Digital Transformation of Enterprises and Inventory Management

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Abstract
Taking the Chinese A-share listed companies from 2012 to 2019 as research sample, this paper examines the impact of digital transformation of enterprises on inventory management. The results show that digital transformation can significantly reduce the inventory level of enterprises and improve the efficiency of inventory management. And this effect is more pronounced in companies in regions with better transportation infrastructure. This paper not only enriches the literature on the economic consequences of digital transformation of enterprises, but also helps managers to understand the role of digitalization in operational management.

Keywords-*digital transformation of enterprises; inventory management; transportation infrastructure*

1. Introduction

Fast-developing digital technologies from big data to machine learning are widespread in the manufacturing sector and are reshaping the broader economic landscape. In 2020, China's digital economy rose 9.7 percent to 6.16 trillion dollars, accounting for 38.6 percent of the country's total GDP. Digital transformation is defined as organizational change that is triggered and shaped by the widespread diffusion of digital technologies [1]. By combining different types of digital technologies (e.g. cloud computing, big data, machine learning, internet of things, blockchain), companies can open up unforeseen possibilities and offer the potential to create entirely new products, services and business models. Ferreira et al. (2019) found a significant positive relationship between the adoption of digital progress and firms' competitive advantage [2]. However, the literature on how digital transformation affects firm value is very rare. In particular, the role of firm embracing digital processes in operations management is still unclear.

Operations management is often referred to as the discipline that uses scientific analytical methods to help firms make the best decisions. In order to solve operations management problem, computing algorithms based on statistical and mathematical models are required. In other words, there is a natural connection between operations management and digital technologies, such as big data and cloud computing [3]. Inventory management is not only a critical issue in operations management, but also critical to ensuring supply chain stability in an uncertain environment. Since the outbreak of COVID-19, supply chain disruptions and inventory management have become a significant impediment to economic growth.

From a macro perspective, because the adjustment cost of inventory investment is lower than that of fixed asset investment, inventory investment is more likely to cause large fluctuations in economic growth when exposed to external shocks. For a company, a high inventory level will reduce capital efficiency, increase storage costs and the risk of inventory depreciation. The inventory level is closely related to product design, marketing methods and logistics distribution. A company holding less inventory is an important sign of good operational management performance and supply chain stability. Existing literature on corporate inventory management found that sales revenue uncertainty and infrastructure construction are important factors affecting corporate inventory. In the era of digital economy, we have more and more available data, which potentially can enhance the performance of forecasting. Improved forecasting capability means decreased sales uncertainty, which helps reduce inventory investment. Unfortunately, except few studies using numerical model optimization methods to explore the impact of digital technologies such as big data and machine learning on inventory decisions, empirical evidence on the relationship between digitalization and inventory levels is scarce.

G. Vilas Bhau et al. (Eds.): MSEA 2022, ACSR 101, pp. 83–89, 2023.
https://doi.org/10.2991/978-94-6463-042-8_14

Therefore, this study aims to fill this gap by analyzing the relationship between digital transformation of enterprise and inventory management. Using a sample of 2328 Chinese listed companies and multivariate statistical analysis, this study shows that digital transformation of enterprises can significantly reduce the inventory level and improve the efficiency of inventory management. And this effect of is more pronounced in companies in regions with better transportation infrastructure.

This study contributes to the extant literature in several ways. First, this paper contributes to the literature focusing on the economic consequences of digital transformation. Existing studies have examined the impact of digital technology on company stock liquidity, financial performance, etc., but few studies have discussed it from the perspective of inventory management. There is still a “black box” of how digital technology improve corporate financial performance. This paper provides evidence that digital transformation improves efficiency of inventory management, filling the gaps in related research. Second, this paper contributes to the literature on inventory management, especially the impact of digital technologies on it. Previous studies focus on the impact of sales uncertainty and trade facilitation on corporate inventories, while less attention is paid to the impact of information technology. This paper proves the positive effect of digital technology on inventory management through empirical analysis of large samples, and enhances the understanding of which factors affect inventory decision-making of the firm.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Digital transformation of enterprises refers to the process in which enterprises integrate digital technologies into the company's business model, so as to improve efficiency of operation management and reshape the way of value creation. From automobiles to mineral resource exploration instruments, products traditionally constructed with mechanical and electrical components are now embedded with sensors, wireless transmitters, and applications connected through networks, becoming "smart connected" products with complex systems [4]. Digital resources are becoming the most important input factor in the production and operation of enterprises, which provide a more agile and flexible way of producing organizations, thereby enhancing the company's competitive advantages. Due to business model innovation, digital technologies are profoundly changing the operation management of enterprises [5-6].

Digital transformation of the enterprise may affect inventory management in the several ways. First, digital transformation can enhance a firm’s forecasting capabilities and reduce sales uncertainty. The economic order quantity (EOQ) model is a classic theoretical model of inventory management [7-8]. It mainly refers to enterprises ordering in batches of economic orders to balance ordering costs and inventory holding costs and minimize inventory costs. The EOQ model assumes that the market demand for a product is uniformly distributed and that there is no interaction among various inventory items. However, it is difficult for the real world to satisfy these assumptions. In order to prevent the company from being out of stock due to the uncertainty of lead time demand, the company will hold excess inventory. Caglayan et al. (2012) found that product revenue uncertainty is positively correlated with corporate inventory levels, confirming that sales uncertainty is one of the important reasons for companies to hold inventory [9]. After the digital transformation, enterprise can obtain massive data, such as user browsing, purchases, and evaluations. The application of big data, artificial intelligence and other technical means enables enterprises to more accurately predict customer needs, thus forming a data-driven product development model. Chong et al. (2017) used online review and marketing data from Amazon, combined with a neural network machine learning approach, to provide evidence that digital marketing helps predict product demand [10]. Other studies also show that incorporating social media data into machine learning models can significantly improve the accuracy of sales forecasts. Second, digital transformation can help achieve flexible supplier selection, improve the efficiency of purchasing decisions, and thus reduce inventory levels. The increasing demand for individualization by consumers has prompted the transformation of the production model of firms to small batches, customization and flexibility. Using digital technologies, firms can achieve build-to-order manufacturing that enables dynamic analysis of supplier selection. Digital manufacturing offers new opportunities to exploit data to improve purchasing decisions and the delivery reliability by dynamic order allocation [11]. Based on the above analysis, the following research hypothesis is proposed:

H1: Digital transformation of enterprises can reduce inventory and improve efficiency of inventory management.

For inventory investment, the enterprise needs to reorder before the inventory drops to a safe level, which is the lead time of inventory management. Logistics distribution is an important factor that affect lead time. Improvements in transportation infrastructure can reduce transit times and lead times for inventory management. Through digital transformation, companies can better forecast consumer demand [12], improve purchasing decisions, and reduce inventory investment. However, this requires good transportation infrastructure as a supporting condition, otherwise it may lead to risks such as supply chain disruption and inventory shortages. In addition, with the increase of participants, digital economy will show the nonlinear characteristics of decreasing marginal production cost and increasing subject effect scale.

Therefore, the higher the level of the regional transportation infrastructure and the more developed the transportation network, the greater the potential and effectiveness of using digital technology to optimize transportation routes and logistics distribution, and the greater the impact on reducing inventory investment. Based on the above analysis, the following research hypothesis is proposed:

H2: Compared with companies in regions with low levels of transportation infrastructure, the impact of digital transformation on inventory is more significant in regions with high levels of transportation infrastructure.

3. RESEARCH DESIGN

3.1. Sample selection and data collection

Using Chinese A-share listed firms from 2012 to 2019 as initial sample. The data are collected from China Stock Market & Accounting Research database (CSMAR). And filter sample according to the following criteria: (1) the data of finance and insurance industry will be excluded; (2) firm-year observations with the transaction status of ST (special treatment), *ST (suspension of trading), or PT (particular transfer) will be discarded; (3) firm-year observations for which relevant data are not available will be excluded. This procedure results in a sample of 12,777 firm-year observations covering 2328 firms. All the continuous variables are winsorized at top and bottom one percentiles to minimize the effect of outliers.

3.2. Variables definition

1) Inventory management (Inven): In this paper, the ratio of total inventory to operating income (*Inven1*) is used as the first measure of inventory management; meanwhile, considering that the impact of digital transformation on inventory is more obvious in finished goods inventory, the ratio of finished goods inventory to operating income (*Inven2*) is used as the second measure of inventory management.

2) Digital Transformation of Enterprises (Digital): Digital transformation is an important part of the company's strategic change, so it is likely to be disclosed in the "Management Discussion and Analysis" section of the annual financial report [13-14]. This paper uses the text analysis method to count the word frequency related to "digitization" in the company's annual report to measure the degree of digital transformation of the company. Specifically, firstly, we build a dictionary of digital transformation of enterprises based on digital-related policy documents, such as: mobile Internet, e-commerce, big data, digital marketing, cloud computing, Internet of Things, smart factories, artificial intelligence, etc. Secondly, use Python software to perform text analysis on the "Management Discussion and Analysis" section of the company's annual report to obtain word frequency statistics related to "digitization". Finally, the ratio of digital-related word frequency statistics to the total number of words in "Management Discussion and Analysis" is used as a measure of the degree of enterprise digitalization.

3) Level of regional transport infrastructure (Td): In this paper, it is measured by the ratio of the road mileage at the end of the year in the province where the listed company is located in the gross domestic product (GDP) of the province.

4) Control variables: Based on the key literature in the field, a set of control variables complements our model. The control variables employed here include: firm size (*Size*), *financial leverage (Lev),* return on assets (*ROA*), *sales growth* (*Sg*), and *r*egional economic development level (*GDP*)*, a*s well as industry fixed effect and year fixed effect.

3.3. Model specification

This study applies a multiple regression model to test the relationship between the degree of digital transformation and inventory management. The proposed model is as follows:

$$\begin{aligned} Inven_{i,t} &= \beta_0 + \beta_1 Digital_{i,t-1} + \beta_2 \mathrm{Size}_{i,t-1} + \beta_3 \mathrm{Lev}_{i,t-1} + \beta_4 \mathrm{Roa}_{i,t-1} \\ &+ \beta_5 \mathrm{Sg}_{i,t-1} + \beta_6 \mathrm{GDP}_{i,t-1} + \beta_7 \mathrm{Ind} + + \beta_8 Year + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where, the dependent variable is *Inven*, which denotes the inventory level of the enterprise, and *Inven1* and *Inven2* are used as proxy variables respectively. The independent variable is *Digital*, which represents the degree of digital transformation of enterprise. *Size, Lev, Roa, Sg, MB, GDP* are control variables. In order to alleviate the endogeneity problem, this paper will lag the explanatory variables and the control variables by one period.

To test Hypothesis 2, the proposed model is as follows:

$$\begin{aligned} Inven_{i,t} &= \beta_0 + \beta_1 Digital_{i,t-1} \times \mathrm{Td}_{i,t-1} + \beta_2 Digital_{i,t-1} + \beta_3 Td_{i,t-1} \\ &+ \beta_4 \mathrm{Size}_{i,t-1} + \beta_5 \mathrm{Lev}_{i,t-1} + \beta_6 \mathrm{Roa}_{i,t-1} + \beta_7 \mathrm{Sg}_{i,t-1} \\ &+ \beta_8 \mathrm{GDP}_{i,t-1} + \beta_9 \mathrm{Ind} + + \beta_{10} Year + \varepsilon_{i,t} \end{aligned} \tag{2}$$

Where, moderating variable is *Td*, which denotes the level of regional transport infrastructure. We focus on the interaction term of *Digital*×*Td*, if the coefficient β_1 is significantly negative, then hypothesis 2 holds.

4. EMPIRICAL RESULTS

4.1. Descriptive statistics

Table 1 reports the descriptive statistics of main variables. The average ratio of inventory to operating income (*Inven1*) of Chinese listed companies is 37.5%, and the maximum value is as high as 516.7%. This shows that the inventory of Chinese enterprises is relatively high, and it also confirms the importance of reducing inventory problems. The average value of the digital transformation degree of enterprises is 0.207, and the minimum value is 0, indicating that there are significant differences in the process of embracing emerging digital technologies and strategic transformation of different enterprises. The mean value of the level of regional transportation infrastructure (*Td*) is 4.984, the standard deviation is 4.67, and the maximum value is 43.178, indicating that there are significant differences in the level of transportation infrastructure in China. The statistical values of other control variables are basically consistent with the existing studies, and all are within a reasonable range.

TABLE 1. DESCRIPTIVE STATISTICS

Variables	N	Mean	SD	Min	Med	Max
Inven1	12777	0.370	0.656	0.001	0.190	5.167
Digital	12777	0.246	0.353	0.000	0.095	1.936
Td	12777	4.984	4.670	0.364	3.112	43.178
Size	12777	22.261	1.320	19.574	22.063	26.398
Lev	12777	0.431	0.205	0.0349	0.424	0.881
Roa	12777	0.036	0.055	-0.468	0.035	0.205
Sg	12777	0.186	0.420	-0.485	0.110	2.646
GDP	12777	11.370	0.474	9.864	11.449	12.153

4.2. Regression Results:Digital Transformation of Enterprises and Inventory Management

TABLE 2. REGRESSION ANALYSIS : DIGITAL TRANSFORMATION OF ENTERPRISES AND INVENTORY MANAGEMENT

	(1)	(2)
	Inven1	Inven2
Digital	-0.044*** (-2.825)	-0.017*** (-3.656)
Size	-0.007 (-0.876)	-0.005*** (-3.175)
Lev	0.095* (1.864)	-0.028** (-2.454)
Roa	-0.609*** (-4.513)	-0.182*** (-6.487)
Sg	-0.057*** (-3.322)	-0.009*** (-4.568)
GDP	-0.030** (-2.041)	-0.005 (-1.201)
Constant	0.923*** (4.068)	0.360*** (6.200)
Ind	Yes	Yes
Year	Yes	Yes
Adj.R^2	0.557	0.186
N	12777	12777

Note: t statistics in parentheses; ***、** and * denotes coefficients significant at the 1%、5% and 10% level respectively.

We first run Model (1) to examine whether digital transformation has a significant impact on a firm's inventory levels. The results are reported in Table 2. Column (1) is the impact of the degree of digital transformation of the enterprise on the total inventory, and column (2) is the impact of the degree of digital transformation of the enterprise on the inventory of finished goods. The results show that the coefficients of digital transformation of enterprises (Digital) are both significantly negative at the 1% level. It suggests that hypothesis H1 holds.

4.3. The moderating effect of regional transport infrastructure

We run Model (2) to examine whether regional transport infrastructure has a moderating effect on the relation between digital transformation and inventory management. The results are reported in Table 3. The results show that the regression coefficients of the interaction term (*Digital×Td*) are both significantly negative, indicating that the level of regional transportation infrastructure will significantly moderate the destocking effect of digital transformation of enterprises. The more developed the level of regional transportation infrastructure, the stronger the effect of digital transformation on reducing enterprise inventory. In other words, hypothesis H2 is supported by empirical results.

TABLE 3. REGRESSION ANALYSIS : THE MODERATING EFFECT OF REGIONAL TRANSPORT INFRASTRUCTURE

	(1)	(2)
	Inven1	Inven2
Digital×Td	-0.003** (-2.094)	-0.001** (-2.321)
Digital	-0.034*** (-3.192)	-0.014** (-2.524)
Td	-0.001 (-0.525)	0.001** (1.995)
Size	-0.014* (-1.866)	-0.005*** (-4.158)
Lev	0.288*** (3.863)	-0.018** (-2.422)
Roa	-0.469*** (-2.394)	-0.128*** (-5.706)
Sg	-0.031 (-1.212)	-0.009*** (-3.142)
GDP	-0.038** (-2.351)	-0.010*** (-4.781)

Constant	0.523** (2.468)	0.299*** (5.070)
Ind/Year	Yes	Yes
Adj.R^2	0.558	0.192
N	12777	12777

Note: t statistics in parentheses; ***、** and * denotes coefficients significant at the 1%、5% and 10% level respectively.

4.4. Robustness tests

1) Endogeneity issues: This paper finds that the increase in the level of digital transformation of enterprises can reduce the inventory level. Although this *study* has alleviated the endogeneity problem by lagging the explanatory variables by one period, it may still lead to endogeneity *issues* due to omitted variables and other reasons. To further alleviate concerns about endogeneity, this paper *applies* the instrumental variable *(*IV*)* method *to* re-regresses Model *(1)*. Specifically, referring to Liu et al. (2014) [10], this paper *use*s the mean value of the degree of digital transformation of enterprises in the province where the company is located as an instrumental variable. The overall level of digital transformation in the region will affect the choice of digital transformation of the enterprise, which will affect the investment in the enterprise's inventory. However, the inventory of a single company is unlikely to affect the extent of digital transformation of companies across the region. Table 4 reports the regression results after using the instrumental variables. Column (1) is the regression result of the degree of digital transformation of the region on the digital transformation of enterprises in the first stage. The coefficient of the instrumental variables is significantly positive at the 5% level, indicating that the instrumental variable meets the correlation requirements. Columns (2) and (3) are the regression results of the enterprise inventory level after using the instrumental variables. The coefficient of the digital transformation of enterprises (*Digital*) is still significantly negative, which is consistent with the previous results.

TABLE 4. ROBUSTNESS TEST: IV METHOD

	(1)	(2)	(3)
	Digital	Inven1	Inven2
IV	-0.567*** (12.455)		
Digital		-0.128** (-1.993)	-0.051*** (-4.147)
Size	0.012*** (4.217)	-0.006 (-1.177)	-0.005*** (-5.442)
Lev	-0.071*** (-4.113)	0.081** (2.523)	-0.031** (-3.892)
Roa	0.013 (0.228)	-0.604*** (-5.394)	-0.177*** (-9.046)
Sg	0.024*** (4.074)	-0.052*** (-3.017)	-0.009*** (-4.184)
GDP	-0.030** (-2.053)	-0.021** (-2.430)	-0.002 (-1.382)
Constant	0.080 (1.049)	0.793*** (5.487)	0.333*** (9.120)
Ind/Year	Yes	Yes	Yes
Adj.R^2	0.458	0.560	0.176
N	12777	12777	12777

Note: t statistics in parentheses; ***、** and * denotes coefficients significant at the 1%、5% and 10% level respectively.

2) Replace the Measure of inventory management: Existing research also uses the logarithm of inventory amount and inventory turnover rate to measure the level of enterprise inventory management. Therefore, this paper takes the logarithm of the total inventory and finished product inventory to obtain (Ln_Inven1) and (Ln_Inven2), and calculates the turnover rate of the total inventory (Inven1_To) and finished product inventory (Inven2_To) at the same time. It should be noted that the higher the logarithmic inventory value (Ln_Inven), the lower the inventory management efficiency; and the higher the inventory turnover rate (Inven_To), the higher the inventory management level. The results of re-regression after replacing the measure of inventory management are shown in Table 5. The results in columns (1) and (2) show that when inventory management is measured by the logarithm of the inventory amount, the coefficient of the degree of digital transformation is still significantly negative, consistent with the previous results. The results in columns (3) and (4) show that the coefficient of digital transformation is significantly positive when inventory efficiency is measured using the inventory turnover ratio, that is, digital transformation can improve the efficiency of inventory management, which is also consistent with the previous conclusion.

TABLE 5. ROBUSTNESS TEST: REPLACE THE MEASURE OF INVENTORY MANAGEMENT

	(1)	(2)	(3)	(4)
	Ln_Inven1	*Ln_Inven2*	*Inven1_To*	*Inven2_To*
Digital	-0.208*** (-5.055)	-0.561*** (-4.137)	6.763*** (4.523)	13.151*** (5.270)
Size	0.862*** (14.907)	0.748*** (13.703)	1.143*** (2.853)	2.309*** (2.782)
Lev	1.354*** (7.192)	0.956*** (3.245)	-11.603*** (-4.525)	12.385** (2.466)
Roa	1.233*** (5.359)	1.615** (2.151)	8.680 (1.239)	7.286 (1.370)
Sg	0.014 (0.456)	0.086 (0.708)	2.105** (2.072)	2.989 (1.521)
GDP	0.048** (2.358)	-0.292*** (-3.149)	-0.401 (-0.689)	4.224*** (3.114)
Constant	0.208 (0.643)	5.427*** (3.495)	-16.079* (-1.666)	-14.836*** (-3.413)
Ind/Year	Yes	Yes	Yes	Yes

Adj.R^2	0.645	0.313	0.121	0.212
N	12777	12777	12777	12777

Note: t statistics in parentheses; ***、** and * denotes coefficients significant at the 1%、5% and 10% level respectively.

5. CONCLUSION

The digital economy is becoming an important force driving economic growth and reshaping the global competitive landscape. The use of digital technology to improve operational efficiency is of great significance for companies to gain a competitive advantage. This paper uses the data of Chinese A-share listed companies from 2012 to 2019 as a sample to investigate the impact of digital transformation on corporate inventory management. The results show that digital transformation of enterprises can significantly reduce inventory investment and increase efficiency of inventory turnover. Further research shows that the effect digital transformation on improving efficiency of inventory management varies with the level of transportation infrastructure. In areas with more developed transportation networks, digital transformation is more effective in reducing inventory.

Our results generate a series of managerial implications. First, managers should actively promote enterprises to accelerate digital transformation. The empirical analysis in this paper proves that digital transformation can improve the efficiency of operation and management, and is an important strategic change for enterprises to gain competitive advantage in the new era and market environment. Managers should more fully understand the development trend of technology, break the inherent thinking framework, and start implementing digital transformation as soon as possible. Second, when enterprises choose digital transformation, they should also consider whether external conditions are met. Second, company executives should consider whether external resources can contribute to the role of digital transformation. For example, whether the area where the company is located has good transportation infrastructure, whether it is easy to hire employees with digital technology skills, and whether local residents recognize and accept digital sales. This paper finds that the effect of digital transformation on reducing corporate inventory is more significant in regions with more developed transportation infrastructure, indicating that the development of digital technologies also depends on the level of traditional infrastructure construction. The digital economy has the characteristics of exponential growth in value along with network nodes. The developed grid transportation infrastructure is conducive to the greater potential of digital technologies.

ACKNOWLEDGMENT

This study acknowledges the financial support from the General Project of Shaanxi Soft Science Research Program (Nos. 2022KRM124).

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