Article:

Wang, L. orcid.org/0000-0001-6807-5496, Xu, Y. orcid.org/0000-0002-1076-6734, Wang, J.X. et al. (1 more author) (2025) Should mining enterprise adopt digital transformation for environmental performance? A supply chain power structure perspective. Business Strategy and the Environment, 34 (2). pp. 2469-2484. ISSN 0964-4733

https://doi.org/10.1002/bse.4102

Should mining enterprise adopt digital transformation for environmental performance? A supply chain power structure perspective

Journal:	*Business Strategy and the Environment*
Manuscript ID	BSE-24-4176.R2
Wiley - Manuscript type:	Research Article
Topic Area:	Supply chains and the environment
Keywords:	Supply chain management, Digital transformation, Environmental performance, Mining industry

Should mining enterprise adopt digital transformation for environmental performance? A supply chain power structure perspective

Abstract:

This research explores how digital transformation (DT) affects environmental performance (EP) in mining companies, considering supply chain power dynamics involving suppliers and retailers. We construct theoretical models to depict the game process of DT strategy of mining company under different supply chain power structure. We then validate our theoretical model through a sample of 1155 A-shared listed mining companies with complete financial data in China. Regression models with fixed effects are applied to estimate the potential parameters. The empirical findings are consistent with theoretical results, showing that DT improves the EP for mining companies. The EP is weaker when DT is treated at higher supplier and retailer concentration. This study can guide policy frameworks at COP28, promoting sustainable mining practices aligned with global climate goals.

Keywords: Supply chain management, Digital transformation, Environmental performance, Mining industry

1. Introduction

Addressing climate change is a key global challenge. The COP28 conference in Dubai was pivotal for the mining industry, with a "Mining Day" and the launch of the Global Roadmap for Sustainable Minerals. This emphasized the importance of responsible mining and digital technologies to improve environmental performance (EP), aligning with this study's focus on digital transformation (DT) and its impact on the mining supply chain. Examining the interplay of these elements under different power structures not only contributes to understanding the effectiveness of digital tools but also informs the implementation of COP28 commitments and shapes a sustainable future for the mining sector. These initiatives are aimed at diminishing the release of greenhouse gases and addressing the repercussions of climate change (Drent et al., 2023). Therefore, mining companies, like many other sectors, must play their part in mitigating environmental pollution and embracing sustainable practices (Liu et al., 2023; Xu et al., 2023; Bhling et al., 2019). In this context, as a high-polluting industry, it becomes imperative for mining companies to recognize and embrace the increasing political and societal awareness regarding environmental issues. Thus, they can not only fulfill their environmental responsibilities but also strengthen their business competitiveness. Implementing effective environmental protection strategies has become crucial for mining companies in optimizing their operations and expanding their impact.

The growing impact of environmental challenges on the economy and society has driven researchers across disciplines—including environmental science, atmospheric physics, economics, and social sciences—to focus on understanding and addressing environmental degradation. These scholars assess the current situation and develop strategies for green development, exploring areas such as collaborative green research and development (Chen et al., 2019), carbon capture and storage (Luo et al., 2016), and the effectiveness of policy interventions across local, national, and global levels (Fabrizi et al., 2018; Bird and Graham, 2016). Within this context, DT emerges as a key factor, enhancing enterprises' environmental protection capabilities. By promoting investment in innovative resources and reducing debt costs, DT supports the adoption of advanced pollution control measures across the production process for mining companies, from source to end (Charles et al., 2023). Thus, the evolving landscape of DT in mining companies plays a vital role in advancing environmental protection goals.

DT represents the comprehensive integration of digital technologies, strategies, and data-driven practices by businesses to drive efficiency, innovation, competitiveness, and adaptability in the digital age (Liu et al., 2023; Xu et al., 2023). Existing research indicates that firms adopting DT can achieve more efficient and environmentally responsible operations, resulting in reduced environmental footprints and improved EP (Emrouznejad et al., 2023; Luo et al., 2016). By incorporating digital technologies into various aspects of operations, including production, logistics, and energy management, DT optimizes energy supply efficiency and serves as a foundation for upgrading resource flow and supply methods (Yang et al., 2023). Moreover, it facilitates digital-enabled energy procurement, collection, and management, offering greater control and predictability over energy production, transportation, and consumption (He et al., 2022). These advancements lead to improved energy utilization efficiency, enabling firms to achieve their emissions reduction goals (Drent et al., 2023). National Energy Shendong Coal Group equipped with "Kuanghong" information system provided the best practical example, which help the company improve their EP, reduce resource waste and environmental pollution, and improve sustainable management through real-time monitoring and data analysis[1]. However, evidence specifically investigating the influence of DT on EP within the mining companies remains limited. Based on this, we propose the first question: *Does DT of mining companies enhance EP?*

The complexity of digital transformation and environmental management, particularly their required application at the supply chain level, infers that (environmental) performance impact may not be necessarily straightforward. It is interesting to examine the moderating effects in the relationship and develop corresponding business strategies. In the mining industry, supply chain characteristics have a very influential effect on operations and planning, because the raw material sourcing is highly concentrated, and specialist refinery operations and the distributions of finished goods are strongly densified (Constantinides et al., 2018). The particular configuration of mining supply chains is likely to shape the supply chain collaborations on digitalization and its effectiveness in the transfer of environmental outcomes. In this study, our attention is directed towards the supply chain concentration, referring to the size of the supplier and customer base of our sample mining companies. We believe supply chain concentration affects the mining firms' exposure to wider environmental demand,

[1] https://new.qq.com/omn/20210917/20210917A0CN1L00.html

transaction risks, long-term investment in digitalization, and environmental fruition, and thus influence the relationship between DT and EP. Consequently, the second question is addressed: *How supply chain concentration affects the relationship between DT and EP in mining companies?*

To address the research questions, we establish a comprehensive three-level supply chain model, including a supplier, mining company, and retailer, to depict the game process of the mining company and their up- and downstream companies. We consider three game models: supplier Stackelberg (SS), retailer Stackelberg (RS), and vertical Nash (VN) models, as well as decentralized and centralized game decisions. We explore the impact of DT on the EP of mining company under different game strategies, as well as the conflicts of interest and cooperation mechanisms among different decision participants. Employing our theoretical model as a foundation, we conduct empirical testing using data collected from listed mining companies in China from 2010 to 2021 to explore the impact of DT on EP. A high concentration in the supply chain indicates a limited number of dominant suppliers and retailers. This concentration bestows upon supplier considerable influence in dictating environmental standards and practices across the entire supply chain (Jia et al., 2023). The SS and RS models are instrumental in delineating the dominant positions of suppliers and retailers, respectively. Considering this, our study explicates how supplier concentration (SC) and retailer concentration (RC) may moderate the potential linkage between DT and EP in the mining sector.

Our research makes contributions to the existing literature in the following three aspects. First, this research develops comprehensive three-level supply chain game models and conducts empirical analysis to investigate how DT in mining companies influences their EP through strategic interactions with suppliers and retailers. This approach provides a rigorous and systematic framework for examining the complex relationships between DT, EP, and supply chain dynamics. By analyzing the decision-making processes and interactions among mining companies, suppliers, and retailers, this study offers an in-depth understanding of the dynamics and impacts within a three-level supply chain (Chen et al., 2023; Drent et al., 2023; Luo et al., 2016). Second, from the viewpoint of supply chain power structure, by specifically examining the role of SC and CC, this study adopts a unique perspective on supply chain power structure. It goes beyond the conventional focus on decision technology and incorporates the dynamics of power relationships within the supply chain. This perspective adds new dimensions to the understanding of how power dynamics influence EP (Biswas et al., 2016; Edirisinghe et al., 2011). Finally, the study helps mining companies understand the significance of their decision-making processes and technologies by analyzing the impact of decision technology on EP. Additionally, through the exploration of the game process with suppliers and retailers, the research underscores the significance of relationships within the supply chain. It explains how SC and RC influence the relationship between DT and EP. Mining companies can use this knowledge to manage their relationships with key suppliers and retailers, leading to shared goals and improved EP.

The rest of the paper is organized as follows: Section 2 offers a review of the existing literature. In Section 3, we present the game models employed in our study. Section 4 details the data, variable selection, models utilized in our empirical investigation, and empirical findings, followed by implications in Section 5. Lastly, Section 6 summarizes the findings and concludes the study.

2. Literature review

2.1 Digital transformation of mining companies and environmental performance

DT involves leveraging modern information technologies to enhance efficiency, improve decision-making, and create new value propositions. It transcends adopting individual technologies and instead represents a holistic shift toward a digitally enabled and innovative organizational structure (Emrouznejad et al., 2023; Feng and Shanthikumar, 2018; Xu et al., 2023). DT within mining companies encompasses the utilization of information technologies like the Internet of Things (IoT) (Mu and Maxwell, 2024), big data (Wang et al., 2020; Kuo and Andrew, 2019), blockchain (Khan et al., 2021) and artificial intelligence (Smyth et al., 2024) to reshape the process of realizing mining products, the operation and management mode of mining enterprises, and the information talent service system, fundamentally improving the fundamental competitive edge of mining companies, and achieving the strategic vision of high-quality development (Emrouznejad and Charles, 2022; Xu et al., 2023) such as "green safety, cost reduction and efficiency increase, and lean management." According to the degree of digital integration, DT of the mining industry can be divided into five stages: mechanical, digital, perception, smart, and meta mines[2].

DT in mining companies has been shown to significantly enhance EP through several key mechanisms, particularly in the context of the industry's unique challenges. First, DT enables mining companies to optimize operations, resulting in increased efficiency and reduced resource consumption.

[2] https://mp.weixin.qq.com/s/Q2C3cIL3IGMfggrQVqCH_w

By leveraging advanced technologies such as data analytics, machine learning, and automation, mining companies can identify operational inefficiencies, minimize waste, and streamline production processes. These improvements not only enhance operational productivity but also reduce the environmental footprint of mining activities by conserving natural resources and decreasing waste generation (Emrouznejad et al., 2023). Second, DT often leads to the adoption of sustainable technologies, such as renewable energy sources, electric mining vehicles, and advanced emissions reduction technologies. These innovations directly contribute to reducing greenhouse gas emissions, lowering water pollution, and reducing dependence on fossil fuels. In the mining sector, where environmental sustainability is a growing concern, embracing such technologies allows companies to not only enhance their EP but also align with global efforts to combat climate change (Du et al., 2023). Moreover, the integration of digital tools allows for real-time environmental monitoring, with technologies like sensors, drones, and satellite imaging providing continuous data collection. These tools enable mining companies to monitor their environmental impact more effectively, identifying potential risks before they escalate. With accurate and timely information, companies can implement proactive measures to mitigate environmental threats, including monitoring water quality, managing air emissions, and ensuring biodiversity preservation (Yang et al., 2023). This real-time monitoring capability is particularly crucial in the mining sector, where environmental impacts can be both immediate and long-term, and quick intervention can significantly reduce potential harm.

The extant literature on DT and EP focuses on organizational-level impacts, overlooking the intricacies of how DT cascades through the entire supply chain. The lack of a comprehensive view across the supply chain stream hinders a complete comprehension of the environmental implications and potential synergies that may arise. As digital technologies continue to reshape business processes, research that explores the cascading effects is essential, considering both the upstream and downstream dimensions, to provide a more nuanced and complete understanding of DT- EP relationship in the context of supply chain sustainability.

2.2 Role of supply chain concentration

Supply chain characteristics are influential factors to the effectiveness of digital transformations on environmental performance. Especially in the mining industry, the firms strongly rely on their customers' and suppliers' collaboration to utilize digital technologies in environmental monitoring and management, because of the concentrated resource distribution and specialist refining operations. In this study, we particularly are interested in 'supply chain concentration,' which denotes to a firm's size of supplier and customer base. It changes ability of a particular entity within the supply chain (e.g., suppliers, retailers) to influence decisions, control resources, and shape the behavior of other members of the chain (Wang et al., 2023; Edirisinghe et al., 2011). In the context of mining supply chains, it is probable that this factor affects the distribution of risks and rewards between supply chain partners in their use of digitalization transformation and its application to environmental management.

In a highly concentrated supplier base, mining firms can strategically focus their digital transformation with selected suppliers in a long-term relationship to develop positive environmental outcomes (as the environmental fruition commonly request long-term investment and collaboration). However, from a transaction cost economics perspective, such long-term and concentrated investments with a few suppliers may increase asset specificity and opportunistic risk to mining firms. Particularly, digital transformation indicates wider supply chain visibility and transparency, including sensitive business data. The digital transformation may not be necessary in line with the mining firm's expectation of environmental management. In a word, theoretically, a high degree of supplier concentration may pose both positive and negative impacts.

In a highly concentrated customer base, the heterogeneous market demand on environmental management and effective use of digital technology in the sustainability aspects may not be widely exposed to the upstream mining firms, and thus reduce the positive environmental outcomes. Upstream companies face heterogeneous and diverse market demands on environmental performance; they are found to selectively mimic their customers' actions as a response (Shah and Soomro, 2020). The reduced size of the customer base is likely to limit mining firms' understanding and knowledge to the complex environmental requests. Their effective use of digital technology and improvement in environmental performance may be diminished. In contrast, a mining firm that has diverse and numerous customers is less likely to effectively identify the customers to collaboratively apply digital technologies in environmental management. Their customers are might also not be willing to invest in long-term environmental projects with a less dependent supply chain partner (i.e., the mining company) (Servaes and Tamayo, 2013).

Given the counterarguments, and a scarcity of empirical evidence in the literature regarding the impact of supply chain concentration on the correlation between DT and environmental performance, we propose the competing effects in our study. The result will interestingly disclose the supply chain design strategies in the digitalization and sustainability context.

In the summary of our development of theoretical foundation, we intend to fill the research gap on how digital transformation can effectively improve environmental performance, using mining supply chain as a context. there is limited research investigating the specific impact mechanisms and effects of SC or CC in mining sector on the potential correlation between DT and the EP. Therefore, it is necessary to explore how supply chain concentration acts as a key role in shaping the connection between DT adoption and the EP of mining companies. By examining the interplay between supply chain concentration, DT adoption, and EP, researchers can acquire a more comprehensive understanding of the complex dynamics and potential trade-offs that emerge from the implementation of DT from the supply chain sustainability perspective.

3. Game models and equilibrium analysis

3.1 Game models

The strengthening of digital construction is beneficial for optimizing the performance of all supply chain partners (Liu et al., 2022). This results in heightened retailer satisfaction for both parties, consequently boosting demand. Therefore, we posit that enterprises in the supply chain can benefit from DT (Jia et al., 2023). Furthermore, with the rise in environmental consciousness, an increasing number of retailers are inclined to pay a premium for products with low-carbon attributes (Wang et al., 2017). Product demand is shaped not only by pricing but also by the extent of DT within the supply chain. This, in turn, relies on the level of involvement of supply chain entities in DT initiatives. Greater participation from companies results in enhanced product and service capabilities, consequently driving up consumer demand (Feng and Shanthikumar, 2018). Therefore, it is imperative for companies to take into account this change in retailer behavior when making critical strategic and operational choices. This shift has been acknowledged in numerous prior literatures, which incorporate carbon emission-sensitive demand into pricing, order quantities, and other supply chain decisions (Chen et al., 2019). Therefore, we assume that end consumers are sensitive to the reduction of unit carbon emissions.

Based on the above analysis, this study considers a three-level supply chain game model consisting of a supplier, mining company, and retailer: the retailer purchases products from the mining company, and the mining company purchases products from the supplier. The retailer demand is sensitive to retail prices p_c and unit carbon emissions reductions r_c, and the decision variables of retailers are the retail prices p_c and cost coefficient of DT investment k_c. The decision variables of mining company are the wholesale prices p_m and cost coefficient of their DT investment k_m. The decision variables for supplier are the wholesale prices p_s and cost coefficient of their DT investment k_s. The supply chain involves two stages of game (refer to Figure 1). In the initial stage, suppliers, mining companies, and retailers strategically decide on investments in DT. In the subsequent stage, suppliers, mining companies, and retailers determine wholesale, selling, and retail prices.

Supply chain research focuses more on the roles of suppliers and retailers, as they have a more direct impact on the potential correlation between DT and EP in mining sector. Therefore, this study mainly considers three game models: VN, SS, and RS. The VN model is a widely used game theory model that captures the interactions and decision-making processes among multiple entities in a supply chain. The SS model is a game theory model that focuses on the leadership role of the supplier in setting prices or quantities in the supply chain. Similar to the SS model, the RS model examines the leadership role of the retailer in the supply chain. It allows for the analysis of how the mining company's technology decision impacts EP when the retailer acts as the leader. By applying these three models, we can comprehensively analyze different power structures, decision-making dynamics, and interactions within the mining supply chain. Especially, the SS and RS models, through their focus on leadership roles, provide a framework to investigate how decision-making by dominant parties (such as suppliers or retailers) can affect the adoption of digital technologies and, ultimately, the environmental outcomes within the supply chain. This multidimensional approach allows you to acquire a more profound comprehension of the effects of DT, SC, and CC on EP. The chosen models provide a suitable framework to capture the complexities and nuances of the examined relationships in the context of the mining supply chain. This study conducts in-depth research on the impact of DT on the EP of mining companies under different game models. Figure 2 shows the bargaining power of the three game models discussed in our study. The arrows in the figure indicate that the former possesses greater bargaining power than the latter. For example, if S possesses greater bargaining power in the supply chain than M, it is represented as S → M in the figure, where S, M, and C represent the supplier, mining enterprise, and retailer, respectively. The symbols used in this research are shown in Table 1.

Referring to Luo et al. (2016) and Chen et al. (2019), we assume that the demand function of companies after DT is

$$D = a - bp_c + \eta(r_s + r_m + r_c + \beta_s r_s + \beta_m r_m + \beta_c r_c), \quad (1)$$

where a indicates the maximum market demand (final consumer demand); b indicates the price sensitivity coefficient ($b>0$); η is the sensitivity coefficient, which represents the carbon reduction emissions of supplier, mining company, and retailer ($\eta > 0$); r_s, r_m, and r_c are the unit carbon reduction of supplier/mining company/retailer after DT investment, respectively; β_s, β_m, and β_c are the overflow rate of supplier/mining company/retailer to other supply chain partner, respectively. If the company has not invested in DT, then $d_0 = a - bc > 0$. Therefore, the revenue functions of supplier $\pi_s(p_s, r_s)$, mining company $\pi_m(p_m, r_m)$, and retailer $\pi_c(p_c, r_c)$, and supply chains $\pi_{sc}(p_s, p_m, p_c, r_s, r_m, r_c)$ are

$$\pi_s(p_s, r_s) = (p_s - c)[a - bp_c + \eta(r_s + r_m + r_c + \beta_s r_s + \beta_m r_m + \beta_c r_c)] - \frac{1}{2}k_s r_s^2, \quad (2)$$

$$\pi_m(p_m, r_m) = (p_m - p_s)[a - bp_c + \eta(r_s + r_m + r_c + \beta_s r_s + \beta_m r_m + \beta_c r_c)] - \frac{1}{2}k_m r_m^2, \quad (3)$$

$$\pi_c(p_c, r_c) = (p_c - p_m)[a - bp_c + \eta(r_s + r_m + r_c + \beta_s r_s + \beta_m r_m + \beta_c r_c)] - \frac{1}{2}k_c r_c^2, \text{ and} \quad (4)$$

$$\pi_{sc} = \pi_s(p_s, r_s) + \pi_m(p_m, r_m) + \pi_c(p_c, r_c). \quad (5)$$

Referring to Chen et al. (2019), a firm's EP E_i is represented by the reduction in carbon emissions after DT investment by mining supply chain partners (supplier, mining company, and retailer):

$$E_i = r_i * D. \quad (6)$$

Referring to Chen et al. (2019), consumer surplus is expressed as the difference between the product price and consumer willingness to pay: $CS = \int_{p_{\min}}^{p_{\max}} d(p)\, dp = \frac{D^2}{2b}$; the social welfare of mining supply chain companies (supplier, mining company, retailer) is

$$S_i = CS + \pi_i(p_i, r_i) = \frac{D^2}{2b} + \pi_i(p_i, r_i), \quad (7)$$

where $i = s, m, c$.

3.2 Equilibrium analysis

This section provides a detailed description of the decision sequences involving three game strategies—VN, SS, and RS models—under two different decision-making frameworks: decentralized and centralized decision-making. In a centralized decision-making framework, a single decision-maker, typically the leader (either the supplier or retailer), has control over the key strategic decisions in the supply chain. In contrast, decentralized decision-making involves multiple independent decision-makers, each optimizing their own objectives without necessarily aligning with others. To solve these models systematically, we apply the reverse induction method. This method first involves analyzing the reaction functions of the followers, which represent the strategies developed by the followers based on the leader's decisions. Once these response functions are established, they are incorporated into the leader's decision-making process to determine the optimal strategy for the leader, whether the supplier or the retailer. By using this step-by-step reverse induction approach, we derive the equilibrium solution for each game strategy, providing a deeper understanding of the strategies and behaviors of all parties under the two different decision-making frameworks (see the Appendix for the specific solution process).

3.2.1 Vertical Nash model

The VN model offers a framework for evaluating individual companies and overall performance in the mining supply chain. By analyzing the equilibrium results, companies in the supply chain can evaluate their relative performance concerning revenue efficiency relative to other entities in the supply chain.

Decentralized decision. In the initial stage, the supplier, mining company, and retailer autonomously decide on their individual levels of DT to optimize their respective profits. Subsequently, in the second stage, the supplier, mining company, and retailer independently and concurrently establish their selling prices. Thus, the process of the VN model can be delineated as follows:

$$\left.\begin{array}{c}\max\limits_{r_s}\pi_s(p_s,r_s)\\ \max\limits_{r_m}\pi_m(p_m,r_m)\\ \max\limits_{r_c}\pi_c(p_s,r_s)\end{array}\right\}\rightarrow\left\{\begin{array}{c}\max\limits_{p_s}\pi_s(p_s,r_s)\\ \max\limits_{p_m}\pi_m(p_m,r_m)\\ \max\limits_{p_c}\pi_c(p_c,r_c)\end{array}\right..$$

Centralized decision. During the initial stage, the supplier, mining company, and retailer collaboratively make decisions regarding DT investments to optimize the total revenue of the supply chain. Subsequently, in the second stage, the supplier, mining company, and retailer concurrently set the product selling price. Thus, the cooperative VN model can be outlined as follows:

$$\max_{r_s,r_m,r_c} \pi_{sc}(p_c,r_s,r_m,r_c) \to \begin{cases} \max_{p_s} \pi_s(p_s,r_s) \\ \max_{p_m} \pi_m(p_m,r_m) \\ \max_{p_c} \pi_c(p_c,r_c) \end{cases}.$$

3.2.2 Supplier Stackelberg model

In the mining supply chain, suppliers are responsible for purchasing, manufacturing, and delivering the required items to the mining company. They can influence the behavior of the mining company by determining supply and price. The mining company then determines the order quantity based on the supplier's decision, and ultimately the retailer decides the demand quantity. This aligns with the logic of leaders taking action first and followers taking action later in Stackelberg games.

Decentralized decision. In the initial stage, the supplier, mining company, and retailer independently determine their respective DT investments to maximize their profits. In the second stage, the supplier sets a wholesale price p_s, after which the mining company and retailer concurrently establish their selling price p_m and retail price p_c based on the wholesale price as a response. Thus, the process of the SS model can be described as follows:

$$\left.\begin{matrix} \max_{r_s} \pi_s(p_s,r_s) \\ \max_{r_m} \pi_m(p_m,r_m) \\ \max_{r_c} \pi_c(p_s,r_s) \end{matrix}\right\} \to \max_{p_s} \pi_s(p_s,r_s) \to \left\{ \begin{matrix} \max_{p_m} \pi_m(p_m,r_m) \\ \max_{p_c} \pi_c(p_c,r_c) \end{matrix}\right..$$

Centralized decision. In the initial stage, the supplier, mining company, and retailers collectively determine DT investments aimed at maximizing the total revenue of the supply chain $\pi_{sc}(p_c,r_s,r_m,r_c)$. In the second stage, supplier provides wholesale price p_s, and then mining company and retailer respond by determining their selling price p_m and retail price p_c based on the wholesale prices. Therefore, the process of the SS model can be outlined as follows:

$$\max_{r_s,r_m,r_c} \pi_{sc}(p_c,r_s,r_m,r_c) \to \max_{p_s} \pi_s(p_s,r_s) \to \left\{ \begin{matrix} \max_{p_m} \pi_m(p_m,r_m) \\ \max_{p_c} \pi_c(p_c,r_c) \end{matrix}\right..$$

3.2.3 Retailer Stackelberg model

Retailers have a more direct understanding of market demand and value and can influence the behavior of mining companies by making price decisions. Mining companies can then influence suppliers by making order volume decisions. This aligns with the logic of leaders taking action first and followers taking action later in Stackelberg games. In the mining supply chain, information flow is usually from retailers to suppliers. Retailers are closer to the market and have a more accurate understanding of market trends and demands, while suppliers rely on order information from mining companies. Therefore, in the decision-making sequence, retailers first make decisions that better reflect market demand, and then mining companies decide on order quantity based on retailers' decisions. Finally, suppliers proceed with production and supply.

Decentralized decision. In the initial stage, supplier, mining company, and retailer independently determine their respective DT investments to maximize their profits. In the second stage, retailers provide the retail prices p_c, and then mining companies and suppliers decide on their selling price p_m and wholesale price p_s in response. Therefore, the process of the RS model unfolds as follows:

$$\left.\begin{matrix}\max\limits_{r_s} \pi_s(p_s,r_s)\\ \max\limits_{r_m} \pi_m(p_m,r_m)\\ \max\limits_{r_c} \pi_c(p_s,r_s)\end{matrix}\right\} \to \max\limits_{p_c} \pi_c(p_c,r_c) \to \left\{\begin{matrix}\max\limits_{p_m} \pi_m(p_m,r_m)\\ \max\limits_{p_s} \pi_s(p_s,r_s)\end{matrix}\right. p_m \quad .$$

Centralized decision. In the initial stage, suppliers, mining companies, and retailers collaboratively make decisions regarding DT investments aimed at maximizing the total revenue of the supply chain $\pi_{sc}(p_c,r_s,r_m,r_c)$. In the second stage, the retailer provides the retail price p_c, and then the mining company and supplier jointly determine their selling price and wholesale price p_s in response. Therefore, the process of the RS cooperation model unfolds as follows:

$$\max\limits_{r_s,r_m,r_c} \pi_{sc}(p_c,r_s,r_m,r_c) \to \max\limits_{p_c} \pi_c(p_c,r_c) \to \left\{\begin{matrix}\max\limits_{p_m} \pi_m(p_m,r_m)\\ \max\limits_{p_s} \pi_s(p_s,r_s)\end{matrix}\right. .$$

Tables 2 summarizes the premium results of mining company under different game models. In the table, $L_s = \dfrac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m = \dfrac{\eta^2(1+\beta_m)^2}{4k_m b}$, and $L_c = \dfrac{\eta^2(1+\beta_c)^2}{4k_c b}$ represent the DT level of supplier, mining company, and retailer, respectively. The analysis reveals that as the cost coefficient of DT investment (k_s, k_m, k_c) decreases, the DT level within the mining supply chain companies tends to increase. However, a higher cost coefficient of DT investment indicates lower investment efficiency, which means that more investment is required to attain an equivalent reduction in unit carbon emissions. To guarantee the presence of product pricing and carbon reduction decisions, we assume that in the VN model, $0 < L_s + L_m + L_c < \frac{2}{3}$ and in the SS and RS models, $0 < L_s + L_m + L_c < \frac{8}{7}$.

Proposition 1: The EP of mining company improves with the increasing DT under different game models.

Proposition 2: Mining company tends to have better EP under the VN model compared with SS and RS models.

Proposition 3: The economic performance of mining company improves with the increasing DT under different game models.

Proposition 4: Mining company tends to have better economic performance under VN model compared with SS and RS models.

Proposition 5: The social performance of mining company improves with the increasing DT under different game models.

Proposition 6: Mining company tends to have better social performance under VN model compared with SS and RS models.

4. Empirical analysis

Based on our game models, there is a positive correlation between a mining company's adoption of DT and its economic, environmental, and social performance. Moreover, comparative analysis across different models indicates that the mining company demonstrates superior economic, environmental, and social performance under the VN model compared to the SS and RS models. Additionally, empirical analysis using panel data from listed mining companies in China is conducted to validate the conclusions drawn from the game models.

4.1 Data and sample

This study focuses on mining companies and constructs a sample to investigate the relationship between DT and EP. First, A-share listed mining companies for 2010–2021 are identified from the CSMAR database, a comprehensive research-oriented database specializing in China's Finance and

Economy[3]. Specifically, we collected relevant information for A-share listed mining companies with industry codes B6, B7, B8, B9, B10, and B11 according to the *Classification of National Economy Industries*. Subsequently, we obtained EP and social performance rating data from the Hexun database[4], which provides comprehensive, accurate, and authoritative data of listed companies, and financial performance and other relevant financial data from the CSMAR database. The sample underwent screening to remove the following: (1) observations with incomplete data, (2) observations lacking pertinent information within the CSMAR database, and (3) observations labelled as "ST" (Special Treatment) or "PT" (Particular Transfer). Finally, the sample consisted of 1155 mining companies for 2010–2021. Based on the constructed sample, this study gathered data from diverse sources to validate the propositions proposed in the study. The annual report data of listed companies, EP and social performance rating data of companies, and financial data are obtained from the Juchao Information website, Hexun database, and CSMAR database, respectively.

4.2 Variables

4.2.1 Independent variables

Digital transformation. Our study employs a combined approach of text mining and term frequency analysis to assess the DT of companies (Xu et al., 2023). The primary step involves selecting the dataset for analysis to gain an in-depth understanding of a company's level of DT. Drawing from classic literature, such as Holmström et al. (2019), we compile a list of 76 characteristic terms related to the DT level of publicly listed companies, spanning five key dimensions[5]. As publicly listed companies often aspire to disclose their DT level in annual reports to gain investor approval, annual reports become the ideal source for screening DT terms. This study uses Python web crawlers to collect annual reports of A-share mining industry companies listed on the Shanghai and Shenzhen stock exchanges. Adobe Acrobat is then employed to extract textual content for filtering DT terms. Subsequently, the occurrence frequency of these terms in the annual reports is computed and presented as a percentage relative to the total vocabulary. To address the possibility that some mining companies may not have implemented DT, term frequencies are weighted and logarithmically summed to provide a comprehensive evaluation

[3] https://data.csmar.com/
[4] https://www.hexun.com/
[5] https://www.macrodatas.cn/article/1147466994

of DT levels. This approach quantitatively assesses the presence of DT in the annual reports of publicly listed companies and offers insights into the extent of DT utilization.

4.2.2 Dependent variables

Environmental performance. We measure a firm's EP using environment scores from the Hexun ESG database. The ESG Report Rating Standard is against 27 domestic and foreign ESG standards, such as the Global Reporting Initiative's Sustainable Development Reporting Standard (GRI Standard), the Sustainable Development Accounting Standard (SASB), the EU Corporate Sustainability Reporting Directive (CSRD), and the Guidelines on Environmental, Social and Governance Reporting of the Stock Exchange of Hong Kong, and other exchange guidelines. We specifically selected the environmental score (E) as the measure of environmental performance in this study. This approach aims to mitigate redundancy in data collection while ensuring comprehensive coverage of environmental performance metrics.

4.2.3 Moderating variable

Supplier concentration and *retailer concentration*. As centralized supply chain structure tends to have a stronger bargaining power (Kamann and Johnsen, 2019), we use SC and CC to represent the SS and RS models. Referring to Yang et al. (2023), we establish the aggregate of the percentage of purchases from the top five suppliers as the measure for SC, and the aggregate of the percentage of sales to the top five retailers as the measure for CC:

$$SC = \sum_{i}^{5} \frac{Purchasing_i}{Total\ purchasing} \text{ and} \tag{8}$$

$$CC = \sum_{j}^{5} \frac{Sale_j}{Total\ sale}, \tag{9}$$

where i, j represent 1, 2, 3, 4, 5.

4.2.4 Control variables

To control the extraneous effects by numerous variables related to firm of our sample, we introduce five firm-level control variables. *Age* (AGE) is quantified as the cumulative sum of years from the company's listing date, as younger-listed companies may exhibit higher EP compared to those established for longer periods (Kim and Henderson, 2015); *firm size* (SIZE) is represented by the natural logarithm of the company's total assets (Yang et al., 2023); *financial leverage* (LEV) is determined by the ratio of total debt to total assets, given that firms with higher leverage often experience lower profit margins, which in turn can influence the firm's DT degree (Xu et al., 2023); *turnover* (TURN) is assessed by the ratio of main business income to average cash balance, potentially impacting the efficiency of EP implementation (Xu et al., 2023); *number of employees* (NOE) refers to the total count of employees disclosed in the annual report, including registered (in-service) employees, for the listed company (Liu et al., 2023). We performed the following data preprocessing steps. First, to mitigate the potential influence of outliers stemming from extreme values in the dataset, we employed a 99% winsorization process. Subsequently, to address concerns regarding multicollinearity, we conducted variance inflation factor (VIF) tests on the variables following the methodology outlined in Weisberg (2005). The test outcomes revealed that all predictor variables exhibited VIF values below 5, indicating that multicollinearity was not a significant concern. Table 3 presents the correlation matrix, means, and standard deviations of the variables utilized in this study. These findings suggest that the variables associated with the sample firms are not excessively high and remain relatively stable.

4.3 Empirical models

By incorporating fixed firm and year effects in our panel data analysis, we account for unobserved heterogeneity and time-varying factors, enhancing the robustness and causal inference of our examination on the relationship between DT and EP. Following the approach outlined in Xu et al. (2023), we include dummy variables for firms and years in our analysis. Additionally, we adjust standard errors to address heteroskedasticity and represent clustering of observations. This estimation model allows us to control for individual firm characteristics and common factors across years, optimizing the efficiency and reliability of our analysis in exploring the DT–EP relationship. The equations used for estimation are as follows:

$$EP_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \sum \beta * Control_{i,t} + Year_t + Firm_i + \varepsilon_1 \text{ and} \tag{10}$$

$$EP_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 M_{i,t} + \beta_3 DT_{i,t} * M_{i,t} + \sum \beta * Control_{i,t} + Year_t + Firm_i + \varepsilon_2 \quad , \tag{11}$$

where $EP_{i,t}$ denotes the EP of mining firm i in year t; $DT_{i,t}$ denotes the level of DT of mining firm i in year t; $Controls_{i,t}$ denotes the control variables; ε_1 and ε_2 denote the random disturbance terms; $M_{i,t}$ denotes SC of firm i in year t and CC of firm i in year t, respectively; $Year_t$ is a dummy variable equal to 1 when the sample is in the year t, and 0 otherwise; $Firm_i$ is a dummy variable equal to 1 when the sample is firm i, and 0 otherwise.

4.4 Empirical results

4.4.1 Main findings

The regression results are shown in Table 4. The second column displays the estimation result of Model 1, the coefficient of independent variable- DT exhibits significant positive correlation at the 0.1% level ($\beta_{DT} = 3.137$, $\rho < 0.001$). This indicates that DT is strongly associated with improvements in EP. The column 3 of Table 4 presents the results of estimating Model 2. The coefficient of DT ($\beta_{DT} = 3.130$, $\rho < 0.01$) is significantly positive, but the coefficient of DT*SC ($\beta_{DT*SC} = -0.056$, $\rho < 0.1$) is significantly negative. This suggests that SC negatively moderates the relationship between DT and EP, implying that higher SC may reduce the effectiveness of DT initiatives in improving EP. Column 4 indicates that the coefficient of DT ($\beta_{DT} = 3.073$, $\rho < 0.001$) is significantly positive, but the coefficient of DT*CC ($\beta_{DT*CC} = -0.336$, $\rho < 0.001$) is significantly negative, suggesting that CC negatively moderates the DT-EP relationship. This suggests that a high degree of CC may similarly dampen the EP gains from DT efforts. Theoretically, the results suggest that a lack of diversification in supplier and customer bases can restrict the flexibility of companies to adapt their DT strategies in ways that optimize environmental outcomes. Practically, both SC and CC point to the need for mining companies to consider more diversified and resilient supply chain and customer structures when pursuing DT initiatives aimed at improving sustainability.

4.4.2 Endogeneity

To mitigate the endogeneity issue stemming from potential reverse causality between the EP of mining companies and DT, the study employs the two-stage least squares (2SLS) method. This approach helps alleviate bias resulting from the endogenous relationship between the variables. In the initial stage of the 2SLS method, the study estimates DT using control variables while incorporating fixed firm and year effects. The proportion of Research and Development (RandD) spending relative to operating income acts as an instrumental variable, anticipated to be correlated with DT but not directly linked to

EP. In the second stage, the study explains the EP of mining companies using the fitted values of DT obtained from the first stage. This approach allows for an examination of the causal relationship between DT and EP while accounting for the potential endogeneity.

The results of the first stage of the 2SLS method, presented in Table 5 (column 1), indicate a significant correlation between the instrumental variable and EP of mining companies ($\rho < 0.1$). This suggests that the instrumental variable used in the analysis has a valid and significant impact on DT. Table 6 reports the regression results from the two-stage model and demonstrates the robustness of our results. By addressing this issue and employing the 2SLS method, the study provides more reliable and unbiased insights into the correlation between DT and EP among mining enterprises.

4.4.3 Robustness

To evaluate the influence of our DT measurement on the outcomes, we employ an alternative measure available in the CSMAR database as a robustness check. This new proxy variable captures five dimensions: artificial intelligence, block chain, cloud computing, big data, and the application of digital technologies. We apply the sum of these measurements after adding one to each. Table 6 demonstrates that our study's results remain consistent with the earlier analysis, suggesting the robustness and reliability of our conclusions.

4.4.4 Further analysis

Propositions 3–6 advocate that the economic and social performance of mining company improve with the increasing DT, and mining company tends to have better economic and social performance under the VN model compared with the SS and RS models. To validate the conclusion of the theoretical models, we further conduct the empirical examination to investigate the broader impact of DT, including its effects on economic performance and social responsibility, and gain a more holistic understanding of how this technological shift influences the mining industry. This comprehensive view can provide a more balanced perspective on the benefits and challenges. The column (1)-(3) of Table 7 show the results of testing the relationship between DT and social responsibility. The column (4)-(6) of Table 7 show the results of testing the relationship between DT and economic performance.

5 Implications

5.1 Theoretical implication

Our study provides novel insights into the linkage between DT and EP within the Chinese mining sector. Additionally, this study delves into the underlying mechanisms from the perspective of supply chain power structure, focusing on the moderating roles of SC and CC. Through our research, our study adds unique contributions to the current body of literature in several meaningful ways.

First, our study is among the first to develop a three-tier supply chain game model enhanced with empirical analysis, providing a unique perspective on how DT initiatives by mining companies affect their EP through strategic interactions with suppliers and retailers. Unlike previous research, which largely focuses on the impact of mining operations on the economic and environmental development of local communities (Xu et al., 2023), our study shifts attention to the strategic dynamics within the supply chain. We reveal how DT initiatives in the mining sector drive improvements in EP through coordinated decision-making across companies, suppliers, and retailers. This approach not only clarifies the strategic decision-making processes among these stakeholders but also demonstrates how their interactions lead to tangible EP outcomes.

Second, our research takes a distinct approach by exploring how SC and CC influence the intricate relationship between DT initiatives in mining companies and their EP. We find that both SC and CC negatively moderate the DT-EP relationship. This finding supports the view that concentrated supply chains are more vulnerable to disruptions, such as natural disasters or unexpected incidents (Hendricks, Singhal, and Zhang, 2009). Moreover, limited sourcing diversification within highly concentrated supply chains can heighten environmental risks, making it challenging for companies to adapt to changing sustainability requirements (Jia et al., 2023). However, this insight contrasts with certain perspectives that highlight the interconnected nature of environmental practices, particularly in supply chains focused on circular economy models. This perspective emphasizes inter-firm trading relationships, where waste and byproducts are repurposed as raw materials in successive production processes, reinforcing the potential environmental benefits of integrated supply chains.

Third, we develop both theoretical and empirical models to examine how DT strategies of mining companies impact EP across various supply chain power structures. These models offer a framework for analyzing the interactions and dynamics within the supply chain and their influence on EP outcomes. By combining theoretical and empirical approaches, our study provides a comprehensive understanding of the relationship between DT and EP in the mining industry. This integrated approach not only enriches current insights into DT strategies in mining but also lays a foundation for future research, contributing to a stronger body of knowledge on sustainable practices within the sector.

5.2 Practical implication

First, this study demonstrates that DT acts as a catalyst for enhancing EP in the mining industry. Mining companies can confidently invest in DT initiatives, recognizing their positive impact on environmental outcomes. The practical implications of these findings highlight the importance of channeling resources into technologies like IoT, data analytics, and automation to promote environmental sustainability. Companies are encouraged to embed environmental goals within their DT strategies, reinforcing the alignment of digital advancements with sustainability objectives. This approach ensures that technology not only minimizes environmental impact but also optimizes resource use, contributing directly to sustainable development in the sector.

Second, the negative impact of SC structure and CC on the relationship between DT and EP carries important practical implications for mining companies. Understanding these effects is crucial for identifying the challenges and limitations that may arise when implementing DT initiatives aimed at improving EP. A high level of SC typically means that mining companies rely on a small number of dominant suppliers, which can limit their bargaining power and control over sustainable practices within the supply chain. This makes it more difficult for companies to enforce sustainability standards or encourage greener practices among suppliers. Similarly, high CC can restrict the mining company's ability to influence the environmental expectations and requirements of retailers, as retailers may focus more on price competitiveness than on sustainability. These challenges highlight the need for mining companies to foster stronger collaboration and engagement with both suppliers and retailers to address sustainability issues effectively. By building robust relationships and strategic partnerships that prioritize sustainable practices across the entire supply chain, companies can mitigate the negative effects of high SC and CC. This approach enables a more comprehensive adoption of DT, ultimately helping to enhance EP and drive sustainable transformation within the mining industry.

6 Conclusion

This study explores the complex interplay between DT and EP within mining supply chains, aligning with the priorities highlighted during COP28's "Mining Day." Our findings confirm that DT enhances EP, supporting the objectives of the Global Roadmap for Sustainable Minerals introduced at

COP28. However, the study also uncovers a critical challenge: power imbalances, reflected in greater supplier concentration and customer concentration, can diminish the positive effects of DT on EP. These findings underscore the need for businesses to address governance structures within mining supply chains to fully leverage the benefits of digitalization for environmental sustainability.

From a strategic perspective, the implications are significant. Companies in the mining sector must integrate digital tools with sustainable supply chain practices while actively mitigating power asymmetries to foster collaboration among stakeholders. Businesses should prioritize transparent governance, shared decision-making, and capacity-building initiatives to ensure that digital transformation drives both operational efficiency and environmental goals. Furthermore, aligning digital strategies with global sustainability initiatives, such as those outlined at COP28, will enhance their market positioning and contribute to achieving climate targets.

Recognizing its limitations, this study highlights opportunities for future research and strategic action. Expanding the scope beyond listed mining companies in China to encompass diverse regions, mining types, and market conditions will provide a more comprehensive view of how businesses globally can adapt and implement these insights. For business leaders, this calls for proactive engagement in cross-sectoral collaborations and investments in digital innovations tailored to regional and operational contexts.

References

Ahmed, M. U., & Shafiq, A. (2022). Toward sustainable supply chains: Impact of buyer's legitimacy, power and aligned focus on supplier sustainability performance. International Journal of Operations and Production Management, 42(3): 280–303. doi:10.1108/IJOPM-08-2021-0540.

Bhling, K., Murguia, D.I., Godfrid, J. (2019). Sustainability reporting in the mining sector: exploring its symbolic nature. Business & Society, 58, 191–225. doi: 10.1177/0007650317703658.

Bird, Graham. (2016). The influence of the scale of mining activity and mine site remediation on the contamination legacy of historical metal mining activity. Environmental Science and Pollution Research. 23, 1–11. doi: 10.100 7/s11356-016-7400-z.

Biswas, I., Avittathur, B., & Chatterjee, A. K. (2016). Impact of structure, market share and information asymmetry on supply contracts for a single supplier multiple buyer network. European Journal of Operational Research, 253(3): 593–601. doi:10.1016/j.ejor.2016.03.014.

Charles, V., Emrouznejad, A., & Gherman, T. (2023). A critical analysis of the integration of blockchain and artificial intelligence for supply chain. Annals of Operations Research, 327: 1–41. doi:10.1007/s10479-023-05169-w.

Chen, J., Hu, Q., & Song, J. S. (2017). Effect of partial cross ownership on supply chain performance. European Journal of Operational Research, 258(2): 525–536. doi:10.1016/j.ejor.2016.08.046.

Chen, X., Wang, X., & Jing, H. (2023). Technology licensing strategies for three cost-differential manufacturers. European Journal of Operational Research, 308(2): 622–635. doi:10.1016/j.ejor.2022.11.027.

Chen, X., Wang, X., & Zhou, M. (2019). Firms' green RandD cooperation behaviour in a supply chain: Technological spillover, power and coordination. International Journal of Production Economics, 218: 118–134. doi:10.1016/j.ijpe.2019.04.033.

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018), Introduction—Platforms and infrastructures in the digital age. INFORMS.

Drent, M., Moradi, P., & Arts, J. (2023). Efficient emission reduction through dynamic supply mode selection. European Journal of Operational Research, 311(3): 925–941. doi:10.1016/j.ejor.2023.06.004.

Du, S., Huang, C., Yan, X., & Tang, W. (2023). Voluntary green technology adoption: The effects of regulatory uncertainty and competition. European Journal of Operational Research. doi:10.1016/j.ejor.2022.07.041.

Edirisinghe, N. C. P., Bichescu, B., & Shi, X. (2011). Equilibrium analysis of supply chain structures under power imbalance. European Journal of Operational Research, 214(3): 568–578. doi:10.1016/j.ejor.2011.05.008.

Emrouznejad, A., & Charles, V. (2022). Big data and blockchain for service operations management. Berlin: Springer.

Emrouznejad, A., Chowdhury, S., & Dey, P. K. (2023). Blockchain in operations and supply Chain Management. Annals of Operations Research, 327(1): 1–6. doi:10.1007/s10479-023-05451-x.

Fabrizi, A., Guarini, G., & Meliciani, V. (2018). Green patents, regulatory policies and research network policies. Research Policy, 47(6): 1018–1031. doi:10.1016/j.respol.2018.03.005.

Feng, Q., & Shanthikumar, J. G. (2018). How research in Production and Operations Management May Evolve in the Era of Big Data. Production and Operations Management, 27(9): 1670–1684.

doi:10.1111/poms.12836.

Ghasemi, R., Akhavan, P., Fatahi Valilai, O., & Abbasi, M. (2023). Improving a supplier-managed inventory order assignment model Based on blockchain technology. Production and Operations Management.

Glover, J. (2020). The dark side of sustainable dairy supply chains. International Journal of Operations and Production Management, 40(12): 1801–1827. doi:10.1108/IJOPM-05-2019-0394.

Hendricks, K. B., Singhal, V. R., & Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. Journal of Operations Management, 27(3): 233–246. doi:10.1016/j.jom.2008.09.001.

Holmström, J., Holweg, M., Lawson, B., Pil, F. K., & Wagner, S. M. (2019). The digitalization of operations and supply chain management: Theoretical and methodological implications. Journal of Operations Management, 65(8): 728–734. doi:10.1002/joom.1073.

Jia, F., Xu, Y., Chen, L. J., & Fernandes, K. (2023). Does supply chain concentration improve sustainability performance: The role of operational slack and information transparency. International Journal of Operations and Production Management. doi:10.1108/IJOPM-12-2022-0807.

Kamann, D. F., & Johnsen, T. E. (2019). Coping with the future: Picking your battles. Journal of Purchasing and Supply Management, 25(1): 1–4. doi:10.1016/j.pursup.2018.12.002.

Khan, S. A. R., Razzaq, A., Yu, Z., & Miller, S. (2021). Retracted: Industry 4.0 and circular economy practices: A new era business strategies for environmental sustainability. Business Strategy and the Environment, 30(8), 4001-4014. doi: 10.1002/bse.2853

Kim, Y. H., & Henderson, D. (2015). Financial benefits and risks of dependency in triadic supply chain relationships. Journal of Operations Management, 36(1): 115–129. doi:10.1016/j.jom.2015.04.001.

Kuo, Yong-Hong, & Andrew Kusiak. (2019). From data to big data in production research: the past and future trends. International Journal of Production Research, 57(15-16): 4828-4853. doi: 10.1080/00207543.2018.1443230

Lanier, D., Wempe, W. F., & Zacharia, Z. G. (2010). Concentrated supply chain membership and financial performance: Chain- and firm-level perspectives. Journal of Operations Management, 28(1): 1–16. doi:10.1016/j.jom.2009.06.002.

Liu, W., Wei, S., Li, K. W., & Long, S. (2022). Supplier participation in digital transformation of a two-echelon supply chain: Monetary and symbolic incentives. Transportation Research: Part E, 161: 1–22.

Liu, X., Liu, F., & Ren, X. (2023). Firms' digitalization in manufacturing and the structure and direction of green innovation. Journal of Environmental Management, 335: 117525. doi:10.1016/j.jenvman.2023.117525.

Luo, Z., Chen, X., & Wang, X. (2016). The role of co-opetition in low carbon manufacturing. European Journal of Operational Research, 253(2): 392–403. doi:10.1016/j.ejor.2016.02.030.

Mu, Xiaoshao, & Maxwell Fordjour Antwi-Afari. (2024). The applications of Internet of Things (IoT) in industrial management: a science mapping review. International Journal of Production Research, 62(5): 1928-1952. doi: 10.1080/00207543.2023.2290229

Servaes, H., Tamayo, A., (2013). The impact of corporate social responsibility on firm value: the role of customer awareness. Management Science, 59, 1045–1061. doi:10.1287/mnsc.1120.1630

Shah, N., & Soomro, B. A. (2021). Internal green integration and environmental performance: The predictive power of proactive environmental strategy, greening the supplier, and environmental collaboration with the supplier. Business Strategy and the Environment, 30(2), 1333-1344. doi: 10.1002/bse.2687

Smyth, Conn, Denis Dennehy, Samuel Fosso Wamba, Murray Scott, & Antoine Harfouche. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: a systematic literature review and research agenda. International Journal of Production Research, 4(23): 1-25. doi:10.1080/00207543.2024.2341415

Tang, X., & Rai, A. (2012). The moderating effects of supplier portfolio characteristics on the competitive performance impacts of supplier-facing process capabilities. Journal of Operations Management, 30(1–2): 85–98. doi:10.1016/j.jom.2011.07.001.

Wang, C., Zhang, Q., & Zhang, W. (2020). Corporate social responsibility, green supply chain management and firm performance: the moderating role of big-data analytics capability. Research in Transportation Business & Management, 37: 100557. doi:10.1016/j.rtbm.2020.100557

Wang, L., Li, M., Wang, W., Gong, Y., & Xiong, Y. (2023). Green innovation output in the supply chain network with environmental information disclosure: an empirical analysis of Chinese listed firms. International Journal of Production Economics, 256, 108745. doi: 10.1016/j.ijpe.2022.108745

Wang, W., Krishna, A., & Mcferran, B. (2017). Turning off the lights: Consumers' environmental efforts depend on visible efforts of firms. Journal of Marketing Research, 54(3): 478–494. doi:10.1509/jmr.14.0441.

Weisberg, S. (2005), Applied linear regression. Chichester: John Wiley and Sons.

Xu, Y., Wang, L., Xiong, Y., Wang, M., & Xie, X. (2023). Does digital transformation foster corporate social responsibility? Evidence from Chinese mining industry. Journal of Environmental Management, 344: 118646. doi:10.1016/j.jenvman.2023.118646.

Yang, Z., Hu, W., Shao, J., Shou, Y., & He, Q. (2023). How does digitalization alter the paradox of supply base concentration? The effects of digitalization intensity and breadth. International Journal of Operations and Production Management, 43(11): 1690–1722. doi:10.1108/IJOPM-10-2022-0685.

He, Z., Kuai, L., & Wang, J. (2023). Driving mechanism model of enterprise green strategy evolution under digital technology empowerment: A case study based on Zhejiang Enterprises. Business Strategy and the Environment, 32(1), 408-429. doi: 10.1002/bse.3138

Table 1 Notions

Notions	Description
p_s, p_m, p_c	Unit product selling price of supplier/mining company/retailer
r_s, r_m, r_c	Unit carbon reduction of supplier/mining company/retailer after DT investment
k_s, k_m, k_c	Cost coefficient of DT investment for supplier/mining company/retailer
β_s, β_m, β_c	Overflow rate of supplier/mining company/retailer to other supply chain partner, $0 \le \beta_s, \beta_m, \beta_c \le 1$
a	Market size of the product
b	Price sensitivity coefficient of the product
c	Unit production cost, including material cost and process cost, $p_c > p_m > p_s > c$
η	Sensitivity coefficient of market demand to DT

Note: The subscripts of the symbols s, m, and c in the table represent the supplier, mining company, and retailer, respectively.

Table 2 Optimal results of mining company under different game models

	π_m	E_m	S_m
Decentralized VN	$\frac{d_0^2(2-L_m)}{8b(2-L_s-L_m-L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{8bk_m(2-L_s-L_m-L_c)^2}$	$\frac{d_0^2(3-L_m)}{8b(2-L_s-L_m-L_c)^2}$
Centralized VN	$\frac{d_0^2(2-9L_m)}{8b[2-3(L_s+L_m+L_c)]^2}$	$\frac{3d_0^2\eta(1+\beta_m)}{8bk_m[2-3(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(3-9L_m)}{8b[(2-3(L_s+L_m+L_c}$
Decentralized SS	$\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{2k_mb(8-4L_s-2L_m-L_c)^2}$	$\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c}$
Centralized SS	$\frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$	$\frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c}$
Decentralized RS	$\frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{2bk_m(8-L_s-2L_m-4L_c)^2}$	$\frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c}$
Centralized RS	$\frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$	$\frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c}$

Table 3 Correlation matrix and descriptive statistics

	1	2	3	4	5	6	7	8	9
EP	1								
DT	0.978**	1							
SC	-0.089**	-0.088**	1						
CC	-0.202**	-0.217	0.364***	1					
AGE	-0.157***	-0.150*	-0.121**	0.236	1				
SIZE	0.196**	0.194***	-0.305	-0.196	0.132	1			
LEV	-0.024	-0.024	-0.075	-0.052	0.040	-0.135**	1		
TURN	0.016	0.015	-0.035	-0.035	0.010	0.256***	0.071	1	
NOE	0.217	0.207**	-0.329*	-0.269*	0.077	0.854**	-0.067	0.294*	1
Mean	4.012	4.241	0.431	0.297	13.65	22.978	0.537	2.066	8.516
S.D.	3.901	2.448	0.259	0.246	4.868	1.711	0.958	1.106	1.708

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 4 Regression results

	Model 1	Model 2	Model 3
DT	3.137*** (0.021)	3.130** (0.015)	3.073*** (0.027)
SC		-0.011* (0.005)	
CC			-0.267 (0.237)
DT*SC		-0.056* (0.035)	
DT*CC			-0.336*** (0.081)
AGE	-0.013* (0.008)	-0.013* (0.010)	-0.019** (0.009)
SIZE	-0.082* (0.055)	-0.081* (0.055)	-0.072* (0.055)
LEV	-0.022 (0.129)	-0.020 (0.129)	0.002 (0.127)
TURN	-0.008 (0.025)	-0.008 (0.025)	-0.013 (0.025)
NOE	0.130** (0.055)	0.132** (0.056)	0.149** (0.055)
R-squared	0.559	0.558	0.596

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 5 Robustness results

	(1) Stage 1	(2) Stage 2	(3)	(4)
Innovation	0.833* (0.592)			
DT		0.194* (0.107)	0.067* (0.044)	0.237* (0.155)
SC			-2.462* (1.681)	
CC				-5.360** (0.194)
DT*SC			-0.771* (0.657)	
DT*CC				0.860* (0.800)
AGE	0.112** (0.037)	-0.268* (0.113)	-0.284* (0.114)	-0.210* (0.114)
SIZE	-0.039 (0.237)	0.440* (0.269)	0.382* (0.227)	0.442* (0.268)
LEV	-0.335 (0.550)	-0.137 (0.690)	-0.091 (0.694)	-0.228 (0.698)
TURN	-0.241* (0.107)	-0.164 (0.253)	-0.111 (0.256)	-0.191 (0.252)
NOE	-0.233* (0.202)	0.803* (0.334)	0.806* (0.336)	0.599* (0.337)
R-squared	0.159	0.173	0.173	0.183

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 6 Robustness results

	(1)	(2)	(3)
DT	0.074** (0.033)	0.026* (0.017)	0.073* (0.057)
SC		-0.978* (0.796)	
CC			-3.603*** (1.041)
DT*SC		-0.149* (0.115)	
DT*CC			-0.004 (0.175)
AGE	-0.237*** (0.042)	-0.243*** (0.041)	-0.196*** (0.043)
SIZE	0.425* (0.263)	0.418* (0.264)	0.445* (0.262)
LEV	-0.229 (0.612)	-0.261 (0.613)	-0.373 (0.611)
TURN	-0.228* (0.119)	-0.219* (0.119)	-0.204* (0.119)
NOE	0.743** (0.263)	0.691** (0.266)	0.571* (0.266)
R-squared	0.077	0.077	0.087

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 7 Effect on social responsibility and economic performance

	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.217*** (0.039)	0.289*** (0.074)	0.215** (0.052)	0.003* (0.002)	0.005* (0.002)	0.002* (0.001)
SC		1.040* (0.419)			0.039** (0.013)	
CC			-0.516* (0.462)			-0.033* (0.014)
DT*SC		-0.170* (0.135)			-0.007* (0.004)	
DT*CC			-0.020 (0.157)			-0.001 (0.004)
AGE	0.004 (0.017)	0.008 (0.017)	0.010 (0.017)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
SIZE	0.425** (0.344)	0.356*** (0.107)	0.347** (0.107)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
LEV	-0.765** (0.248)	-0.733** (0.248)	-0.787** (0.249)	-0.119*** (0.007)	-0.117*** (0.007)	-0.120*** (0.007)
TURN	0.057 (0.048)	0.047 (0.048)	0.061 (0.048)	0.003* (0.001)	0.003* (0.002)	0.004* (0.002)
NOE	-0.084 (0.107)	-0.051 (0.108)	-0.108 (0.109)	0.001 (0.003)	0.002 (0.003)	-0.001 (0.003)
R-squared	0.066	0.070	0.066	0.187	0.192	0.191

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

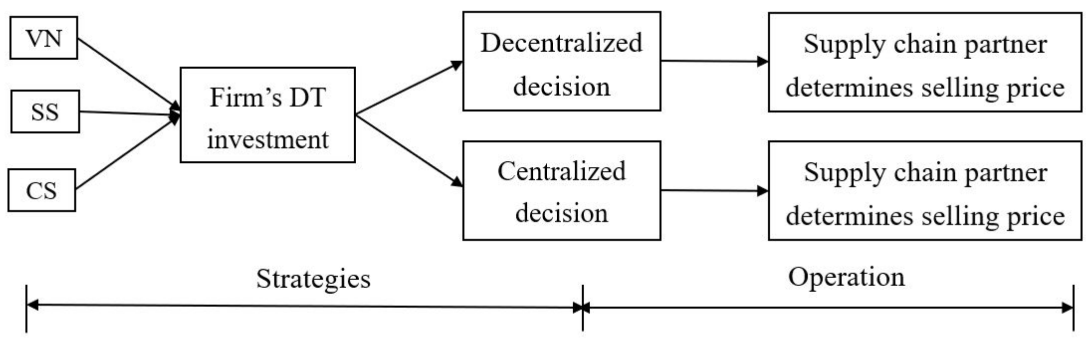
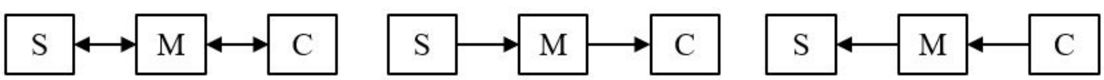


Fig. 1 Decision sequence of game models



(a) vertical Nash model (b) supplier Stackelberg model (c) retailer Stackelberg model

Fig 2. Bargaining power of the three game models

Appendix

(1) Solving the VN Model for decentralized decision: From the revenue function of supplier, mining company and retailer, we consider the second derivative of p_s, p_m, p_c, obtaining $\frac{d^2\pi_s(p_s,r_s)}{dp_s^2}=-2b<0$, $\frac{d^2\pi_m(p_m,r_m)}{dp_m^2}=-2b<0$, $\frac{d^2\pi_c(p_c,r_c)}{dp_c^2}=-2b<0$; therefore, $\pi_s(p_s,r_s)$, $\pi_m(p_m,r_m)$, and $\pi_c(p_c,r_c)$ are convex functions about p_s, p_m, and p_c, respectively. Let $\frac{d\pi_c(p_c,r_c)}{dp_c}=\frac{d\pi_m(p_m,r_m)}{dp_m}=\frac{d\pi_s(p_s,r_s)}{dp_s}=0$, obtain $p_s=\frac{a+3bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{4b}$, $p_m=\frac{a+bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$, $p_c=\frac{3a+bc+3\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{4b}$.

Replace p_s, p_m, p_c in $\pi_s(p_s,r_s),\pi_m(p_m,r_m),\pi_c(p_c,r_c)$, obtain $\frac{d^2\pi_s(p_s,r_s)}{dr_s^2}=\frac{\eta^2(1+\beta_s)^2}{8b}-k_s$, $\frac{d^2\pi_m(p_m,r_m)}{dr_m^2}=\frac{\eta^2(1+\beta_c)^2}{8b}-k_m$, $\frac{d^2\pi_c(p_c,r_c)}{dr_c^2}=\frac{\eta^2(1+\beta_c)^2}{8b}-k_c$. Let $\frac{\eta^2(1+\beta_s)^2}{8b}-k_s<0$, $\frac{\eta^2(1+\beta_c)^2}{8b}-k_m<0$, $\frac{\eta^2(1+\beta_c)^2}{8b}-k_c<0$, so $\pi_c(p_c,r_c)$, $\pi_m(p_m,r_m)$, $\pi_s(p_s,r_s)$ are all convex functions about r_c, r_m, r_s. Let $\frac{d\pi_c(p_c,r_c)}{dr_c}=\frac{d\pi_m(p_m,r_m)}{dr_m}=\frac{d\pi_s(p_s,r_s)}{dr_s}=0$, obtain

$r_s^{DV}=\frac{d_0\eta(1+\beta_s)}{4k_s b(2-L_s-L_m-L_c)}$, $r_m^{DV}=\frac{d_0\eta(1+\beta_m)}{4k_m b(2-L_s-L_m-L_c)}$, $r_c^{DV}=\frac{d_0\eta(1+\beta_c)}{4k_c b(2-L_s-L_m-L_c)}$, where $L_s=\frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m=\frac{\eta^2(1+\beta_m)^2}{4k_m b}$, $L_c=\frac{\eta^2(1+\beta_c)^2}{4k_c b}$; therefore, $L_s<2$, $L_m<2$, $L_c<2$. Replace r_s^{DV}, r_m^{DV}, r_c^{DV} in p_s, p_m and p_c, obtain $p_s^{DV}=c+\frac{d_0}{2b(2-L_s-L_m-L_c)}$, $p_m^{DV}=c+\frac{d_0}{b(2-L_s-L_m-L_c)}$, $p_c^{DV}=c+\frac{3d_0}{2b(2-L_s-L_m-L_c)}$. Therefore, the demand function is $d^{DV}=\frac{d_0}{2(2-L_S-L_m-L_c)}$ and the profit of mining company is $\pi_m^{DV}=\frac{d_0^2(2-L_m)}{8b(2-L_s-L_m-L_c)^2}$. The EP of mining company is $E_m^{DV}=\frac{d_0^2\eta(1+\beta_m)}{8bk_m(2-L_s-L_m-L_c)^2}$, and the social welfare of mining company is $S_m^{DV}=\frac{d_0^2(3-L_m)}{8b(2-L_s-L_m-L_c)^2}$. (2) Solving the VN Model for centralized decision: According to the solution results of the first stage of the VN model under decentralized decision-making, we replace

$p_s = \frac{a+3bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{4b}$, $p_m = \frac{a+bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$, $p_c = \frac{3a+bc+3\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{4b}$ in $\pi_{sc}(p_c,r_s,r_m,r_c)$. We consider the second derivative of r_s, r_m, r_c, obtain $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s^2} = \frac{3\eta^2(1+\beta_s)^2-16bk_s}{16b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m^2} = \frac{3\eta^2(1+\beta_m)^2-16bk_m}{16b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c^2} = \frac{3\eta^2(1+\beta_c)^2-16bk_c}{16b}$. Let $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_m} = \frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_s} = \frac{3\eta^2(1+\beta_s)(1+\beta_m)}{8b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_c} = \frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_s} = \frac{3\eta^2(1+\beta_s)(1+\beta_c)}{8b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_m} = \frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_c} = \frac{3\eta^2(1+\beta_c)(1+\beta_m)}{8b}$. Let the second derivative result be less than zero, and the Hessian matrix $\begin{vmatrix} \frac{d^2\pi_{sc}^c}{dr_s^2} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_c} \\ \frac{d^2\pi_{sc}^c}{dr_m dr_s} & \frac{d^2\pi_{sc}^c}{dr_m^2} & \frac{d^2\pi_{sc}^c}{dr_m dr_c} \\ \frac{d^2\pi_{sc}^c}{dr_c\,dr_s} & \frac{d^2\pi_{sc}^c}{dr_c\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_c^2} \end{vmatrix} > 0$, we obtain $0 < L_s + L_m + L_c < \frac{2}{3}$, where, $L_s = \frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m = \frac{\eta^2(1+\beta_m)^2}{4k_m b}$, $L_c = \frac{\eta^2(1+\beta_c)^2}{4k_c b}$.

Therefore, $\pi_{sc}(p_c,r_s,r_m,r_c)$ is the convex function about r_c, r_m, r_s. Let $\frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s} = \frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m} = \frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c} = 0$, we obtain $r_s^{CV} = \frac{3d_0\eta(1+\beta_s)}{4k_s b[2-3(L_s+L_m+L_c)]}$, $r_m^{CV} = \frac{3d_0\eta(1+\beta_m)}{4k_m b[2-3(L_s+L_m+L_c)]}$, $r_c^{CV} = \frac{3d_0\eta(1+\beta_c)}{4k_c b[2-3(L_s+L_m+L_c)]}$. Replace p_c, p_m, p_s in $p_s^{CV} = c + \frac{d_0}{2b[2-3(L_s+L_m+L_c)]}$, $p_m^{CV} = p_s^{CV} + \frac{d_0}{2b[2-3(L_s+L_m+L_c)]}$, $p_c^{CV} = p_m^{CV} + \frac{d_0}{2b[2-3(L_s+L_m+L_c)]}$. Therefore, the demand function is $d^{CV} = \frac{d_0}{2[2-3(L_S+L_m+L_c)]}$, the profit of mining company is $\pi_m^{CV} = \frac{d_0^2(2-9L_m)}{8b[2-3(L_s+L_m+L_c)]^2}$. The EP of mining company is $E_m^{CV} = \frac{3d_0^2\eta(1+\beta_m)}{8bk_m[2-3(L_s+L_m+L_c)]^2}$, the social welfare of mining company is

$S_m^{CV} = \frac{d_0^2(3-9L_m)}{8b[(2-3(L_s+L_m+L_c)]^2}$. (3) Solving the SS Model for decentralized decision: From the revenue function of mining company, we take the second derivative of p_m, obtaining $\frac{d^2\pi_c(p_c,r_c)}{dp_c^2} = -2b < 0$; therefore, $\pi_c(p_c,r_c)$ is convex function about p_c. Let $\frac{d\pi_c(p_c,r_c)}{dp_c} = 0$, obtain $p_c = \frac{a+bp_m+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$. Replace p_c in $\pi_m(p_m,r_m)$, then $\frac{d^2\pi_m(p_m,r_m)}{dp_m^2} = -b < 0$; therefore, $\pi_m(p_m,r_m)$ is a convex function about p_m. Let $\frac{d\pi_m(p_m,r_m)}{dp_m} = 0$, obtain $p_m = \frac{a+bp_s+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$. Replace p_m in $\pi_s(p_s,r_s)$, then $\frac{d^2\pi_s(p_s,r_s)}{dp_s^2} = -\frac{b}{2} < 0$; therefore, $\pi_s(p_s,r_s)$ is a convex function about p_s. Let $\frac{d\pi_s(p_s,r_s)}{dp_s} = 0$, obtain $p_s = \frac{a+bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$. Replace p_c, p_m, and p_s in $\pi_c(p_c,r_c)$, $\pi_m(p_m,r_m)$, and $\pi_s(p_s,r_s)$, respectively; then, we take the second derivative of r_c, r_m, and r_s, and obtain $\frac{d^2\pi_c(p_c,r_c)}{dr_c^2} = \frac{\eta^2(1+\beta_c)^2}{32b} - k_c$, $\frac{d^2\pi_m(p_m,r_m)}{dr_m^2} = \frac{\eta^2(1+\beta_c)^2}{16b} - k_m$, and $\frac{d^2\pi_s(p_s,r_s)}{dr_s^2} = \frac{\eta^2(1+\beta_s)^2}{8b} - k_s$. Let $\frac{\eta^2(1+\beta_c)^2}{32b} - k_c < 0$, $\frac{\eta^2(1+\beta_m)^2}{16b} - k_m < 0$, $\frac{\eta^2(1+\beta_s)^2}{8b} - k_s < 0$; therefore, $\pi_c(p_c,r_c)$, $\pi_m(p_m,r_m)$, and $\pi_s(p_s,r_s)$ are convex functions about r_c, r_m, and r_s, respectively. Let $\frac{d\pi_c(p_c,r_c)}{dr_c} = \frac{d\pi_m(p_m,r_m)}{dr_m} = \frac{d\pi_s(p_s,r_s)}{dr_s} = 0$, we obtain

$$r_s^{DS} = \frac{d_0\eta(1+\beta_s)}{k_s b(8-4L_s-2L_m-L_c)},\quad r_m^{DS} = \frac{d_0\eta(1+\beta_m)}{2k_m b(8-4L_s-2L_m-L_c)},\quad r_c^{DS} = \frac{d_0\eta(1+\beta_c)}{4k_c b(8-4L_s-2L_m-L_c)},$$

where $L_s = \frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m = \frac{\eta^2(1+\beta_m)^2}{4k_m b}$, $L_c = \frac{\eta^2(1+\beta_c)^2}{4k_c b}$; therefore, $L_s < 2$, $L_m < 4$, $L_c < 8$.

Replace r_s^{DS}, r_m^{DS}, r_c^{DS} in p_s, p_m, p_c, we obtain $p_s^{DS} = c + \frac{4d_0}{b(8-4L_s-2L_m-L_c)}$, $p_m^{DS} = c + \frac{6d_0}{b(8-4L_s-2L_m-L_c)}$, and $p_c^{DS} = c + \frac{7d_0}{b(8-4L_s-2L_m-L_c)}$. Therefore, the demand function is $d^{DS}=\frac{d_0}{8-4L_S-2L_m-L_c}$, profit of mining company is $\pi_m^{DS}=\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c)^2}$, EP of mining company is $E_m^{DS}=\frac{d_0^2\eta(1+\beta_m)}{2k_m b(8-4L_s-2L_m-L_c)^2}$, and social welfare of mining company is $S_m^{DS}=\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c)^2}$. (4) Solving the SS Model for centralized decision: Replace $p_c=\frac{a+bp_m+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$, $p_m=\frac{a+bp_s+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$, $p_s=\frac{a+bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{2b}$ in π_{cs}; then, we take the second derivative of r_s, r_m, r_c, and obtain $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s^2}=\frac{7\eta^2(1+\beta_s)^2-32bk_s}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m^2}=\frac{7\eta^2(1+\beta_m)^2-32bk_m}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c^2}=\frac{7\eta^2(1+\beta_c)^2-32bk_c}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_m}=\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_s}=\frac{7\eta^2(1+\beta_s)(1+\beta_m)}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_c}=\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_s}=\frac{7\eta^2(1+\beta_s)(1+\beta_c)}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_m}=\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_c}=\frac{7\eta^2(1+\beta_c)(1+\beta_m)}{32b}$. Let the second derivative result be less than zero, and Hessian matrix $\begin{vmatrix}\frac{d^2\pi_{sc}^c}{dr_s^2} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_c}\\ \frac{d^2\pi_{sc}^c}{dr_m dr_s} & \frac{d^2\pi_{sc}^c}{dr_m^2} & \frac{d^2\pi_{sc}^c}{dr_m dr_c}\\ \frac{d^2\pi_{sc}^c}{dr_c\,dr_s} & \frac{d^2\pi_{sc}^c}{dr_c\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_c^2}\end{vmatrix}>0$, we obtain $0<L_s+L_m+L_c<\frac{8}{7}$, where $L_s=\frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_c=\frac{\eta^2(1+\beta_c)^2}{4k_c b}$, $L_m=\frac{\eta^2(1+\beta_m)^2}{4k_m b}$; therefore, $\pi_{sc}(p_c,r_s,r_m,r_c)$ is a convex function about r_c, r_m, r_s. Let $\frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s}=\frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m}=\frac{d\ \pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c}=0$, we obtain $r_s^{CS}=\frac{7d_0\eta(1+\beta_s)}{4k_s b[8-7(L_s+L_m+L_c)]}$, $r_m^{CS}=\frac{7d_0\eta(1+\beta_m)}{4k_m b[8-7(L_s+L_m+L_c)]}$, $r_c^{CS}=\frac{7d_0\eta(1+\beta_c)}{4k_c b[8-7(L_s+L_m+L_c)]}$; then, replacing them in p_c, p_m, p_s, we obtain $p_s^{CS}=c+\frac{4d_0}{b[8-7(L_s+L_m+L_c)]}$,

$p_m^{CS} = p_s^{CS} + \frac{2d_0}{b[8-7(L_s+L_m+L_c)]}$, $p_c^{CS} = p_m^{CS} + \frac{d_0}{b[8-7(L_s+L_m+L_c)]}$. Therefore, the demand function is $d^{CS} = \frac{8d_0}{8-7(L_S+L_m+L_c)}$, profit function of mining company is $\pi_m^{CS} = \frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$, EP of mining company is $E_m^{CS} = \frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$, and social welfare function of mining company is $S_m^{CS} = \frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c)]^2}$. (5) Solving the RS Model for decentralized decision: Assuming that the marginal profit of retailer is e_{mc} and marginal profit of supplier is e_{sm}, then $p_c = p_m + e_{mc}$, $p_m = p_s + e_{sm}$. Replacing $p_c = p_m + e_{mc}$, $p_m = p_s + e_{sm}$ in $\pi_m(p_m, r_m)$, $\pi_s(p_s, r_s)$, we obtain $\frac{d^2\pi_s(p_s,r_s)}{dp_s^2} = -2b < 0$; therefore, $\pi_s(p_s, r_s)$ is the convex function of p_s. Let $\frac{d\pi_s(p_s,r_s)}{dp_s} = 0$, then $p_s = \frac{a+b(c-p_c)+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{b}$. Replacing p_s in $\pi_m(p_m, r_m)$, we obtain $\frac{d^2\pi_m(p_m,r_m)}{dp_m^2} = -4b < 0$; therefore, $\pi_m(p_m, r_m)$ is the convex function of p_m. Let $\frac{d\pi_m(p_m,r_m)}{dp_m} = 0$, then $p_m = \frac{3a+b(c-3p_c)+3\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{b}$. Replacing p_m in $\pi_c(p_c, r_c)$, we obtain $\frac{d^2\pi_c(p_c,r_c)}{dp_c^2} = -8b < 0$. Let $\frac{d\pi_c(p_c,r_c)}{dp_c} = 0$, then $p_c = \frac{7a+bc+7\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$. Replacing p_c in p_s and p_m, then $p_m = \frac{3a+5bc+3\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$ and $p_s = \frac{a+7bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$. Replacing p_c, p_m, and p_s in $\pi_c(p_c, r_c)$, $\pi_m(p_m, r_m)$, and $\pi_s(p_s, r_s)$, respectively, then $\frac{d^2\pi_c(p_c,r_c)}{dr_c^2} = \frac{\eta^2(1+\beta_c)^2}{8b} - k_c$, $\frac{d^2\pi_m(p_m,r_m)}{dr_m^2} = \frac{\eta^2(1+\beta_m)^2}{16b} - k_m$, $\frac{d^2\pi_s(p_s,r_s)}{dr_s^2} = \frac{\eta^2(1+\beta_s)^2}{32b} - k_s$. Let $\frac{\eta^2(1+\beta_c)^2}{8b} - k_c < 0$, $\frac{\eta^2(1+\beta_m)^2}{16b} - k_m < 0$, $\frac{\eta^2(1+\beta_s)^2}{32b} - k_s < 0$, then $\pi_c(p_c, r_c)$, $\pi_m(p_m, r_m)$, and $\pi_s(p_s, r_s)$ are convex functions about r_c, r_m, and r_s, respectively. Let $\frac{d\pi_c(p_c,r_c)}{dr_c} = \frac{d\pi_m(p_m,r_m)}{dr_m} = \frac{d\pi_s(p_s,r_s)}{dr_s} = 0$, then

$r_s^{DC} = \frac{d_0\eta(1+\beta_s)}{4k_s b(8-L_s-2L_m-4L_c)}$, $r_m^{DC} = \frac{d_0\eta(1+\beta_m)}{2k_m b(8-L_s-2L_m-4L_c)}$, $r_c^{DC} = \frac{d_0\eta(1+\beta_c)}{k_c b(8-L_s-2L_m-4L_c)}$,

where $L_s = \frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m = \frac{\eta^2(1+\beta_m)^2}{4k_m b}$, $L_c = \frac{\eta^2(1+\beta_c)^2}{4k_c b}$, then $L_s < 8$, $L_m < 4$, $L_c < 2$.

Replace r_s^{SM}, r_m^{SM}, and r_c^{SM} in p_s, p_m, and p_c, respectively, then

$p_s^{DC} = c + \frac{d_0}{b(8-L_s-2L_m-4L_c)}$, $p_m^{DC} = c + \frac{3d_0}{b(8-L_s-2L_m-4L_c)}$, and

$p_c^{DC} = c + \frac{7d_0}{b(8-L_s-2L_m-4L_c)}$. Therefore, the demand function is $d^{DC} = \frac{d_0}{8-L_S-2L_m-4L_c}$, profit function of mining company is $\pi_m^{DC} = \frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c)^2}$, EP of mining company is

$E_m^{DC} = \frac{d_0^2\eta(1+\beta_m)}{2bk_m(8-L_s-2L_m-4L_c)^2}$, social welfare function is $S_m^{DC} = \frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c)^2}$. (6)

Solving the RS Model for centralized decision: Replace

$p_c = \frac{7a+bc+7\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$,

$p_m = \frac{3a+5bc+3\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$,

$p_s = \frac{a+7bc+\eta(r_s+r_m+r_c+\beta_s r_s+\beta_m r_m+\beta_c r_c)}{8b}$ in $\pi_{sc}(p_c,r_s,r_m,r_c)$, and take the second derivative of r_s, r_m, and r_c, then $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s^2} = \frac{7\eta^2(1+\beta_s)^2-32bk_s}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m^2} =$

$\frac{7\eta^2(1+\beta_m)^2-32bk_m}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c^2} = \frac{7\eta^2(1+\beta_c)^2-32bk_c}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_m} =$

$\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_s} = \frac{7\eta^2(1+\beta_s)(1+\beta_m)}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_s\,dr_c} = \frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_s} =$

$\frac{7\eta^2(1+\beta_s)(1+\beta_c)}{32b}$, $\frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_c\,dr_m} = \frac{d^2\pi_{sc}(p_c,r_s,r_m,r_c)}{dr_m dr_c} = \frac{7\eta^2(1+\beta_c)(1+\beta_m)}{32b}$. Let the second derivative result be less than zero, and Hessian matrix $\begin{vmatrix} \frac{d^2\pi_{sc}^c}{dr_s^2} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_s\,dr_c} \\ \frac{d^2\pi_{sc}^c}{dr_m dr_s} & \frac{d^2\pi_{sc}^c}{dr_m^2} & \frac{d^2\pi_{sc}^c}{dr_m dr_c} \\ \frac{d^2\pi_{sc}^c}{dr_c\,dr_s} & \frac{d^2\pi_{sc}^c}{dr_c\,dr_m} & \frac{d^2\pi_{sc}^c}{dr_c^2} \end{vmatrix} > 0$, then $L_s + L_m + L_c < \frac{8}{7}$, where $L_s = \frac{\eta^2(1+\beta_s)^2}{4k_s b}$, $L_m = \frac{\eta^2(1+\beta_m)^2}{4k_m b}$, $L_c = \frac{\eta^2(1+\beta_c)^2}{4k_c b}$; therefore, $\pi_{sc}(p_c, r_s, r_m, r_c)$ is the convex function about r_c, r_m, r_s. Let $\frac{d\ \pi_{sc}(p_c, r_s, r_m, r_c)}{dr_s} = \frac{d\ \pi_{sc}(p_c, r_s, r_m, r_c)}{dr_m} = \frac{d\ \pi_{sc}(p_c, r_s, r_m, r_c)}{dr_c} = 0$, we obtain $r_s^{CC} = \frac{7d_0\eta(1+\beta_s)}{4k_s b[8-7(L_s+L_m+L_c)]}$, $r_m^{CC} = \frac{7d_0\eta(1+\beta_m)}{4k_m b[8-7(L_s+L_m+L_c)]}$, $r_c^{CC} = \frac{7d_0\eta(1+\beta_c)}{4k_c b[8-7(L_s+L_m+L_c)]}$, then replace them in p_c, p_m, and p_s, we obtain $p_s^{CC} = c + \frac{d_0}{b[8-7(L_s+L_m+L_c)]}$, $p_m^{CC} = C + \frac{3d_0}{b[8-7(L_s+L_m+L_c)]}$, and $p_c^{CC} = C + \frac{7d_0}{b[8-7(L_s+L_m+L_c)]}$. Therefore, the demand function is $d^{CC} = \frac{8d_0}{8-7(L_S+L_m+L_c)}$, profit function of mining company is $\pi_m^{CC} = \frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$, EP of mining company is $E_m^{CC} = \frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$, social welfare of the mining company is $S_m^{CC} = \frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c)]^2}$.

Table 1 Notions

Notions	Description
p_s , p_m , p_c	Unit product selling price of supplier/mining company/retailer
r_s , r_m , r_c	Unit carbon reduction of supplier/mining company/retailer after DT investment
k_s , k_m , k_c	Cost coefficient of DT investment for supplier/mining company/retailer
β_s , β_m , β_c	Overflow rate of supplier/mining company/retailer to other supply chain partner, $0 \le \beta_s, \beta_m, \beta_c \le 1$
a	Market size of the product
b	Price sensitivity coefficient of the product
c	Unit production cost, including material cost and process cost, $p_c > p_m > p_s > c$
η	Sensitivity coefficient of market demand to DT

Note: The subscripts of the symbols s , m, and c in the table represent the supplier, mining company, and retailer, respectively.

Table 2 Optimal results of mining company under different game models

	π_m	E_m	S_m
Decentralized VN	$\frac{d_0^2(2-L_m)}{8b(2-L_s-L_m-L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{8bk_m(2-L_s-L_m-L_c)^2}$	$\frac{d_0^2(3-L_m)}{8b(2-L_s-L_m-L_c)^2}$
Centralized VN	$\frac{d_0^2(2-9L_m)}{8b[2-3(L_s+L_m+L_c)]^2}$	$\frac{3d_0^2\eta(1+\beta_m)}{8bk_m[2-3(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(3-9L_m)}{8b[(2-3(L_s+L_m+L_c}$
Decentralized SS	$\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{2k_m b(8-4L_s-2L_m-L_c)^2}$	$\frac{d_0^2(4-L_m)}{2b(8-4L_s-2L_m-L_c}$
Centralized SS	$\frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$	$\frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c}$
Decentralized RS	$\frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c)^2}$	$\frac{d_0^2\eta(1+\beta_m)}{2bk_m(8-L_s-2L_m-4L_c)^2}$	$\frac{d_0^2(4-L_m)}{2b(8-L_s-2L_m-4L_c}$
Centralized RS	$\frac{d_0^2(128-49L_m)}{8b[8-7(L_s+L_m+L_c)]^2}$	$\frac{14d_0^2\eta(1+\beta_m)}{bk_m[8-7(L_s+L_m+L_c)]^2}$	$\frac{d_0^2(384-49L_m)}{8b[(8-7(L_s+L_m+L_c}$

Table 3 Correlation matrix and descriptive statistics

	1	2	3	4	5	6	7	8	9
EP	1								
DT	0.978**	1							
SC	-0.089**	-0.088**	1						
CC	-0.202**	-0.217	0.364***	1					
AGE	-0.157***	-0.150*	-0.121**	0.236	1				
SIZE	0.196**	0.194***	-0.305	-0.196	0.132	1			
LEV	-0.024	-0.024	-0.075	-0.052	0.040	-0.135**	1		
TURN	0.016	0.015	-0.035	-0.035	0.010	0.256***	0.071	1	
NOE	0.217	0.207**	-0.329*	-0.269*	0.077	0.854**	-0.067	0.294*	1
Mean	4.012	4.241	0.431	0.297	13.65	22.978	0.537	2.066	8.516
S.D.	3.901	2.448	0.259	0.246	4.868	1.711	0.958	1.106	1.708

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 4 Regression results

	Model 1	Model 2	Model 3
DT	3.137*** (0.021)	3.130** (0.015)	3.073*** (0.027)
SC		-0.011* (0.005)	
CC			-0.267 (0.237)
DT*SC		-0.056* (0.035)	
DT*CC			-0.336*** (0.081)
AGE	-0.013* (0.008)	-0.013* (0.010)	-0.019** (0.009)
SIZE	-0.082* (0.055)	-0.081* (0.055)	-0.072* (0.055)
LEV	-0.022 (0.129)	-0.020 (0.129)	0.002 (0.127)
TURN	-0.008 (0.025)	-0.008 (0.025)	-0.013 (0.025)
NOE	0.130** (0.055)	0.132** (0.056)	0.149** (0.055)
R-squared	0.559	0.558	0.596

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 5 Robustness results

	(1) Stage 1	(2) Stage 2	(3)	(4)
Innovation	0.833* (0.592)			
DT		0.194* (0.107)	0.067* (0.044)	0.237* (0.155)
SC			-2.462* (1.681)	
CC				-5.360** (0.194)
DT*SC			-0.771* (0.657)	
DT*CC				0.860* (0.800)
AGE	0.112** (0.037)	-0.268* (0.113)	-0.284* (0.114)	-0.210* (0.114)
SIZE	-0.039 (0.237)	0.440* (0.269)	0.382* (0.227)	0.442* (0.268)
LEV	-0.335 (0.550)	-0.137 (0.690)	-0.091 (0.694)	-0.228 (0.698)
TURN	-0.241* (0.107)	-0.164 (0.253)	-0.111 (0.256)	-0.191 (0.252)
NOE	-0.233* (0.202)	0.803* (0.334)	0.806* (0.336)	0.599* (0.337)
R-squared	0.159	0.173	0.173	0.183

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 6 Robustness results

	(1)	(2)	(3)
DT	0.074** (0.033)	0.026* (0.017)	0.073* (0.057)
SC		-0.978* (0.796)	
CC			-3.603*** (1.041)
DT*SC		-0.149* (0.115)	
DT*CC			-0.004 (0.175)
AGE	-0.237*** (0.042)	-0.243*** (0.041)	-0.196*** (0.043)
SIZE	0.425* (0.263)	0.418* (0.264)	0.445* (0.262)
LEV	-0.229 (0.612)	-0.261 (0.613)	-0.373 (0.611)
TURN	-0.228* (0.119)	-0.219* (0.119)	-0.204* (0.119)
NOE	0.743** (0.263)	0.691** (0.266)	0.571* (0.266)
R-squared	0.077	0.077	0.087

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

Table 7 Effect on social responsibility and economic performance

	(1)	(2)	(3)	(4)	(5)	(6)
DT	0.217*** (0.039)	0.289*** (0.074)	0.215** (0.052)	0.003* (0.002)	0.005* (0.002)	0.002* (0.001)
SC		1.040* (0.419)			0.039** (0.013)	
CC			-0.516* (0.462)			-0.033* (0.014)
DT*SC		-0.170* (0.135)			-0.007* (0.004)	
DT*CC			-0.020 (0.157)			-0.001 (0.004)
AGE	0.004 (0.017)	0.008 (0.017)	0.010 (0.017)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
SIZE	0.425** (0.344)	0.356*** (0.107)	0.347** (0.107)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)
LEV	-0.765** (0.248)	-0.733** (0.248)	-0.787** (0.249)	-0.119*** (0.007)	-0.117*** (0.007)	-0.120*** (0.007)
TURN	0.057 (0.048)	0.047 (0.048)	0.061 (0.048)	0.003* (0.001)	0.003* (0.002)	0.004* (0.002)
NOE	-0.084 (0.107)	-0.051 (0.108)	-0.108 (0.109)	0.001 (0.003)	0.002 (0.003)	-0.001 (0.003)
R-squared	0.066	0.070	0.066	0.187	0.192	0.191

Note: ***, **, and * represent significance at 0.1%, 1%, and 10% levels, respectively.

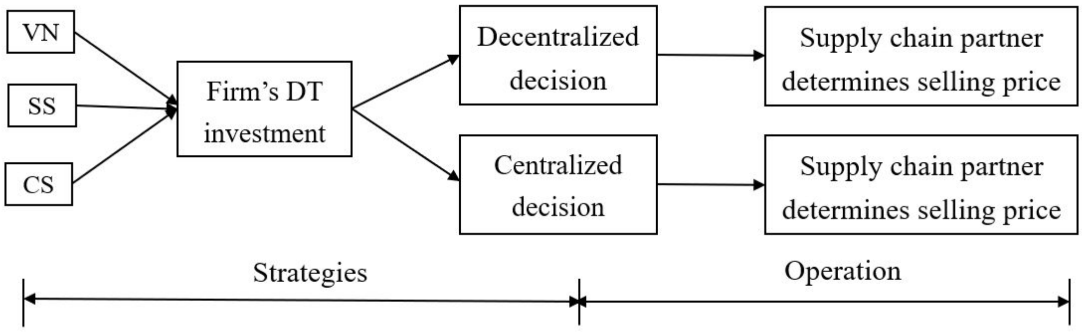


Fig. 1 Decision sequence of game models

(a) vertical Nash model (b) supplier Stackelberg model (c) retailer Stackelberg model

Fig 2. Bargaining power of the three game models