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Wang, W., Zhen, Z., Li, M. et al. (1 more author) (2025) The effects of market power discrepancy on trade credit scales: a paradoxical perspective of digitalization. Journal of Business Logistics, 46 (4). e70039. ISSN: 0735-3766

https://doi.org/10.1111/jbl.70039

The effects of market power discrepancy on trade credit scales: A paradoxical perspective of digitalization

Journal:	*Journal of Business Logistics*
Manuscript ID	JBL-Dec-2023-8761.R3
Wiley - Manuscript type:	Special Issue Article
Methodology:	Experimental Design
Keywords:	trade credit, supply chain finance, digital transformation, market power discrepancy

Abstract: We examine the relationship between corporate market power discrepancy (MPD) and trade credit, and whether digital transformation (DT) moderates this relationship. This research adopts trade credit, one of the most important financing schemes in supply chain finance (SCF), to represent the SCF-based financing ability of a firm, and conducts empirical research using a sample of Chinese publicly traded firms and their suppliers and customers spanning from 2011 to 2022. We first investigate the effect of the MPD, including both suppliers' market power discrepancy (SMPD) and customers' market power discrepancy (CMPD), on the scales of focal firms' trade credit. We find that the SMPD is positively correlated with the trade credit of focal firms, while the CMPD is negatively correlated with its trade credit. Further, we find that DT enhances the effect of SMPD on trade credit scales but weakens the effect of CMPD on trade credit scales. This study advances understanding of MPD's effects on trade credit from a paradoxical perspective of digitalization, offering practitioners insights into the impact of deploying digital technologies on supply chain relationships.

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Abstract

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Keywords:

market power discrepancy, trade credit, supply chain finance, digital transformation

1 Introduction

Supply chain finance (SCF) has emerged as a critical financing tool for firms, particularly in managing liquidity and optimizing working capital (Gelsomino et al., 2016). It facilitates smooth transactions between buyers and suppliers, allowing firms to access trade credit (TC) as a way to bridge financial gaps (Lee, Zhou and Wang, 2018; Gofman and Wu, 2022). As one of the most important SCF financing schemes, trade credit enables firms to purchase goods on credit and delay payment to suppliers. With its flexible financing terms and streamlined procedures, it serves as an effective way for firms to secure external short-term financing (Frennea, Han and Mittal, 2019; Liu and Wang, 2023). In a sample of 34 countries, account payables represent 25% of the average firm's total debt liabilities (Levine, Lin and Xie, 2018), and this proportion is even higher in China (An et al., 2021).

Despite the recognized importance of trade credit in SCF, existing literature has primarily focused on general financial stability and liquidity challenges, with limited attention given to the nuances of market power dynamics in the context of trade credit (Levine, Lin and Xie, 2018). Market power is a crucial determinant of operational behavior and the distribution of profits among supply chain partners (Brito and Miguel, 2017; Reimann and Ketchen Jr., 2017; De Ridder, 2024). It reflects firms' ability to control prices, with those able to raise prices above the market average having greater market power. The discrepancy of market power between the focal firm and its supplier (or customer), which is known as the market power discrepancy (MPD), influences firms' resource allocation and shapes supply chain relationships (Gu et al., 2024). Separately, the discrepancy of market power between the focal firm and its supplier (SMPD) determines the firm's bargaining position in procurement and payment negotiations, which in turn impacts the amount of trade credit extended to the focal firm by its upstream partners (Nair, Narasimhan and Bendoly, 2011). The difference of market power between the focal firm and its customer (CMPD) drives the firm's ability to manage downstream payment terms, thereby affecting the extent to which trade credit is offered to customers (Rahaman, Zhang and Feng, 2022). China has a vast number of small and medium-sized enterprises (SMEs), many of which are highly dependent on focal firms. These SMEs often occupy a relatively weak position within supply chains, relying on dominant firms for access to orders and financing opportunities. This 'strong–weak' structural relationship provides a valuable context for examining how MPD influences firms' behavior and outcomes (Huo, Flynn and Zhao, 2017).

A notable example is Wal-Mart, which, in comparison to its SME competitors, enjoys greater market power and consistently benefits from higher trade credit scales (Mottner and Smith, 2009). By collaborating with its SME suppliers, Wal-Mart leverages its bargaining power to gain an advantage in price setting and secure lower procurement prices. This price control behavior enables Wal-Mart to negotiate longer supplier payment periods, thereby expanding its access to trade credit financing[1]. Collaboration between firms with varying market power can simultaneously enhance small firms' access to transactions while allowing large firms to capture higher profits through pricing advantages, thereby boosting commercial credit exchanges for both parties. However, under conditions of asymmetric market power and low information transparency, firms often struggle to establish cooperation due to a fundamental lack of trust (Michalski, Montes and Narasimhan, 2018). In trade credit

[1] https://en.walmart.cn/newsroom-en/231.html

relationships, firms with lower market power often face stricter trade terms and longer payment periods, sometimes leading them to extend the credit period upon the request of stronger partners. Prior research suggests that partnerships with similar market power levels are more beneficial for financial performance (Gu et al., 2024). Additionally, the presence of information asymmetry between small and large firms tends to heighten the caution of weaker firms when extending credit. These opposing effects motivate us to investigate how MPD between focal firms and their supply chain partners affects trade credit.

The market power disparity among firms within the supply chain raises important questions about whether differences in market power between focal firms and their supply chain partners influence the scale of trade credit. In reality, firms are often integral parts of a complex triadic structure, where focal firms are simultaneously influenced by both suppliers and customers. From a management perspective, by collaborating with firms of varying market power within the supply chain, focal firms can enable shared 'credit' (i.e., financial resources) between them—an important aspect of inter-firm resource sharing (Madhavaram et al., 2023). Typically, after obtaining trade credit from their upstream partners, focal firms are able to extend more favorable trade credit terms to downstream customers, creating a triadic relationship-based trade credit system (Gofman and Wu, 2022). Therefore, the scale of trade credit is likely influenced by MPD, including both SMPD and CMPD. However, the distinct effects of MPD from suppliers and customers on corporate trade credit remain understudied. Therefore, the first research question that this paper addresses is: *What is the relationship between the firm's MPD and its trade credit?*

Digital transformation (DT) has rapidly spread across industries and introduced new paradigms in trade credit research. For example, firms are increasingly inclined to conduct transactions through digital platforms, which significantly enhance operational efficiency (Zhang, Liu, Li and Xing, 2023), reduce operational risks (Kusiak, 2017) and improve information transparency (Xie et al., 2022). These improvements facilitate stronger collaboration between firms and their upstream or downstream partners with unequal market power. DT has demonstrated unique advantages, providing firms with opportunities to obtain information flows within the supply chain and to use this information to send credible signals to partners with asymmetric market power, thereby enhancing collaboration (Zhang, Xu and Ma, 2023). Moreover, DT reduces firms' credit and logistics risks (Faruquee, Paulraj and Irawan, 2021; Li et al., 2023), thereby fostering stronger partnership opportunities between focal firms with dominant market power and their suppliers or customers operating under asymmetric bargaining positions. In addition, DT enhances firms' financing capacity by reducing credit risk and increasing credit limits, thereby strengthening the their willingness to provide trade credit (Liu and Wang, 2023). Digital technologies, having been embedded into business processes, enhance firms' information processing capabilities while providing timely information, transparency, and visibility to ensure information sharing and business connectivity with partners (Xie et al., 2022). Research has shown that DT has been extensively integrated into supply chain operations, facilitating business model innovation while significantly improving operational efficiency and reducing costs (Matarazzo et al., 2021). Since DT has improved collaborations between supply chain partners, one may reasonably expect that DT can moderate the impact of MPD on trade credit. Therefore, this paper asks the second question: *Does DT of focal firms moderate the impact of MPD on trade credit?*

We empirically investigate the relationship between MPD and trade credit. We hypothesize, based on the buyer market theory framework (Murfin and Njoroge, 2015), that SMPD has a positive impact on firms' trade credit but CMPD has a negative impact on firms' trade credit. We also hypothesize that DT moderates those effects. We use a regression analysis to test these hypotheses, using firm-level data of public companies in China. China's digital economy has experienced remarkable development in recent years, emerging as one of the world's largest and fastest-growing digital markets. In 2023, China's digital transformation expenditures reached CNY 2.3 trillion (USD 322 billion), reflecting a 9.5% year-on-year growth (Zhou and Zhang, 2025). We construct the DT metrics manually through textual analysis of sample firms' annual reports using natural language processing (NLP) techniques. Our empirical results are consistent with the hypotheses, showing that firms with strong market power convince their supply chain partners to give more favourable trade credit conditions. Furthermore, we find that the DT amplifies the positive association between SMPD and trade credit, but suppresses the negative relationship between CMPD and trade credit. These findings demonstrate that DT enables firms to balance trade credit dynamics across supply chain tiers. Specifically, when acting as customers with weaker market power, focal firms leverage DT to enhance information transparency and contract enforceability, thereby strengthening relationships with upstream suppliers. When acting as suppliers, focal firms utilize DT to digitalize transactions and payment processes, which reduces operational risks and costs and enhances their confidence in extending trade credit to downstream customers. Our results are robust to the use of alternative variables to measure MPD and DT, and to the application of instrumental variable (IV) estimations to address potential endogeneity concerns.

Our research makes several contributions to the literature. First, we enrich the trade credit financing literature by empirically examining the relationship between MPD and trade credit scales. Previous research (Fabbri and Klapper, 2016) analyzes survey data on small firms and finds that firms with customers holding a large market share offer more trade credit. While prior studies suggest that large customers influence focal firms' intentions to provide trade credit, this finding has yet to be validated using data from publicly listed corporations, as large and established firms, benefiting from scale, strong market power and diversified business channels, are often assumed to be less influenced by their supply chain partners. Our study demonstrates that the effect of MPD on trade credit is significant for publicly listed corporations. This finding is somewhat surprising and indicates that MPD remains highly relevant even among large and established firms. Furthermore, we show that SMPD and CMPD have distinct impacts on trade credit. Overall, this study advances the understanding of buyer market theory (Kopp and Sexton, 2021) by providing a novel perspective—trade credit—on the role of market power in supply chain management.

Second, our research provides a novel and novel perspective on digitalization in the context of MPD's effects on trade credit scales. While extant literature has documented a positive effect of DT on corporate financial performance (e.g., Chen and Srinivasan, 2024), its implications for reshaping trade credit relationships remain unexplored. By incorporating DT into the study of the relationship between market power and trade credit, this research provides novel findings that enrich the literature. Our results suggest that DT strengthens the relationship between SMPD and trade credit, while weakening the relationship between CMPD and trade credit. This finding offers practical implications for supply chain managers, highlighting the benefits of DT in enhancing information processing capabilities and improving operational efficiency. Specifically, DT strengthens a firm's information processing capacity and reduces information asymmetry, which facilitates the establishment and maintenance of trade credit relationships between supply chain partners. By improving information transparency and digital service capabilities, DT enables firms to disclose more comprehensive and reliable information to suppliers and customers with varying levels of market power, thereby fostering trust and long-term cooperation (Sousa-Zomer, Neely and Martinez, 2020). The enhanced information flow also enables buyers with stronger market power to leverage DT more effectively to secure greater trade credit amounts and extended payment terms from sellers (Zhang et al., 2022). Moreover, focal firms undergoing DT often incur substantial costs, which those with greater market power can partially shift to upstream suppliers by negotiating better trade credit terms.

The optimization of capital and logistics driven by DT brings practical implications for supply chain managers and firms. First, digitalized processes and blockchain-based smart contracts enable conditional automatic payments, allowing firms with varying levels of market power to monitor financial flows in real time, thereby reducing the incidence of intentional payment delays (Kamble, Gunasekaran and Sharma, 2020). Second, DT helps alleviate firms' financing constraints and diversify funding sources (Li et al., 2024). Improved liquidity enables firms to make timely payments in trade credit transactions (Levine, Lin and Xie, 2018). Third, DT facilitates the optimization of logistics management between focal firms and suppliers (customers) with asymmetric market power, thereby promoting trade credit relationships(Sternberg, Mathauer and Hofmann, 2023). Specifically, by establishing a shared logistics data pool, focal firms can provide suppliers with real-time information on goods in transit, inventory levels, and delivery verification (Matarazzo et al., 2021). This level of transparency allows suppliers to better plan their production and respond more promptly to focal firms' order demands. These DT-driven improvements in capital and logistics flows contribute to fostering stronger interfirm relationships and enhancing suppliers' willingness to extend trade credit. On the customer side, DT-based logistics visibility reduces delivery disputes and payment risks, thereby increasing focal firms' willingness to extend trade credit to customers. Last but not least, DT enhances data analytics capabilities and enables the development of visualized workflows, thereby reducing operational and credit risks (Fayyaz, Rasouli and Amiri, 2020).

The remainder of this study is organized as follows. Section 2 discusses the theoretical background and hypothesis development. Section 3 describes the data, sample, and variable construction. Section 4 presents the model and empirical results. Section 5 discusses the theoretical and practical implications of this paper. Section 6 summarizes the paper and gives recommendations for future studies.

2 Theoretical background and hypothesis development

2.1 Impact of MPD on firm trade credit

Firms with varying market power often adopt different trade credit strategies to reduce costs and enhance returns, a phenomenon rooted in the supply chain power theory (Reimann and Ketchen Jr., 2017). Specifically, firms with stronger market power are able to negotiate more favourable trade credit terms with their suppliers, extending their payment periods and improving their working capital management (Lee, Zhou and Wang, 2018). The provided trade credit gives focal firms a cost advantage by reducing the demand for external finance that carries interest expenses. This cost advantage arises not only from a powerful firm's strong bargaining power but also through supply chain governance mechanisms, as powerful firms often impose relational contracts that align suppliers' incentives with their own financial objectives (Giannetti, Burkart and Ellingsen, 2011). This suggests that firms with greater market power can leverage their position to secure more advantageous trade credit terms, which in turn enhance their financial performance (Nair, Narasimhan and Bendoly, 2011). From a SCF perspective, this dynamic reflects how market power asymmetries redistribute financial resources within the supply chain network (Wuttke, Blome and Henke, 2013).

Conversely, firms with lower market power face more stringent trade credit terms, including shorter payment periods and higher interest rates, leading to a heavier liquidity burdens and a higher cost of external finance. This is demonstrated in a study by Petersen and Rajan (1997), where the authors find that smaller firms with less market power have more difficulty obtaining trade credit and are more likely to face financial constraints. Therefore, the impact of MPD on trade credit is crucial, with firms that have greater market power being able to negotiate more profitable terms and reduce financing costs, improving their financial performance, while those with lower market power may face challenges in securing trade credit and managing their working capital efficiently.

Buyer market theory (Kopp and Sexton, 2021) emphasizes the dominant position of buyers in transactions. Specifically, in a buyer-dominated supply chain relationship, buyers typically have stronger bargaining power, allowing them to secure favourable trade credit terms for three main reasons: First, powerful buyers demand better payment terms from suppliers, such as longer payment periods or lower interest rates, using their strong bargaining power (Petersen and Rajan, 1997; Murfin and Njoroge, 2015). Second, suppliers, dependent on buyers' large market share and high order volumes, are more willing to provide trade credit to maintain long-term relationships (Fabbri and Klapper, 2016). Third, powerful buyers can influence the flow of funds in the supply chain, securing more credit, while suppliers have to accept less favorable terms to sustain the partnership (Banerjee, Dasgupta and Kim, 2008). These factors illustrate how buyer power can shape trade credit dynamics within supply chains. The buyer's market compels firms to enhance collaboration with both upstream and downstream partners in order to reduce costs, improve service quality, strengthen supply chain coordination and integration, optimize the allocation of resources such as cash flows, and improve overall supply chain management.

2.1.1 SMPD on firm trade credit

Firms with stronger market power often leverage their dominant position in the supply chain to secure more favourable trade credit terms. Firms with strong market power are able to lower costs and raise prices above competitive levels within the industry, reflecting their dominance in the market (De Loecker, Eeckhout and Unger, 2020). Information asymmetry within supply chains intensifies the disparity in financing capacity among firms. Specifically, buyers with strong market power have better access to market and transaction information, which enables them to secure financing more easily, while suppliers with weaker bargaining power and limited financing channels may face higher financing costs (Nair, Narasimhan and Bendoly, 2011). While such power asymmetries may undermine long-term inter-firm relationship stability (Gu et al., 2024), powerful firms in practice often use their dominance to push down purchasing prices and reduce operating costs (Murfin and Njoroge, 2015).

From a theoretical standpoint, both buyer market theory and resource dependence theory predict a positive association between SMPD and trade credit. Buyer market theory emphasizes that dominant buyers can exert pressure on suppliers to secure more favourable trading terms, as suppliers rely on them for market access and sales stability (Kopp and Sexton, 2021). Resource dependence theory further suggests that when resource imbalances exist, firms with lower market power must accommodate stronger partners to secure essential resources, including financial support in the form of trade credit (Craighead, Ketchen Jr. and Darby, 2020; Jiang et al., 2023). Thus, under conditions of significant MPD, focal firms with stronger market power are more likely to obtain preferential credit terms, reinforcing the positive relationship between SMPD and trade credit. Accordingly, we hypothesize that SMPD is positively associated with the scale of trade credit.

H1: The SMPD is positively correlated with the trade credit of the focal firm.

2.1.2 CMPD on firm trade credit

From a cost perspective, trade credit essentially represents a form of "implicit financing," where the supplier bears the opportunity cost of tied-up capital (Wu, Muthuraman and Seshadri, 2019). When customers possess strong market power, focal firms are often compelled to offer more lenient payment terms to sustain business relationships, thereby increasing the provision of trade credit (Giannetti, Serrano-Velarde and Tarantino, 2021). Conversely, when focal firms hold stronger bargaining power in the market, customers tend to exhibit higher dependence on their products and services, which means that firms no longer need to rely on trade credit to stimulate sales or maintain cooperation. Under such circumstances, granting trade credit merely leads to capital lock-up and reduced capital utilization efficiency (Astvansh and Jindal, 2022). Moreover, firms with dominant market power usually enjoy greater access to financing channels and lower cost of external financing, making them more inclined to allocate resources to higher-yielding investment opportunities rather than passively providing financing to customers (Rahaman, Zhang and Feng, 2022). Therefore, as focal firms' market power increases, they are more likely to reduce the extension of trade credit to customers in order to avoid incurring additional financing costs.

From a risk-control perspective, trade credit is inherently associated with credit risk and the possibility of bad debts. When firms hold a dominant position in the market, their products or services are often less substitutable for customers, placing them in a stronger bargaining position (Fabbri and Klapper, 2016). This advantage allows them to mitigate default risk by requiring advance payments or by shortening payment periods, without needing to provide trade credit as an incentive to secure transactions. Furthermore, firms with significant market power tend to prioritize financial stability and liquidity safety (Barra and Zotti, 2019); they often reduce account receivables to limit exposure to credit risk, thereby enhancing overall risk management (Billett, Freeman and Gao, 2025). Consequently, when firms possess greater market power, they are more inclined to restrict trade credit provision to customers as a means of minimizing credit risk and safeguarding financial security. Accordingly, we hypothesize that CMPD is negatively correlated with a firm's trade credit scale.

H2: The CMPD is negatively correlated with the trade credit of the focal firm.

2.2 Moderating roles of digitalization

The sustainable development of SCF requires active participation and exchange among firms with different levels of market power. Modernization efforts encourage trading between firms with different market power, with "chain masters" like Walmart leveraging their strong market position to support SMEs by enhancing their sales channels while promoting their own development (Matarazzo et al., 2021; Hu, 2023). To foster collaboration among firms with heterogeneous market power, reducing information asymmetry and enhancing mutual trust are essential for expanding trade credit opportunities. DT emerges as a pivotal mechanism to address these challenges.

Digital tools help focal firms efficiently manage the flow of information, funds, and goods in the supply chain.Through data mining and intelligent analytics, DT enhances supply chain transparency, enabling firms to leverage digital channels for real-time market information and mitigate information disparities (Budler, Quiroga and Trkman, 2024; Zhu and Yu, 2024). Specifically, by leveraging DT technologies—such as blockchain, supply chain management platforms, ERP systems, and big data analytics—firms can access real-time information (e.g., inventory, orders, and production schedules) across the supply chain, enhance their ability to predict the behavior of suppliers and customers, and promptly identify and respond to potential risks such as defaults or delivery delays (Knudsen et al., 2021). Data-driven insights enable firms to optimize the selection of suppliers and customers, thereby strengthening managerial capabilities, fostering trust, and promoting long-term collaborative relationships (Brau et al., 2024).

DT is likely to moderate the impact of MPD on trade credit by optimizing cash flows and logistics. The adoption of technologies such as IoT sensors further improves the transparency of logistics data by sharing data with suppliers, reducing information uncertainty caused by power asymmetries (i.e., powerful buyers) and thereby strengthening suppliers' willingness to provide trade credit (Akkermans et al., 2024). A profound understanding of certain digital technologies can assist firms in accessing real-time information promptly, enhancing information transparency, including transactional data, raw material availability, and inventory levels (Xie et al., 2022).

DT can effectively reduce various types of firm-level risks, such as credit risk and logistics risk. The credit period tends to be longer and payment delays occurs more often between firms with asymmetric market power because the imbalance in bargaining positions often forces weaker firms to accept unfavorable payment terms. Moreover, MPD is often accompanied by heightened information asymmetry, which limits weaker firms' ability to assess the creditworthiness of dominant partners, thus amplifying the credit risk(Wang et al., 2023). Logistics risks also arise when firms impose stringent delivery requirements or adjust order volumes unpredictably. DT-based logistics visibility helps suppliers monitor shipments, inventory, and delivery conditions, thereby reducing uncertainty and operational disruptions. By leveraging data sharing and online collaboration platforms, firms can better predict and reduce risks and implement timely countermeasures. The reduction of such risks facilitates more stable partnerships and encourages trade credit transactions between firms with differing levels of market power.

Firms adopting DT can either develop digital processes or procure digital service systems to optimize operations and improve efficiency (Matarazzo et al., 2021). The use of digital platforms lowers firms' operating expenses and enhances their liquidity (Chen and Zhang, 2024), boosting its bargaining power within the supply chain (Abou-foul, Ruiz-Alba and

Soares, 2021; Zhang, Liu, Li and Xing, 2023; Chen and Srinivasan, 2024). Improved liquidity increases firms' confidence in engaging in trade credit sales with partners holding unequal market power. With advanced technologies such as real-time data sharing and demand forecasting (Brau et al., 2024), firms can lower transaction costs, thereby increasing their willingness to engage in trade credit with suppliers/customers.

2.2.1 DT on the relationship between SMPD and firm trade credit

Prior literature indicates that DT has the following effects in moderating the relationship between SMPD and trade credit: First, the adoption of digital technologies enhances firms' information systems, increasing inter-organizational information transparency. Zhang et al. (2022) find that strengthening DT within a firm improves its ability to efficiently collect and process information across the entire supply chain, including relevant information from both upstream and downstream partners. Even when suppliers themselves are less digitally advanced, the DT of focal firms and enhanced visibility reduces their uncertainty concerns regarding the focal firm's operational reliability (Faruquee, Paulraj and Irawan, 2021). As a result, suppliers are more inclined to meet the focal firm's demand and offer more (or extend existing) trade credit.

Second, DT enhances the credibility of focal firms in managing payments and capital flows. DT significantly improves the efficiency and controllability of corporate fund flows through technological restructuring of the entire capital lifecycle management. By integrating ERP systems, procurement platforms, and market data, enterprises can develop precise cash flow forecasting models to optimize capital flow efficiency (Brau et al., 2024). For instance, Unilever improved its cash flow prediction accuracy to 80% through AI-powered forecasting tools, enabling three-month advance planning for supplier payment schedules[2]. Furthermore, DT facilitates the establishment of open supplier portals where demand forecasts and inventory levels are shared, allowing suppliers to adjust production plans based on real-time data, thereby reducing capital lock-up (Zissis, 2023). Blockchain-based smart contracts enable conditional automated payments—such as post-delivery verification—minimizing manual approval processes (Chod et al., 2020). These DT-driven optimizations in supply chain capital flows help reduce suppliers' concerns, fostering stronger inter-firm relationships and enhancing suppliers' willingness to meet the focal firm's demand and extend trade credit.

Third, DT can optimize logistics management, enhancing suppliers' trust in the focal firm and facilitating trade credit transactions. Specifically, by establishing shared logistics data pools, focal firms can provide suppliers with real-time data on shipments in transit, inventory levels, and delivery acceptance (Matarazzo et al., 2021). This data availability enables suppliers to better plan production and offer more timely order quantities to the focal firm. Furthermore, blockchain-based immutable records of critical supply chain activities, such as quality inspection reports and logistics receipts, can prevent focal firms from unilaterally rejecting shipments or suppressing prices, thereby reducing trade credit risks for suppliers (Kamble, Gunasekaran and Sharma, 2020). These DT-driven applications strengthen the relationship between focal firms and suppliers with asymmetric market power, ultimately increasing suppliers' willingness to extend trade credit to the firm.

Finally, focal firms may use their strong market power to shift the cost of establishing the DT system to their suppliers in the form of trade credit. Specifically, focal firms undertaking

[2] Transcending boundaries: Unilever's cash flow forecasting foresight - EuroFinance | The global treasury community

DT often incur substantial costs. Firms with great market power may shift a portion of these costs to their upstream suppliers through either pricing strategies or contractual arrangements, i.e., trade credits (Reimann and Ketchen Jr., 2017; De Ridder, 2024). This cost transfer relies on the focal firm's market power, characterized by a high SMPD. Accordingly, we predict that DT amplifies the positive relationship between SMPD and trade credit, as DT is associated with high costs that powerful firms want to shift to their suppliers. From the supplier's perspective, we expect suppliers to be more willing to offer trade credit to maintain stable supply chain relationships and ensure the smooth functioning of their digitally upgraded supply chains (Huo, Flynn and Zhao, 2017; De Ridder, 2024).

Motivated by the discussions above, we hypothesize that DT moderates the relationship between SMPD and trade credit, by enhancing information transparency, financial reliability, logistics coordination, and cost transfer. These mechanisms reduce suppliers' risk and strengthen inter-firm trust, increasing the likelihood of trade credit provision from suppliers. Given the evidence documented in the literature to support each channel, our hypothesis is developed to test the synthesized effect. We do not argue that one single mechanism dominates the empirical relationship.

H3: The positive effect of SMPD on trade credit is strengthened by a firm's DT.

2.2.2 DT on the relationship between CMPD and firm trade credit

Prior literature indicates that DT has the following effects in moderating the relationship between CMPD and trade credit: First, DT facilitates improved communication, collaboration, and risk assessment across supply chains, helping focal firms mitigate transaction and credit risks posed by more powerful customers (Faruquee, Paulraj and Irawan, 2021; Chen and

Srinivasan, 2024). Focal firms leverage DT to integrate multi-dimensional data, including customers' historical payment timeliness, executive-associated risks, and supply chain collaboration metrics (e.g., upstream/downstream stability), to construct comprehensive, multidimensional customer profiles (Fayyaz, Rasouli and Amiri, 2020). Machine learning models dynamically update credit ratings, enabling real-time risk prediction and mitigation strategies for customers with asymmetric market power, thereby reducing transactional risks for focal firms (Zhou and Li, 2023). Furthermore, DT shifts traditional processes from manual contract reviews to blockchain-powered smart contract verification, effectively curbing order fraud (Wang et al., 2023). It also replaces reactive payment collection with AI-driven early-warning systems that identify high-risk customers 30 days in advance (Brau et al., 2024). These DT-enabled enhancements allow focal firms to expand trade credit offerings to asymmetric-power customers while maintaining risk control, demonstrating how algorithmic governance can recalibrate unbalanced market relationships.

Second, DT enhances logistics risk management and supply chain visibility, which in turn reduces the risks involved in offering extended payment terms or higher credit limits to customers. Specifically, through the adoption of technologies such as IoT sensors, GPS, and RFID, firms can monitor the real-time location, temperature and humidity, and transportation conditions (e.g., shocks and tilts) of goods to ensure secure delivery (Warner and Wäger, 2019). Key logistics milestones, such as loading, customs clearance, and proof of receipt, are recorded on the blockchain, preventing customers from unilaterally denying receipt or delaying payment (Kamble, Gunasekaran and Sharma, 2020). These DT initiatives enhance logistics transparency and mitigate logistical risks, which in turn reduce information asymmetry in credit assessments and increase the trustworthiness of customers in the eyes of focal firms (Cui, Gaur and Liu, 2023). As a result, focal firms become more willing to offer extended payment periods and raise trade credit limits, with the effect of MPD becoming weaker.

Third, DT enables focal firms to enhance operational efficiency and reduce both internal coordination costs and external financing frictions (Zhu and Yu, 2024), thereby enabling them to offer more flexible trade credit, such as extended payment terms and increased credit limits, to customers with lower risk. By digitizing and automating procurement, payment, and transaction processes, DT helps reduce administrative burdens and mitigate inefficiencies arising from market power asymmetry (Abou-foul, Ruiz-Alba and Soares, 2021). In parallel, DT improves credit assessment accuracy and lowers financing costs by facilitating better access to diverse financing channels, such as e-payments, digital factoring, and supply chain finance platforms (Murfin and Njoroge, 2015; Zhang, Liu, Li and Xing, 2023). These improvements enable focal firms to allocate more capital to trade credit expansion and customize credit terms for customers with varying market power, accompanied by a weakening effect of MPD. Through digitalization, focal firms benefit from more financing options, lower financing costs, and better payment terms and credit conditions for influential customers (Guo et al., 2022; Zhang, Liu, Li and Xing, 2023), facilitating easier access to capital and enhancing the willingness of focal firms to extend trade credit.

Motivated by the discussions above, we hypothesize that DT moderates the relationship between CMPD and trade credit by strengthening credit risk management, enhancing logistics visibility, improving operational efficiency, and reducing financing and coordination costs. These mechanisms mitigate the negative effect of CMPD on trade credit. Given the evidence documented in the literature to support each channel, our hypothesis is developed to test the overall effect. We do not argue that one single mechanism dominates the empirical relationship.

H4: The negative effect of CMPD on trade credit is weakened by a firm's DT.

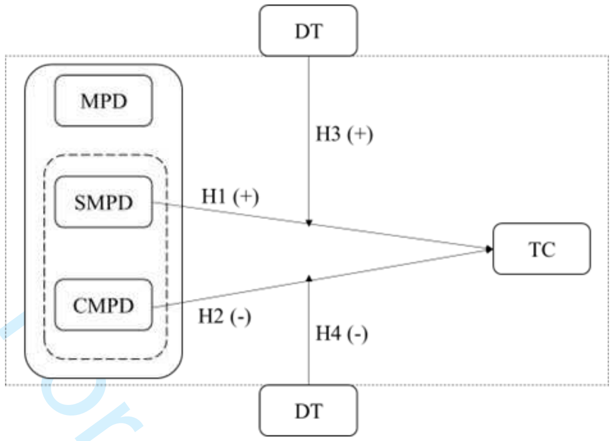

Figure 1 Theoretical framework

3 Methodology

3.1 Research design and data collection

To examine the impact of MPD on firms' trade credit and the moderating role of digital transformation (DT), we use three main variables: MPD, including both SMPD and CMPD; trade credit scales (TC); and digital transformation (DT). The study utilizes a panel data model to test the proposed hypotheses. We address potential endogeneity concerns by estimating a two-way fixed effects model that controls for both firm and year fixed effects, with heteroskedasticity-consistent standard errors clustered at the firm level to account for within-firm correlations in standard errors.

We source our data from the China Stock Market & Accounting Research (CSMAR) Database[3] and the Chinese Research Data Services Platform[4], as well as supplier-firm matched

[3] https://data.csmar.com
[4] https://www.cnrds.com

data from annual reports and interim announcements of listed companies. Following Yang et al (2023), the DT metrics are manually constructed through textual analysis of firms' annual reports (2011-2022) using natural language processing (NLP) techniques. In recent years, China has rapidly advanced digitalization through policy support and internet-driven strategies. Given that DT was first formally proposed by IBM in 2012[5], our analysis utilizes firm-level panel data spanning from 2011 (the pre-policy baseline year) through 2022 to establish causal identification. In addition, to prevent abnormal data from interfering with the results and conclusion, we follow the literature (Zhou and Li, 2023) and conducted the following data processing: we remove special treatment (ST) firms and firms in the financial industry, as well as firms with missing major variables. Following Isaksson, Simeth and Seifert (2016),we construct observations of a focal firm-supplier/customer-year dataset, considering that a focal firm may have multiple suppliers or customers. Finally, we obtain a sample of 1,236 focal firm-supplier-year observations and 1,596 focal firm-customer-year observations.

The financial report data is collected from CSMAR. We use accounts payable and accounts receivable data to calculate trade credit received and trade credit provided, respectively. We use the price-cost margin (PCM) to calculate a firm's market power. We adjust the market power of each firm relative to the industry annual average.

3.2 Dependent variable

The main explained variable in this study is trade credit. When analysing, we split trade credit into two categories: received trade credit (RTC) and provided trade credit (PTC). We measure RTC as the ratio of accounts payable divided by its purchases in year t, following Murfin and

[5] https://www.ibm.com/cn-zh/topics/digital-transformation

Njoroge (2015), Wu, Muthuraman and Seshadri (2019), and Astvansh and Jindal (2022). Purchases are the cost of goods sold plus the change in inventory for firm i in year t. We measure PTC using the ratio of accounts receivable to sales, following Astvansh and Jindal (2022) and Gofman and Wu (2022). We calculate the two variables separately and then sum them to get the overall trade credit, following Ferrando and Mulier (2013). Eq. (1) below shows the calculation of TC:

$$TC_{i,t} = RTC_{i,t} + PTC_{i,t} = \frac{account\ payable_{i,t}}{purchases_{i,t}} + \frac{account\ receivable_{i,t}}{sales_{i,t}} \tag{1}$$

3.3 Independent variables

The main explanatory variable in this study is the discrepancy of market power between the focal firm and its supply chain partners. We follow the existing studies (e.g., Gaspar and Massa, 2006; Chortareas, Noikokyris and Rakeeb, 2021; Rahaman, Zhang and Feng, 2022; Gu et al., 2024) and measure market power using the PCM. Eq. (2) below shows the calculation of the PCM:

$$PCM_{i,t} = \frac{Sales_{i,t} - COGS_{i,t}}{Sales_{i,t}} \qquad (2),$$

where $COGS_{i,t}$ represents the cost of goods sold by firm *i* in year *t*. A higher value of PCM represents greater market power. To account for industry heterogeneity, we standardize each value of PCM by subtracting the weighted average PCM for a specific industry year. This adjustment helps eliminate the bias caused by variation at the industry-year levels. We then calculate SMPD and CMPD using the focal firm's PCM minus the supplier and customer's PCM, respectively:

$$SMPD = PCM_{i,t} - PCM_{i,s,t} \tag{3}$$

$$CMPD = PCM_{i,t} - PCM_{i,c,t} \qquad (4),$$

where $PCM_{i,t}$ represents the (industry-adjusted) PCM of focal firm i in year t. $PCM_{i,s,t}$ represents the PCM of the focal firm's supplier (s) in year t. $PCM_{i,c,t}$ represents the PCM of the focal firm's customer (c) in year t. The MPD reflects the difference in market power between the two parties.

3.4 Moderating variable

The moderating variable is DT. We follow Yang et al (2023) and use textual analysis method to construct measures of DT. This measure captures DT because the frequency of DT-related terms in annual reports reflects the extent of digital technology adoption. It is reliable as it is based on regulated, publicly disclosed documents and follows a consistent, replicable procedure validated in prior research (Zhou and Li, 2023).

The data for DT calculation is sourced from the annual reports of firms spanning from 2011 to 2022. These annual reports are procured from the China Securities Regulatory Commission-designated China Information Network[6], which serves as a primary information source for Chinese listed companies. The annual report provides a comprehensive overview of the firm's operations throughout a given year. We perform a Computer-Aided Textual Analysis (CATA) of companies' annual reports using a customized Chinese dictionary containing digital transformation keywords based on national policy documents and academic literature. We obtain the keywords of the focal firm's DT to form the phrase dictionary, and conduct statistics on each digital technology to calculate the DT. We divide these words into eleven categories and calculate the DT, following Yang et al. (2023).The specific process can be divided into the following steps:

[6] cninfo.com.cn

First, we collect the annual reports of all A-share companies listed on the Shanghai and Shenzhen Stock Exchanges, using Python web scraping functionality. Then, we utilize the Java PDFbox library to extract all textual content, forming a data pool for subsequent feature word selection. The most popular keywords include artificial intelligence, machine learning, deep learning, virtual reality, big data, intelligent data analysis, blockchain, cloud computing, distributed computing, graph computing, stream computing, data visualization, fintech, mobile payment, ERP systems, supplier portals, intelligent robotics, Internet of Things, and e-commerce.

Second, we identify and treat digital technology-related phrases as recording units. In the selection of phrases related to DT, we engage in discussions based on both academic and policy domains. In the academic domain, we draw insights from the literature (e.g., Hickman et al., 2022; Hossnofsky and Junge, 2019; Knudsen et al., 2021; Ricci et al., 2020; Verhoef et al., 2021). In the policy domain, we refer to the 'Special Action Plan for Empowering Digitalization of SMEs[7]', the '2020 Digital Transformation Trend Report[8]', and recent 'Government Work Reports[9]', which serve as the foundation for compiling a specific DT-related keyword dictionary.[10]. These policies act as catalytic drivers for DT, providing both institutional frameworks and financial incentives for firm-level adoption. We construct the dictionary of DT by expanding the vocabulary using Python's jieba library, removing stop words, and counting the frequency of different digital transformation terms appearing in the full text of annual reports.

[7] https://www.gov.cn/zhengce/zhengceku/202412/content_6992542.htm
[8] https://www.gov.cn/xinwen/2021-07/03/content_5622668.htm
[9] Government Work Reports are official annual policy documents delivered by the Chinese Premier at the National People's Congress, outlining the government's economic, social, and policy priorities for the coming year.
[10] https://www.gov.cn/xinwen/2021-07/03/content_5622668.htm

Third, we utilize NLP methods to categorize the keywords and cluster the phrases in the dictionary, thereby identifying eleven dimensions of digital technology. Specifically, the keywords fall into the following eleven categories: artificial intelligence, augmented reality, big data analytics, blockchain, cloud computing, digital twin, fintech, identification technology, the internet of Things, robotics and digital technology application technology.

Then, the frequency of each digital technology is counted to establish an index system for firm DT. Specifically, we adopt widely used digital transformation feature terms and structured classifications in China, summing up the total frequency of key terms. To avoid losing firm-year observations with zero values, the natural logarithm is taken after adding 1 to the actual values, following Zhang, Liu, Li and Xing (2023).

Finally, we calculate the DT of each firm based on the phrase count in CATA and the number of digital technology categories. Building upon prior studies, for instance, Sousa-Zomer, Neely and Martinez (2020) employing the word count of digital technology terms as a metric, and Chen and Srinivasan (2023) utilizing the frequency of digital technology as a measurement indicator, we adopt a similar approach to construct our DT measure. We draw on Yang et al (2023) to measure DT as the ratio of the sum of digital technology phrases adopted by firms to the types of digital technologies adopted by firms. This measure reflects a firm's level of commitment to each category of digital technology. Specifically, the DT of firm i in year t is expressed by the following formula:

$$DT_{i,t} = \sum_k n_{i,k,t} / \sum_k DT_{i,k,t} \qquad (5),$$

where $DT_{i,k,t}$=1 if the k-th category of DT is mentioned at least once in the annual report of firm i at year t, and 0 otherwise. $n_{i,k,t}$ represents the number of times the *k*-th relevant phrase appears in firm i 's annual report for year t.

We use $DT\_Intensity_{i,t}$ as the second metric for DT, which is derived from the breakdown of intangible assets disclosed in the notes to firms' financial statements, following the literature (Sousa-Zomer, Neely and Martinez, 2020; Zhang and Zhao, 2023; Li and Zhao, 2024; Gu et al., 2025). Specifically, we identify line-items that contain keywords that we use to construct the DT measure, and classify them as digital-technology intangible assets. For each firm–year observation, the book values of all such assets are aggregated and then divided by the firm's total intangible assets; the resulting ratio serves as an alternative proxy for the DT. To ensure measurement accuracy, every identified item is manually cross-checked. The DT intensity metric is computed as:

$$DT\_Intensity_{i,t} = \sum\nolimits_{n=1}^{N} Digital\_Assets_{i,t,n} \big/ Total\_Intangibles_{i,t} \qquad (6).$$

3.5 Control variables

Following prior literature (Gu et al., 2024; Ricci et al., 2020; Yang et al., 2023; Zhang, Liu, Li and Xing, 2023), this study includes a set of control variables that may impact a firm's use of trade credit. These control variables include firm age (Age), firm size (Size), growth rate of main business income (Growth), net cash flow per share (CFPS), book-to-market ratio (BM), return on assets (ROA), number of board members (Board), cash holdings ratio (CHR), debt ratio (DR) and the number of independent directors (IDN). All continuous variables are winsorized at the 1st and 99th percentiles to reduce the impact of outliers.

Table 1 Variables and its descriptions.

Variable	Symbol	Type	Measurement
Trade credit	TC	Dependent	$TC = \frac{account\ payable_{i,t}}{purchases_{i,t}} + \frac{account\ receivable_{i,t}}{sales_{i,t}}$

Received trade credit	RTC	Dependent	$RTC = \frac{account\ payable_{i,t}}{purchases_{i,t}}$
Provided trade credit	PTC	Dependent	$PTC = \frac{account\ receivable_{i,t}}{sales_{i,t}}$
Market power discrepancy	MPD	Independent	The difference between the PCM of the two companies
Price-cost margin	PCM	Independent	$PCM_{i,t} = \frac{Sales_{i,t} - COGS_{i,t}}{Sales_{i,t}}$
Digital Transformatio	DT	Moderator	$DT_{i,t} = \sum_k n_{i,k,t} / \sum_k DT_{i,k,t}$
DT intensity	DT_intensity	Moderator	$DT\_Intensity_{i,t} = \sum Digital\_Assets_{i,t} / Total\_Intangibles_{i,t}$
Firm size	Size	Control	The natural logarithm of total assets
Firm age	Age	Control	Logarithm of the number of years since the firm was founded
Sales growth rate	Growth	Control	(Sales in year *t* minus Sales in year *t-1*) divided by Sales in year *t-1*
Return on Assets	ROA	Control	Net income/ Total assets
Net cash flow	CFPS	Control	The net cash flow generated from operating
Book-to-market ratio	BM	Control	The ratio of book value to total market value
Number of board members	Board	Control	The natural logarithm of board size
Cash holdings ratio	CHR	Control	Cash and cash equivalents /total assets
Debt ratio	DR	Control	Total liabilities/total assets
Independent Director Number	IDN	Control	Number of independent directors
Markup	Markup	Independent	$Markup_{i,t} = \frac{Sales_{i,t}}{Sales_{i,t} - EBIT_{i,t}}$

4 Results

4.1 Descriptive statistics and collinearity test

The descriptive statistics of the variables are presented in Table 2. The mean value of TC is 2.161, and the median is 0.776. The standard deviation is 10.55, showing that the volatility of TC is large. RTC has a mean value of 1.885, a median value of 0.453 and a standard deviation of 10.52. This shows that the instability of TC mainly results from RTC. The mean value of PTC is 0.267, showing that the firm's accounts receivable accounts for, on average, 26.7% of total revenue. The average PCM after adjusting for the industry annual average is negative, showing that the average firm's net profit margin is below zero. This negative figure indicates that the average firm is having a loss, indicating challenges in pricing, cost control, and market competition. The average value of SMPD is 0.248, with a standard deviation of 9.492, showing that the market power of an average focal firm is greater than its suppliers. Similarly, the average value of CMPD is 2.056, with a standard deviation of 38.48, indicating a large dispersion. The mean value of DT is 2.745, and the standard deviation is 6.319. The large value of standard deviation reveals the dramatic difference in DT across firms. Due to significant differences in starting points among firms, as well as varying needs and strategic plans, some firms have undertaken multiple advanced digital transformation initiatives, while others with weak foundations have not yet started their DT processes. This fact leads to substantial disparities in DT across firms and explains the large standard deviation. The mean value of DT_intensity is 0.075, and the standard deviation is 0.134. The DT_intensity variable seems to be less influenced by outliers than the DT variable.

Table 2 Descriptive statistics

Variable	N	Mean	SD	99%	Median	1%
TC	5,447	2.161	10.55	63.65	0.776	-40.69
RTC	5,447	1.885	10.52	63.54	0.453	-40.69
PTC	5,436	0.267	0.295	7.528	0.196	0
PCM	5,189	-0.107	38.50	166.2	0.008	-921.7
SMPD	1,236	0.248	9.492	166.1	-0.004	-166.2
CMPD	1,596	2.056	38.48	921.4	0.013	-920.7
DT	5,447	2.745	6.319	101.8	1.000	0

DT_intensity	4,037	0.075	0.134	0.500	0.019	0
Age	5,447	9.148	8.229	31.00	8.000	-5.000
Growth	5,447	0.414	8.294	461.0	0.107	-0.952
CFPS	5,447	0.212	1.443	37.13	0.016	-11.68
BM	5,447	0.587	0.310	1.430	0.636	0
ROA	5,447	0.022	0.572	1.207	0.038	-30.69
Size	5,447	21.78	1.701	28.50	21.71	0
Board	5,447	8.123	2.787	18.00	9.000	0
CHR	5,447	0.173	0.147	0.993	0.128	-0.165
DR	5,447	0.477	2.466	178.3	0.419	0.011
IDN	5,447	3.156	0.596	6.00	3.000	1.000
Smarkup	1,190	0.127	5.272	156.0	-0.008	-27.00
Cmarkup	1,553	0.390	9.373	316.3	0.012	-4.174
Loan	5,447	15.20	8.177	25.00	18.85	0
SM&A	4,627	0.087	0.432	3.385	0.016	0
CM&A	6,019	0.025	0.047	0.791	0.010	0

We perform the Pearson correlation analysis, and the results are displayed in Table 3. The correlation between the variables does not exceed 0.5, showing that there is no obvious collinearity problem between the variables. In Table 4, we report the variance inflation factor (VIF) for each variable. The mean value is 1.89, which is substantially lower than 10. Therefore, we can assume that there is no multicollinearity problem following Potter and Wilhelm (2020). Additionally, the low correlation between DT and DT_intensity indicates they evaluate DT from distinct perspectives.

Table 3 Correlation Analysis

	TC	SMPD	CMPD	DT	DT_intensity	Age	Growth	CFPS	BM	ROA	Size	DR	CHR	DR	IDN
TC	1														
SMPD	-0.008	1													
CMPD	0.008	0.473***	1												
DT	0.019	-0.004	-0.009	1											
DT_intensity	-0.008	-0.028	-0.020	0.310***	1										
Age	-0.009	0.0320	-0.028	-0.049***	-0.096***	1									
Growth	-0.005	-0.046	0.001	-0.007	0.006	0.027**	1								
CFPS	0.004	0.117***	0.026	0.041***	0.075***	-0.101***	0.015	1							
BM	0.006	0.034	0.010	-0.047***	-0.162***	0.293***	-0.022	0.015	1						
ROA	0.009	0.106***	0.083***	0.004	-0.01	-0.065***	0.005	0.021	0.020	1					
Size	-0.095***	0.011	0.001	0.017	-0.174***	0.446***	0.013	-0.023*	0.563***	0.040***	1				
Board	0.018	0.004	0.014	0.065***	-0.099***	0.358***	-0.010	-0.025*	0.457***	-0.022	0.451***	1			
CHR	-0.012	0.013	0.030	0.143***	0.210***	-0.270***	-0.011	0.371***	-0.088***	0.053***	-0.221***	-0.022	1		
DR	0.010	-0.022	-0.090***	-0.016	-0.006	0.063***	0.001	-0.011	-0.016	-0.068***	-0.020	0.010	-0.050***	1	
IDN	0.026*	0.038	-0.013	-0.016	-0.092***	0.161***	-0.026*	-0.031**	0.200***	0	0.272***	0.479***	-0.073***	0.009	1

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 Variance Inflation Factors Test

Variable	VIF	1/VIF
RTC	1.14	0.876
PTC	1.26	0.796
SMPD	1.52	0.658
CMPD	1.63	0.614
DT	1.38	0.727
DT_intensity	1.43	0.702
Age	1.56	0.641
Growth	1.17	0.857
CFPS	1.38	0.724
BM	1.50	0.667
ROA	1.41	0.711
Size	1.83	0.548
Board	4.50	0.222
CHR	1.74	0.574
DR	2.08	0.481
IDN	4.68	0.214
Mean VIF	1.89	

4.2 The effect of MPD on trade credit

To explore how the MPD, including both SMPD and CMPD, affects trade credit, we use an OLS model with firm and year fixed effects, and construct equation (7):

$$TC_{i,t} = \beta_0 + \beta_1 SMPD_{i,t} + \beta X_{i,t} + \text{Year}FixedEffect_t + FirmFixedEffect_i + \varepsilon_{i,t} \qquad (7),$$

where $TC_{i,t}$ represents the focal firm's trade credit in year t. $SMPD_{i,t}$ represents the difference in market power between firm i and its supplier in year t, $X_{i,t}$ includes all control variables defined in the previous section. $\varepsilon_{i,t}$ are error terms with mean zero and clustered at the firm level. To investigate the impact of CMPD, we replace $SMPD_{i,t}$ with $CMPD_{i,t}$ and construct equation (8):

$$TC_{i,t} = \beta_0 + \beta_1 CMPD_{i,t} + \beta X_{i,t} + \text{Year}FixedEffect_t + FirmFixedEffect_i + \varepsilon_{i,t} \qquad (8).$$

Table 5 presents the regression results of the baseline effects. In column (2), the coefficient of SMPD on TC is 0.021, statistically significant at the 5% level, indicating a positive correlation between trade credit scale and SMPD. This result supports Hypothesis

1, showing that an increase in SMPD is associated with more trade credits. Similarly, in column (3), the coefficient between the firm's trade credit and the CMPD is -0.045, statistically significant at the 10% level, indicating a negative correlation between trade credit scale and CMPD. This result supports Hypothesis 2, showing that an increase in CMPD is associated with fewer trade credits. Overall, the results in Table 2 demonstrate that market power discrepancy is correlated with trade credit scale.

Table 5 The effect of MPD on TC

	(1) TC	(2) TC	(3) TC
SMPD		0.021^{*}	
		(0.009)	
CMPD			-0.045^{+}
			(0.027)
Age	0.069	-0.068	0.032
	(0.109)	(0.201)	(0.020)
Growth	-0.001	-0.362	0.008
	(0.006)	(0.428)	(0.024)
CFPS	0.020	-0.107	0.020
	(0.109)	(0.276)	(0.015)
BM	0.747	3.630^{+}	-0.219
	(1.148)	(2.198)	(0.148)
ROA	0.568^{**}	-2.574	0.595^{*}
	(0.173)	(4.559)	(0.272)
Size	0.565	0.549	0.222^{+}
	(0.411)	(1.241)	(0.132)
Board	-0.134	-0.163	0.015
	(0.119)	(0.330)	(0.015)
CHR	-0.320	-2.959	-0.358
	(1.567)	(4.430)	(0.249)
DR	0.142^{***}	-2.410	0.155^{*}
	(0.014)	(5.309)	(0.073)
IDN	-0.122	2.040^{+}	-0.085
	(0.479)	(1.163)	(0.129)
Firm	Yes	Yes	Yes
Time	Yes	Yes	Yes
_cons	-9.941	-14.267	-4.014
	(8.445)	(24.865)	(2.828)

adj. R^2	0.01%	0.03%	7.6%

Note: N = 5,436 for all variables unless otherwise noted. SMPD = 1236, CMPD =1596. Heteroskedasticity-robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In a recent study, Fabbri and Klapper (2016) use survey data on small firms to demonstrate that customers with a large share influence focal firms' intentions to provide trade credit, but this finding has not yet been validated with data on large public corporations. Large firms, benefiting from scale, strong bargaining and pricing power, and diversified business channels, are expected to be more immune to the influence of their supply chain partners; thus, evidence based on small firms may not apply. Our study, using publicly listed corporations and an alternative measure for market power (i.e. MPD), demonstrates that market power remains highly relevant in determining trade credit policy even for large and established firms.

4.3 The moderating role of DT

With deeper digitalization, firms have stronger ability to obtain and analyse information. Improving organizational information processing capabilities can help companies improve operating efficiency, reduce operational risks and strengthen supply chain relationships. Following our hypotheses 3 and 4, we employ equations (9) and (10) below to test the moderating role of DT:

$$TC_{i,t} = \beta_0 + \beta_1 SMPD_{i,t} + \beta_2 DT_{i,t} + \beta_3 DT_{i,t} * SMPD_{i,t} + \beta X_{i,t} + \text{Year}FixedEffect_t + FirmFixedEffect_i + \varepsilon_{i,t} \quad (9)$$

$$TC_{i,t} = \beta_0 + \beta_1 CMPD_{i,t} + \beta_2 DT_{i,t} + \beta_3 DT_{i,t} * CMPD_{i,t} + \beta X_{i,t} + \text{Year}FixedEffect_t + FirmFixedEffect_i + \varepsilon_{i,t} \quad (10),$$

where, $DT_{i,t}$ captures the level of digitalization of firm i in year t. In column (1) of Table 6, we introduce the independent variable SMPD, the moderating variable DT, and the interaction term SMPD*DT. The coefficient of the interaction term SMPD*DT is 0.003, exhibiting a statistically significant effect at the 0.1% level. Its sign is positive, suggesting that DT moderates the relationship between trade credit and SMPD with a positive strengthening effect. This result supports our Hypothesis 3. On the customer side, in column (2) of Table 6, we introduce the independent variable CMPD, the moderator variable DT, and the interaction term CMPD*DT. The coefficient of the interaction term CMPD*DT is 0.067, significant at the 10% level. The sign of the interaction term is opposite to the baseline effect of CMPD on TC, suggesting that DT moderates the relationship between trade credit and CMPD with a weakening effect. This result supports our Hypothesis 4.

Table 6 The Moderating Role of DT

	(1) TC	(2) TC
SMPD	-0.070	
	(0.058)	
SMPD*DT	0.003^{***}	
	(0.000)	
CMPD		-0.104
		(0.120)
CMPD*DT		0.067^{+}
		(0.040)
DT	0.000	-0.005
	(0.009)	(0.004)
Age	-0.008	0.036^{+}
	(0.023)	(0.020)
Growth	-0.002	0.010
	(0.062)	(0.028)
CFPS	-0.012	0.037
	(0.018)	(0.027)
BM	0.182	-0.137
	(0.152)	(0.147)
ROA	-0.648	0.619^{*}
	(0.847)	(0.304)
Size	0.127	0.158
	(0.149)	(0.146)
Board	-0.014	0.014

	(0.017)	(0.015)
CHR	-0.092	-0.282
	(0.366)	(0.335)
DR	0.141	0.648^{+}
	(0.472)	(0.344)
IDN	0.186	-0.103
	(0.123)	(0.129)
Firm	Yes	Yes
Time	Yes	Yes
_cons	-2.331	-2.899
	(2.875)	(3.060)
adj. R^2	2.4%	8.5%

Note: N = 5,436 for all variables unless otherwise noted. SMPD = 1236, CMPD =1596.
Heteroskedasticity-robust standard errors (clustered at the firm level) are reported in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4 Robustness tests and endogeneity concerns

The relationship between trade credit and MPD may be plagued by the following endogeneity concerns. First, there is still controversy over the measurement of digitalization at the firm level. Second, the trade credit extended by firms may contribute to the enhancement of their market power, potentially influencing MPD, thereby raising concerns about a reverse causality or simultaneity. To address these endogeneity concerns and validate the robustness of our findings, we conduct the following tests:

4.4.1 Replacing independent variables

We use Markup as an alternative measure to substitute the measure of the firm's market power as the independent variable. Markup is calculated as the ratio of the firm's sales to sales minus EBIT, following Koch et al. (2021). Its definition is shown in eq. (11) below:

$$Markup_{i,t} = \frac{Sales_{i,t}}{Sales_{i,t} - EBIT_{i,t}} \quad (11),$$

where $EBIT_{i,t}$ is the profit before interest and tax of firm i in year t. Markup is the ratio of sales revenue to the operating cost, then net of the industry annual average, which shows the market power of a firm. We then follow the same procedure for MPD to deduct supplier's (or customer's) Markup to calculate Smarkup and Cmarkup. In the regression, we use Smarkup to capture the market power difference between the focal firm and its suppliers, and Cmarkup to measure the market power difference between the focal firm and its customers. The regression results are shown in Table 7.

Using Markup to measure a firm's market power, we find that the findings in the previous sections continue to hold. Specifically, the coefficients of Smarkup on TC are positive and statistically significant at the 1% level. The coefficient of Cmarkup on TC remains negative and statistically significant at the 10% level. The coefficient of the interaction term Smarkup*DT is 0.009, exhibiting a statistically significant effect at the 5% level. These results indicate that our main findings are robust to using Markup as an alternative measure of market power.

Table 7 Regression results by changing explanatory variables

	(1) TC	(2) TC	(3) TC	(4) TC
Smarkup	1.697**	1.573*		
	(0.651)	(0.720)		
Smarkup*DT		0.009*		
		(0.004)		
Cmarkup			-0.003+	-0.004*
			(0.002)	(0.002)
Cmarkup*DT				0.008
				(0.042)
DT		-0.092		-0.003
		(0.177)		(0.006)
Age	-0.095	-0.137	0.032	0.037
	(0.186)	(0.221)	(0.020)	(0.023)
Growth	-0.337	1.299	0.008	0.006
	(0.422)	(1.581)	(0.024)	(0.025)
CFPS	-0.058	-0.336	0.019	0.033+

	(0.276)	(0.619)	(0.015)	(0.019)
BM	1.872	3.407+	-0.233	-0.274
	(1.747)	(1.869)	(0.149)	(0.178)
ROA	-0.644	-1.797	0.219	0.102
	(4.523)	(3.908)	(0.246)	(0.253)
Size	0.727	1.155	0.227+	0.231
	(1.171)	(1.571)	(0.131)	(0.161)
Board	-0.018	-0.195	0.015	0.011
	(0.322)	(0.346)	(0.015)	(0.017)
CHR	-3.286	-1.985	-0.349	-0.416
	(4.500)	(5.479)	(0.251)	(0.291)
DR	-2.489	-5.636	0.089	0.018
	(4.977)	(5.961)	(0.072)	(0.087)
IDN	1.545	1.607	-0.083	-0.134
	(1.166)	(1.516)	(0.129)	(0.158)
Firm	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
_cons	-16.727	-24.447	-4.073	-3.925
	(23.453)	(32.369)	(2.821)	(3.433)
N	1190	1054	1444	1154
adj. R2	0.008%	0.123%	8.110%	11.605%

Note: N = 5,436 for all variables unless otherwise noted. Smarkup =1190, Cmarkup =1553. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We lag the independent variables by one period to reduce the concern of simultaneity. The regression results in Table 8 show that the coefficients of lagged SMPD and CMPD remain statistically significant and economically meaningful. The robustness of the results has been verified.

Table 8 Lagging variable regression results

	(1)	(2)	(3)	(4)
	TC	TC	TC	TC
L.SMPD	28.691*	22.850+		
	(13.654)	(13.285)		
L.SMPD*L.DT		4.066**		
		(1.320)		
L.CMPD			-17.013*	-16.978+
			(8.251)	(9.583)
L.CMPD*L.DT				-0.029
				(0.453)

L.DT		0.042		-0.079
		(0.163)		(0.099)
L.Age	-0.093	-0.090	0.272	0.299
	(0.233)	(0.242)	(0.240)	(0.247)
L.Growth	2.568***	2.571***	-1.417	-1.391
	(0.401)	(0.387)	(1.085)	(1.064)
L.CFPS	-0.081	-0.075	-0.129	-0.126
	(0.184)	(0.186)	(0.259)	(0.254)
L.BM	-8.879+	-8.986+	-0.580	-0.501
	(5.023)	(4.974)	(1.905)	(1.941)
L.ROA	-3.889	-3.744	2.354	2.443
	(12.784)	(12.775)	(3.413)	(3.399)
L.Size	-0.256	-0.233	-0.389	-0.376
	(0.254)	(0.258)	(0.273)	(0.270)
L.Board	0.138	0.147	0.125	0.154
	(0.229)	(0.236)	(0.245)	(0.247)
L.CHR	2.268	1.487	0.085	-0.761
	(5.779)	(5.898)	(4.326)	(4.371)
L.DR	-7.475	-7.513	0.423	0.762
	(6.935)	(6.975)	(4.388)	(4.539)
L.IDN	-3.356**	-3.372**	0.749	0.747
	(1.260)	(1.259)	(1.795)	(1.808)
_cons	26.670**	26.243**	3.070	2.453
	(9.506)	(9.710)	(7.837)	(8.014)
adj. R2	10.70%	10.97%	2.064%	1.942%

Note: N = 5,436 for all variables unless otherwise noted. L.SMPD =686, L.CMPD =979. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.4.2 Replacing moderating variables

To ensure the robustness of the empirical results, we replace the original measurement of DT with a dummy variable approach. This dummy variable has a value of 1 for the firms exhibiting significant DT efforts, and 0 otherwise. Following Chen and Srinivasan (2024), we treat the firm as “exhibit significant DT effects” if they are more engaged in DT than the industry annual average, to control for industry heterogeneity in DT. By applying this alternative measure, we re-run the regression analyse to test the moderating effect of DT. The results reaffirmed our main findings, demonstrating that using a binary measure of DT does not substantially alter the relationship. The regression results in columns (1) and (2) of Table 9, show that the coefficient of the interaction term SMPD*DT_dummy is 0.288, which is significantly positive at the 10% level, and that the coefficient of the interaction term CMPD*DT_dummy is 14.212, which is significantly positive at the 5% level. The moderating effects of DT remain consistent, confirming that the influence of DT, whether measured as a continuous variable or as a binary variable, robustly supports our Hypotheses H3 and H4.

We also use DT_intensity, the ratio of digital intangible assets, as an alternative measure of firm digitalization to check the robustness of our main finding. The results in columns (3) and (4) of Table 9 show that our finding, the moderating role of DT, remains robust. Specifically, in column (3), the interaction between SMPD and DT_intensity has a coefficient of 0.416, which is statistically significant at the 0.1% level, indicating that DT_intensity amplifies the positive association between SMPD and trade credit. This finding is consistent with those based on the DT proxy and lends further support to Hypothesis H3. Likewise, the interaction between CMPD and DT_intensity has a coefficient of 0.724, which is statistically significant at the 10% level, implying that DT attenuates the negative relationship between CMPD and trade credit. This result also mirrors the result based on DT, thereby corroborating Hypothesis H4.

Table 9 Regression results by changing DT variables

	(1)	(2)	(3)	(4)
	TC	TC	TC	TC
SMPD	-0.208		-0.060	
	(0.136)		(0.094)	
CMPD		-2.211		-0.097
		(4.372)		(0.181)

SMPD*DT_intensity			0.416***	
			(0.084)	
CMPD*DT_intensity				0.724+
				(0.430)
SMPD*1.DT_dummy	0.288^{+}			
	(0.149)			
CMPD*1.DT_dummy		14.212*		
		(6.198)		
DT_intensity			-0.231	0.686+
			(0.816)	(0.374)
1.DT_dummy	-0.193**	-1.965		
	(0.067)	(1.344)		
Age	0.004	-0.116	-0.039	0.018
	(0.021)	(0.175)	(0.028)	(0.024)
Growth	-0.018	-0.374	0.075	-0.014
	(0.065)	(0.424)	(0.088)	(0.019)
CFPS	-0.012	-0.078	0.009	0.036
	(0.018)	(0.275)	(0.016)	(0.026)
BM	0.169	2.091	0.050	-0.258
	(0.147)	(1.759)	(0.274)	(0.238)
ROA	-0.698	-2.185	-0.293	-0.016
	(0.800)	(4.499)	(0.796)	(0.602)
Size	0.116	0.630	0.353+	0.359*
	(0.125)	(1.181)	(0.192)	(0.150)
Board	-0.005	-0.062	0.086+	0.090
	(0.016)	(0.359)	(0.049)	(0.063)
CHR	-0.064	-4.091	-0.551	-0.539
	(0.337)	(4.503)	(0.434)	(0.468)
DR	0.182	-2.159	-0.094	0.404
	(0.419)	(4.961)	(0.633)	(0.435)
IDN	0.162	1.560	0.092	-0.188
	(0.120)	(1.192)	(0.265)	(0.274)
_cons	-2.070	-13.639	-7.252+	-7.232*
	(2.389)	(23.328)	(3.711)	(3.291)
adj. R^2	3.5%	0.4%	6.2%	10.9%

Note: N = 5,436 for all variables unless otherwise noted. SMPD = 1236, CMPD =1596. Heteroskedasticity-robust standard errors (clustered at the firm level) are reported in parentheses.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4.3 Instrumental variable

Due to the potential reverse causality between MPD and TC, an OLS estimation may lead to biased estimates. Specifically, we use the instrumental variable (IV) method to address the endogeneity concern. This approach leverages the exogenous nature of Mergers and Acquisitions (M&As) in upstream and downstream sectors—focal firms typically lack the market power to influence consolidation trends among their supply chain partners' industries, satisfying the exclusion restriction for causal identification (Chen et al., 2025).

Specifically, we use the M&As occurring in the suppliers or customers' industries as an instrumental variable, following Chen et al.(2025). To construct this instrumental variable, we obtain data on firm's M&As from the CNRDS database. We measure the five-year average industry-level M&As intensity as the average M&As intensity of an industry over the past five years, where M&As intensity is calculated as the M&As expenses divided by the firm's total sales revenue in a given year. Finally, for firm i (and its major suppliers j and customers k) in year t, supplier industry M&As (SM&A) is defined as the weighted sum of the five-year M&As intensities of the industries to which its major suppliers belong, weighted by the percentage of the firm's procurement amount from each major supplier. Similarly, customer industry M&As (CM&A) is the weighted sum of the five-year M&As intensities of the industries to which its major customers belong, weighted by the percentage of the firm's sales to each major customer. The variables are defined as follows:

$$SM\&A_{\mathrm{i,t}} = \sum_{j=1}^{n} \%Sales_{ijt} \times Industry\_average\left(\frac{M\&A\cos ts}{Sales}\right)_{jt} \tag{12}$$

$$CM\&A_{\mathrm{i,t}} = \sum_{\mathrm{k}=1}^{n} \%Sales_{ikt} \times Industry\_average\left(\frac{M\&A\cos ts}{Sales}\right)_{kt} \tag{13}$$

We use SM&A and CM&A as instrumental variables for SMPD and CMPD, respectively. Table 10 presents both the first-stage regression results and the outcomes of the second-stage regression. The first-stage F-statistics in columns (1), (2), (4) and (5) are greater than 10, indicating a strong correlation between the instrumental variables and the endogenous regressors. In the 2nd stage regressions (column 3), DT*SMPD is positive and statistically significant, showing that DT strengthens the relationship between SMPD and TC. In column (6), DT*CMPD is positive and statistically significant, showing that DT significantly weakens the relationship between CMPD and TC. These findings are consistent with our Hypotheses 3&4, showing that our main findings are robust to using an IV approach to address the endogeneity concern. Similarly, in Table 11, we use SM&A and CM&A as instrumental variables for SMPD and CMPD, respectively, and use DT_intensity to measure digitalization. Our base results continue to hold.

Table10 IV (DT) Regression Results

	First stage	First stage	Second stage	First stage	First stage	Second stage
	SMPD	SMPD*DT	TC	CMPD	CMPD*DT	TC
SM&A	-0.573***	0.093**				
	(0.103)	(0.031)				
SM&A*DT	-0.187**	-0.029**				
	(0.070)	(0.010)				
SMPD			4.148***			
			(0.728)			
SMPD*DT			0.647*			
			(0.308)			
CM&A				-0.292***	0.725***	
				(0.066)	(0.169)	
CM&A*DT				0.247***	-0.059***	
				(0.052)	(0.015)	
CMPD						-5.567+
						(2.903)
CMPD*DT						0.935+
						(0.541)
DT	-0.001***	0.009***	-0.003	0.001**	0.004**	-0.010*
	(0.000)	(0.001)	(0.005)	(0.000)	(0.001)	(0.005)
Age	0.001+	0.002***	-0.016***	0.001***	0.002	0.009
	(0.000)	(0.000)	(0.004)	(0.000)	(0.001)	(0.006)
Growth	-0.014***	0.007***	0.048	-0.011***	-0.002***	-0.014
	(0.002)	(0.001)	(0.044)	(0.002)	(0.001)	(0.033)
CFPS	-0.019***	-0.008+	0.078***	-0.006***	0.018*	-0.032
	(0.003)	(0.004)	(0.023)	(0.001)	(0.009)	(0.023)
BM	0.041***	-0.013	-0.423***	-0.082***	-0.087+	-0.771***

	(0.010)	(0.014)	(0.091)	(0.010)	(0.048)	(0.214)
ROA	-2.000***	-0.082+	6.278***	-1.181***	-0.016*	-6.840*
	(0.166)	(0.043)	(1.441)	(0.120)	(0.008)	(3.304)
Size	-0.030***	0.006+	0.181***	-0.012***	0.042***	0.166***
	(0.003)	(0.004)	(0.030)	(0.003)	(0.008)	(0.038)
Board	-0.029***	0.022***	0.102**	-0.001	0.001	-0.061
	(0.003)	(0.003)	(0.035)	(0.002)	(0.007)	(0.038)
CHR	0.043	0.017	-0.059	0.083***	-0.251*	-0.553
	(0.035)	(0.034)	(0.207)	(0.025)	(0.101)	(0.354)
DR	0.027	-0.180***	0.431+	0.222***	-0.000	-0.768
	(0.018)	(0.023)	(0.237)	(0.020)	(0.001)	(0.909)
IDN	0.087***	-0.013	-0.200*	-0.032***	-0.160***	0.364
	(0.008)	(0.008)	(0.088)	(0.005)	(0.019)	(0.237)
_cons	0.690***	-0.247***	-3.256***	0.342***	-0.489**	-1.935*
	(0.055)	(0.071)	(0.673)	(0.048)	(0.155)	(0.792)
First-stage F	64.56	22.85		66.81	17.18	
adj. R^2	0.361	0.060	-0.527	0.360	0.013	-3.340

Note: N = 5,436 for all variables unless otherwise noted. SMPD =1236, CMPD =1596. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table11 IV (DT_intensity) Regression Results

	First stage	First stage	Second stage	First stage	First stage	Second stage
	SMPD	SMPD*DT_ intensity	TC	CMPD	CMPD*DT_ intensity	TC
SM&A	-1.094***	0.001**				
	(0.190)	(0.000)				
SM&A*DT_ intensity	2.607**	-0.191***				
	(0.852)	(0.032)				
SMPD			5.107***			
			(1.276)			
SMPD*DT_ intensity			18.411*			
			(7.367)			
CM&A				-0.572***	0.011	
				(0.107)	(0.011)	
CM&A*DT _intensity				0.994***	0.264***	
				(0.215)	(0.080)	
CMPD						-2.758***
						(0.795)
CMPD*DT_ intensity						6.920+
						(4.040)
DT_intensity	0.016	0.005***	-0.015	-0.024+	-0.081***	-0.053
	(0.017)	(0.001)	(0.165)	(0.014)	(0.010)	(0.438)

Age	-0.002***	0.000	0.004	0.002***	0.000	-0.004
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.005)
Growth	0.006***	0.001***	0.105*	0.002**	-0.000+	-0.069**
	(0.001)	(0.000)	(0.043)	(0.001)	(0.000)	(0.025)
CFPS	-0.004*	-0.000*	-0.018	-0.002*	0.002**	-0.027+
	(0.002)	(0.000)	(0.018)	(0.001)	(0.001)	(0.015)
BM	-0.015	0.001*	0.002	0.004	0.013***	-0.379***
	(0.011)	(0.000)	(0.097)	(0.010)	(0.003)	(0.078)
ROA	-0.094***	0.003***	1.496***	-0.065***	0.183***	0.212+
	(0.019)	(0.001)	(0.202)	(0.009)	(0.004)	(0.128)
Size	0.010***	0.000	-0.101**	0.003	-0.009***	0.113***
	(0.002)	(0.000)	(0.032)	(0.003)	(0.001)	(0.023)
Board	0.011***	0.000**	0.073***	-0.003+	0.001	-0.057***
	(0.002)	(0.000)	(0.018)	(0.002)	(0.001)	(0.014)
CHR	0.105***	0.002*	-1.301***	-0.027	-0.033**	0.106
	(0.018)	(0.001)	(0.259)	(0.018)	(0.011)	(0.241)
DR	-0.051***	0.001	0.379**	-0.052***	0.027***	1.050**
	(0.013)	(0.000)	(0.121)	(0.009)	(0.001)	(0.390)
IDN	-0.049***	-0.001***	0.013	0.015**	0.015***	-0.187
	(0.009)	(0.000)	(0.074)	(0.005)	(0.002)	(0.120)
_cons	-0.160**	0.000	2.690***	-0.118*	0.142***	-0.880*
	(0.049)	(0.002)	(0.641)	(0.054)	(0.012)	(0.442)
First-stage F	15.83	21.36		12.69	225.63	
adj. R^2	0.058	0.022	-0.432	0.046	0.234	-5.070

Note: N = 5,436 for all variables unless otherwise noted. SMPD =1236, CMPD =1596. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.5 Heterogeneity analysis

We conduct heterogeneity analysis from the direction of trade credit. The results are presented in Tables 12. We divide trade credit into two categories: RTC and PTC. The regression results reveal a significant relationship between these types of trade credit and MPD between firms and their supply chain partners. Specifically, the column (1) of Table 12 shows that the SMPD is positively associated with RTC, indicating that firms with greater SMPD can obtain more trade credit from suppliers. This finding aligns with research suggesting that firms with stronger bargaining positions often leverage their power to negotiate favourable credit conditions (Petersen and Rajan, 1997; Fabbri and Klapper, 2016). The effect is enhanced by DT, which are consistent with our Hypotheses 3. Conversely, the CMPD shows a negative association with trade credit provided in column (4), suggesting that when focal firms hold great market power, it tends to reduce the amount of trade credit they extend to their customers. Such dynamics highlight the challenges that arise in power-dominant supply chains, which obtain more power can dictate financial terms favourable to the firm (Nair, Narasimhan and Bendoly, 2011; Fabbri and Klapper, 2016).

The heterogeneity analysis underscores the complex nature of trade credit practices and how they are influenced by the distribution of market power within supply chains. This dual perspective adds depth to the understanding of supply chain financial interactions and aligns with recent literature emphasizing power asymmetries in supply chain management (Astvansh and Jindal, 2022; Rahaman, Zhang and Feng, 2022).

Table 12 The heterogeneity results of different trade credit ways

	(1)	(2)	(3)	(4)
	RTC	RTC	PTC	PTC
SMPD	5.987^{+}		-0.151	
	(3.075)		(0.094)	
SMPD*DT	0.012***		-0.000	
	(0.003)		(0.000)	
CMPD		1.231		-0.134**
		(3.349)		(0.046)
CMPD*DT		0.023		0.000
		(0.022)		(0.000)
DT	-0.047	0.002	0.003	-0.001
	(0.114)	(0.040)	(0.002)	(0.001)
Age	-0.099	0.362*	0.003	0.002
	(0.197)	(0.146)	(0.006)	(0.003)
Growth	-0.365	0.330	-0.009^{+}	-0.010
	(0.429)	(0.485)	(0.005)	(0.011)
CFPS	-0.104	0.252	-0.019*	-0.006*
	(0.314)	(0.188)	(0.009)	(0.003)
BM	2.131	-0.477	0.039	0.064*

	(1.861)	(2.706)	(0.034)	(0.025)
ROA	9.843	2.075	0.176	0.019
	(9.343)	(3.300)	(0.189)	(0.030)
Size	0.943	1.006	0.004	0.013
	(1.428)	(0.772)	(0.046)	(0.020)
Board	-0.003	-0.166	0.003	0.004
	(0.353)	(0.227)	(0.005)	(0.003)
CHR	-3.657	-2.794	0.074	-0.089^{+}
	(5.066)	(3.251)	(0.104)	(0.053)
DR	-2.559	2.383	-0.049	-0.011
	(5.694)	(2.363)	(0.130)	(0.022)
IDN	1.742	-0.724	-0.024	0.000
	(1.268)	(1.030)	(0.029)	(0.014)
Firm	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
_cons	-22.801	-20.327	0.184	-0.085
	(28.935)	(15.952)	(0.932)	(0.426)
adj. R^2	-0.04%	1.6%	9.4%	8.7%

Note: N = 5,436 for all variables unless otherwise noted. SMPD =1236, CMPD =1596. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.6 Post-hoc analyses

Short-term loans refer to debt financing instruments maturing within one year, obtained from financial institutions such as banks or other credit providers. Short-term loans serve as a complementary financing method to trade credit (Afrifa et al., 2023). When firms seek financing, they utilize various channels to optimize their liquidity and financial structure. Both short-term loans and trade credit are forms of liquid capital financing used by firms to maintain their operating funds (Giannetti, Burkart and Ellingsen, 2011; Levine, Lin and Xie, 2018). Trade credit is usually provided by suppliers based on the trading relationship without needing additional collateral, while short-term loans are obtained from banks or other financial institutions, which may require collateral or other guarantees (Buch, Koch and Koetter, 2013; Chong, Lu and Ongena, 2013; Bertrand and Murro, 2022). Therefore, short-term loans can provide additional liquidity support when a firm's trade credit is insufficient, and vice versa. This complementarity may vary in different market environments, depending on factors such as the firm's market power, the strength of relationships with suppliers or customers, and the availability of bank credit.

Based on the findings that SMPD exhibits a positive correlation with trade credit while CMPD shows a negative correlation, and given that trade credit and short-term loans serve as complementary financing methods, the results for short-term loans should demonstrate an inverse pattern to those observed for trade credit. The results are shown in Table 13. In column (1), the coefficient of the firm's short-term loan on the SMPD is -2.411, significant at the 10% level, indicating a negative correlation between the firm's short-term loan and SMPD. Short-term loans, as a financing method, complement trade credit.

Table 13 Results of short-term loan.

	(1) Loan	(2) Loan	(3) Loan	(4) Loan
SMPD	-2.411+	-2.412+		
	(1.439)	(1.440)		
SMPD*DT		-0.001		
		(0.003)		
CMPD			-0.005	-0.001
			(0.004)	(0.001)
CMPD*DT				-0.018*
				(0.009)
Age	-0.192	-0.191	-0.092	-0.102
	(0.123)	(0.123)	(0.097)	(0.097)
Growth	-0.510	-0.509	-0.127	-0.134
	(0.454)	(0.454)	(0.247)	(0.246)
CFPS	0.340*	0.340*	0.277*	0.264*
	(0.132)	(0.133)	(0.107)	(0.107)
BM	2.702**	2.699**	-0.442	-0.545
	(0.922)	(0.922)	(1.005)	(1.013)
ROA	0.710	0.714	-0.960	-0.988
	(5.977)	(5.980)	(1.502)	(1.491)
Size	0.554***	0.555***	1.104***	1.100***
	(0.142)	(0.142)	(0.144)	(0.144)
Board	-0.102	-0.102	-0.126	-0.110

	(0.156)	(0.156)	(0.152)	(0.154)
CHR	-4.984	-4.985	-14.859***	-14.600***
	(4.462)	(4.463)	(2.736)	(2.739)
DR	13.828***	13.821***	1.364	1.323
	(3.488)	(3.488)	(0.964)	(0.958)
IDN	0.323	0.324	0.202	0.222
		(0.725)	(0.652)	(0.654)
Firm	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
_cons	-2.453	-2.459	-4.640	-4.594
	(4.502)	(4.509)	(3.515)	(3.496)
adj. R2	10.2%	10.1%	17.1%	17.5%

Note: N = 5,436 for all variables unless otherwise noted. SMPD =1236, CMPD =1596. Heteroskedasticity-consistent robust standard errors (clustered at the firm level) are reported in parentheses. $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

5 Discussion

5.1 Theoretical implications

First, our study advances the knowledge on trade credit financing by introducing the novel MPD perspective, integrating supply chain power theory with SCF research to reveal how market power asymmetries shape interfirm financing decisions. This research explores the disparity in market power between firms and their supply chain partners, enriching the understanding the impact of market power. Previous research on market power mainly focuses on the impact of firm's own performance (e.g., Dass, Kale and Nanda, 2015; Hossnofsky and Junge, 2019; De Loecker, Eeckhout and Unger, 2020; Rahaman, Zhang and Feng, 2022), whereas the impact of the market power discrepancy between supply chain partners remains underexplored, with an exception of Gu et al. (2024) who study the impact of MPD on firms' financial performance measured by the return on assets (ROA). Our research makes a distinction by examining separately the MPD between focal firms and their suppliers, as well as between focal firms and their customers, on the use of trade credit. Moreover, we calculate MPD as a directional difference rather than an absolute value, which allows for a more accurate representation of the directionality of market power within the supply chain. Our research contributes to the literature on supply chain power dynamics by distinguishing between SMPD and CMPD, and examining their differential effects on trade credit. By identifying the directionality of power asymmetry—rather than relying solely on absolute differences—we provide a more granular understanding of how power structures affect financial interactions among firms, which is often overlooked in existing studies.

Second, our study examines how the MPD between focal firms and their suppliers or customers influences the focal firm's use of trade credit, taking into account both trade credit provided and trade credit received. Unlike Fabbri and Klapper (2016) who investigate small firms and study how the customer's market share influences the supplier's willingness to provide trade credit (i.e., more likely to extend trade credit, have a larger share of goods sold on credit, and offer a longer payment period before imposing penalties), our study demonstrates that the effect of MPD is also significant for publicly listed companies. This finding is surprising, as traditional wisdom expects public firms to be less influenced by their supply chain partners due to their stronger financial resources and bargaining power. However, our results reveal that MPD remains highly relevant even among these large and established corporations. Since MPD serves as a critical criterion for assessing the attainment of collaboration by a firm (Gu et al., 2024), investigating the impact of MPD on a firm's trade credit within the supply chain is of paramount importance. Overall, this research addresses an existing gap in the literature and offers a novel avenue for future research.

Third, our study contributes to the growing literature on DT by serving as the first attempt to examine its moderating effect on the relationship between MPD and trade credit utilization within the context of SCF. By integrating DT into the power-credit framework, we offer a novel theoretical perspective on how digital capabilities can either amplify or mitigate the effects of power asymmetries, depending on the direction of MPD. This finding sheds new light on how technology adoption reshapes relational governance mechanisms, particularly in financing arrangements across supply chain partners. Furthermore, our research advances the emerging literature on digital SCF by deepening the understanding of how digital conditions interact with market power to influence trade credit decisions. While prior studies have predominantly explored the direct impact of DT on firm-level financial performance, our study fills a critical gap by highlighting its moderating role in the dynamics of supply chain power structures. The introduction of DT as a moderating variable reveals how technological advancements can shift the supply chain relationship and affect firms' access to trade credit, offering a more nuanced view of interfirm financial relationships. Given that trade credit plays an increasingly important role in firm financing activities (Bertrand and Murro, 2022; Gofman and Wu, 2022), our findings suggest that DT can relax the constraints on trade credit faced by disadvantaged firms due to excessive market power disparities. It can promote the diversification of financing channels for enterprises in the supply chain, improve the flow of information between companies to reduce information asymmetry, and enhance supply chain synergy.

5.2 Practical implications

The findings of this study offer practical insights for firms across the supply chain to leverage DT strategies under market power discrepancy.

First, this study provides practical insights into how DT can moderate the relationship between SMPD and trade credit. The finding that SMPD positively influences trade credit—and that this effect is strengthened by DT—suggests that firms can leverage their supply chain position to secure better financial terms. DT enhances this relationship by optimizing information, capital, and logistics flows. It strengthens focal firms' advantages in data access, financing, and logistics management, increasing the dependence of less powerful suppliers and thus encouraging them to extend more trade credit. At the same time, DT reduces information asymmetry, ensures more timely payments, and minimizes logistics disputes, further improving supplier trust and willingness to provide trade credit despite power imbalances. Moreover, DT often entails substantial investment costs for focal firms. Those powerful firms are able to shift part of these costs to upstream suppliers through contractual arrangements (i.e., trade credit). This finding provides practical implications for focal firms implementing DT. For firms, especially those in competitive and supplier-dependent industries, investing in DT initiatives can bolster their market influence and negotiation capabilities (Kamble, Gunasekaran and Sharma, 2020; Abou-foul, Ruiz-Alba and Soares, 2021). By adopting advanced digital tools such as data analytics, automated supply chain systems, and collaborative platforms, firms can improve their financial position and facilitate better trade credit arrangements. This strategy can create resilience within the supply chain and offer firms an edge in procurement and financing operations.

Second, this study examines the negative impact of CMPD on trade credit from the buyer market theory perspective and elaborates on how DT can weaken the relationship between them. DT enables firms to enhance operational efficiency, and reduce operational risks, thereby improving their overall competitiveness (Matarazzo et al., 2021; Chen and

Srinivasan, 2023). More importantly, the application of digital technologies helps core firms mitigate key risks associated with trade credit, such as credit risk and logistics risk, particularly when dealing with partners with asymmetric market power (Chod et al., 2020; Abou-foul, Ruiz-Alba and Soares, 2021). We show that, with improved transparency, real-time monitoring, and process automation, DT increases focal firms' confidence in extending trade credit to less powerful partners. This promotes more inclusive and stable financial relationships within the supply chain and supports the development of resilient, digitally empowered supply chain ecosystems. Firms dealing with more powerful customers can prioritize digital solutions to diversify their funding sources, enhance operational efficiency, and provide trade credit more securely to customers with asymmetric market power. This study provides practical insights for the development of digital supply chains, suggesting that firms can leverage technologies such as blockchain and big data to achieve end-to-end visibility and informed decision-making, thereby influencing resource allocation and cooperation within increasingly complex supply chain ecosystems.

Third, from the perspective of logistics management, this study highlights how DT can significantly enhance the efficiency, transparency, and reliability of logistics operations within supply chains. By adopting digital technologies such as IoT, blockchain, and real-time data sharing platforms, focal firms can improve the visibility of goods in transit, optimize inventory management, and reduce delivery uncertainties. These improvements not only strengthen trust between supply chain partners but also mitigate logistics-related risks that often hinder trade credit decisions. Particularly in cases of asymmetric market power, enhanced logistics transparency enables focal firms to foster more stable and cooperative relationships with suppliers and customers, thereby facilitating smoother trade credit transactions and improving overall supply chain resilience. These findings offer valuable guidance for supply chain managers, suggesting that strategic investment in logistics-focused digital tools can serve as a critical lever for reducing risk and enhancing financial collaboration across the supply chain.

6 Conclusions and limitations

This study delves into the effect of MPD on trade credit, and evaluates separately the focal-supplier relationship and the focal-customer relationship. We find that, when a focal firm has greater market power over its suppliers, it can secure more trade credit. DT enlarges this effect, implying that firms leveraging digital technologies can improve information transparency, optimize cash flows and payment management, enhance logistics management or shift the cost to the upstream, securing more trade credits from their suppliers. Conversely, when a focal firm holds greater market power over its customers, trade credit tends to decrease. DT weakens this effect, implying that firms can leverage digital technologies to promote communication and collaboration, reduce risks and operational costs, and improve operating efficiency, thereby increasing their willingness to extend trade credit to customers. Moreover, when focal firms possess less market power than their customers, DT can help mitigate the unbalanced trade credit constraints imposed by more dominant buyers. Firms can use digital tools to mitigate excessive trade credit demands from customers, thereby reducing their financial pressure.

Our study gives the following recommendations to future studies: First, we study the relationship between the focal firm and its suppliers (customers) without considering more complex situations. Supply chain relationships between firms could be more complex, including not only simple supplier-customer relationships but also multidimensional relationships (Mentzer et al., 2001). Future research can study the multidimensional relationships in the supply chain. For example, inter-firm investment and affiliation relationships could be taken into consideration. Second, the perspective of our research is firm-centred, and for supply chains, variables at the overall supply chain level (such as overall supply chain integration, coordination efficiency, or total network market power) also hold significant research value. We encourage future studies to account for these factors. Third, we observe a firm's trade credit from an overall perspective (i.e., scale). At present, there is a lack of a definitive measurement methodology and data availability for determining the proportion of trade credit extended by a specific supplier or customer to a firm. Future studies may provide new evidence by investigating this data, when it becomes available. We leave these points for future studies.

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Appendix

Referring to the classification of DT terms in the previous literature (Yang et al., 2023) and China's policy paper (page 9), we categorize the keywords of DT into the following 11 categories. We built a database for our variables by counting the frequency of each DT-related phrase in annual reports. Below are some examples of firms adopting digital technologies from their annual reports:

The 2019 Annual Report of ChangshanBeiming (000158) states: "The company's subsidiary, Beiming Software, is a comprehensive service provider offering next-generation IT technologies and solutions. It has distinctive strengths in various fields, including the construction of new smart cities, the online diversified resolution of social conflicts in the judicial sector, innovative social governance utilizing **big data**, **artificial intelligence**, and **blockchain** technologies, as well as intelligent management in multiple domains. The company is committed to leveraging next-generation technological means to support digital transformation across sectors and to build an information service system that connects everything and covers all aspects of society." (Page 9).

In its 2022 annual report, Yunding Technology (000409) stated that its information technology service business is primarily based on a self-developed industrial Internet platform. By leveraging **cloud computing**, **big data**, and **IoT** technologies, the company provides full-lifecycle services—including system development, design, implementation, operation, and maintenance—for the informatization, digitalization, and intelligent transformation of industries such as mining, chemicals, power, and new energy (Page 11).

In its 2022 annual report, Aerospace Development (000547) stated: "Committed to building a secure and efficient service system, focusing on areas such as cybersecurity, **big data** services, data protection and disaster recovery, graded protection evaluation, and e-government." (Page 11).

Table A1 Categories of digital technologies

Category	Keywords	Keywords in Chinese
Artificial intelligence	Artificial intelligence, AI， brain-inspired computing, cognitive computing, business intelligence, image understanding, investment decision aid systems, machine learning, deep learning, autonomous driving, natural language processing	人工智能、类脑计算、认知计算、商业智能、图像理解、投资决策辅助系统、机器学习、深度学习、自动驾驶、自然语言处理
Augmented reality	Augmented reality, mixed reality, virtual reality	增强现实、混合现实、虚拟现实
Big data analytics	Big data, data mining, intelligent data analysis, text mining, heterogeneous data, credit investigation	大数据、数据挖掘、智能数据分析、文本挖掘、异构数据、征信
Blockchain	blockchain, digital currency, secure multi-party computing, differential privacy technology, smart financial contracts	区块链、数字货币、多方安全计算、差分隐私技术、智能金融合约
Cloud computing	Cloud computing, distributed computing, graph computing, stream computing, memory computing, green computing, fusion architecture, 100 million level concurrency, EB level storage	云计算、分布式计算、图计算、流计算、内存计算、绿色计算、融合架构、亿级并发、EB级存储
Digital twin	Data visualization, information physical systems	数据可视化、信息物理系统
Fintech	Internet finance, digital finance, fintech, fintech, mobile payment, third party payment, NFC payment	互联网金融、数字金融、Fintech、金融科技、移动支付、第三方支付、NFC 支付
Identification technology	semantic recognition, biometrics, facial recognition, speech recognition, Authentication	语义搜索、生物识别技术、人脸识别、语音识别、身份验证
Internet of Things	Internet of Things, IoT	物联网
Robotics	Intelligent robotics	智能机器人
Digital technology	ERP systems, supplier portals，supply	ERP 系统、供应商门

application	chain management platforms, Mobile Internet, Industrial Internet, mobile Internet, Internet medical, e-commerce, intelligent energy, B2B, B2C, C2B, C2C, O2O, Internet connection, smart wear, smart agriculture, intelligent transportation, intelligent medical, intelligent customer service, Smart home, smart investment, smart travel, smart environmental protection, smart grid, smart marketing, digital marketing, unmanned retail, quantitative finance, open banking	户、供应链管理平台、移动互联网、工业互联网、移动互联、互联网医疗、电子商务、智能能源、B2B、B2C、C2B、C2C、O2O、网联、智能穿戴、智慧农业、智能交通、智能医疗、智能客服、智能家居、智能投顾、智能文旅、智能环保、智能电网、智能营销、数字营销、无人零售、量化金融、开放银行