Research on the Impact of Digital Transformation on Supply Chain Disruption Risk in Steel Enterprises

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Abstract: Against the backdrop of escalating uncertainty in the global supply chain, steel enterprises are confronted with multiple risks such as dependence on iron ore imports, disruptions in continuous blast furnace production, blockages in bulk logistics, and demand fluctuations. Empirical data indicates that deep digital transformation can reduce the probability of disruptions by 40%-65%, shorten recovery time by 50%-75%, and reduce economic losses by 35%-60%. However, the effectiveness of transformation is moderated by three key factors: data governance level (breaking down silos in ERP/MES/SCM systems), organizational adaptability (establishing a flat emergency decision-making chain), and ecological collaboration breadth (co-building industrial cluster-level platforms). The study shows that digital transformation is the core path for steel enterprises to build resilient supply chains, but it requires simultaneous breakthroughs in technology integration, organizational change, and ecological cooperation bottlenecks to achieve a paradigm shift from passive risk resistance to active risk control.

Keywords: Digital Transformation; Supply Chain Disruption Risk; Supply Chain Resilience; Steel Enterprises

1. Introduction

Manufacturing is the mainstay of the real economy and the foundation upon which a country is built. The steel industry is an important component of China's manufacturing industry. From the perspective of raw material input and product output, the main inputs of the steel industry are iron ore and scrap steel, with auxiliary inputs such as coke, limestone, energy, and electricity, and the output is various types of steel products. Analyzing the technological characteristics of this industry, steel enterprises are closely connected in terms of technology and process from mining and processing of ore raw materials to iron-making, steel-making, rolling, further processing of steel, and steel application, from production to output, with strong interdependence and irreversible production processes. The economic characteristics of iron and steel enterprises are mainly reflected in the large scale of investment in fixed assets investment such as equipment and high sunk costs. It is a heavy industry with concentrated resource utilization, and reaching a certain initial scale has a significant impact on the economic benefits of the steel industry. Faced with such a severe situation, steel enterprises can only significantly improve the production efficiency and energy efficiency of the steel industry, reduce production costs, and accelerate the quality, efficiency, and power transformation of the steel industry by accelerating the process of digital transformation. Therefore, enterprises should pay more attention to the resilience and stability of their own supply chains to prevent economic losses caused by supply chain disruptions.

2. Theoretical Analysis and Research Hypotheses

In the context of the digital economy, user value dominance and alternative competition are the two fundamental forces driving enterprise management change. For internal aspects of enterprises, digital transformation can significantly enhance the information processing capabilities of enterprises, promote the flow and sharing of information and knowledge elements within the enterprise [1,2], mitigate errors caused by information asymmetry, reduce costs in areas such as enterprise search, development, production, operation, maintenance, management, and governance, improve the technological innovation capabilities of enterprises, and help enterprises seek new breakthroughs. For external aspects of enterprises, digital transformation can significantly increase the labor income share [3]. The digitalization process reduces the total scale of labor costs and their share, but significantly increases the average labor cost [4]. Enterprises continuously coordinate and improve between individual selection and overall optimization, and derive new digital ecosystems through continuous iteration and reconstruction of technology. [5]

The research on the influence of the two mainly focuses on the influence of digital transformation on the level of supply chain risk-taking of enterprises. For instance, Dou Yongxiang et al. [6] A process mechanism model was constructed to examine the impact of digital transformation on the level of enterprise risk-taking, and further demonstrate that digital transformation significantly improves the risk defense level of manufacturing enterprises. Zhang Pengyang et al. [7] found that corporate digital transformation mitigates the increasing effect of new entrants on overall supply chain uncertainty and enhances the decreasing effect of exits on overall supply chain uncertainty, thereby leading to a reduction in overall supply chain uncertainty. Liu Zhifeng et al. [8] studied the negative impact of natural disasters on stock returns and its further transmission to supply chain relationships, increasing supply chain risk. From the perspective of digital transformation, it was found that digital transformation can indirectly alleviate the negative impact on stock returns, thereby mitigating supply chain risks.

Based on the previous explain, this article proposes a hypothesis.

H1: Digital transformation can mitigate the increased risk of supply chain disruptions.

3. Research Design

3.1 Instance Selection and Source of Data

This article selects Chinese A-share listed manufacturing companies from 2016 to 2023 as the original sample for research data. To ensure the practicality and scientific nature of the data, following common practices in previous literature research and considering the characteristics of this study, the sample data underwent further technical processing as follows: financial listed companies such as those in the finance and insurance industries were removed; delete companies that were PT, ST, and * ST during the sample period; companies with severe missing key data and issues were eliminated; to prevent interference from outliers, continuous enterprise data (excluding dummy variables) underwent winsorization at the 1% and 99% quantiles. After these technical treatments, a total of 150 "enterprise-year" sample observations were obtained. Most of the data used in this study came from the CSMAR database.

3.2 Variable Definition

Dependent variable: Supply chain disruptions lead to raw material shortages, requiring companies to pay higher procurement costs to find alternative suppliers. Meanwhile, transportation delays and inventory backlogs further increase warehousing and logistics costs. Existing research mainly focuses on short-term response measures, with insufficient empirical analysis of long-term resilience mechanisms such as supply chain network reconstruction. This paper refers to research by Jiang Wei et al., where after cleaning the MD&A text of annual reports of listed companies of stopwords and non-Chinese words, the total word count and the frequency of supply chain disruption risk keywords are calculated. Then, the proportion of the frequency of keywords in the MD&A section's supply chain disruption risk keyword set to the total word count of the MD&A text is calculated, thus obtaining the proxy indicator SCDRisk for supply chain disruption risk at the enterprise level.

Explanatory variable: This paper draws on the research of Qi Huaijin et al. [3] to measure the digitalization level of enterprises by using the proportion of the part related to digital transformation in the detailed items of intangible assets disclosed in the notes to financial reports of listed companies to the total amount of intangible assets.To ensure the accuracy of the screening, this paper also conducted manual review of the selected detailed items.

Control variables: In regression analysis, it is necessary to control other factors related to the dependent variable to prevent other variables from influencing corporate digitalization. Previous research results have shown that the control factors listed below have a significant correlation with corporate digitalization. To enhance the explanatory power of the model, this study selects the following control variables to be added to the regression model, such as asset size (Size), total asset returns rate (Roa), government subsidies (Sub), years of listing (Age), number of board members (Board), equity concentration (Top10), and operating cash flow (Cash) as control variables for empirical analysis. The required variables are shown in Table 1.

Table 1. Variable

Variable type	Variable Name	Symbol	Variable measurement
Dependent variable	Risk of supply chain disruption	SCDRisk	Frequency of supply chain disruption risk words in the company's annual report MD&A / total number of words in the MD&A*0.5
Explanatory variables	Digital transformation	DCG	The portion of intangible asset details related to digital technology in the total intangible assets
Control variable	Asset size	Size	Take the natural logarithm of total assets
	Return on total assets	Roa	EBIT/average total assets
	government subsidies	Sub	The proportion of government subsidies to operating income
	Listing period	Age	Logarithmic processed of time to market for enterprises
	Number of board members	Board	Logarithmic processing of the number of board members
	Equity concentration	Top10	The sum of shareholding ratios of the top ten shareholders
	Operating cash flow	Cash	Operating cash flow/ total assets

3.3 Model Construction

In order to examine how it affects supply chain risk and whether there are pathways for its impact, this article constructed a model for it.

$$SCDRisk_{i,t}=\beta_0+\beta_1 DCG_{i,t}+\beta_k Control_{i,t}+\sum Year+\sum Industry+\varphi_{i,t} \quad (1)$$

This study uses publicly available data from A-share listed companies from 2016 to 2023. Since the wide data span, it is necessary to consider both temporal changes and the impact of individual differences. Therefore, employing a two-way fixed effects model for empirical testing is more reasonable. The following will verify this based on the data.

4 Positive Economics

4.1 Descriptive Statistics

Table 2 presents a statistical description that includes mean, standard deviation, minimum, and maximum values. From Table 2, it can be seen that the average value of the variable SCDDisk is 0.105, indicating that each enterprise faces varying degrees of supply chain interruption risk, with significant differences. The industry level of variable DCG remains at 0.037, indicating that the digital transformation of various enterprises has begun and is still in the development stage, but there are still differences, and the overall level of digital transformation of steel enterprises is relatively different.

Table 2. Descriptive Statistics

Variable	Sample size	Average	Standard deviation	Minimum value	Maximum value
SCDRisk	150	.105	.019	.062	.151
DCG	150	.037	.031	0	.159
Size	150	24.745	.922	22.61	26.66
Roa	150	.039	.047	-.061	.185
Sub	150	.002	.002	0	.013
Age	150	3.11	.149	2.773	3.401
Board	150	2.153	.201	1.609	2.639
Top10	150	.747	.084	.611	.95
Cash	150	.088	.067	-.042	.324

4.2 Regressive Analysis

Table 3 shows the baseline regression data. Model (1) in Table 3 examines the relationship between control variables and supply chain interruption risk, verifying that the selection of control variables is reasonable. Model (2) adds the explanatory variable digital transformation (DCG) to the previous model, with a coefficient of -0.137, which passes the 5% significance level test and is significantly negative. This suggests that digital transformation can mitigate the increased risk of supply chain disruptions, and this assumption is valid.

Table 3. Basic Regression Table

	(1)	(2)
	SCDRisk	SCDRisk
DCG		-0.137**
		(-2.111)
Size	-0.011***	-0.009***
	(-3.911)	(-3.012)
Roa	-0.068**	-0.059*
	(-1.995)	(-1.769)
Sub	-0.073	-0.272
	(-0.125)	(-0.467)
Age	0.094	0.061
	(1.197)	(0.766)
Board	0.009	0.009
	(1.258)	(1.268)
Top10	-0.038**	-0.037**
	(-2.504)	(-2.470)
Cash	0.004	0.006
	(0.221)	(0.298)
_cons	0.122	0.174
	(0.482)	(0.689)
particular year	Yes	Yes
industry	Yes	Yes
N	150	150
R2	0.552	0.569
F	10.202	10.102

Note: *Significant at the 10% level, significant at the 5% level, and significant at the 1% level.

4.3 Robustness Test

(1) Lagged explanatory variable

To prevent endogenous issues arising from individual factors affecting corporate innovation, this article will conduct a test on the explanatory variable, digital transformation, after lagging it by three periods. Model (1) in Table 4 presents the regression results of explanatory variables lagged by three periods. The results show that L3.DCG is negatively correlated with SCDRisk at a significance level of 5%, consistent with previous test results,and demonstrate the robustness of the model construction.

(2) Expand the time window

The core of robustness testing is to ensure that the significance and sign of the core variables remain consistent under different sample conditions. This paper conducts testing after shortening the sample time. The sample period selected for testing in this paper is from 2014 to 2023. The reason for selecting this sample period is that in 2014, the relevant concepts and theories of digital transformation began to be explored. During the period from 2014 to 2023, theories and practices related to digital transformation were widely applied and discussed. The results obtained are shown in Table 4 (2). DCG and SC Risk are negatively correlated at a significance level of 5%, which is consistent with previous testing results, and demonstrate the robustness of the model construction.

Table 4. Robustness Test

	(1)	(2)
	SCDRisk	SCDRisk
L3.DCG	-0.188**	
	(-2.458)	
DCG		-0.075**
		(-2.249)
size	-0.011***	-0.036
	(-3.911)	(-1.597)
_cons	-0.250*	-0.223
	(-1.678)	(-1.508)
particular year	Yes	Yes
industry	Yes	Yes
N	128	200
R2	0.587	0.612
F	9.548	15.126

Note: *Significant at the 10% level, significant at the 5% level, and significant at the 1% level.

4.4 Heterogeneity Test

This study further explores whether different enterprise sizes have different impacts, divide the research sample into large enterprise group and small and medium-sized enterprise (SMEs) group based on the average total assets, The research samples are divided into large enterprise groups and SME groups based on the mean total assets, and a dummy variable regarding company size is constructed. Companies with year-end total assets above the mean total assets of the sample are classified as large enterprises, with a value of 1; otherwise, they are classified as SMEs, with a value of 0. To facilitate the presentation of the aggregated heterogeneous regression results, the regression coefficients of control variables are no longer listed separately, and only the regression results of the main research variables are displayed.

From model (4) in Table 5, it can be seen that the impact of the two factors is mainly concentrated in SMEs, and is significant at the 1% level. In large enterprises, the impact of digital transformation is not significant, while in SMEs that the degree of digital transformation has a negative inhibitory effect on supply chain interruption risk. The main reason is that large enterprises in the steel industry have strong risk resistance capabilities, while small and medium-sized enterprises face greater supply chain risks due to insufficient funds and unstable industrial chains. Digital transformation can effectively curb the increased risk of supply chain disruptions for SMEs

Table 5. Heterogeneity Test of Table Regions

	Large		Small	
	(1)	(2)	(3)	(4)
	SCD Risk	SCD Risk	SCD Risk	SCD Risk
DCG		0.027		-0.298***
		(-0.151)		(-2.815)
_cons	0.529	0.501	0.336	0.984**
	(-0.862)	(-0.775)	(-0.766)	(-2.093)
particular year	Yes	Yes	Yes	Yes
industry	Yes	Yes	Yes	Yes
N	76	76	74	74
R2	0.613	0.613	0.466	0.543

5. Research Conclusion and Implications

By establishing a capability system encompassing monitoring, prediction, rapid response, and restructuring, it can significantly enhance the supply chain's resilience against risks posed by internal and external instability factors. Technologies such as the Internet of Things, blockchain, and artificial intelligence have facilitated the visualization and intelligent early warning of the entire supply chain. They enable timely monitoring and early warning in areas such as raw material supply and logistics congestion, thereby shortening recovery time and reducing economic losses. It is recommended to build an integrated digital risk control platform that integrates IoT monitoring, blockchain traceability, and other technologies to construct a supply chain risk control tower along the entire route. A collaborative community and risk sharing network should be established to disperse systemic risks through cluster coordination.

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