China Economic Review 94 (2025) 102502

Contents lists available at ScienceDirect

China Economic Review

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

The mitigating effects of blockchain adoption on supply chain financing disruptions under crises: Evidence from China[☆]

Haolin Li[a], Sirui Cheng[b], Xiuping Hua[c,*], Yong Wang[d]

[a] Faculty of Science and Engineering, University of Nottingham Ningbo China, Ningbo 315100, PR China
[b] Lingnan College, Sun Yat-sen University, Guangzhou 510275, PR China
[c] Nottingham University Business School China, University of Nottingham Ningbo China, Ningbo 315100, PR China
[d] Institute of New Structural Economics (INSE), Peking University, Room 503, Langrun Garden, 5 Yiheyuan Road, Haidian District, Beijing 100871, PR China

ARTICLE INFO

Keywords:
Blockchain
Supply chain finance
COVID-19
Textual analysis

ABSTRACT

The paper investigates the negative effect of the COVID-19 crisis on supply chain financing in China. It examines the role of blockchain adoption in mitigating such disruptions by using data from Chinese firms between 2015 and 2022 and employs textual analysis to construct indexes on firms' blockchain innovation and supply chain risk exposure. We find that firms with high supply chain risk experience a more significant reduction in formal and informal financing during the COVID-19 pandemic. Nevertheless, blockchain adoption helps provide more resilience to supply chain financing disruptions in the crisis by enhancing information transparency, corporate governance, and production network efficiency. Further analysis shows that the alleviation effect is heterogeneous and more pronounced for firms with private ownership and lower social trust. The main results remain consistent using alternative measures based on Generative Pre-trained Transformer (GPT), a large language model. Our paper highlights the importance of digital technology advancement in protecting supply chain security under crises.

1. Introduction

The coronavirus (COVID-19) pandemic starting in 2020 has significantly affected the political landscape, economic systems, societal structures, and cultural practices across numerous nations globally (Ding, Fan, & Lin, 2022; Li, Li, Macchiavelli, & Zhou, 2021; Liang, Shi, Tang, & Xu, 2022). The impact of the COVID-19 pandemic on firms is particularly significant. It has exacerbated supply chain risks and intensified the challenges faced by businesses that are more vulnerable to disruptions in their supply networks (Bedendo, Garcia-Appendini, & Siming, 2023). The pandemic prompted many countries and regions to enforce lockdowns and quarantines, which, although effective in controlling the virus, led to unstable and vulnerable supply chains. The uncertainty from the epidemic affected the entire supply chain, with upstream firms unable to supply raw materials reliably, impacting downstream firms' production schedules and downstream enterprises struggling to meet financial obligations, thereby exerting financial pressure on upstream enterprises as well (Breza & Liberman, 2017; Wang, Dong, & Liu, 2022). Up to 2022, the number of companies experiencing

☆ This article is part of a Special issue entitled: 'China's Open Economy under Multiple Crises' published in China Economic Review.

* Corresponding author.
E-mail addresses: haolin.li@nottingham.edu.cn (H. Li), chengsr6@mail.sysu.edu.cn (S. Cheng), Xiuping.Hua@nottingham.edu.cn (X. Hua), yongwang@nsd.pku.edu.cn (Y. Wang).

https://doi.org/10.1016/j.chieco.2025.102502
Received 2 August 2024; Received in revised form 28 March 2025; Accepted 11 July 2025
Available online 12 July 2025
1043-951X/

production constraints because of supply shortages surged to 3.5 times the long-term average.[1]

In this paper, we contemplate that COVID-19 led to a significant reduction in formal and informal supply chain finance for firms with higher supply chain risk. We then investigate how blockchain technology mitigated this negative impact. As a decentralized and tamper-proof distributed ledger system, blockchain technology is a newly developed digital technology that enhances the trust and robustness between the upstream and downstream of the supply chain (Cong & He, 2019). It has been rapidly developed due to the encouragement and support from the Chinese government in the last few years (Chong et al., 2019a; Biswas, Jalali, Ansaripoor, & De Giovanni, 2023).

Take JD Finance's and China's Construction Banks' blockchain applications in supply chain finance as examples. JD Technology has introduced a dual-chain linkage model of "Digital Supply Chain + Supply Chain Finance" in 2022, utilizing its supply chain finance technology platform to facilitate digital transformation for core enterprises and promote the development of supply chain finance. China Construction Bank has implemented the *"BCTrade"* blockchain trade finance platform, which has achieved transaction volume exceeding 1 trillion yuan and has become the industry's leading blockchain trading platform. The platform addresses pain points in traditional trade finance, such as lengthy processes and the susceptibility of documents to tampering, by providing a multi-win trade finance ecosystem. By leveraging its inherent security features and transparency, companies can establish a more secure, transparent, and efficient supply chain management system (Chong et al., 2019b; Cho, Lee, Cheong, No, & Vasarhelyi, 2021). This integration not only bolsters the resilience of individual firms but also strengthens the interconnectedness and reliability of the entire supply chain ecosystem.

The paper focuses on Chinese-listed firms for the following reasons. First, due to a "dynamic zero-COVID quarantine policy" in China, the negative impact of COVID-19 on the supply chain systems was more severe in China (Ding, Levine, Lin, & Xie, 2021; Costello, Minnis & Rabinovich, 2024; Wang, Wang, Li, & Zhao, 2022; Shen & Sun, 2023). Many Chinese firms and their supply chains were suddenly in a position in which production and sales of goods or services were disrupted, and severely damaged supply chains and even mass layoffs or closures were widely reported (Shen & Sun, 2023). In the face of the unprecedented challenges posed by the pandemic, trust and information transparency between upstream and downstream are seriously affected in such circumstances. This makes China's data a unique case for analyzing how blockchain adoption can mitigate supply chain financing disruptions during crises.

To analyze whether the firms with high supply chain risk experienced a more significant reduction in trade credit during the COVID-19 pandemic, we use textual analysis to construct indexes on blockchain innovation and supply chain risk exposure of Chinese listed firms. Despite the recognized importance of supply chains in business operations, research into supply chain risk remains constrained by data scarcity. Using a word embedding model, this paper constructs a lexicon for supply chain risk. By conducting text analysis of news and patent data of listed companies in China, it further develops an index for blockchain technology index.

We then employ the COVID-19 shock to construct a difference in difference (DID) model. We find that firms with high supply chain risk experienced a more significant reduction in both trade credit and bank credit during the COVID-19 epidemic. We further confirm the mitigation effect of blockchain technology on decreases in supply chain financing. The results are robust after a series of robustness checks. In addition, the paper finds that blockchain adoption provides resilience to supply chain finance in the COVID-19 crisis, mainly by enhancing information transparency, corporate governance, and product network efficiency to the firms in the supply chain. Further analysis shows that the alleviation effect is heterogeneous and significantly more pronounced for firms with private ownership and lower social trust. The main results remain consistent with alternative measures based on the Generative Pre-trained Transformer (GPT), a large language model.

Our paper highlights the importance of digital technology advancement in protecting supply chain security under crises. The key takeaway is that blockchain-related digital technology initiatives or innovations help firms with high supply chain risks to bolster their financial resilience and operational agility, ensuring they are better equipped to navigate and overcome challenges in the dynamic business landscape. Thus, to enhance supply chain resilience, policies should encourage Chinese enterprises, particularly small- and medium-sized companies, to embrace blockchain technology or adoption in their operation system to promote financial inclusion.

We contribute to the literature in several ways. First, we contribute to the literature on disruptions in supply chain financing in the open economy during crises. Prior literature has proposed a variety of factors that affect supply chain financing (Ding, Liu, Shi, Wang, & Wu, 2023; Lee & Stowe, 1993; Verma & Gustafsson, 2020). Verma and Gustafsson (2020) find that global crises, such as the COVID-19 pandemic, generate spillover effects among global and regional supply chain finance, which cause damage to demand and supply. Ding et al. (2023) investigate how shared managers and directors with major suppliers affect a firm's access to trade credit. Our paper contributes to this strand of literature by further indicating that information sharing for firms with high supply chain risks deteriorated under isolation during COVID-19 and caused a decrease in supply chain financing provision. To our knowledge, the catastrophic impact of the COVID-19 break on supply chain financing at the firm level remains underexplored in the literature.

Second, the paper contributes to the literature on the applications of blockchain innovation in economics (Biais, Bisiere, Bouvard, & Casamatta, 2019; Biswas et al., 2023; Chong et al., 2019a; Cong, Li, & Wang, 2022; Hou, Wang, & Luo, 2020). Blockchain has been rapidly developed in the last few years, with encouragement and support from the Chinese state (Chong et al., 2019b). With China's surge in blockchain technology, Hou et al. (2020) point out that the government needs to enhance its advocacy for the "blockchain technology plus distributed energy resources" initiative, especially for firms and developers, which benefits from understanding the advancement of this approach. Cong et al. (2022) provide evidence that blockchain technology helps to alleviate the issue of underinvestment by resolving the challenge of time inconsistency faced by owners. Our study builds upon this line of studies by

[1] www.spglobal.com. (2022). The Great Supply Chain Disruption | S&P Global. [online] Available at: https://www.spglobal.com/market-intelligence/en/mi/Info/0122/great-supply-chain-disruption.html.

presenting evidence that integrating blockchain technology at the corporate level enhances the robustness of supply chain financing operations, particularly in adverse conditions that impact supply chain business environments.

Third, the paper contributes to the literature on textual analysis methods in economics studies (Kelly, Papanikolaou, Seru, & Taddy, 2021; Bowen III, Frésard, & Hoberg, 2023). Kelly et al. (2021) use textual similarity to identify the significant patent. Bowen III et al. (2023) define the rapidly evolving innovation for patents and startup firms using the BoW (Bag of Words) method. These papers mainly focus on text data in English. Our paper contributes to the literature by constructing a blockchain dictionary using the textual analysis method on Chinese text data, and by using a machine learning approach, the paper constructs a firm-level blockchain adoption index based on news and patent textual data in the Chinese context. It is among the first attempts to employ natural language analyses to explore the economic impact of recent digital technology advancements in China.

The rest of the paper is organized as follows: Section 2 provides a literature review and hypothesis development. Section 3 describes data and key variables. Section 4 discusses the research design. The main results are provided in Section 5. Section 6 presents further analyses of our research, and Section 7 concludes.

2. Literature review and hypothesis development

The COVID-19 pandemic, as an unforeseen event, shocked the global community, resulted in adverse effects on businesses, and posed challenges to companies' investment initiatives (O'Hara & Zhou, 2021) and the financial market (Kargar et al., 2021). Specifically, the pandemic led to significant disruptions in supply chain finance, with the vast majority of companies facing devastating impacts on their supply, demand, and logistics infrastructure (Shen & Sun, 2023). Due to the unpredictability of quarantine measures implemented in response to the COVID-19 outbreak, the supply chains of Chinese enterprises have been subjected to considerable tension and strain (Wang, Wang, Li, & Zhao, 2022; Shen & Sun, 2023). Lockdowns during the pandemic caused factory shutdowns and worker isolation, significantly reducing goods and services production. In addition, cities' lockdown impeded cross-regional transportation, with highways becoming inaccessible and significantly undermining the stability of supply chains, as seen in the drastic drop in logistics volume in 2022.[2] Quarantine uncertainty and financial strain also reduced investor and customer confidence, causing some businesses to exit the market and leading to cash flow issues and restricted trade credit.

The impact of the COVID-19 pandemic on businesses and the ensuing uncertainty have caused disruptions in numerous financial markets. Several empirical studies have provided evidence suggesting a correlation between the COVID-19 pandemic and a decline in corporate performance (Garel & Petit-Romec, 2021) and less financing (Didier, Huneeus, Larrain, & Schmukler, 2021). This downturn in corporate performance resulted from various factors, including supply chain disruptions and reduced consumer demand, which have collectively strained business operations. Moreover, the reduced financing has impeded the ability of firms to weather the economic storm as they struggle to secure the necessary capital for ongoing operations and recovery efforts, thereby deepening the economic impact of the pandemic on the corporate sector.

In China, the COVID-19 pandemic has triggered financial disturbances within supply chains due to the lockdowns that have affected the demand and supply dynamics of various goods and services, particularly impacting the physical movement of products (Wang, Wang, Li, & Zhao, 2022). Many cities have experienced periodic lockdowns throughout the pandemic's three-year span; these disruptions have exacerbated businesses' challenges in maintaining their supply chain operations. These intermittent lockdowns in China have strained the local economies and have ripple effects on global supply chains, given the country's integral role in international trade.

As an informal financing mechanism, trade credit thrives on reduced information asymmetry between suppliers and buyers (Lee & Stowe, 1993; Cunat, 2007). The seller provides goods or services to the buyer, and the buyer can pay for them after a certain period, which constitutes a form of short-term credit (Breza & Liberman, 2017). However, the COVID-19-induced disruptions have strained these relationships, as the pandemic's constraints have made it more difficult for suppliers to assess buyers' creditworthiness, thus increasing the risk of extending credit. This heightened risk aversion among suppliers and the economic downturn has likely led to a more cautious approach toward extending trade credit, impacting many businesses' liquidity and operational capabilities. The restrictions on transportation and communication within supply chain networks have led to increased information asymmetry and elevated adverse selection costs for businesses. As a result, it is suggested that during the COVID-19 era, there has been a reduction in the trade credit extended by firms.

Bank credit-related supply chain financing is designed to assist businesses within the supply chain in fulfilling their regular financial requirements. It comprises a suite of strategies aimed at curtailing the costs associated with financing and enhancing the overall productivity of the supply chain's business processes (Lam & Zhan, 2021). As a formal channel, bank supply chain finance is mainly divided into three typical models: accounts receivable financing, prepayment financing, and inventory pledge financing (Chakuu, Masi, & Godsell, 2019; Lam & Zhan, 2021). Accounts receivable financing is aimed at small and medium-sized financing enterprises upstream of the supply chain. Through this method, small and medium-sized enterprises rely on the relatively higher credit of downstream core enterprises for financing (Van der Vliet, Reindorp, & Fransoo, 2015; Wuttke, Rosenzweig, & Heese, 2019). Payment financing is a service provided for small and medium-sized enterprises downstream of the supply chain, which introduces third-party logistics and supervises collateral. Inventory pledge financing targets enterprises with high inventory levels and long

[2] During March and April 2022, the amount of national public logistics was about 80.96 % of the average in 2019 and was lower than 20 % for Shanghai. This data is obtained from G7 database, a database that provides logistics bigdata in China, and an analysis report from China Securities Co. Ltd. The website address of G7 database is https://insight.g7e6.com.cn/insight/.

turnover times in the supply chain, enabling inventory as a liquid asset to be transformed into more easily supervised collateral to obtain financing from banks and other financial institutions. The COVID-19 pandemic can disrupt this equilibrium by introducing unprecedented challenges, such as disrupted cash flows and increased operational costs, which can strain the financial health of businesses within the supply chain. Thus, we propose our main hypothesis.

H1. Firms with high supply chain risk experienced a more significant reduction in both formal and informal financing during the COVID-19 pandemic.

Blockchain technology, characterized by its decentralized and immutable nature, has emerged as an innovative digital ledger system and has rapidly transformed the digital economy and industry in recent years (Cong & He, 2019; Moll & Yigitbasioglu, 2019). Blockchain technology has been applied in supply chain management, trade finance, and financial transactions, with examples including its adoption by major entities such as Nasdaq, the Australian Stock Exchange, and Ripple (Biais et al., 2019; Biswas et al., 2023). These organizations have leveraged blockchain's decentralized and secure ledger to enhance their operations' transparency, efficiency, and trust. Its decentralized and tamper-proof ledger offers a transparent and secure way to track and record transactions, enhancing trust and efficiency in these critical areas. By providing an immutable record of each transaction, blockchain reduces the risk of fraud and streamlines processes, which is particularly beneficial in complex supply chains and financial dealings involving multiple parties. This technology's ability to ensure data integrity and automate processes has the potential to revolutionize traditional methods, offering new levels of security, traceability, and efficiency.

As blockchain technology rapidly transforms the digital economy and industry (Moll & Yigitbasioglu, 2019), the Chinese government has listed the development of blockchain technology as one of its national strategies. The unique feature of blockchain technology gives companies a competitive advantage in the supply chain. For instance, blockchain technology eliminates the single control point in traditional centralized systems through its decentralized network structure feature (Ziolkowski, Miscione, & Schwabe, 2020). Integrating blockchain technology into supply chain financing offers significant advantages, particularly during times of crisis. The inherent features of blockchain, such as its transparency and immutability, can foster greater trust among investors and business partners. This trust is especially valuable when corporate governance is under scrutiny, as it can help mitigate concerns about the reliability of financial information and the integrity of transactions (Lins, Servaes, & Tamayo, 2017). During a crisis, where uncertainty is high, the ability of blockchain to provide a secure and verifiable record of supply chain activities can be a critical asset for companies seeking to maintain or enhance their credibility and secure financing.

In addition, blockchain technology facilitates complete traceability of products and materials throughout their lifecycle. This feature helps companies manage logistics and inventory in the supply chain, improving supply chain management efficiency (Cho et al., 2021). Each participant can verify the authenticity and legitimacy of transactions through shared data on the blockchain, reducing information asymmetry and enhancing trust in the supply chain. Moreover, smart contracts on the blockchain automate and expedite transactions, cutting costs and increasing supply chain efficiency. They ensure timely contract fulfillment, fostering strong business relationships (Yermack, 2017). As a result, blockchain technology can mitigate the epidemic crisis's negative effects, helping companies mitigate the reduction in informal and formal financing. Thus, we propose our second research hypothesis.

H2. Blockchain technology helps mitigate the negative effect of the COVID-19 pandemic on informal and formal financing in firms with high supply chain risks.

Information transparency is recognized as a key factor in firm financing, including bond financing (Bessembinder, Maxwell, & Venkataraman, 2006), cost of capital (Yu, 2005), financial structure (Chen, Dasgupta, & Yu, 2014), and supply chain financing. For instance, Dass, Kale, and Nanda (2015) show that the clarity of information plays an important role in fostering a positive relationship between the specific investments made in relationships and the extension of trade credit. Wang, Liu, Chan, and Zhang (2023) suggest that the clear visibility of retailers' credit ratings serves as an early warning signal for suppliers when extending credit in trade transactions.

Blockchain technology provides a decentralized network where participants have a copy of the ledger and various raw data containing key information that can be extracted from the on-chain system based on the consensus mechanism. The information recorded in a ledger on the chain is more traceable, which ensures an improved openness within a particular supply chain into the details of the provenance of consumer goods, and it is transparent to all stakeholders involved in the transaction (Chong et al., 2019a). Adopting blockchain enhances transparency in a firm's supply chain and acquires advantageous financing terms at lower costs for signaling (Chod, Trichakis, Tsoukalas, Aspegren, & Weber, 2020). Therefore, we hypothesize that blockchain adoption helps promote supply chain financing by improving the firm's information transparency, especially in a crisis where the need for firm transparency is much greater (Bouvard, Chaigneau, & Motta, 2015).

H3a. Blockchain adoption provides resilience to the supply chain finance in the COVID-19 crisis by enhancing information transparency.

Emerging theories that connect crises or disasters with company traits highlight corporate governance as a key factor in a firm's ability to withstand and recover from adverse events (Li, Liu, Mai, & Zhang, 2021). Blockchain technology has important implications for governance frameworks (Brennan, Subramaniam, & Van Staden, 2019), as it enables firms to maintain records of share ownership and financial transactions (Yermack, 2017). Within corporate governance, the integration of blockchain technology offers the capacity to enable real-time accounting processes, enabling financial data to be updated daily rather than relying on the conventional periodic updates that occur monthly or quarterly. Enabling real-time accounting, blockchain technology shifts away from the traditional updating of financial information monthly or quarterly. It allows for daily record-keeping, which resolves the issue of temporal discrepancy for stakeholders by providing up-to-date financial insights (Cong et al., 2022). This feature of blockchain is set to enhance the reliability of financial reporting, given the immutable nature of the records once they are entered into the system.

In addition, smart contracts significantly influence trade credit and corporate governance. These contracts operate on a self-executing basis, meaning they carry out their terms as soon as the conditions are met, thereby streamlining transactions among participants (Cong et al., 2022). In trade agreements, using smart contracts can lead to the automation of payment procedures. This automation ensures that payments are triggered and completed promptly once the agreed-upon criteria of a trade are satisfied, without the need for manual processing. This efficiency in the provision of trade credit is beneficial during times of crisis, as it maintains operational continuity even when standard business activities face disruption. Therefore, we hypothesize that when the firm faces a higher level of supply chain risk, blockchain adoption helps promote supply chain financing by improving the firm's corporate governance during the COVID-19 crisis.

H3b. Blockchain adoption provides resilience to the supply chain finance in the COVID-19 crisis by enhancing corporate governance.

The third mechanism in our analysis is the effect of blockchain technology on product network efficiency. Bray, Serpa, and Colak (2019) uncover that the spatial separation between upstream component manufacturers and downstream assembly facilities hurts product quality. This is because of the reduced effectiveness of communication, oversight, and responsiveness that distance entails. Bernard, Moxnes, and Saito (2019) suggest the significant impact of geographic proximity on the structure and efficiency of production networks. They show closer proximity, which allows customers to more effectively identify and select high-quality suppliers, deepen their collaborative relationships, and improve overall operational performance. This is achieved by lowering the costs of searching for suppliers and managing the outsourcing process. Additionally, Chu, Tian, and Wang (2019) identify a positive correlation between geographic proximity and innovation within supply chains. These studies collectively support the idea that product network efficiency encourages closer relationships between suppliers and customers.

Blockchain technology enhances production network efficiency by leveraging its decentralized nature to eliminate single points of failure and ensure data continuity. It enables real-time updates for immediate access to the latest data by all network participants. The immutability of the data once recorded on the blockchain bolsters its credibility, reducing the time and effort required for data verification. Furthermore, it facilitates multi-party collaboration by allowing different organizations and individuals to share information without central control, thus improving overall efficiency in information exchange and product production. Ouyang, Xiong, Liu, and Yao (2024) prove that geographic proximity can impact trade credit. Hence, we hypothesize that when the firm faces a higher supply chain risk, blockchain adoption helps promote supply chain financing by improving the firm's product network efficiency during the COVID-19 crisis.

H3c. Blockchain adoption provides resilience to the supply chain finance in the COVID-19 crisis by enhancing production network efficiency.

3. Measuring the key variables and data description

3.1. Supply chain risk exposure

This section outlines our approach to using textual analysis to measure the firm-level supply chain risk exposure of individual listed firms in China. Along with the development of computing power and textual analysis techniques, prior research has attempted to construct measures for a firm's political uncertainty (Hassan, Hollander, Van Lent, & Tahoun, 2019), climate change exposure (Sautner, Van Lent, Vilkov, & Zhang, 2023), or exposure to diseases (Hassan, Hollander, Van Lent, Schwedeler, & Tahoun, 2023). Although the supply chain is a crucial factor for enterprises to maintain smooth and continuous production and operation, it was not until recently that research (Wu, 2024) tried to measure the supply chain risks of enterprises using text analysis methods.

Following the method of Wu (2024), we adopt a strategy to assess individual firms' distinct supply chain risk exposure annually through textual analysis. This process involves identifying the terms describing supply chain and risk, constructing Supply Chain and Risk Dictionaries, subsequently identifying the co-occurrence of supply chain terms and terms meaning risk, and quantifying the ratio of the terms describing supply chain that proximate to terms describing risk.

We use the annual report's Manager Discussion and Analysis (MD&A) section instead of other textual data sources, such as analyst investigation Q&A records or online conference calls. This choice is motivated by the higher quality of information provided in annual reports, regulated by the China Securities Regulatory Commission and mandated to be released annually. Unlike other sources, annual reports ensure comprehensive coverage of listed firms. Additionally, other sources of information, such as online earnings conference calls in China, often lack restrictions on the qualification of disclosure.

We then use the Word2vec model to generate the Supply Chain Dictionary and Risk Dictionary, which contain terms describing supply chain or risk topics. Each term in the textual data is represented by a 200-dimensional word vector, enabling the calculation of pairwise word similarity. We select the 100 terms most similar to the word "supply chain" or "risk" to form the initial "candidate terms lists." After manually checking these candidate terms, we retain the most relevant ones to create the Supply Chain and Risk Dictionary.

Next, we count the co-occurrences of terms from the Supply Chain Dictionary within a 40-character window surrounding terms from the Risk Dictionary and divide this count by the total number of terms in the transcript. Specifically, we first identify the position of supply chain terms from the Supply Chain Dictionary in the MD&A text. Let $\mathbb{U}$ be the set of terms from the Risk Dictionary, and $\mathbb{S}$ be the set of terms from the Supply Chain Dictionary. For the MD&A text of firm j in year t, we count the number of occurrences ($ns_{j,t}$) of the supply chain terms ($s \in \mathbb{S}$) within a distance D characters of any risk terms ($s \in \mathbb{S}$). The term set $S_{j,t}$ consists of all supply chain terms $r \in \mathbb{U}$ in the MD&A text of firm j in year t. Then, we calculate the ratio of occurrence frequencies to the length of MD&A text data ($L_{j,t}$). This ratio is summed up for each of the supply chain terms:

$$SCRatio_{j,t} = \sum_{s}^{S_{j,t}} \frac{ns_{j,t}[s \in \mathbb{S}] \times \mathbb{1}[|r - p| < D]}{L_{j,t}}, for\ r \in \mathbb{U} \tag{1}$$

In this context, following the approach of Wu (2024), we initially set the distance parameter D to 40 Chinese characters. Wu (2024) chose a distance parameter of 10 English bigrams; generally speaking, 10 English bigrams are equivalent to 40 Chinese characters from a linguistic perspective.[3] We also set the distance parameter D to 30 and 50 Chinese characters for robustness checks, respectively, to construct alternative supply chain risk variables.

Intuitively, formula (1) shows how we compute the ratio of the number of occurrences of the terms from the Supply Chain Dictionary within a certain range around terms from the Risk Dictionary to the total number of words or terms in the MD&A text and how we yield each firm's supply chain risk exposure measure each year. There exists the possibility that the COVID-19 pandemic is inversely affecting corporate supply chain risks. To avoid the exogenous shock in our Difference-in-Differences model setting is related to the selection of the treatment group, we follow the approach of Li, Liu, et al. (2021) and use the averaged corporate supply chain risk levels before the outbreak of the pandemic from 2017 to 2019, to construct the corporate supply chain risk level variable (*SCRisk*). Appendix 1 presents a word cloud of supply chain terms, where the size of each term is set based on the frequency of its occurrence in annual report texts, screened by using Model (1). The higher the frequency of a term, the larger its size in the word cloud. Shown in the word cloud, enterprises' concerns regarding supply chain risks mainly lie in issues such as suppliers, marketing channels, capital flow, logistics, and warehousing.

We further analyze the results of the text analysis. We separate the data by major industry categories[4] and calculate the averaged term frequency and proportion of supply chain risk for enterprises across industries. Appendix 2 shows the comparisons between industries. The industries that most frequently mention supply chain risks are leasing and business services, transportation and storage, and wholesale and retail. The primary business of the Transportation and storage industry inherently belongs to the supply chain. The operating mode and profitability of the Wholesale and Retail industry are highly dependent on supply chain efficiency. Meanwhile, the financial leasing business based on the supply chain is important for firms in the leasing and business services industry. Thus, these industries are closely related to supply chain risks. Additionally, manufacturing and real estate also have relatively high correlations with supply chain risks, which aligns with the business characteristics of these industries. The service industries, including Education, Health and Social Work, and Accommodation and Catering, generally have lower supply chain risks. These results are similar to Wu's conclusions (2024), which demonstrate that the supply chain risk of the manufacturing industry and retail industry is significantly higher than that of the service industry due to the features of their supply chain.

Since our research is the first to adopt text analysis and corporate annual reports to measure Chinese enterprises' supply chain risk exposure, we refer to Wu (2024) and use corporate financial data for validation. Research demonstrates that higher supply chain risks lead to a higher inventory buffer (Tomlin, 2006), a higher cash buffer (Bernanke, 1983), and less trade credit provision (Chod, 2017). Therefore, we use these indicators to validate our supply chain risk exposure measure by regressing these indicators with *SCRatio*. The results of the validation are shown in Appendix 3. The associations between *SCRatio* and inventory to asset ratio or cash to asset ratio are positive and significant, and the association to the account payable to asset ratio is negative and significant, corresponding to the theories' prediction in literature. Overall, these analysis and regression results validate our firm's supply chain risk measure.

In addition, by following the idea of Jha, Qian, Weber, and Yang (2024), we use a Generative Pre-trained Transformer (GPT) "KIMI" to extract firm-level supply chain risk and aim to provide an alternative measure to our study. Specifically, we provide the following prompt to KIMI: "*This is an annual report from a listed company. Assuming you are an expert in finance and economics, please answer the following question based solely on the information provided in this report: Is the 'supply chain risk or uncertainty' faced by this listed company high or not? According to your judgment, select one option from the following five choices and provide a one-sentence justification: Very Low Supply Chain Risk, Low Political Supply Chain Risk, Moderate Supply Chain Risk, High Supply Chain Risk, or Very High Supply Chain Risk. Your response should be in the format of 'Option - Justification.' If there is no relevant information, please answer 'No Relevant Information'.*"

We assign scores to the output results of KIMI's analysis using the annual reports from 2017 to 2019 and calculate the average to measure firms' supply chain risk (SCRiskGPT). We categorized the enterprises into treatment and control groups (*TreatGPT*) based on the median value of *SCRiskGPT*. This measure serves as an alternative measure of firms' supply chain risk in robustness checks.

3.2. Formal supply chain finance adoption

Based on the classification of the recent studies (Chakuu et al., 2019), we define three types of formal supply chain financing: accounts receivable (*ARFin*), pre-paid (*PPFin*), and inventory financing (*InvFin*) related bank loans. We construct dictionaries for these

[3] Bigram is defined as two-word combinations of in English. The "word" in English often has a corresponding meaning to the "word" in Chinese, and the majority of Chinese words are composed of two characters (Ma et al., 2017). Therefore, in terms of semantics, 10 English bigrams are approximate to to 20 English words or Chinese words, which are also approximate to 40 Chinese characters.

[4] Based on the Industry Classification Guidelines for Listed Companies issued by the China Securities Regulatory Commission, we have classified listed companies into nineteen industries according to their primary businesses in the data analysis of this section. In our analysis, we excluded the Other Services industry as this industry only has one firm, and the data results may introduce noise.

three supply chain financing modes using word2vector models and define whether a company has adopted a certain supply chain financing tool in a given year by screening for the occurrence of relevant vocabulary in its annual reports. Then, we construct a formal supply chain finance adoption variable to proxy whether the company has used at least one of the three supply chain financing tools (*SCFin*).

3.3. Blockchain technology adoption

We construct indicators to measure enterprises' adoption of blockchain technology based on their patent and news texts. Since companies rarely disclose which specific technologies they have used in documents such as annual reports, the invention patent texts that record the technological innovations and applications of enterprises, as well as the news texts that report on the practical applications of blockchain technology in enterprises, are more ideal sources of information for measuring blockchain adoption.

We construct a blockchain technology dictionary using word vector models. We screen through the patent texts and news texts to obtain the proportion of patents or news texts that contain blockchain technology-related words or terms for each enterprise each year. We use this to measure the firms' adoption of blockchain technology each year. The possibility of enterprises adopting blockchain technology exists due to the COVID-19 pandemic. In such case, our empirical study results may identify the reverse impact of the COVID-19 pandemic on blockchain technology rather than blockchain technology mitigating the negative effects of the COVID-19 pandemic. Therefore, to address this issue, we refer to the approach of Li, Liu, et al. (2021) and use the average value of enterprise blockchain technology adoption indicators before the pandemic, from 2017 to 2019, to measure the level of enterprise blockchain technology adoption (*BCPat* for the adoption variable constructed by patent data and *BCNews* for the variable constructed by news data). This approach can also mitigate the problem of time-varying changes in the development of blockchain technology over the past few years, thereby enhancing the credibility of our empirical results.

We compare the adoption of blockchain technology among listed companies across different industries. Regarding the blockchain technology adoption indicators based on patent data, we find that apart from the Information Services Industry, which naturally has more blockchain software development, Finance, Transportation and Storage, and Manufacturing also exhibit a high level of blockchain technology adoption. In the Finance industry, the efficiency promotion due to blockchain technology's decentralized and tamper-proof nature and the development of digital currencies based on blockchain technology are closely related. In the Transportation, Storage, and Manufacturing industries, blockchain technology plays a role in supply chain management by enhancing information transmission efficiency and improving information credibility. Additionally, the Health and Social Work industry exhibits a higher proportion of blockchain technology innovation, which can be attributed to the fact that blockchain technology helps healthcare organizations improve data-sharing capabilities while protecting patient privacy. The data developed using news data exhibits similar results, except those from manufacturing and blockchain applications in manufacturing firms are concentrated in production processes.

3.4. Social media attention variable

To construct a social media attention measure, we collect over 7 million user comments and analyses on various listed companies from Snowball.com (Xueqiu.com), one of the largest online forums in China for stock investment. We construct the social media attention index by counting the comments made on each listed company for each year (*SocialMedia*). The higher this value is, the more information is shared on Snowball's website.

4. Data description and regression models

4.1. Description of samples and the source of data

Our empirical study focuses on companies listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. We collect annual report files from exchanges' official websites and use the text from annual reports to construct the supply-chain risk exposure and formal tools usage measure of the supply-chain financing. We collect the patent data from Incopat.com and the news data from Tonglian.com to construct measures for blockchain technology usage. We collect the users' comments on the Snowball website (Xueqiu.com) to construct the social media attention variable.

The rest of the variables are collected from the CSMAR database. Given that we study the change in trade credit usage before and after the COVID-19 pandemic, we retain observations from the 2015–2022 period, from the five years before to three years after the outbreak of this pandemic. We exclude the following firms from the sample: (1) Special Treatment (ST) and Particular Transfer (PT) companies; (2) financial companies (e.g., banks, insurance companies, and securities companies) due to heavily regulated and the difference between their return-generating processes and those of other companies; (3) companies with missing values. The final sample consists of 4433 listed firms with 44,810 firm-year observations.

4.2. Regression model

We conduct a DID (Difference-in-Differences) study to examine whether COVID-19 led to decreased supply chain financing for enterprises with higher supply chain risks during this pandemic. Specifically, we estimate the following difference-in-differences (DID) regression model:

$$SupplyChainFinance_{i,t} = \alpha + \beta_1 Treat_i + \beta_2 Treat_i{*}Post_t + \beta_3 Post_t + \beta_4 Controls_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \tag{2}$$

where i denotes firm and t denotes years. The dependent variable $SupplyChainFinance_{i,t}$ represents the variables of informal and formal supply chain financing usage of firm i in year t, including the trade credit financing variable (*TradeCredit*), accounts receivable (*ARFin*), pre-paid (*PPFin*), and inventory financing variables (*InvFin*). $Treat_i$ is a treatment group indicator that equals to one if the firm i has a higher supply chain risk. To mitigate the potentially adverse impact of the COVID-19 pandemic on enterprises' supply chain risks, we followed the methodology of Li, Liu, et al. (2021) and measured the supply chain risks exposure by using data of three years prior to the emergence of the pandemic. We average the supply chain terms ratio developed from the annual report between 2017 and 2019 for each firm and identify the firms with higher averaged supply chain terms ratio as the treatment group, otherwise as the control group. $Post_t$ is the time indicator that equals 1 if the year of observation is not earlier than 2020, otherwise equals to 0, because 2020 is the first year of the outbreak of COVID-19 pandemic. The key independent variable is the interaction term $Treat_i{*}Post_t$. The year indicator $Post_t$ is omitted due to its collinearity with the year fixed effect.

$Controls_{i,t}$ is the control variable set. Following Kong, Pan, Tian, and Zhang (2020), we incorporate the controls for operational status, corporate governance of firms, and personal information of managers, including the return on asset (*ROA*), firm size (*Firmsize*), leverage of firm (*Lev*), Tobin's Q (*TobinQ*), fixed asset investment ratio (*Fixed*), ratio of cash holding to asset (*Cash*), SOE or non-SOE (*SOE*), the age of firm (*FirmAge*), the ratio of female managers (*Female*), and the average age of managers (*TMTAge*). The model controls for year-fixed effects (γ_t) and industrial-fixed effects (δ_i) to capture time-invariant characteristics at the yearly and industrial levels. We chose industrial-fixed effects in our baseline model because the firm-fixed effects variable has collinearity issues with the treatment group indicator. We provide the results of regression controlling firm-fixed effect in robustness check. We cluster standard errors by the firm in the baseline model to account for correlated errors.

4.3. Summary statistics

Table 1 reports descriptive statistics for our main regression model variables, including the trade credit variable, supply-chain risk exposure before the COVID-19 pandemic, and the firm-level control variables for the full sample, respectively. We provide the number of observations, the average value, the median value, the standard deviation, the minimum value, and the maximum value for each variable.

The average value of the trade credit variable is 0.252, the standard deviation is 0.165, and the maximum value is 0.941. This indicates that supply-chain financing accounted for a significant proportion of corporate liabilities from 2015 to 2022. Some enterprises have more than 90 % of their debt financing sourced from trade credit, more than three times higher than the standard deviation. This suggests that a few enterprises completely rely on this informal supply-chain financing.

The average value of the supply-chain risk exposure variable *SCRisk* is 0.459, the median is 0.232, and the maximum value is 18.475. Since this variable is processed by multiplying by 10,000 to the ratio of supply-chain terms in annual reports, the average value of *SCRisk* indicates that, on average, there are 4.59 supply-chain risk-related words per 100,000 words in an annual report. The company that most frequently mentions supply chain risks has approximately 185 supply chain risk-related words per 100,000 words in its annual report. This variable also has a certain degree of left skewness, indicating that a few companies recognize a high exposure to supply chain risks.

5. Main results

5.1. Baseline regression results

We conduct the difference-in-difference regression model to find the association and causality of how COVID-19 causes a reduction in trade credit usage in firms with higher supply chain exposure (2). We estimate the Ordinary Last Squares regressions coefficients. The coefficient of interest is β_2. It captures the difference between changes in trade credit usage in firms with higher supply chain risk exposure and those with lower supply chain risk exposure due to the outbreak of the COVID-19 pandemic in 2020.

Table 2 presents the baseline results of the regressions. Column (1) shows the result of the regression model without control variables and fixed effects, and Columns (2), (3), and (4) show the results of regression models with controls and fixed effects. In both columns, the coefficients of the key independent variables *Treat*Post* are all negative and significant at a 1 % significant level. These results indicate a robust relationship between the outbreak of COVID-19 and the less trade credit usage for the firms with higher supply chain risk exposure; that is, the firms more exposed to the supply chain risk are more vulnerable in COVID-19 pandemic in terms of supply chain financing.

In terms of economic importance, we find that the firms with higher supply chain risk exposure suffered a 1.2 % ratio of trade credit to debt decrease after the outbreak of the COVID-19 pandemic, a value of about 4.76 % of the averaged ratio of trade credit to debt and 7.27 percentage of the standard deviation of this ratio, which equals to a decrease of 900 million[5] RMB trade credit usage for each higher supply chain risk firm or a decrease of more than 114.8 billion RMB of trade credit usage for all higher supply chain risk firms listed in the A-share market. Hence, our results align with our hypothesis that the COVID-19 pandemic depresses trade credit usage

[5] The estimated trade credit usage decrease is calculated based on the liability value of the higher supply chain risk exposure firms during 2019.

Table 1
Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	N	Mean	Median	SD	Min	Max
TradeCredit	27,810	0.252	0.222	0.165	0.000	0.941
SCRisk	27,810	0.459	0.232	0.820	0.000	18.475
Treat	27,810	0.506	1.000	0.500	0.000	1.000
Post	27,810	0.451	0.000	0.498	0.000	1.000
ROA	27,810	0.038	0.000	0.139	−9.117	12.211
Firmsize	27,810	22.272	0.040	1.344	15.979	28.636
Lev	27,810	0.431	22.079	1.123	0.008	178.345
TobinQ	27,810	2.232	0.406	5.120	0.609	729.629
Fixed	27,810	0.198	1.648	0.155	0.000	0.954
Cash	27,810	0.182	0.164	0.129	0.000	0.978
SOE	27,810	0.308	0.148	0.462	0.000	1.000
FirmAge	27,810	2.985	0.000	0.301	1.386	4.174
Female	27,810	20.560	2.996	11.691	0.000	73.330
TMTAge	27,810	49.505	19.050	3.259	35.620	62.880
BCPat	25,810	0.014	49.600	0.054	0.000	1.000
BCNews	25,810	0.014	0.000	0.015	0.000	0.455

Note: This table reports the number of observations, mean, median, standard deviation, minimum, and maximum for the variables used in the baseline regression model. The main sample consists of 4433 firm-year observations from 2015 to 2022.

Table 2
Baseline results.

	(1)	(2)	(3)	(4)
Variables	*TradeCredit*	*TradeCredit*	*TradeCredit*	*TradeCredit*
Treat	−0.018***	−0.003	0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
*Treat*Post*	−0.012***	−0.011***	−0.012***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
ROA		0.035***	0.039***	0.039***
		(0.013)	(0.014)	(0.014)
Firmsize		−0.036***	−0.034***	−0.034***
		(0.002)	(0.002)	(0.002)
Lev		−0.001	−0.001	−0.001
		(0.002)	(0.002)	(0.002)
TobinQ		−0.001***	−0.001***	−0.001***
		(0.000)	(0.000)	(0.000)
Fixed		−0.059***	−0.034***	−0.031**
		(0.014)	(0.013)	(0.013)
Cash		0.018	0.022**	0.022**
		(0.011)	(0.011)	(0.011)
SOE		0.011***	0.018***	0.019***
		(0.004)	(0.004)	(0.004)
FirmAge		−0.046***	−0.035***	−0.044***
		(0.007)	(0.007)	(0.008)
Female		−0.000	0.000	−0.000
		(0.000)	(0.000)	(0.000)
TMTAge		0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
Observations	27,810	27,810	27,810	27,810
Year FE	NO	NO	NO	YES
Industry FE	NO	NO	YES	YES
adj. R^2	0.001	0.081	0.225	0.225

Note: This table presents the DID regression estimates of the outbreak of COVID-19 on the firm's trade credit usage. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

more for firms with higher supply chain risk exposure.

Furthermore, we repeat the Model (2) regression using the treatment and control groups constructed based on the supply chain risk indicators measured by GPT. The regression results are presented in Appendix 4. Variable coefficients and significance levels remain, providing robustness to our research findings.

5.2. Dynamic DID and placebo tests

We conduct dynamic DID and placebo tests to assess whether our results may be driven by concurrent changes unrelated to the board reforms. In our dynamic DID model, we replace the event indicator with indicator variables that track the effect of COVID-19 before and after its outbreak, as shown in the Model (3):

$$\begin{aligned} SupplyChainFinance_{i,t} = \alpha + \beta_k \sum_{k=0,k\notin 4}^{7} Treat_i \times Period_{2015+k} \\ +\beta_8 Controls_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In the Model (3), we include the interaction terms $\beta_k \sum_{k=0,k\notin 4}^{7} Treat_i \times Period_{2015+k}$, which represent the year indicators $Period_{2015+k}$ are multiplied by the treatment group indicator $Treat_i$ to form the interaction terms and regress with the dependent variable. The interaction term $Treat_i \times Period_{2019}$ is omitted due to the collinearity issue.

Column (1) of Table 3 presents the results. The estimated coefficients of the interaction variables $\beta_k \sum_{k=0}^{3} Treat_i \times Period_{2015+k}$ are all insignificantly different from zero, which suggests that the trade credit usage between higher supply chain risk exposed firms and lower exposed firms are not statistically different before the outbreak of COVID-19. Moreover, we find the negative effect of trade credit usage in the first year after the outbreak of COVID-19 at the beginning of 2020, as the coefficients of the interaction terms $\beta_k \sum_{k=5}^{7} Treat_i \times Period_{2015+k}$ are all negative and significant. Specifically, the results show that the ratio of trade credit to debt on average increases by 0.9 % in the first year after the outbreak of COVID-19, and the effect lasts from the first year to the third year. Fig. 1 also presents the coefficients estimated in dynamic DID regressions and their 95 % confidence interval. This result demonstrates the parallel trend of trade credit usage between higher and lower supply chain risk exposure firms before the COVID-19 outbreak and the decrease in trade credit usage by higher exposed firms after the outbreak.

We also conduct a placebo test by falsely assuming that the COVID-19 outbreak occurred in the different years before or after the outbreak year. Similar to our main sample specification, we restrict our sample to 5 years before and three years after each pseudo-outbreak. A total of 500 simulations are conducted, and the distribution of coefficients is shown in Fig. 1b. The estimated coefficients from the simulations cannot be rejected as being unequal to zero, which indicates that the models in this paper do not produce spurious correlations and that the estimated effects in the previous text are credible.[6] The findings from our dynamic DID tests and placebo tests suggest that the outbreak of COVID-19 on higher supply chain risk exposed firms' supply chain finance usage, which is most likely causal.

5.3. Robustness checks

In this section, we conduct several robustness checks on our baseline results. We only present the results of the key interaction terms of the regression model here. Firstly, although we construct a supply chain risk measure for Chinese listed companies by referring to the methodology of Wu (2024), for the robustness of our results, we also apply the method of weighting political bigrams based on their frequency of occurrence to the word frequencies of supply chain terms counted in Model (1), as employed by Hassan et al. (2019) when constructing firm-level political risk. Specifically, we first calculate the proportion of each supply chain term's frequency to the total frequency of all supply chain terms and then assigned these weights to the supply chain terms selected by Model (1). These weighted terms are then aggregated and processed to obtain a weighted treatment variable for corporate supply chain risk (*TreatW*). We replace the original treatment variable with this weighted one and repeated Model (2) regression tests. The results are shown in Column (1) of Panel A in Table 4, where the coefficient of the interaction term is positive and significant, indicating the robustness of our main conclusions.

Second, we construct the firm's supply chain risk exposure by calculating the frequency and proportion of supply chain-related terms within a 40-character range before and after the risk-related terms in the annual report text. The choice of this range may impact the regression results and potentially lead to incidental outcomes. To test the robustness of our main findings, we vary the length of the range from 40 characters to 30 or 50 characters, obtaining alternative measurements of the firm's supply chain risk exposure based on these different definitions. We then replace the original supply chain risk exposure indicator used to define the treatment group with these two alternative indicators and repeated the regression analysis of the model (2). The regression results are in Columns (2) and (3) in the Panel A of Table 4. The coefficients of the interaction terms are all negative and significant at the 1 % level.

Third, we follow (Bray & Mendelson, 2012) and use the deviation between production and demand fluctuations to measure supply chain risks. A larger value indicates a more severe imbalance and higher supply chain risk, while a smaller value implies lower risk. The measurement is calculated as shown in Model (4), where the supply chain risk level (*Bullwhip*) is the ratio of quarterly production to quarterly demand standard deviations. *Production* and *Demand* represent quarterly production volume and sales, respectively. Before calculating the standard deviation, quarterly production and sales are log-transformed and first-differenced. Additionally, this paper uses quarterly cost of sales to replace quarterly sales to measure production fluctuations, recalculating a new supply chain risk measure

[6] As Stata software cannot plot excessively small coefficients, we multiply both the coefficient estimated with actual outbreaking year (0.012) and coefficients estimated with pseudo outbreaking year by one hundred before we plot these coefficients.

Table 3
Dynamic DID.

	(1)
Variables	*TradeCredit*
*Treat*Year (−5)*	−0.005
	(0.005)
*Treat*Year (−4)*	0.004
	(0.004)
*Treat*Year (−3)*	0.006*
	(0.004)
*Treat*Year (−2)*	0.002
	(0.003)
*Treat*Year (1)*	−0.009***
	(0.003)
*Treat*Year (2)*	−0.014***
	(0.003)
*Treat*Year (3)*	−0.007**
	(0.003)
Controls	YES
YearFE	YES
IndustryFE	YES
Observations	27,817
adj. R^2	0.224

Note: This table presents the dynamic DID regression estimates of the outbreak of COVID-19 on the firm's trade credit usage. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

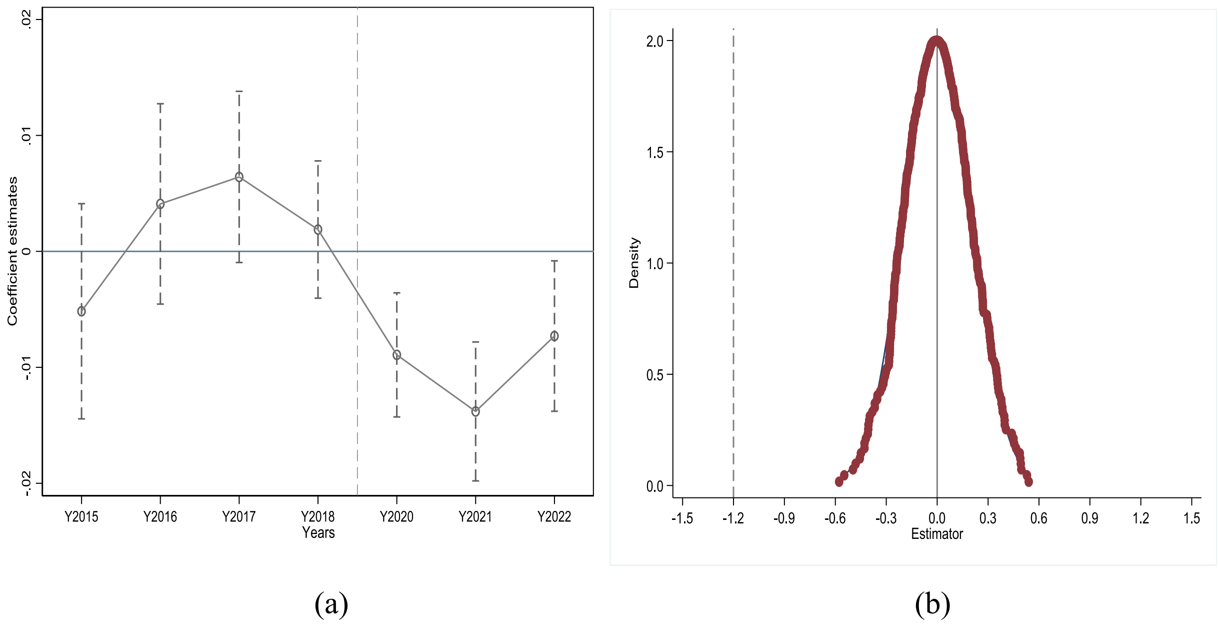


Fig. 1. The plot of the parallel trend and placebo test.

(*Bullwhip1*) for testing. The paper checks the robustness of our main results by replacing the treatment variables in Model (2) with alternative treatment variables *TreatBW* and *TreatBW1* constructed by *Bullwhip* and *Bullwhip1* using the calculation method in Model (1), respectively, and repeating the regression. The regression results are in Columns (4) and (5) in the Panel A of Table 4. The

Table 4
Robustness checks.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*TradeCredit*					
*TreatW*Post*	−0.009***					
	(0.003)					
*Treat30*Post*		−0.010***				
		(0.003)				
*Treat50*Post*			−0.015***			
			(0.003)			
*TreatBW*Post*				−0.008**		
				(0.003)		
*TreatBW1*Post*					−0.010***	
					(0.003)	
*TreatCC*Post*						−0.008**
						(0.004)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	27,810	27,810	27,810	27,810	27,810	27,810
adj. R^2	0.225	0.225	0.226	0.140	0.141	0.209

Panel B					
	(1)	(2)	(3)	(4)	(5)
Variables	*APtoAsset*	*TradeCredit*			
*Treat*Post*	−0.004***	−0.009***	−0.017***	−0.016***	−0.018***
	(0.001)	(0.043)	(0.004)	(0.005)	(0.004)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	NO	YES	YES	YES
FirmFE	YES	YES	NO	NO	NO
Observations	27,810	27,810	27,810	22,808	18,663
adj. R^2	0.379	0.075	0.081	0.323	0.244

Note: This table presents the robustness checks for the DID regression estimates of the outbreak of COVID-19 on the firm's trade credit usage with different definitions of dependent variables, independent variables, fixed effects, the way of clustering, and observations. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

coefficients of the interaction terms are all negative and significant. Therefore, our main finding is robust even if we change the treatment group's definition.

$$Bullwhip_{it} = \frac{\sigma(Production_{it})}{\sigma(Demand_{it})} \tag{4}$$

Although annual report text data has high quality and coverage advantages, its disclosure frequency is lower than some quarterly disclosures or more frequently disclosed data. Therefore, we check the robustness of our main results by constructing an alternative treatment variable (*TreatCC*) using the conference call textual data, replacing the treatment variables in Model (2) with this variable, and repeating the regression. *TreatCC* is a supply chain risk exposure dummy variable measured using Q&A session text data from conference call meeting records between 2017 and 2019 and applying the calculation method in Model (1) to measure corporate supply chain risk (*TreatCC*). The test results, as presented in Columns (6) in Panel A of Table 4, indicate that the coefficient of the interaction term remains negative and significant, confirming the robustness of our main findings.

A single definition for the dependent variable may yield incidental results. Therefore, we replaced the trade credit variable definition from the "account receivable divided by liability" to "account receivable divided by total assets" and used this alternative definition as the dependent variable for robustness checks. The results are shown in Column (1) in the Panel B of Table 4. The coefficient of the interaction term *Treat*Post* is negative and significant at a 1 % level, indicating a robust result to our main finding.

To avoid the issue of multicollinearity, we chose industrial fixed effects in the regression of our baseline study. We also provide regression results using company-fixed effects to examine the robustness of our main results. The *Treat* variable is omitted due to collinearity when we employ company-fixed effects. The result is shown in Column (2) in Panel B of Table 4. The negative and significant coefficients indicate robustness in our main findings.

The standard errors that we use in our baseline regressions are clustered at the enterprise level. However, the higher the clustering level, the larger the calculated standard errors tend to be, which may make it more difficult for the estimated coefficients to reach statistical significance (Abadie, Athey, Imbens, & Wooldridge, 2023). Therefore, for the robustness of our results, we repeat the regression of model (2) but used standard errors clustered at the industry level. The result is in the Column (3) in Panel B of Table 4. The negative and significant coefficient suggests the robustness of our main finding.

Manufacturing enterprises tend to be more dependent on supply chains, making them more likely to suffer from supply chain disruptions following the outbreak of COVID-19. Therefore, in our robustness check, we keep the samples of manufacturing enterprises and repeat the regression of the model (2). Again, the negative and significant coefficient of the interaction term in Column (4) in Panel B of Table 4 suggests that our main finding remains.

When we separate companies into treatment and control groups based on the median value of their supply chain risk indicator, companies positioned at the 49th and 51st percentiles are assigned to different groups despite having similar levels of supply chain risk. This may lead to bias. To address this issue, we divide firms into three groups based on their average supply chain risk levels from 2017 to 2019 and exclude the group with a middle level of supply chain risk, retaining only the samples of firms with high and low supply chain risk. We repeat the regression for Model (2), and the results are shown in Column (5) of Panel B in Table 4. The results indicate that the coefficient of the interaction term remains negative and significant, suggesting that this potential bias has not affected the robustness of our main conclusions.

5.4. Bank credit financing

Besides the trade credit suppliers provide in the supply chain, supply chain finance encompasses information technology and third-party-driven solutions to enhance business productivity and lower financing costs for buyers and suppliers engaged in payment transactions (Lam & Zhan, 2021). Given that this type of supply chain finance typically involves bank financing, it is also referred to as bank credit supply chain financing (bank SCF), including financing based on account receivables, inventory-backed financing, and pre-paid financing (Chakuu et al., 2019). Therefore, to conduct a more comprehensive study on the impact of the COVID-19 pandemic on supply chain finance, we examine how COVID-19 impacts the bank SCF availability of firms with different levels of supply chain risk exposure.

To examine the negative impact, we replace the dependent variable in Model (1) from the trade credit variable with three variables representing bank supply chain finance adoption (*InvFin*, *ARFin*, and *PPFin*) as well as an aggregated variable (*SCFin*) and use the setting of the model (1) but using a logistics regression model. Table 5 presents the results of the analysis. Column (1) of Table 5 shows the regression result of an aggreged variable, and Columns (2), (3), and (4) show the results of three types of bank supply chain financing. The coefficients of the variable *Treat*Post* in Columns (1), (2), and (3) are negative and significant. These results indicate that the outbreak of the COVID-19 pandemic not only hurt informal supply chain financing but also affected bank supply chain financing, primarily by reducing inventory-based and account receivable-based financing. These results also reconfirm that the outbreak of the COVID-19 pandemic has a greater negative impact on the use of supply chain finance for firms with higher supply chain risk exposure.

6. Further analyses

6.1. Blockchain technology and resilience

We propose that blockchain technology can provide resilience for enterprises, particularly those with higher supply chain risk exposure that the COVID-19 outbreak has significantly impacted. Supply chain finance is built on the foundation of information advantages and mutual trust generated through cooperation among enterprises in the supply chain. However, the impacts of the COVID-19 pandemic, such as lockdowns and isolations, can hinder information exchange and other forms of cooperation among enterprises in the supply chain, weakening this mutual trust. Enterprises with higher supply chain risk exposure tend to lose the trust of

Table 5
Supply chain risk exposure, COVID-19, and the bank supply chain financing.

Variables	(1)	(2)	(3)	(4)
	SCFin	*InvFin*	*ARFin*	*PPFin*
Treat	0.183**	0.644***	0.174**	0.463**
	(0.089)	(0.089)	(0.088)	(0.088)
*Treat*Post*	−0.174**	−0.398**	−0.144*	−0.080
	(0.080)	(0.175)	(0.080)	(0.205)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	24,055	23,867	24,055	23,867

Note: This table presents the DID regression estimates of the outbreak of COVID-19 on the firm's bank supply chain financing usage. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

supply chain finance providers due to supply chain disruptions, reducing their access to supply chain finance. Blockchain technology can provide more information support to enterprises in the supply chain through their decentralization, openness, and immutability characteristics, thus mitigating the negative impact brought by the COVID-19 pandemic.

We conduct an empirical test to validate this hypothesis. For this purpose, we utilized the firm's blockchain technology usage measures constructed from patent text and news text data in Section 3.

$$\begin{aligned} SupplyChainFinance_{i,t} &= \alpha + \beta_1 Treat_i{*}Post_t{*}BlockChain_i \\ &+\beta_2 Treat_i{*}Post_t + \beta_3 Treat_i{*}BlockChain_t + \beta_4 BlockChain_i{*}Post_t \\ &+\beta_5 Treat_i + \beta_6 Post_t + \beta_7 BlockChain_i + Controls_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \end{aligned} \quad (5)$$

Specifically, in Model (5), we multiply the blockchain technology adoption measures ($BlockChain_i$), which are the variables *BCPat* and *BCNews*, with the interaction term *Treat*Post* from Model (2). We mainly focus on the magnitude and significance of the coefficients of the interaction term *Treat*Post*BCPat* and *Treat*Post* BCNews*. Suppose the coefficient of this interaction term is positive and significant. In that case, it indicates that blockchain technology can mitigate the negative impact of the COVID-19 outbreak on higher supply chain risk-exposed firms.

The regression results are in Table 6. Columns (1) and (2) in Table 6 show the results of the mitigating effect of the blockchain technology usage developed by patent data. For robustness checks, we conduct the regressions with the term of blockchain technology usage developed by news data, and Columns (3) and (4) in Table 6 show the results. In these columns, the coefficients of the *Treat*Post* term remain negative and significant. However, the coefficients of the interaction terms with the blockchain technology usage term are all positive and significant. This suggests that while firms with high exposure to supply chain risks may experience a decrease in the availability and utilization of supply chain finance during the COVID-19 pandemic, blockchain technology can mitigate the negative impact of COVID-19 on supply chain finance.

We conduct three tests for robustness checks and present the results of key interaction terms in the Appendix Tables. First, we repeat Model (5) regression using the treatment and control groups constructed based on the supply chain risk indicators measured by GPT. The regression results are presented in Appendix 5. The variable coefficients of the interaction terms *TreatGPT*Post*BCPat* and *TreatGPT*Post* BCNews* are also positive and significant, providing robustness to our research findings. Second, we replace *Treat* variable with *Treat*30 and *Treat*50 and repeat the regression test of Model (5). The test results are presented in Column (1) to (4) in Panel A of Appendix 6, which indicates that the coefficients of the interaction terms remain positive and significant, demonstrating the robustness of our results. Third, we replace the *Treat* variable with *TreatW* and repeat the regression test of Model (5). The test results are presented in Columns (1) and (2) in Panel B of Appendix 6, which indicates that the coefficients of the interaction term remain

Table 6
Blockchain technology and resilience provision.

Variables	(1)	(2)	(3)	(4)
	TradeCredit	*TradeCredit*	*TradeCredit*	*TradeCredit*
Treat	0.014***	0.014***	0.022***	0.018***
	(0.005)	(0.005)	(0.009)	(0.008)
*Treat*Post*	−0.012***	−0.011***	−0.019***	−0.020***
	(0.003)	(0.003)	(0.006)	(0.005)
*Treat*Post*BCPat*	0.443***	0.483***		
	(0.173)	(0.159)		
Treat BCPat*	−0.101	−0.070		
	(0.138)	(0.139)		
Post BCPat*	−0.016	−0.015		
	(0.074)	(0.070)		
BCPat	0.129	0.108		
	(0.081)	(0.082)		
*Treat*Post*BCNews*			0.773***	1.050***
			(0.394)	(0.371)
Treat BCNews*			−0.826	−0.045
			(0.540)	(0.519)
Post BCNews*			−0.064	−0.004
			(0.124)	(0.118)
BCNews			−0.361	−0.261
			-(0.317)	-(0.306)
Controls	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	25,814	25,814	25,814	25,814
adj. R^2	0.195	0.265	0.195	0.264

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

positive and significant, demonstrating the robustness of our results. Fourth, we replace the *Treat* variable with the *TreatCC* variable and repeated the regression analysis of Model (5). The results are presented in Columns (3) and (4) in Panel B of Appendix 6. Fifth, we construct an alternative blockchain adoption variable, *BCCC*, using conference call data, replacing the original blockchain adoption variables with *BCCC*, and repeat the regression test of Model (5). The results are presented in Columns (5) in Panel B of Appendix 6. These findings indicate that using variables constructed from conference calls to represent a firm's supply chain risk or blockchain adoption does not alter our main results, demonstrating the robustness of our main findings.

In addition, we conduct tests to mitigate endogeneity concerns. Larger firms or those with fewer financial constraints may possess greater capacity to invest in blockchain technology and experience less pressure related to supply chain financing. To address these endogeneity issues, we employed two methods. We compare the firm size and financial constraints among enterprises with different levels of blockchain adoption. If the firm size is not significantly higher and the financial constraints are not significantly lower for the firms with blockchain adoption, blockchain adoption is unlikely to be an endogenous factor mitigating the negative impacts of COVID-19 due to firm size or financial constraints. We divide the samples into two groups based on whether the enterprises adopted blockchain between 2017 and 2019 and calculate the mean values of firm size and financial constraints for the firms in each group. A *t*-test is conducted to compare the differences in these mean values. For financial constraints, to ensure the robustness of our results, we adopt both the SA index (*SAIndex*) and WW index (*WWIndex*) developed by Hadlock and Pierce (2010) and Whited and Wu (2006) to proxy the degree of financial constraints faced by enterprises. Higher values of these indices indicate more severe financial constraints. Appendix 7 presents the results, which show no significant difference in firm size between the two groups and that the enterprises with blockchain adoption face equal or significantly higher levels of financial constraints than others, according to the WW index or SA index. These findings suggest that blockchain adoption is unlikely to be influenced by firms' characteristics of larger size or lower financial constraints, thereby alleviating endogeneity concerns.

We also mitigate endogeneity issues by dividing the samples into two groups based on firm size or degree of financial constraints and conducted regression tests of Model (5) separately. Suppose blockchain adoption is effective due to larger firm size or lower financial constraints. In that case, the coefficient of the interaction term *Treat*Post*BCPat* in the regression results of both groups should no longer be significant in the grouped tests. However, the regression results show that the coefficient of the interaction term remains positive and significant in all regression results of each group, as presented in Appendix 8. This result also alleviates concerns about causality issues arising from endogeneity factors such as firm size in blockchain adoption.

6.2. Mechanisms

We investigate how blockchain technology provides resilience to firms with higher supply chain risk exposure during the COVID-19 pandemic.

First, blockchain technology provides resilience by promoting a firm's transparency. Blockchain technology has the characteristics of decentralization, openness, and immutability. Thus, enterprises adopting this technology can enhance transparency, increase suppliers' trust, and obtain more supply chain financing during the pandemic. If this mechanism holds, we conjecture that this effect is more pronounced for enterprises with originally low transparency, as the improvement in transparency for enterprises with high transparency is relatively limited even when blockchain technology is adopted. Based on this inference, we believe that the resilience brought by blockchain technology will be more significant in enterprises with low information transparency.

To verify this conjecture, we use two indicators to proxy the transparency of enterprises. The first is the transparency index of listed companies evaluated and disclosed by the Shanghai Stock Exchange and Shenzhen Stock Exchange (*Opacity*). This index divides the

Table 7
Mechanism: Transparency enhancement.

Variables	(1)	(2)	(3)	(4)
	Opacity		SocialMedia	
	Higher	Lower	Higher	Lower
	TradeCredit	*TradeCredit*	*TradeCredit*	*TradeCredit*
*Treat*Post*	−0.009*	−0.011**	−0.010**	−0.011**
	(0.006)	(0.006)	(0.004)	(0.005)
*Treat*Post*BCPat*	0.307	0.438**	0.289	0.439**
	(0.204)	(0.220)	(0.208)	(0.220)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	9685	14,556	11,248	14,566
adj. R^2	0.240	0.216	0.200	0.216

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

information transparency of listed companies into four levels. After processing, a higher value of this variable represents a higher level of transparency in the enterprise. The second variable measures the degree of attention enterprises receive on social media based on the number of comments on Xueqiu.com (*SocialMedia*). When an enterprise receives more attention and discussion on social media, its information will be disclosed and analyzed more thoroughly (Wong, Yu, Zhang, & Zhang, 2024), thus leading to higher transparency.

We divide the samples into two groups based on the values of *Opacity* and *SocialMedia* variables; the division is according to the median values of these indicators. We repeated the regression of Model (5) for each group separately. Table 7 shows the coefficients of key interaction terms (*Treat*Post* and *Treat*Post*BCPat*). The coefficients of the interaction term *Treat*Post*BCPat* are non-significant in the regressions to the firm with higher opacity, more social media attention, and higher transparency. On the contrary, the coefficients of the interaction term *Treat*Post*BCPat* are all positive and significant. These results indicate that blockchain technology has a more significant role in providing resilience for enterprises with lower transparency, suggesting that one of the channels through which blockchain provides resilience is enabling enterprises to achieve higher transparency.

Second, we also propose that blockchain technology provides resilience by enhancing corporate governance. The provision of supply chain finance originates from suppliers' trust in enterprises. Research has shown that companies with better corporate governance tend to have better business performance and future development prospects (Bhagat & Bolton, 2008). Therefore, suppliers are more likely to trust enterprises with good corporate governance and provide more supply chain financing, and vice versa. The immutability characteristic of blockchain technology can help enterprises with internal controls and improve their governance, thereby helping them gain suppliers' trust and access more supply chain financing. This will be more effective for enterprises that originally lacked good corporate governance, as there is more room for improvement in their corporate governance. Therefore, blockchain technology is more effective for enterprises with weaker corporate governance if this channel holds.

We obtain the ESG ratings developed and disclosed by Sino-Security and used the governance dimension as a proxy for the level of corporate governance. This ESG rating is well-used in financial research (Lin, Fu, & Fu, 2021). Based on the median score of this governance indicator, we have divided the sample into two groups: good corporate governance and weak corporate governance. Moreover, we follow the methodology of Bhandari and Golden (2021) in employing the Big4 auditor indicator (Big4) as another proxy for corporate governance. The Big 4 signifies audit quality, a dummy variable equal to 1 when a company undergoes an audit conducted by the Big 4 accounting firms and 0 otherwise. We have then conducted separate regressions for each group. Table 8 shows that the coefficients of the interaction term Treat*Post*BCPat are significant only in the subgroup of weaker governance firms or firms that do not employ big4 auditors, the weaker governance subgroup, suggesting that blockchain technology provides resilience through enhancing corporate governance.

Third, as proposed in the hypothesis development section, blockchain technology provides resilience by enhancing the ability and efficiency of enterprises in production networking with their supplier or customers. Communication between enterprises and suppliers or customers is carried out through business transactions and site visits (Cao, Gong, Kim, Shi, & Wang, 2025). Field research and observation by personnel can provide enterprises with more authentic and effective information, thus supporting their decision-making in supply chain financing. However, the lockdowns and quarantines due to the COVID-19 pandemic have made it more difficult for personnel to move between cities, especially those traveling long distances.

Blockchain technology's decentralization and immutability characteristics can provide enterprises on the chain with more authentic and abundant supply chain information, thus alleviating the difficulties in long-distance personnel exchanges between enterprises during the COVID-19 pandemic and enhancing their supply chain financing capabilities. If this channel holds, blockchain technology plays a more significant role for enterprises with longer geographically distant suppliers or customers, as their business visits are more disrupted, and their production network efficiency is more severely impaired.

Table 8
Mechanism: Corporate governance.

Variables	(1)	(2)	(3)	(4)
	Governance Index		Big4	
	Higher	Lower	Big4	Non-Big4
	TradeCredit	*TradeCredit*	*TradeCredit*	*TradeCredit*
*Treat*Post*	−0.013***	−0.009**	−0.021**	−0.012**
	(0.004)	(0.004)	(0.009)	(0.004)
*Treat*Post*BCPat*	0.200	0.604***	0.547	0.434**
	(0.128)	(0.181)	(0.351)	(0.185)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	9460	16,354	1575	24,239
adj. R^2	0.225	0.197	0.397	0.185

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

To test this conjecture, we divide the samples into two groups based on the median of the average geographical distance between enterprises and their suppliers or customers. We repeat the tests in Table 9 for each group separately. Columns (1) and (2) in Table 9 show the results. The coefficient in the longer distance sample is positive and significant, while the coefficient in another group is negative and no longer significant. These results support our conjecture that blockchain technology provides resilience by enhancing the ability and efficiency of enterprises to share information with their supplier or customers.

6.3. Heterogeneity

In this section, we explore several heterogeneities of how blockchain provides resilience to higher supply chain risk-exposed firms during the COVID-19 pandemic. We aim to deepen our comprehension of the underlying causes and factors that may exacerbate or mitigate these effects.

First, we examine the heterogeneity between state-owned enterprises (SOEs) and privately-owned enterprises (POEs). SOEs are often perceived to have better access to governmental and economic support, such as better access to external funds and subsidies. Additionally, SOEs' operational activities are not considered profit-driven but aimed at fulfilling government-mandated tasks (Chen, Sun, Tang, & Wu, 2011). Therefore, on the one hand, due to their lower financial distress, SOEs are less motivated to use blockchain technology to obtain more supply chain financing during the COVID-19 pandemic compared to non-SOEs. On the other hand, the purpose of SOEs developing or adopting blockchain technology may not be for economic benefits but rather to complete the government's digital transformation mandate. Consequently, we conjecture that the role of blockchain technology in providing resilience during the pandemic would be more significant among non-SOEs. We divide the sample into two groups based on SOE and non-SOE status and conduct separate regression for each group. The results are shown in Columns (1) and (2) in Panel A of Table 10. We find that the *Treat*Post*BCPat* variable is positive and significant only in the non-SOE group, the results that support our conjecture.

Second, social trust represents mutual trust among people in a certain region. When people have more trust in each other, businesses can establish trust at a lower cost. In regions with low social trust, businesses need to enhance trust from other businesses or individuals through technologies like blockchain and obtain more supply chain financing. Therefore, we believe blockchain technology provides more resilience to businesses in regions with low social trust during pandemics. To test this hypothesis, we refer to Wu, Firth, and Rui (2014) and use social trust data to divide the sample into two groups based on the social trust level of the location of the company's headquarters: high and low. Regression tests are then conducted separately for each group. The results are in Columns (3) and (4) in Panel A of Table 10. The coefficient of *Treat*Post*BCPat* is positive and significant only in the subgroup with lower social trust. This result verifies our conjecture that blockchain technology works better in lower social trust regions.

Third, we further explore firm-specific exposure to international trade by using outward foreign direct investment (OFDI) and firm-level overseas business revenue. Firms with higher OFDI and overseas business revenue are more integrated into the global market, making them more vulnerable to international shocks such as the COVID-19 pandemic. These firms faced significant challenges during the pandemic, including supply chain disruptions, trade restrictions, and demand fluctuations. Their international connections meant they were more susceptible to the pandemic's impact, experiencing issues like delayed shipments, raw material shortages, and increased logistics costs. In this context, blockchain technology is able to provide more resilience to businesses. Smart contracts on blockchain platforms automated and accelerated customs documentation processes, reducing delays at ports and borders. Additionally, blockchain creates shared and secure platforms for stakeholders, facilitating collaborative risk management strategies such as alternative sourcing and inventory optimization.

We split the dataset into two groups based on the median of outward foreign direct investment and overseas business revenue. The results are shown in the Panel B of Table 10 below. As we can see from the results below, in Column (1) and Column (3), where the firm has a higher level of OFDI or Foreign revenue, the coefficients of *Treat*Post*BCPat* are positive and statistically significant at the 5 % level. However, the results are insignificant in Columns (2) and (4). The results meet our expectations.

7. Conclusions

In this research, we examine the effects of the COVID-19 pandemic on supply chain financing, examining the role of blockchain technology in alleviating these effects and enhancing the robustness of credit financing during such a crisis. Using a textual analysis method, we construct blockchain technology and supply chain risk lexicon using the Word2Vec model.

We apply a series of empirical panel regression analyses and use the unexpected COVID-19 shock to economic activity to analyze whether the firms with high supply chain risk experienced a more significant reduction in trade credit during the COVID-19 pandemic. We further investigate whether blockchain technology can help firms mitigate the negative impact of the reduction in trade credit. In addition, our paper provides three possible mechanisms that blockchain adoption provides resilience to the supply chain finance in the COVID-19 crisis by enhancing information transparency, corporate governance, and product network efficiency to the firms in the supply chain.

Our study offers insights suggesting that the advancement and application of blockchain technology can offer increased stability for businesses within the supply chain finance sector, particularly during times of crisis. It provides practical implications. As an innovative solution, blockchain technology delivers traceability and sustainability within the supply chain and adds value by promoting information transparency, corporate governance, and product network efficiency. Companies, particularly small- and medium-sized enterprises, should be encouraged and supported by policies to enhance their proficiency in blockchain-related digital technology initiatives or innovations. Such a strategy will help bolster firms' financial resilience and operational agility, ensuring they are better equipped to navigate and overcome challenges in the dynamic business landscape.

Table 9
Mechanism: Production network efficiency.

Variables	(1)	(2)
	Distance	
	Longer	Shorter
	TradeCredit	*TradeCredit*
*Treat*Post*	−0.011	−0.025**
	(0.012)	(0.006)
*Treat*Post*BCPat*	1.907**	−0.309
	(0.931)	(0.814)
Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Observations	1630	1676
adj. R^2	0.338	0.324

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 10
Heterogeneity.

Panel A				
Variables	(1)	(2)	(3)	(4)
	SOE/non-SOE		SocialTrust	
	SOE	non-SOE	Higher	Lower
	TradeCredit	*TradeCredit*	*TradeCredit*	*TradeCredit*
*Treat*Post*	−0.012**	−0.409***	−0.011**	−0.011**
	(0.005)	(0.194)	(0.005)	(0.005)
*Treat*Post*BCPat*	0.433	0.409**	0.227	1.084**
	(0.277)	(0.194)	(0.166)	(0.424)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	8373	17,441	13,960	11,854
adj. R^2	0.331	0.137	0.192	0.203

Panel B				
Variables	(1)	(2)	(3)	(4)
	OFDI		Foreign revenue	
	Higher	Lower	Higher	Lower
	TradeCredit	*TradeCredit*	*TradeCredit*	*TradeCredit*
*Treat*Post*	−0.007	−0.012***	−0.007	−0.012***
	(0.005)	(0.004)	(0.005)	(0.004)
*Treat*Post*BCPat*	0.484**	0.341	0.484**	0.341
	(0.246)	(0.211)	(0.246)	(0.211)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	10,035	12,516	10,035	12,516
adj. R^2	0.145	0.149	0.145	0.149

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Declaration of competing interest

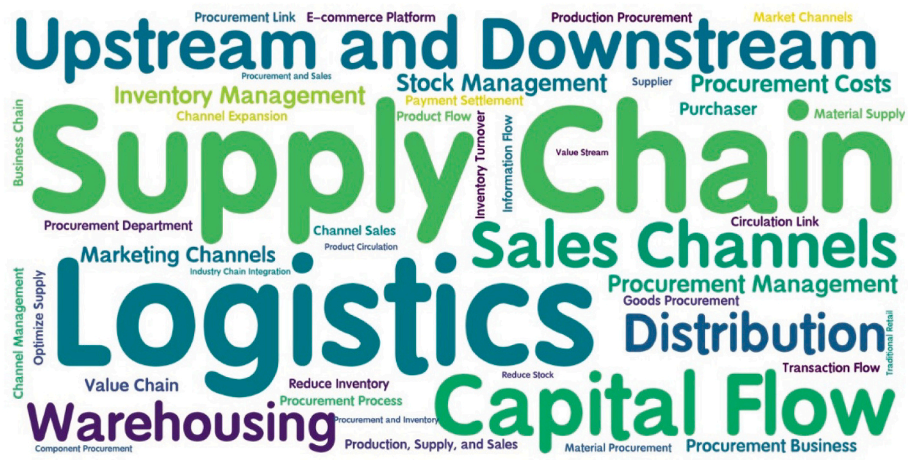
None.

Acknowledgments

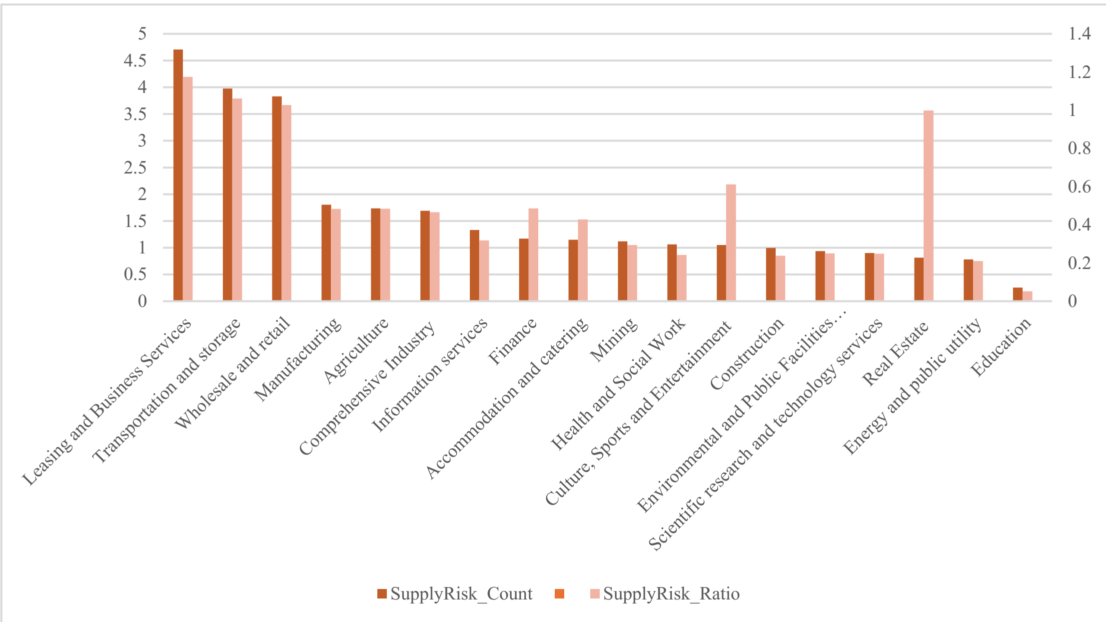
This paper was supported by the Major Program for Philosophy and Social Science at Ministry of Education of China (Project No. 2023J2DZ017), the Key Program for Philosophy and Social Science at Ministry of Education of China (Project No. 23JZD011), Ningbo Science and Technology Bureau for Key Plan Program (Project No. 2022Z243, 2022Z173), and Ningbo Science and Technology Bureau for Soft Science Program (Project No. 2024R034). All errors remain the responsibility of the authors.

Appendix

Appendix 1 Word Cloud of Supply Chain Terms



Appendix 2 The Average Term Frequency and Proportion of Supply Chain Risks for Enterprises Across Industries.



Appendix 3 Validation tests for supply chain risk variable.

Variables	(1)	(2)	(3)
	InventorytoAsset	*CashtoAsset*	*APtoAsset*
SCRatio	44.426***	0.302**	−0.500***
	(8.413)	(0.153)	(0.112)
Control	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Observations	25,921	26,246	26,246
R2	0.397	0.164	0.083

Note: This table presents the regression estimates of financial indicators on the supply chain risk exposure variable. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix 4 Robustness checks for baseline results by using GPT-based measure of supply chain risk.

	(1)	(2)	(3)
Variables	*TradeCredit*		
TreatGPT	−0.006	−0.001	0.010***
	(0.005)	(0.005)	(0.005)
*TreatGPT*Post*	−0.016***	−0.016***	−0.014***
	(0.003)	(0.003)	(0.003)
Controls	NO	NO	YES
Year FE	NO	YES	YES
Industry FE	NO	YES	YES
Observations	27,810	27,810	27,810
adj. R^2	0.011	0.189	0.225

Note: This table presents the DID regression estimates of the outbreak of COVID-19 on the firm's trade credit usage. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix 5 Robustness checks by using GPT-based measure of supply chain risk: blockchain technology and resilience provision.

Variables	(1)	(2)
	TradeCredit	
*TreatGPT*Post*	−0.013***	−0.019***
	(0.003)	(0.006)
*TreatGPT*Post*BCPat*	0.722**	
	(0.298)	
*TreatGPT*Post*BCNews*		0.853**
		(0.435)
Controls	YES	YES
Year FE	YES	YES
Industry FE	YES	YES
Observations	25,814	25,814
adj. R^2	0.266	0.343

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix 6 Blockchain technology and resilience provision: Different treatment variables

Panel A				
Variables	(1)	(2)	(3)	(4)
	TradeCredit			
*Treat30*Post*BCPat*	0.563*** (0.181)			
*Treat50*Post*BCPat*		0.668*** (0.160)		
*Treat30*Post*BCNews*			0.870** (0.440)	
*Treat50*Post*BCNews*				0.934*** (0.351)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	25,814	25,814	25,814	25,814
adj. R^2	0.265	0.265	0.264	0.265

Panel B					
Variables	(1)	(2)	(3)	(4)	(5)
	TradeCredit				
*TreatW*Post*BCPat*	0.128** (0.063)				
*TreatW*Post*BCNews*		0.434** (0.225)			
*TreatCC*Post*BCPat*			0.156** (0.068)		
*TreatCC*Post*BCNews*				1.014*** (0.331)	
*Treat*Post*BCCC*					0.004** (0.002)
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Observations	25,814	25,814	25,814	25,814	25,814
adj. R^2	0.265	0.265	0.260	0.223	0.224

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix 7 Comparison of variables' value by groups.

Variables	Groups	Number of Observations	Value	Difference
(1)	(2)	(3)	(4)	(5)
FirmSize	$BCPat = 0$	21,590	22.267	−0.021
	$BCPat > 0$	6220	22.288	
SAIndex	$BCPat = 0$	21,590	−3.882	−0.076***
	$BCPat > 0$	6220	−3.806	
WWIndex	$BCPat = 0$	21,590	−1.031	−0.005
	$BCPat > 0$	6220	−1.036	

This table shows the value and comparison of firm size and financial constraint variables between the samples of firms with and without blockchain adoption during 2017 to 2019. Column (1) shows the variables that we compare, column (2) shows the types of groups, column (3) shows the number of observations in each type of group, column (4) shows the averaged variables' value in each group, column (5) shows the difference of variables among each pair of groups. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Appendix 8 Blockchain technology and resilience provision: Verifying by groups.

Variables	(1)	(2)	(3)	(4)
	Firm Size		Financial Constraint	
	Higher	Lower	Higher	Lower
	TradeCredit			
*Treat*Post*BCPat*	0.412**	0.479**	0.902***	0.320**
	(0.180)	(0.229)	(0.341)	(0.145)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	13,519	12,295	12,896	12,918
adj. R^2	0.284	0.232	0.287	0.270

Note: This table presents the regression estimates of the interaction terms of blockchain adoption variables multiplied by the treat and post variables by groups, in which samples are separated according to the firm size or financial constraint degree. The control variable consists of firm features and the managers' characteristics. Year and industry fixed effects are included. Heteroscedasticity-consistent standard errors are clustered at the firm level. Robust standard errors are used and reported in parentheses. R^2 values are given in the table. *, **, and *** correspond to statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Data availability

Data will be made available on request.

References

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. M. (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics, 138*(1), 1–35.
Bedendo, M., Garcia-Appendini, E., & Siming, L. (2023). Managers' cultural origin and corporate response to an economic shock. *Journal of Corporate Finance, 80*, Article 102412.
Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics, 98*(1), 85–106.
Bernard, A. B., Moxnes, A., & Saito, Y. U. (2019). Production networks, geography, and firm performance. *Journal of Political Economy, 127*(2), 639–688.
Bessembinder, H., Maxwell, W., & Venkataraman, K. (2006). Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics, 82*(2), 251–288.
Bhagat, S., & Bolton, B. (2008). Corporate governance and firm performance. *Journal of Corporate Finance, 14*(3), 257–273.
Bhandari, A., & Golden, J. (2021). CEO political preference and credit ratings. *Journal of Corporate Finance, 68*, Article 101909.
Biais, B., Bisiere, C., Bouvard, M., & Casamatta, C. (2019). The blockchain folk theorem. *The Review of Financial Studies, 32*(5), 1662–1715.
Biswas, D., Jalali, H., Ansaripoor, A. H., & De Giovanni, P. (2023). Traceability vs. sustainability in supply chains: The implications of blockchain. *European Journal of Operational Research, 305*(1), 128–147.
Bouvard, M., Chaigneau, P., & Motta, A. D. (2015). Transparency in the financial system: Rollover risk and crises. *The Journal of Finance, 70*(4), 1805–1837.
Bowen, D. E., III, Frésard, L., & Hoberg, G. (2023). Rapidly evolving technologies and startup exits. *Management Science, 69*(2), 940–967.
Bray, R. L., & Mendelson, H. (2012). Information transmission and the bullwhip effect: An empirical investigation. *Management Science, 58*(5), 860–875.
Bray, R. L., Serpa, J. C., & Colak, A. (2019). Supply chain proximity and product quality. *Management Science, 65*(9), 4079–4099.
Brennan, N. M., Subramaniam, N., & Van Staden, C. J. (2019). Corporate governance implications of disruptive technology: An overview. *The British Accounting Review, 51*(6), Article 100860.
Breza, E., & Liberman, A. (2017). Financial contracting and organizational form: Evidence from the regulation of trade credit. *The Journal of Finance, 72*(1), 291–324.
Cao, S. S., Gong, G., Kim, Y., Shi, H., & Wang, A. (2025). Site visits and corporate investment efficiency. *Management Science, 71*(1), 635–658.
Chakuu, S., Masi, D., & Godsell, J. (2019). Exploring the relationship between mechanisms, actors and instruments in supply chain finance: A systematic literature review. *International Journal of Production Economics, 216*, 35–53.
Chen, S., Sun, Z., Tang, S., & Wu, D. (2011). Government intervention and investment efficiency: Evidence from China. *Journal of Corporate Finance, 17*(2), 259–271.
Chen, T. Y., Dasgupta, S., & Yu, Y. (2014). Transparency and financing choices of family firms. *Journal of Financial and Quantitative Analysis, 49*(2), 381–408.
Cho, S., Lee, K., Cheong, A., No, W. G., & Vasarhelyi, M. A. (2021). Chain of values: Examining the economic impacts of blockchain on the value-added tax system. *Journal of Management Information Systems, 38*(2), 288–313.
Chod, J. (2017). Inventory, risk shifting, and trade credit. *Management Science, 63*(10), 3207–3225.
Chod, J., Trichakis, N., Tsoukalas, G., Aspegren, H., & Weber, M. (2020). On the financing benefits of supply chain transparency and blockchain adoption. *Management Science, 66*(10), 4378–4396.
Chong, A. Y. L., Lim, E. T., Hua, X., Zheng, S., & Tan, C. W. (2019). Business on chain: A comparative case study of five blockchain-inspired business models. *Journal of the Association for Information Systems, 20*(9), 1310–1339.
Chu, Y., Tian, X., & Wang, W. (2019). Corporate innovation along the supply chain. *Management Science, 65*(6), 2445–2466.
Cong, L. W., & He, Z. (2019). Blockchain disruption and smart contracts. *The Review of Financial Studies, 32*(5), 1754–1797.
Cong, L. W., Li, Y., & Wang, N. (2022). Token-based platform finance. *Journal of Financial Economics, 144*(3), 972–991.
Costello, A. M., Minnis, M., & Rabinovich, I. (2024). Discrimination in the payments chain. *Journal of Financial Economics, 158*, Article 103872.
Cunat, V. (2007). Trade credit: Suppliers as debt collectors and insurance providers. *The Review of Financial Studies, 20*(2), 491–527.
Dass, N., Kale, J. R., & Nanda, V. (2015). Trade credit, relationship-specific investment, and product market power. *Review of Finance, 19*(5), 1867–1923.
Didier, T., Huneeus, F., Larrain, M., & Schmukler, S. L. (2021). Financing firms in hibernation during the COVID-19 pandemic. *Journal of Financial Stability, 53*, Article 100837.
Ding, F., Liu, Q., Shi, H., Wang, W., & Wu, S. (2023). Firms' access to informal financing: The role of shared managers in trade credit access. *Journal of Corporate Finance, 79*, Article 102388.

Ding, H., Fan, H., & Lin, S. (2022). COVID-19, firm exposure, and firm value: A tale of two lockdowns. *China Economic Review, 71*, Article 101721.
Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics, 141*(2), 802–830.
Garel, A., & Petit-Romec, A. (2021). Investor rewards to environmental responsibility: Evidence from the COVID-19 crisis. *Journal of Corporate Finance, 68*, Article 101948.
Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies, 23*(5), 1909–1940.
Hassan, T. A., Hollander, S., Van Lent, L., Schwedeler, M., & Tahoun, A. (2023). Firm-level exposure to epidemic diseases: Covid-19, SARS, and H1N1. *The Review of Financial Studies, 36*(12), 4919–4964.
Hassan, T. A., Hollander, S., Van Lent, L., & Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics, 134*(4), 2135–2202.
Hou, J., Wang, C., & Luo, S. (2020). How to improve the competitiveness of distributed energy resources in China with blockchain technology. *Technological Forecasting and Social Change, 151*, Article 119744.
Jha, M., Qian, J., Weber, M., & Yang, B. (2024). *ChatGPT and corporate policies (No. w32161)*. National Bureau of Economic Research.
Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P. O., & Zúñiga, D. (2021). Corporate bond liquidity during the COVID-19 crisis. *The Review of Financial Studies, 34*(11), 5352–5401.
Kelly, B., Papanikolaou, D., Seru, A., & Taddy, M. (2021). Measuring technological innovation over the long run. *American Economic Review: Insights, 3*(3), 303–320.
Kong, D., Pan, Y., Tian, G. G., & Zhang, P. (2020). Ceos' hometown connections and access to trade credit: Evidence from China. *Journal of Corporate Finance, 62*, Article 101574.
Lam, H. K., & Zhan, Y. (2021). The impacts of supply chain finance initiatives on firm risk: Evidence from service providers listed in the US. *International Journal of Operations & Production Management, 41*(4), 383–409.
Lee, Y. W., & Stowe, J. D. (1993). Product risk, asymmetric information, and trade credit. *Journal of Financial and Quantitative Analysis, 28*(2), 285–300.
Li, K., Liu, X., Mai, F., & Zhang, T. (2021). The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis, 56*(7), 2545–2583.
Li, L., Li, Y., Macchiavelli, M., & Zhou, X. (2021). Liquidity restrictions, runs, and central bank interventions: Evidence from money market funds. *The Review of Financial Studies, 34*(11), 5402–5437.
Liang, Y., Shi, K., Tang, J., & Xu, J. (2022). Pandemic and containment policies in open economy. *Journal of International Money and Finance, 125*, Article 102637.
Lin, Y., Fu, X., & Fu, X. (2021). Varieties in state capitalism and corporate innovation: Evidence from an emerging economy. *Journal of Corporate Finance, 67*, Article 101919.
Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. The. *Journal of Finance, 72*(4), 1785–1824.
Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review, 51*(6), Article 100833.
O'Hara, M., & Zhou, X. A. (2021). Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics, 142*(1), 46–68.
Ouyang, C., Xiong, J., Liu, L., & Yao, J. (2024). Geographic proximity and trade credit: Evidence from a quasi-natural experiment. *Journal of Corporate Finance, 84*, Article 102535.
Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance, 78*(3), 1449–1498.
Shen, Z. M., & Sun, Y. (2023). Strengthening supply chain resilience during COVID-19: A case study of JD. Com. *Journal of Operations Management, 69*(3), 359–383.
Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science, 52*(5), 639–657.
Van der Vliet, K., Reindorp, M. J., & Fransoo, J. C. (2015). The price of reverse factoring: Financing rates vs. payment delays. *European Journal of Operational Research, 242*(3), 842–853.
Verma, S., & Gustafsson, A. (2020). Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. *Journal of Business Research, 118*, 253–261.
Wang, J., Wang, K., Li, X., & Zhao, R. (2022). Suppliers' trade credit strategies with transparent credit ratings: Null, exclusive, and nonchalant provision. *European Journal of Operational Research, 297*(1), 153–163.
Wang, Y., Liu, B., Chan, H. K., & Zhang, T. (2023). Who pays buyers for not disclosing supplier lists? Unlocking the relationship between supply chain transparency and trade credit. *Journal of Business Research, 155*, Article 113404.
Wang, Z., Dong, Y., & Liu, A. (2022). How does China's stock market react to supply chain disruptions from COVID-19? *International Review of Financial Analysis, 82*, Article 102168.
Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies, 19*(2), 531–559.
Wong, T. J., Yu, G., Zhang, S., & Zhang, T. (2024). Calling for transparency: Evidence from a field experiment. *Journal of Accounting and Economics, 77*(1), Article 101604.
Wu, D. (2024). Text-based measure of supply chain risk exposure. *Management Science, 70*(7), 4781–4801.
Wu, W., Firth, M., & Rui, O. M. (2014). Trust and the provision of trade credit. *Journal of Banking & Finance, 39*, 146–159.
Wuttke, D. A., Rosenzweig, E. D., & Heese, H. S. (2019). An empirical analysis of supply chain finance adoption. *Journal of Operations Management, 65*(3), 242–261.
Yermack, D. (2017). Corporate governance and blockchains. *Review of Finance, 21*(1), 7–31.
Yu, F. (2005). Accounting transparency and the term structure of credit spreads. *Journal of Financial Economics, 75*(1), 53–84.
Ziolkowski, R., Miscione, G., & Schwabe, G. (2020). Decision problems in blockchain governance: Old wine in new bottles or walking in someone else's shoes? *Journal of Management Information Systems, 37*(2), 316–348.