5. Stock Return Volatility across SCDRisk Quintiles.

4.4. Model Construction

To examine the relationship between Generative AI application and corporate supply chain disruption risk exposure, this study constructs the following benchmark regression model:

$$SCDRisk_{i,t} = \alpha_0 + \alpha_1 GenAI_{i,t} + \alpha'_2 CVs_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where $SCDRisk_{i,t}$ is the dependent variable, representing the supply chain disruption risk exposure for firm i in year t ; $GenAI_{i,t}$ is the core explanatory variable, representing the firm-level Generative AI application measure defined above; $CVs_{i,t}$ denotes the set of control variables, λ_t is the year fixed effect, μ_i is the firm fixed effect, and $\varepsilon_{i,t}$ is the error term.

5. Empirical Analysis

5.1. Descriptive Statistical Analysis

Table 5 reports the descriptive statistics for the main variables. The mean value of supply chain disruption risk exposure (SCDRisk) is 1.618, with a standard deviation of 0.564, and the minimum and maximum values are 0 and 5.623, respectively. This indicates substantial heterogeneity in supply chain disruption risk exposure across sample firms. The mean value of Generative AI application (GenAI) is 0.134, suggesting that the overall level of Generative AI application among sample firms remains relatively low. Its standard deviation is 0.545, indicating that firms have already begun to diverge in terms of related technology application and disclosure intensity. The means, standard deviations, and value ranges of the remaining control variables are also within reasonable intervals.

Table 5. Descriptive Statistics.

Variable	Obs	Mean	SD	Min	Max
SCDRisk	25,808	1.618	0.564	0.000	5.623
GenAI	25,808	0.134	0.545	0.000	6.103
Listage	25,808	2.246	0.781	0.693	3.401
Soe	25,808	0.306	0.461	0.000	1.000
IndDirectorRatio	25,808	0.380	0.054	0.333	0.571
Mngmhldn	25,808	0.143	0.191	0.000	0.678
Size	25,808	22.371	1.280	19.979	26.210
Roe	25,808	0.034	0.169	−0.911	0.322
Liquid	25,808	2.403	2.215	0.325	15.204
Lev	25,808	0.424	0.200	0.057	0.905
Growth	25,808	0.122	0.341	−0.558	2.032
Cashflow	25,808	0.049	0.065	−0.153	0.236
Separation	25,808	0.045	0.071	0.000	0.589
Top1	25,808	0.327	0.143	0.081	0.738

To preliminarily examine the relationships among the main variables, this study further conducts a correlation analysis. As shown in Figure 6, the correlation coefficient between GenAI and SCDRisk is -0.12 , indicating a negative association and providing preliminary support for the expected relationship between Generative AI application and lower supply chain disruption risk exposure. Meanwhile, the absolute values of the correlation coefficients among the main variables are generally low, and no obvious high correlations are observed.

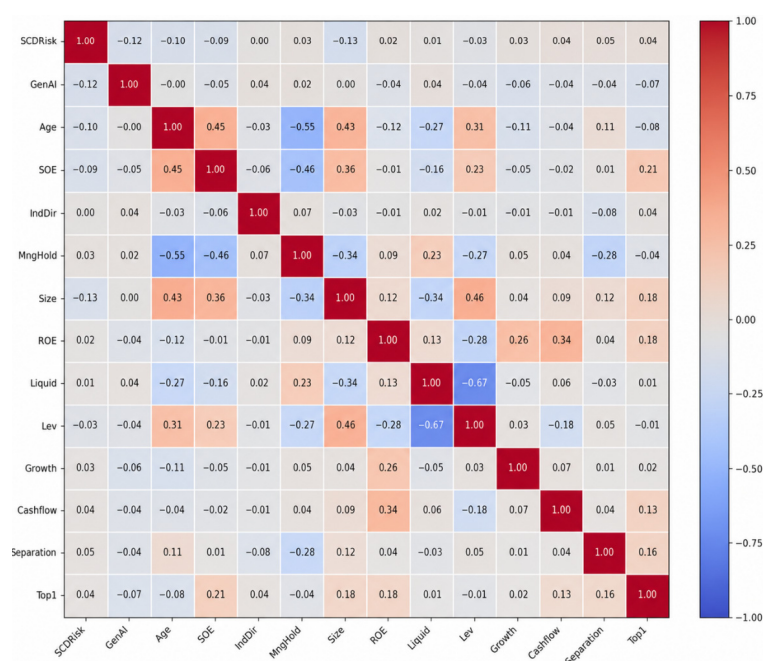


Figure 6. Correlation Heatmap of Main Variables.

To further examine potential multicollinearity, this study calculates the variance inflation factor (VIF) for each regressor, as reported in Table 6. The results show that the VIF values of all variables are below 5, with a maximum VIF of 2.42 and an average VIF of 1.48, both far below the commonly used threshold of 10. This indicates that the model does not suffer from serious multicollinearity, and that the correlations among variables are unlikely to materially interfere with the subsequent regression results.

Table 6. Variance Inflation Factor Test.

Variable	VIF	1/VIF
Lev	2.42	0.4137
Liquid	1.87	0.5343
Listage	1.8	0.557
Size	1.72	0.5807
Mngmhldn	1.72	0.5818
Soe	1.56	0.6418
Roe	1.42	0.7042
Top1	1.21	0.8273
Cashflow	1.17	0.8565
Separation	1.16	0.8636
Growth	1.11	0.902
GenAI	1.02	0.9807
IndDirectorRatio	1.02	0.9818
Mean VIF	1.48	

5.2. Baseline Empirical Analysis

Table 7 reports the baseline regression results. Column (1) controls only for firm fixed effects and year fixed effects. The estimated coefficient of GenAI is -0.030 and is significant at the 1% level, preliminarily indicating that a higher level of Generative AI application is associated with lower corporate supply chain disruption risk exposure. After further controlling for firms' financial characteristics in Column (2) and adding governance and other firm-level characteristics in Column (3), the coefficient of GenAI remains significantly negative. Specifically, a one-unit increase in GenAI is associated with an average decrease of 0.030 units in SCDRisk, which is approximately equivalent to 1.85% of the sample mean. This suggests that the baseline association is not only statistically robust but also economically meaningful, thereby supporting the core hypothesis H1.

Table 7. Baseline Regression Results.

	(1) SCDRisk	(2) SCDRisk	(3) SCDRisk
GenAI	-0.030^{***} (0.005)	-0.030^{***} (0.005)	-0.030^{***} (0.005)
Roe		-0.093^{***} (0.020)	-0.040^{**} (0.020)
Liquid		-0.001 (0.003)	-0.001 (0.003)
Lev		-0.014 (0.047)	0.109^{**} (0.044)
Growth		-0.008 (0.007)	-0.004 (0.007)
Cashflow		0.073^{*} (0.043)	0.053 (0.042)
Listage			-0.027 (0.018)
Soe			0.017 (0.022)
IndDirectorRatio			0.014 (0.086)
Mngmhldn			-0.201^{***}

			(0.052)
Size			−0.104 ***
			(0.014)
Separation			−0.081
			(0.101)
Top1			−0.195 **
			(0.084)
_cons	1.622 ***	1.630 ***	4.060 ***
	(0.001)	(0.024)	(0.300)
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	25,808	25,808	25,808
Adj. R2	0.770	0.771	0.774

Note: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.3. Robustness Checks

5.3.1. Replacing the Core Explanatory Variable

Considering that the Generative AI application measure constructed from annual report texts may still be affected by differences in firms' disclosure styles, following prior research [53], this study further uses the natural logarithm of one plus the number of artificial intelligence patent applications filed by listed firms in a given year to measure firms' related intelligent technology deployment (Patents). Compared with text-based disclosure measures, artificial intelligence patents can more directly reflect firms' related technological accumulation from the perspectives of technological reserves and innovation inputs. The regression results are reported in Column (1) of Table 8. After replacing the explanatory variable, the estimated coefficient of the core explanatory variable is −0.011 and remains significant at the 1% level. This indicates that whether firms' related intelligent technology deployment is measured using annual report text disclosures or artificial intelligence patents, the negative association between Generative AI application and supply chain disruption risk exposure remains robust.

Table 8. Robustness Checks: Alternative Measures, Fixed Effects, Clustering, and Estimation Methods.

	Alternative Explanatory Variable (1)	Alternative Dependent Variable (2)	Alternative Fixed Effects (3)	Alternative Clustering (4)	Lagged Explanatory Variable (5)	Double Machine Learning (6)
	SCDRisk	SCDEvent	SCDRisk	SCDRisk	SCDRisk	SCDRisk
Patents	−0.011 *** (0.004)					
GenAI		−0.007 * (0.004)	−0.036 *** (0.006)	−0.030 *** (0.006)		−0.030 *** (0.005)
L.GenAI					−0.018 *** (0.006)	
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES	YES
Industry × Year FE	NO	NO	YES	NO	NO	NO
Clustered SE	Firm	Firm	Firm	Firm & Industry × Year	Firm	Firm
N	25,808	25,808	25,808	25,808	20,678	25,808
Adj. R2	0.774	0.486	0.781	0.774	0.794	—

Note: Robust standard errors clustered at the firm level are reported in parentheses. *** and * indicate significance at the 1% and 10% levels, respectively.

5.3.2. Replacing the Core Dependent Variable

To enhance the robustness of the dependent variable measurement, this study further constructs a disclosure-based event-type indicator for supply chain disruption risk (SCDEvent) as an alternative measure. Specifically, based on an exact keyword matching method, SCDEvent equals 1 if a firm explicitly discloses expressions related to supply chain disruption events in its annual MD&A text, such as “supply cutoff,” “logistics disruption,” “supplier production suspension,” “raw material shortage,” or “delivery delay,” and 0 otherwise. Compared with the continuous risk measure constructed based on semantic similarity and keyword frequency ratios, SCDEvent adopts a stricter disclosure-based event-type expression identification criterion, which can, to some extent, reduce measurement noise arising from broad business descriptions and semantic expansion. The results in Column (2) of Table 8 show that the estimated coefficient of GenAI is -0.007 and is significantly negative at the 10% level. This indicates that, after adopting a stricter disclosure-based event-type identification approach, GenAI remains negatively associated with SCDEvent, suggesting that the baseline association is robust.

5.3.3. Adjusting Fixed Effects and Standard Error Clustering

Supply chain disruption risk may be affected by common factors such as macroeconomic fluctuations, changes in industrial policies, public health events, logistics shocks, and geopolitical events, which may lead to correlated error terms among firms in the same year or within the same industry-year. To examine whether the results are affected by fixed effect specifications and clustering settings, this study conducts additional robustness checks.

Column (3) of Table 8 introduces industry-year fixed effects in addition to firm fixed effects to absorb time-varying common shocks at the industry level. The results show that the estimated coefficient of GenAI remains significantly negative, indicating that the conclusion is not driven by industry-level annual common shocks. Column (4) of Table 8 further adopts two-way clustered standard errors at the firm and industry-year levels, allowing for error correlations both within the same firm and among firms in the same industry and year. The results show that the estimated coefficient of GenAI is -0.030 and remains significant at the 1% level, confirming the robustness of the baseline association.

5.3.4. Lagged Explanatory Variable

Considering that Generative AI application may require processes such as technological adaptation, process embedding, and organizational coordination, its association with supply chain risk governance may exhibit a certain time lag. Therefore, this study replaces the core explanatory variable with the one-period lagged GenAI and re-estimates the regression. The results in Column (5) of Table 8 show that the estimated coefficient of lagged GenAI remains significantly negative, indicating that a higher level of prior Generative AI application is associated with lower subsequent supply chain disruption risk exposure. This further supports the robustness of the baseline conclusion.

5.3.5. Double Machine Learning Test

To further alleviate potential bias arising from model functional form misspecification and nonlinear relationships among control variables, this study adopts a double machine learning approach to test the robustness of the baseline conclusion. The double machine learning method uses machine learning algorithms to estimate the nonlinear relationships between the control variables and both the core explanatory variable and the dependent variable, and employs orthogonalization to reduce the interference of high-dimensional controls and model specification with the estimation of the core coefficient.

This allows the relationship between Generative AI application and supply chain disruption risk exposure to be examined under a more flexible functional form. The results in Column (6) of Table 8 show that, after applying the double machine learning approach, the estimated coefficient of GenAI is -0.030 and is significantly negative at the 1% level. This result is consistent with the direction and significance of the baseline regression, indicating that the baseline association remains robust after considering more flexible control variable specifications and potential nonlinear relationships.

5.3.6. Excluding the Influence of Broad Artificial Intelligence Expressions

To exclude the influence of broad artificial intelligence and digital-technology-related expressions on the baseline results, this study further includes the BroadAI measure in the baseline model. As shown in Column (1) of Table 9, after controlling for BroadAI, the estimated coefficient of GenAI remains significantly negative at the 1% level. This indicates that the baseline association documented in this study is not driven by general artificial intelligence or digital transformation expressions.

Table 9. Robustness Checks: GenAI Measurement Boundary and Short-Window Tests.

	(1) Controlling for Broad AI SCDRisk	(2) PostGenAI Full sample SCDRisk	(3) PostGenAI 2022–2024 SCDRisk	(4) PostGenAI 2023–2024 SCDRisk
GenAI	-0.026^{***} (0.005)			
PostGenAI		-0.031^{***} (0.005)	-0.011^{***} (0.004)	-0.016^{***} (0.006)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	25,808	25,808	11,157	7150
Adj. R2	0.781	0.774	0.904	0.919

Note: Robust standard errors clustered at the firm level are reported in parentheses. *** indicates significance at the 1% level.

5.3.7. Measurement Boundaries of Generative AI and Short-Window Tests

Considering that the concept of Generative AI began to be widely recognized and reflected in firms' disclosures following the release of ChatGPT in late 2022, constructing the GenAI measure directly from annual report texts over the full sample period may be affected by early broad artificial intelligence expressions or ambiguous conceptual boundaries. To further improve the measurement accuracy of Generative AI, this study constructs the PostGenAI measure, which focuses on identifying more exclusive expressions with clear Generative AI characteristics after the emergence of ChatGPT. We then conduct tests using the full sample, the 2022–2024 sample, and the 2023–2024 sample, respectively.

The results in Column (2) of Table 9 show that, when the PostGenAI measure is used in the full sample, its estimated coefficient is -0.031 and is significantly negative at the 1% level. Furthermore, Columns (3) and (4) of Table 9 restrict the sample to 2022–2024 and 2023–2024, respectively. The results show that the estimated coefficients of PostGenAI are -0.011 and -0.016 , respectively, and both are significantly negative at the 1% level. These findings indicate that even when a stricter Generative-AI-specific dictionary is adopted and the sample is restricted to short-window periods after the rapid diffusion of Generative AI, the baseline association remains robust.

5.4. Endogeneity Tests

5.4.1. Instrumental Variable Approach

Given that the level of Generative AI application may not be fully exogenous, the baseline regression results may suffer from endogeneity bias. On the one hand, firms facing higher supply chain disruption risk exposure may be more likely to adopt Generative AI for risk identification, operational adjustment, and supply chain coordination, thereby giving rise to potential reverse causality. On the other hand, difficult-to-observe factors such as firms' digital foundations, managerial capabilities, technological absorptive capacity, and regional information environments may simultaneously affect Generative AI application and supply chain disruption risk exposure, resulting in omitted variable bias. To mitigate these concerns, this study further adopts an instrumental variable approach as a supplementary test.

Following Wang et al. (2023), this study constructs an instrumental variable based on the fixed-line telephone density per 100 people at the prefecture-city level in 1984 [54]. In terms of relevance, fixed-line telephone networks served as an important foundation for early Internet access and subsequent digital infrastructure development. Cities with higher historical fixed-line telephone density generally had better information and communication conditions and stronger capacity to absorb digital technologies, and thus were more likely to provide infrastructure support for firms' digital transformation and Generative AI application [54,55]. In terms of exclusion, fixed-line telephone density in 1984 was formed before the sample period of this study and reflects cities' early communication infrastructure endowments, making it unlikely to directly affect firms' current supply chain disruption risk exposure. In addition, this study multiplies this historical measure by the previous year's national Internet investment to construct a time-varying instrumental variable, IV1. Furthermore, the instrumental variable regressions control for annual prefecture-city-level characteristics to reduce the possibility that historical communication infrastructure directly affects the dependent variable through channels such as urban development level, industrial structure, or financial environment. The definitions of these variables are reported in Appendix Table A4.

Table 10 reports the instrumental variable regression results. The first-stage results show that the estimated coefficient of IV1 is significantly positive, indicating that the instrumental variable is significantly associated with firms' level of Generative AI application. The Kleibergen-Paap rk Wald F statistic is 32.431, which exceeds the Stock and Yogo critical value at the 10% level, suggesting that there is no obvious weak instrument problem. The second-stage results show that the estimated coefficient of GenAI is −0.241 and is significant at the 10% level, indicating that the baseline association remains observable in the instrumental-variable supplementary analysis.

Table 10. Instrumental Variable Regression Results.

	(1) Stage One	(2) Stage Two
GenAI	GenAI	SCDRisk
		−0.241 *
		(0.171)
IV1	0.018 *** (0.003)	
Controls	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
N	18,696	18,696
Kleibergen-Paap rk LM	34.530 *** ($p = 0.000$)	
Kleibergen-Paap rk Wald F	32.431 > 19.93	

Note: Robust standard errors clustered at the firm level are reported in parentheses. *** and * indicate significance at the 1% and 10% levels, respectively.

5.4.2. Propensity Score Matching (PSM) Test

To mitigate potential selection bias between Generative AI application and corporate supply chain disruption risk exposure, this study further adopts propensity score matching (PSM) as a supplementary test. Considering that the sample contains many zero observations for GenAI, defining the treatment group based on the annual median may lead to an unclear distinction between the treatment and control groups. Therefore, following Yang and Yang (2025), this study defines firms with GenAI greater than 0 in a given year as the treatment group, for which GenAIDummy equals 1, and firms with GenAI equal to 0 as the control group, for which GenAIDummy equals 0 [56]. Specifically, this study uses the control variables in the baseline regression as covariates, estimates firms' propensity scores for entering the treatment group through a logistic regression, and conducts 1:5 nearest-neighbor matching within the common support region.

Figure 7 presents the kernel density distributions of propensity scores for the treatment and control groups before and after matching. The figure shows that before matching, the propensity score distributions of the treatment and control groups differ to some extent. After matching, the two groups' propensity score distributions become much more similar, indicating that the matching procedure effectively improves the comparability of observable characteristics between the treatment and control groups. Figure 8 further reports changes in the standardized biases of covariates before and after matching. The results show that after matching, the standardized biases of all covariates converge substantially toward zero, suggesting that propensity score matching effectively improves the comparability between the treatment and control groups.

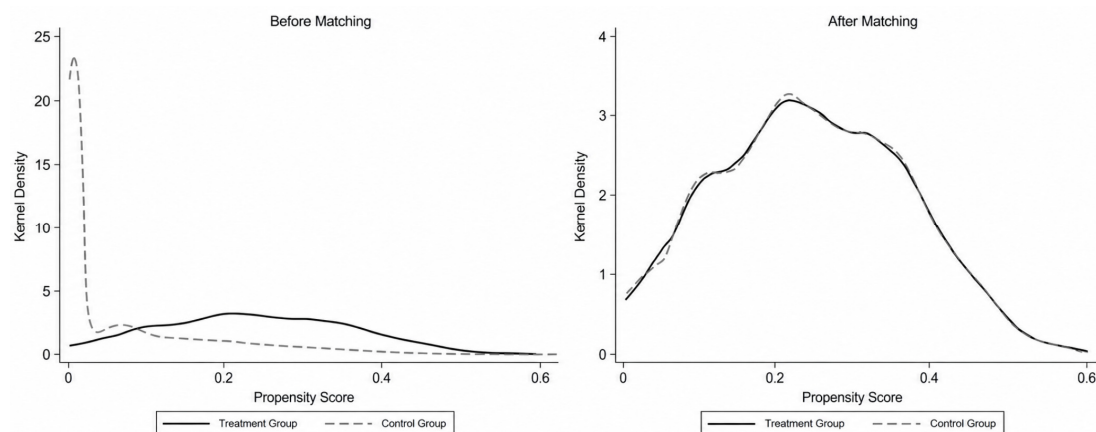


Figure 7. Kernel Density of Propensity Scores Before and After Matching.

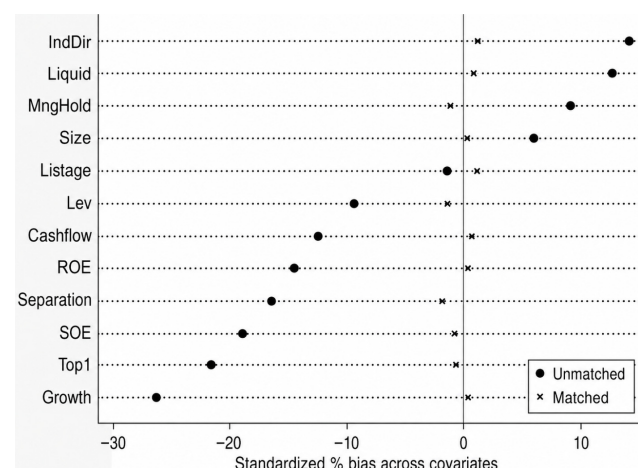


Figure 8. Covariate Balance Before and After PSM.

Table 11 reports the regression results based on the matched samples. Columns (1) and (3) use the 1:5 nearest-neighbor matched sample and estimate the regressions using GenAIDummy and the continuous GenAI measure as the core explanatory variables, respectively. The results show that the estimated coefficients of both GenAIDummy and GenAI are significantly negative at the 1% level. This indicates that, compared with firms without GenAI-related disclosures, firms with GenAI-related disclosures exhibit lower supply chain disruption risk exposure, and that a higher intensity of GenAI-related disclosure is associated with lower supply chain disruption risk exposure. In addition, this study further adopts radius matching as a supplementary test. The results in Columns (2) and (4) show that the estimated coefficients of GenAIDummy and GenAI remain significantly negative at the 1% level. These findings indicate that after mitigating observable differences between the treatment and control groups, the baseline association remains robust.

Table 11. PSM Regression Results.

	Nearest Neighbor (1) SCDRisk	Radius Matching (2) SCDRisk	Nearest Neighbor (3) SCDRisk	Radius Matching (4) SCDRisk
GenAIDummy	−0.028 *** (0.010)	−0.026 *** (0.008)		
GenAI			−0.016 *** (0.006)	−0.013 *** (0.005)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	6339	25,806	6339	25,806
Adj. R2	0.911	0.933	0.911	0.933

Note: Robust standard errors clustered at the firm level are reported in parentheses. *** indicates significance at the 1% level.

5.5. Supplementary SDID Test Based on the ChatGPT Release Shock

To further examine the robustness of the baseline association from the perspective of an external diffusion shock, this study exploits the release of ChatGPT, a landmark event that accelerated the diffusion of Generative AI, and adopts the Synthetic Difference-in-Differences (SDID) method as a supplementary test. Compared with traditional DID, SDID can construct both unit weights and time weights so that the weighted control group more closely approximates the pre-shock trajectory of the treatment group, thereby alleviating potential estimation bias arising from differences in pre-treatment trends between the treatment and control groups.

Specifically, since ChatGPT was released at the end of November 2022, this study defines 2023 and subsequent years as the post-shock period, for which Post equals 1, and the remaining years as the pre-shock period, for which Post equals 0. Meanwhile, to avoid the classification of the treatment group being affected by post-shock changes in Generative AI disclosures, this study constructs the treatment group based on firms' pre-shock artificial intelligence technological foundation. Specifically, the average number of artificial intelligence patent applications filed by a firm during 2017–2021 is used to measure its AI technological foundation before the release of ChatGPT. Firms with values above the sample median are defined as the treatment group, for which Treat equals 1, and the remaining firms are assigned to the control group, for which Treat equals 0. In the SDID estimation, this study retains a balanced panel of firms with continuous observations from 2017 to 2024 and constructs the following model:

$$SCDRisk_{i,t} = \alpha_i + \delta_t + \tau D_{i,t} + \gamma CVs_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$L(\alpha_i, \delta_t, \tau, \gamma) = \sum_{i,t} \hat{\omega}_i \hat{\lambda}_t (SCDRisk_{i,t} - \alpha_i - \delta_t - \tau D_{i,t} - \gamma' CVs_{i,t})^2 \quad (3)$$

where $D_{i,t} = \text{Treat}_i \times \text{Post}_t$ is the treatment variable for the ChatGPT shock, and the other variables are defined as above. The coefficient of interest is τ , which captures the relative change in supply chain disruption risk exposure after the release of ChatGPT for firms with a stronger pre-shock AI technological foundation relative to the control group. Equation (3) presents the weighted least squares objective function of SDID, where $\hat{\omega}_i$ and $\hat{\lambda}_t$ denote unit weights and time weights, respectively. These weights are used to improve the comparability of the pre-shock trajectories between the treatment group and the synthetic control group.

Figure 9 presents the standardized trends in supply chain disruption risk exposure for the treatment group and the synthetic control group under the SDID method. The figure shows that before the release of ChatGPT, the trajectories of the treatment group and the synthetic control group are relatively close. After 2023, however, the supply chain disruption risk exposure of firms in the treatment group declines noticeably relative to that of the synthetic control group. This pattern suggests that after the release of ChatGPT, firms with a stronger pre-shock AI technological foundation exhibited a more pronounced relative decline in supply chain disruption risk exposure during the diffusion of Generative AI.

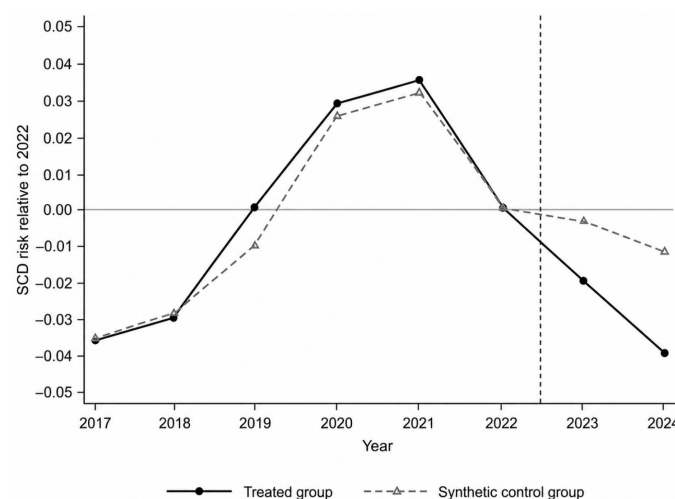


Figure 9. SDID Trend Based on the ChatGPT Release Shock. Solid circles and hollow triangles represent yearly observations for the treated group and the synthetic control group, respectively, and the vertical dashed line indicates the ChatGPT release shock.

Table 12 reports the SDID estimation results. Column (1) defines firms with a pre-ChatGPT AI technological foundation above the sample median as the treatment group. The results show that the ATT is -0.024 and is significant at the 5% level, indicating that after improving the pre-shock comparability between the treatment and control groups through synthetic weights, firms with a stronger AI technological foundation experienced a relative decline in supply chain disruption risk exposure after the release of ChatGPT. Column (2) further defines the treatment group as firms whose pre-shock AI technological foundation is in the top 25%. The ATT is -0.029 and is significant at the 1% level. These results indicate that, when using the release of ChatGPT as a shock to the diffusion of Generative AI and improving the pre-shock trajectory comparability between the treatment and control groups within the SDID framework, firms with a stronger pre-shock AI

technological foundation exhibit a more pronounced decline in supply chain disruption risk exposure after the shock. This finding suggests that when the external availability of Generative AI increases substantially, firms with stronger technological absorptive foundations may respond more rapidly to the diffusion of Generative AI, thereby providing supplementary evidence for the baseline association between Generative AI application and lower corporate supply chain disruption risk exposure.

Table 12. Synthetic DID Estimates around ChatGPT Release.

	(1) Median Split	(2) Top Quartile
ATT	−0.024 ** (0.011)	−0.029 *** (0.011)
Observations	12,944	12,944
Balanced panel	Yes	Yes
Unit weights	Yes	Yes
Time weights	Yes	Yes
Firm controls	Yes	Yes

Note: Bootstrap standard errors based on 200 replications are reported in parentheses. Robust standard errors clustered at the firm level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively.

5.6. Channel Analysis

To further explore the potential channels through which Generative AI application is associated with lower corporate supply chain disruption risk exposure, this study conducts channel analyses from three perspectives: risk identification, resource allocation, and collaborative response. The results are reported in Table 13.

This study examines the risk identification mechanism from two dimensions: internal governance and external information absorption. First, internal control quality reflects the effectiveness of a firm's internal risk identification, information transmission, supervisory feedback, and control implementation. A high-quality internal control system helps firms promptly detect abnormal signals in procurement, production, inventory, sales, and working capital turnover, thereby improving their ability to identify and control potential supply chain risks. This study uses the natural logarithm of one plus the internal control index from the DIB database to measure internal control quality (ICQ). A higher ICQ value indicates higher internal control quality and stronger internal risk identification and control capability. Second, absorptive capacity reflects a firm's ability to acquire, assimilate, and utilize external knowledge and information. Since supply chain disruption risk is often affected by changes in market demand, suppliers' operating conditions, technological evolution, and external environmental shocks, firms with stronger absorptive capacity are better able to transform external market, technological, and supply-chain-related information into risk judgments and operational decisions. Following Yiu and Wu (2021), this study uses the ratio of R&D expenditure to operating revenue to measure firms' absorptive capacity (Absorb) [57]. A higher value of this measure indicates that the firm places greater emphasis on knowledge accumulation, technological learning, and the use of external information.

Panel A of Table 13 reports the test results for the risk identification channel. Columns (1) and (3) show that the regression coefficients of GenAI on internal control quality and absorptive capacity are 0.037 and 0.228, respectively, and both are statistically significantly positive. This suggests that Generative AI application is positively associated with firms' internal risk control processes and their ability to acquire, process, and utilize external information. Columns (2) and (4) further show that both internal control quality

and absorptive capacity are significantly negatively associated with SCDRisk, with coefficients of -0.005 and -0.007 , respectively. Meanwhile, the coefficient of GenAI remains significantly negative. These results are consistent with the view that Generative AI application may strengthen firms' perception of internal operational abnormalities and external supply chain risk signals by improving internal governance efficiency and external information absorption capability. Such improvements may help firms identify potential disturbances earlier and take corresponding response measures, thereby helping explain lower supply chain disruption risk exposure.

This study examines the resource allocation mechanism from two dimensions: inventory allocation efficiency and working capital turnover efficiency. In terms of inventory allocation, improving supply chain operational efficiency depends on more accurate demand forecasting, more reasonable procurement rhythms, and more timely inventory adjustments [58]. This study uses inventory turnover days to measure firms' inventory allocation efficiency (Sce), calculated as $\ln(365/\text{inventory turnover ratio})$. A lower value of this measure indicates a shorter inventory turnover cycle, lower inventory occupation and operational frictions, and a stronger ability to match inventory arrangements with operating demand. In terms of working capital allocation, this study uses the working capital turnover ratio (Wct) to capture the efficiency and scheduling capability of firms' financial resources. Specifically, Wct is calculated as operating revenue divided by working capital and then divided by 100 for scale adjustment. A higher working capital turnover ratio indicates that the firm can support operating activities with lower capital occupation, reflecting stronger capital scheduling capability and operational flexibility.

Panel B of Table 13 reports the test results for the resource allocation channel. Columns (1) and (3) show that the regression coefficients of GenAI on inventory turnover days and working capital turnover ratio are -0.049 and 0.016 , respectively, and both are statistically significant. This suggests that Generative AI application is associated with shorter inventory turnover cycles and higher working capital turnover efficiency. Columns (2) and (4) further show that inventory turnover days are significantly positively associated with SCDRisk, with a coefficient of 0.012 , while working capital turnover ratio is significantly negatively associated with SCDRisk, with a coefficient of -0.006 . Meanwhile, the coefficient of GenAI remains significantly negative. These results suggest that Generative AI application may be associated with lower supply chain disruption risk exposure by improving inventory allocation efficiency and financial resource scheduling capability. In particular, more efficient inventory adjustment and working capital turnover may help firms allocate key resources more effectively when facing demand fluctuations, procurement changes, and financial constraints, which is consistent with the resource allocation channel emphasized in prior supply chain research [45].

This study examines the collaborative response mechanism from two dimensions: supply-demand matching and supply chain diversification. In terms of supply-demand matching, following Bray and Mendelson (2012), this study measures the degree of supply-demand mismatch (Isd) by the extent to which firms' production fluctuations deviate from demand fluctuations [59]. A lower value of this measure indicates a smaller deviation between production arrangements and changes in market demand, and thus a higher level of supply-demand matching. In terms of supply chain diversification, following Chung (2017), this study constructs a power-law model based on the procurement shares of a firm's top five suppliers, estimates the parameters using nonlinear least squares, and infers the unobservable total number of suppliers [60]. The natural logarithm of this inferred supplier number is then used to measure supply chain diversification (Div). A higher Div value indicates a more dispersed supplier base and a higher degree of supply chain diversification.

Panel C of Table 13 reports the test results for the collaborative response channel. Columns (1) and (3) show that the regression coefficients of GenAI on supply-demand mismatch and supply chain diversification are -0.007 and 0.019 , respectively, and both are statistically significant. This indicates that Generative AI application is associated with lower supply-demand mismatch and higher supply chain diversification. Columns (2) and (4) further show that supply-demand mismatch is significantly positively associated with SCDRisk, with a coefficient of 0.014 , while supply chain diversification is significantly negatively associated with SCDRisk, with a coefficient of -0.011 . Meanwhile, the coefficient of GenAI remains significantly negative. These results suggest that Generative AI can enhance firms' ability to reconfigure supply-demand relationships and supply chain network structures by improving demand forecasting, production coordination, and supplier structure adjustment. This may strengthen firms' collaborative response capability when facing supply chain disturbances and help explain lower supply chain disruption risk exposure [7,61].

Overall, the channel analysis provides evidence consistent with three possible channels linking Generative AI application to lower supply chain disruption risk exposure, namely risk identification capability, resource allocation capability, and collaborative response capability. Enhanced risk identification capability enables firms to detect internal operational abnormalities and external supply chain risk signals earlier. Improved resource allocation capability enables firms to adjust inventory, operational, and financial arrangements more effectively. Strengthened collaborative response capability helps firms optimize supply-demand matching and improve supply chain network structures. Specifically, front-end risk signal identification provides the informational basis for subsequent resource adjustment, resource allocation optimization provides operational support for firms to respond to potential disturbances, and improved collaborative response capability further enhances coordination and substitution flexibility between firms and their upstream and downstream partners. These patterns suggest that Generative AI application may be related to lower supply chain disruption risk exposure through improvements in firms' supply chain governance capability.

Table 13. Channel Analysis Results. (A) Risk Identification. (B) Resource Allocation. (C) Collaborative Response.

(A)				
	(1) ICQ	(2) SCDRisk	(3) Absorb	(4) SCDRisk
GenAI	0.037 *** (0.010)	-0.030 *** (0.005)	0.228 ** (0.072)	-0.028 *** (0.005)
ICQ		-0.005 ** (0.002)		
Absorb				-0.007 *** (0.001)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	25,750	25,750	23,607	23,607
Adj. R2	0.214	0.774	0.869	0.773
(B)				
	(1) Sce	(2) SCDRisk	(3) Wct	(4) SCDRisk
GenAI	-0.049 ** (0.022)	-0.021 *** (0.007)	0.016 ** (0.008)	-0.031 *** (0.005)
Sce		0.012 * (0.007)		

Wct				−0.006 ** (0.003)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	22,748	22,748	25,427	25,427
Adj. R2	0.838	0.745	0.027	0.774
(C)				
	(1)	(2)	(3)	(4)
	Isd	SCDRisk	Div	SCDRisk
GenAI	−0.007 ** (0.003)	−0.031 *** (0.005)	0.019 ** (0.008)	−0.031 *** (0.006)
Isd		0.014 * (0.008)		
Div				−0.011 * (0.006)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	24,959	24,959	17,142	17,142
Adj. R2	0.127	0.774	0.408	0.742

Note: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.7. Heterogeneity Analysis

5.7.1. Firm-Level Heterogeneity

At the firm level, external environmental uncertainty may affect the association between Generative AI application and supply chain disruption risk exposure. The higher the level of environmental uncertainty, the greater the pressure firms face from changes in market demand, fluctuations in customer orders, supplier fulfillment risks, and adjustments to operating plans. Under such conditions, information incompleteness and delayed responses in supply chain operations also become more pronounced. Firms therefore have a stronger need to use Generative AI to improve information processing, risk identification, and dynamic adjustment capabilities, thereby mitigating the impact of external environmental fluctuations on supply chain operations. Accordingly, the negative association between Generative AI application and supply chain disruption risk exposure may be more pronounced among firms facing higher environmental uncertainty.

Following Ghosh and Olsen (2009), this study measures environmental uncertainty (Eu) using the industry-adjusted standard deviation of sales revenue over the past five years [62]. A higher Eu value indicates that the firm faces a more uncertain external operating environment. To examine the moderating role of environmental uncertainty, this study adds environmental uncertainty and its interaction term with GenAI, Eu_GenAI, to the baseline model. The regression results are reported in Column (1) of Table 14. The coefficient of the interaction term is significantly negative at the 5% level, indicating that under more complex and volatile external environments, the information processing, risk identification, and resource adjustment functions of Generative AI become more valuable. Generative AI can help firms respond more effectively to demand fluctuations, supply abnormalities, and pressure from operating plan adjustments, which is consistent with a stronger negative association between Generative AI application and supply chain disruption risk exposure among firms facing higher environmental uncertainty.

Table 14. Heterogeneity Analysis Results.

	(1) SCDRisk	(2) SCDRisk	(3) SCDRisk
GenAI	−0.018 ** (0.007)	−0.023 *** (0.006)	−0.226 *** (0.086)
Eu_GenAI	−0.007 ** (0.003)		
Eu	0.007 * (0.004)		
Manuf_GenAI		−0.020 ** (0.009)	
Manuf		−0.019 (0.045)	
EntAct_GenAI			0.015 ** (0.007)
EntAct			−0.012 (0.012)
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	20,205	25,806	23,281
Adj. R2	0.775	0.774	0.778

Note: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.7.2. Industry-Level Heterogeneity

At the industry level, differences in production organization and supply chain dependence across industries may lead to heterogeneous associations between Generative AI application and supply chain disruption risk exposure. Manufacturing firms usually face more complex production processes and supply chain structures and rely more heavily on supply chain stability; therefore, they tend to be more severely affected when disruptions occur. Generative AI can help firms process supply chain information and adjust operating arrangements more promptly by improving demand forecasting, production coordination, supplier monitoring, and risk identification capabilities. Therefore, this association may be more pronounced among manufacturing firms.

To test this conjecture, this study constructs a manufacturing dummy variable, *Manuf*, and adds its interaction term with *GenAI* to the baseline model. The regression results are reported in Column (2) of Table 14. The coefficient of the interaction term is significantly negative at the 5% level, indicating that the baseline association is more pronounced among manufacturing firms. These results suggest that in manufacturing settings, where production processes are more complex and supply chain coordination requirements are higher, Generative AI can play a more prominent role in information processing, risk identification, and dynamic coordination, which is consistent with a stronger baseline association in manufacturing settings.

5.7.3. Regional Heterogeneity

At the regional level, urban entrepreneurial vitality may affect the association between Generative AI application and supply chain disruption risk exposure. Regions with higher entrepreneurial vitality usually have more abundant market participants, more active resource flows, and more developed business ecosystems. Firms in such regions can more easily obtain alternative suppliers, professional services, and external collaborative

resources, and therefore tend to have stronger supply chain risk diversification and self-recovery capabilities. By contrast, firms located in regions with lower entrepreneurial vitality operate in relatively less active market environments, where local supply chain support, external collaborative resources, and alternative options may be more limited. When facing supply chain disturbances, these firms rely more heavily on their own information processing, risk identification, and resource scheduling capabilities. Therefore, Generative AI may have higher marginal governance value in regions with lower entrepreneurial vitality.

To test this logic, following Li et al. (2026), this study measures urban entrepreneurial vitality (EntAct) using the natural logarithm of one plus the number of newly registered industrial and commercial enterprises in the city [63]. Urban entrepreneurial vitality and its interaction term with GenAI are added to the baseline model, and the regression results are reported in Column (3) of Table 14. The results show that the coefficient of the interaction term is significantly positive at the 5% level, indicating that the baseline association is more pronounced in regions with lower entrepreneurial vitality. A possible explanation is that firms in regions with lower entrepreneurial vitality face relatively limited external collaborative resources and supply chain substitution options. Generative AI can compensate for insufficient regional market ecosystems and external support by strengthening information integration, risk warning, and resource scheduling capabilities, which is consistent with a stronger negative association in regions with lower entrepreneurial vitality.

6. Conclusions and Implications

6.1. Conclusions

Supply chain security is an important foundation for firms' sustainable operations and the formation of competitive advantage. Against the backdrop of frequent external shocks and increasingly complex supply chain networks, identifying the factors associated with supply chain disruption risk exposure is of great significance for enhancing corporate resilience and maintaining the stability of industrial and supply chains. Based on the resource-based view and dynamic capability theory, this study uses data from Chinese A-share listed firms from 2017 to 2024 to systematically examine the relationship between Generative AI application and corporate supply chain disruption risk exposure, its potential channels, and its heterogeneous associations. The results show that Generative AI application is significantly associated with lower corporate supply chain disruption risk exposure, and this association remains robust across a series of robustness checks and supplementary endogeneity analyses.

The potential channel analyses further suggest that Generative AI application is related to supply chain risk governance not merely through a single business function, but through improvements in firms' risk governance capabilities. Specifically, Generative AI application is positively associated with internal control quality and absorptive capacity, suggesting a potential link with firms' ability to identify internal abnormalities and external supply chain risk signals. It is also associated with shorter inventory turnover cycles and higher working capital turnover efficiency, which is consistent with improved resource allocation capability. In addition, Generative AI application is associated with lower supply-demand mismatch and higher supply chain diversification, suggesting a potential link with stronger collaborative response capability when firms face supply chain disturbances. The heterogeneity analyses show that the baseline association is more pronounced among firms facing higher environmental uncertainty, manufacturing firms, and firms located in cities with lower entrepreneurial vitality. This suggests that the relationship between Generative AI application and supply chain disruption risk exposure is shaped by firms' external operating environments, industry-specific production organization, and regional market ecosystems.

6.2. Implications and Recommendations

Based on the above findings, firms should promote Generative AI application in specific management functions such as risk identification, resource allocation, and collaborative response, while improving the reliability and controllability of its use through corresponding governance safeguards.

First, firms should establish a human–AI collaborative mechanism for supply chain risk identification. Generative AI can be applied to the identification and integration of information related to supplier abnormalities, logistics delays, demand fluctuations, policy changes, and market shocks, thereby improving firms' ability to capture risk signals and make contextual judgments. On this basis, firms should improve their internal control systems and enhance the efficiency of anomaly identification and feedback in procurement, production, inventory, sales, and working capital turnover. At the same time, firms should strengthen their absorptive capacity for external information related to suppliers, market demand, technological changes, and policy environments, transforming multi-source information into actionable risk judgments. It should be noted that the outputs of Generative AI may involve biases, hallucinations, or inconsistencies. Therefore, key warnings and response recommendations should be jointly reviewed by departments such as procurement, production, logistics, finance, and risk control, so as to avoid excessive reliance on automated judgments.

Second, firms should improve resource allocation and collaborative response capabilities around key operational indicators. Firms should establish continuous monitoring mechanisms around indicators such as inventory turnover, working capital turnover, order fulfillment, capacity arrangements, supply-demand mismatch, and supply chain diversification. They should use Generative AI to support demand forecasting, inventory optimization, capital scheduling, supplier risk assessment, and alternative supply plan generation, thereby improving the timeliness of resource allocation and the collaborative response capability of the supply chain. At the same time, firms should avoid simply equating efficiency improvement with risk reduction. While shortening inventory turnover cycles and improving capital utilization efficiency, they should also maintain necessary safety inventories, backup supplies, and emergency funding arrangements, so as to balance operational efficiency and supply chain resilience.

Third, firms should allocate investment priorities according to application scenarios and establish auditable risk prevention and control mechanisms. Generative AI application should not be promoted uniformly across all functions, but should instead be prioritized in scenarios with higher marginal governance value. For firms facing greater external environmental volatility, priority should be given to strengthening its application in risk warning, demand assessment, and emergency response plan generation. For manufacturing firms, Generative AI should be embedded in production planning, inventory management, supplier coordination, and logistics scheduling. For firms located in regions with lower entrepreneurial vitality, governments and industry organizations should reduce application barriers through digital infrastructure, public data services, and technical support platforms, thereby helping compensate for insufficient external collaborative resources and limited supply chain substitution options. Meanwhile, firms should establish mechanisms for model validation, log retention, result auditing, data classification authorization, and access control to reduce the risks of data leakage, model misjudgment, and cyber and supply chain vulnerabilities arising from digital supply chain integration. They should also clarify the responsibility boundaries of business departments, technical departments, risk control departments, and senior management in key decisions.

6.3. Limitations and Future Research

This study still has several limitations. First, this study constructs the GenAI and SCDRisk measures based on the MD&A texts of listed firms' annual reports. Although this study improves measurement reliability through strict dictionary construction, manual verification, filing information matching, disclosure-based alternative measures, and correlation tests with stock return volatility, annual report texts may still be affected by firms' disclosure strategies, managerial attention, and risk narratives. Therefore, the measures in this study mainly capture firms' textually disclosed Generative AI application and disclosed supply chain disruption risk exposure. Future research can combine filing information, recruitment texts, patent data, system deployment records, and actual disruption event data for cross-validation. Second, although this study uses lagged explanatory variables, the instrumental variable approach, propensity score matching, and the SDID test based on the ChatGPT release shock to mitigate potential endogeneity concerns, there may still be more complex dynamic relationships between Generative AI application and firms' supply chain risk governance. Future research can further use more fine-grained data on firm-level application scenarios, platform access records, or exogenous policy shocks to construct stronger causal identification strategies. Third, the sample of this study mainly consists of Chinese A-share listed firms, and the findings may be influenced by China's capital market disclosure system, the stage of firms' digital development, and supply chain organization modes. Future research can extend the analysis to other countries, non-listed firms, and multinational supply chain networks. By further combining supplier–customer relationships, logistics networks, and upstream and downstream transaction data, future studies can examine the role of Generative AI in risk propagation and systemic resilience in supply chain networks.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Full Keyword List for the Generative AI Application-Level Indicator (GenAI).

Dimension	Full Keywords
Core Concept Terms	Generative artificial intelligence, Generative AI, AIGC, AI-generated content, Large model, Large language model, LLM, Foundation model, AI foundation model, Pre-trained large model, Generative model, Multimodal large model
Core Technology Terms	Transformer, Transformer architecture, Diffusion model, Diffusion Models, Generative adversarial network, Variational autoencoder, Autoregressive model, Autoregressive Models, Flow-based model, Flow-based Models, Retrieval-augmented generation, RAG, Prompt engineering, Reinforcement

Functional Application Terms	learning from human feedback, RLHF, Multimodal generation, Multimodal generative architecture, AI Agent
	Content generation, Text generation, Image generation, Code generation, Speech generation, Audio generation, Video generation, Text-to-image, Text-to-video, Intelligent writing, AI writing, Automated writing, Summary generation, Intelligent question answering, AI question answering, Human-machine dialogue, Speech synthesis, Generative design, Digital human, Virtual human, AI assistant, AI copywriting assistant, Intelligent programming
Representative Model and Platform Terms	GPT, ChatGPT, GPT-3, GPT3, GPT-4, GPT4, GPT-4o, GPT4o, OpenAI, DALL-E, DALL-E, DALLE, Stable Diffusion, Midjourney, Claude, Bard, DeepSeek, DeepSeek Chat, LLaMA, Qwen, Tongyi Qianwen, Qianwen, Wenxin Yiyan, ERNIE Bot, iFlytek Spark, SparkDesk, Pangu large model, Pangu model, Hunyuan large model, Hunyuan model, GLM, ChatGLM, Zhipu AI, Baichuan large model, Baichuan, Kimi, Moonshot AI, OpenFlamingo, mPLUG-Owl, Kosmos-2, ImageBind

Table A2. Full Keyword List for the Broad AI and Digital Technology Indicator (BroadAI).

Dimension	Full Keywords
General AI and Digital Technology Terms	Machine learning, Deep learning, Supervised learning, Unsupervised learning, Self-supervised learning, Transfer learning, Reinforcement learning, Semi-supervised learning, Federated learning, Ensemble learning, Natural language processing, NLP, Knowledge graph, Computer vision, Image recognition, Speech recognition, Pattern recognition, Data mining, Big data, Cloud computing, Edge computing, Internet of Things, IoT, Intelligent computing, Intelligent chips, Intelligent manufacturing, Intelligent risk control, Intelligent finance, Intelligent healthcare, Intelligent education, Autonomous driving, Process automation, BERT, XLM, ViT, LeNet, AlexNet, ResNet, MobileNet, EfficientNet, DETR, CNN, Convolutional neural network, RNN, Recurrent neural network, LSTM, GRU, TensorFlow, PyTorch, Keras, Caffe, MXNet, PaddlePaddle, Torch, Caffe2, DGL, TFX, Catalyst, Horovod, Transformers, Capsule network

Table A3. Full Keyword List for the Post-ChatGPT Generative AI Indicator (PostGenAI).

Dimension	Full Keywords
Post-ChatGPT Generative AI-Specific Terms	ChatGPT, GPT-4, GPT4, GPT-4o, GPT4o, OpenAI, DALL-E, DALL-E, DALLE, Stable Diffusion, Midjourney, Sora, Claude, Gemini, DeepSeek, DeepSeek Chat, LLaMA, Qwen, Tongyi Qianwen, Qianwen, Wenxin Yiyan, ERNIE Bot, iFlytek Spark, SparkDesk, Pangu large model, Pangu model, Hunyuan large model, Hunyuan model, GLM, ChatGLM, Zhipu AI, Baichuan large model, Baichuan, Kimi, Moonshot AI, AIGC, Generative artificial intelligence, Generative AI, Large model, Large language model, LLM, Foundation model, Multimodal large model, AI Agent, Retrieval-augmented generation, RAG, Prompt engineering, Text-to-image, Text-to-video, Content generation, Code generation, AI writing, AI question answering, AI assistant, AI copywriting assistant, Intelligent programming, Digital human, Virtual human

Table A4. Definitions of City-Level Control Variables.

Variable	Definition
Economic development	Natural logarithm of per capita gross regional product
Openness	Total imports and exports divided by gross regional product

Industrial structure	Value added of the tertiary industry divided by gross regional product
Human capital	Number of students enrolled in regular institutions of higher education divided by year-end population
Financial development	Balance of deposits and loans of financial institutions divided by gross regional product
Government intervention	Local general public budget expenditure divided by gross regional product
Fiscal pressure	Difference between local general public budget expenditure and local general public budget revenue, divided by gross regional product

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