Finance Research Letters 51 (2023) 103429

Contents lists available at ScienceDirect

Finance Research Letters

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

Inefficient investment and digital transformation: What is the role of financing constraints?

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A R T I C L E I N F O

Keywords:
Inefficient investment
Digital transformation
Financing constraints
Nature of firm property rights

A B S T R A C T

This paper empirically examines the effect of inefficient corporate investment on digital transformation, using Chinese listed companies from 2007 to 2019 as a sample, and finds that inefficient investment is not conducive to improving digitalization. We find that the greater the financing pressure on a company, the worse the digital transformation, and financing constraints exacerbate this negative effect. Among state-owned, private and highly digitalized companies, the negative impact of inefficient investment on digital transformation intensifies as the pressure of financing constraints increase. To combat inefficient investment, enterprises should optimize their investment structure, reduce their financing constraints, and improve their risk prevention mechanisms.

1. Introduction

The global economy and society are in a critical stage of digital transformation, and the supporting and leading role of the digital economy for industrial development is becoming increasingly important (Wen and Zhong, 2020). As we enter a "new normal" period, where growth rates gradually decrease, the development of the digital economy becomes an important tool for China on its journey to being a high quality, innovative country. With the in-depth implementation of China’s manufacturing sector, network infrastructure and big data strategy, the development of the digital economy has gained momentum, with the overall scale expanding from 18.6 trillion yuan in 2015 to 39.2 trillion yuan in 2022, and the proportion of GDP attributed to the digital economy increasing from 27% to 38.6%, thereby becoming a key driver of stable economic growth. However, these impressive achievements have also raised some concerns. Corporate digital transformation requires investment and high technical standards, leaving some who refuse to transform, as well as those who are ready (Liu et al., 2021). Therefore, understanding the potential value of digital transformation is an issue of great concern to both academia research and policy makers.

There are two main lines of research on the digital economy.

First, the economic effects of digital change are explored at the macro level, such as the role of technological revolutions (industrial, electrical and IT) in driving economic development (Daud et al., 2022). However, unlike previous revolutions, the current one is more comprehensive and fundamental, with a broader and deeper impact. Numerous scholars have recognized the positive role of developing the digital economy in improving household finances, achieving green growth, narrowing the urban-rural gap, optimizing

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https://doi.org/10.1016/j.frl.2022.103429
Received 7 July 2022; Received in revised form 2 October 2022; Accepted 18 October 2022
Available online 19 October 2022

industrial structures, and promoting employment (Agarwal and Chua, 2020; Song, 2017; Autor and Sakomon, 2018; Dauth et al., 2018; Chen and Yang, 2021; Zhang et al., 2022).

Secondly, there are explorations at the micro level. The core connotation of digital transformation as a microcosmic manifestation of the integration and development of the digital economy and the real economy lies in the upgrade of business management systems and production processes through digital technologies (Tang and Jiang, 2021). Companies that implement digital transformation experience improved productivity (Bharadwaj et al., 2013; Zhao et al., 2021) because the application of digital technologies leads to a significant increase in the ability to collect and analyze data, reducing the level of information asymmetry and improving risk resilience (Yi et al., 2021; Jin et al., 2020; Mezghani et al., 2021; Maouchi et al., 2022).

This paper focuses on an in-depth examination of the factors affecting the digital transformation of micro firms in the digital intelligence era. Digital technology has profoundly impacted and reshaped the internal and external environment faced by micro firms (Chu and Fang, 2020; Zhang and Kong, 2022a). Therefore, it is unclear whether findings on the economic consequences of capital allocation efficiency, based on the traditional technology paradigm, are applicable to this new era, and rigorous theoretical analysis and large sample testing are required. This paper examines the impact of corporate investment efficiency on digital transformation in Chinese listed companies from 2007 to 2019.

Our second contribution is our finding that, in economic practice, firms are caught in the dilemma of "not daring to transform", "not willing to transform", and "not knowing how to transform" (Liu, 2020; Zhang and Kong, 2021, 2022b). Therefore, it is important to clarify what factors hinder digital transformation. In the macro context of a lack of effective curbs on the "de-realization" of the economy, this paper examines the effects and mechanisms of investment efficiency and financing constraints on corporate digital transformation.

2. Research design

2.1. Variable measures and data sources

Level of corporate digitization. This is the core explanatory variable in this paper, mainly following Qi et al. (2020) and Song et al. (2022), in using the digital economy-related portion from the reported intangible assets breakdown as a proxy variable for digital transformation. We use a pivot table to aggregate the digital economy-related portion of intangible assets for each company in each year, including keywords "mobile Internet", "Internet of Things", "big data", "cloud computing", "artificial intelligence", etc. are is calculated.

Firm investment efficiency. This is the explanatory variable, following Richardson (2006); Huang et al. (2021) and Zhang & Kong (2022c). We fit the regression of corporate investment $Scale_{ijt}$ with the basic indicators. We then select the model fitting residual term ε_{ijt} as the inefficient investment. The larger the absolute value of residual, the higher the degree of inefficient investment, i.e., the lower the investment efficiency. The regression model is as follows;

$$Scale_{ij,t} = \xi_0 + \xi_1 Growth_{ij,t} + \xi_2 Lev_{ij,t-1} + \xi_3 Cash_{ij,t-1} + \xi_4 Lnage_{ij,t-1} + \xi_5 Size_{ij,t-1} + \xi_6 Ruturn_{ij,t-1} + \xi_7 Scale_{ij,t-1} + \sum Industry + \sum Year + \varepsilon_{ij,t} \tag{1}$$

Financing constraints. These are the moderating and mediating variables following Ju et al. (2013) by using the fitted values of company size and age to measure the SA index of each firm for each year. The formula is as follows;

$$SA = -0.737 * Size + 0.043 * Size^2 - 0.04 * Age \tag{2}$$

Where *Size* is measured by the natural logarithm of total assets, and *Age* is measured by the current year minus the date the firm went public. In addition, the SA index is taken as an absolute value and logarithmically treated; the larger the SA index, the more serious the financing constraint and the greater the financing pressure.

Control variables. This paper selects a total of six control variables, following (Zou and Wang, 2022); Hu et al. (2020) and Zhang and Kong (2022d). These are;

1 Nature of equity (Property): either state owned or private companies.
2 Firm age (Age): the current year minus the date the firm went public.
3 Return on assets (ROA): the ratio of total profit and financial expenses to average total assets[1]
4 Accounts receivable turnover (ART): the ratio of operating revenues to average accounts receivable, where average accounts receivable = (closing balance of accounts receivable + closing balance of accounts receivable of the previous year) / 2.
5 Growth ability (Growth): (Current year current single quarter amount of operating income - Previous single quarter amount of operating income)/(Previous single quarter amount of operating income).
6 Separation of roles (DUA): chairman and general manager are two people = 0; the roles are filled by the same person = 1.

Descriptive statistics of specific variables are shown in Table 1.

Data Sources. The firm-level data used in this paper are mainly from the CSMAR database. Considering the validity of the sample

[1] Average total assets = (Total assets closing balance + Total assets opening balance)/2

Table 1
Variable definitions and descriptive statistics.

Variable	Variable names	Obs	Mean	Std	Min	Max
EDL	Firm digitalization level	21,434	0.1401	0.2489	0.0000	1.0000
Iveffect	Investment efficiency	28,229	0.0467	0.0536	0.0004	0.4401
SA	Financing constraints	28,542	1.4056	0.3634	−0.6439	2.2921
Property	Firm ownership	30,147	0.1869	0.3848	0.0000	1.0000
Age	Firm age	28,625	10.1892	6.6817	1.0000	27.0000
ROA	Return on Assets	30,147	0.0577	0.0720	−0.3857	0.6429
ART	Accounts Receivable Turnover Ratio	30,147	52.4030	251.6903	0.1909	3969.8800
Growth	Growth capacity	30,147	0.2077	0.6048	−0.8486	7.9565
DUA	Two jobs in one	15,624	0.3533	0.4780	0.0000	1.0000
Mean_iveffect	Industry investment efficiency average	28,625	0.0467	0.0170	0.0005	0.2828

Table 2
Baseline regression results.

Variables	(1) *EDL*	(2) *EDL*	(3) *EDL*	(4) *EDL*
Iveffect	−0.2123***	−0.2711***	0.0558	0.3171
	(0.0411)	(0.0517)	(0.1816)	(0.2191)
SA			−0.0687***	−0.0725***
			(0.0067)	(0.0112)
Iveffect×SA			−0.2114*	−0.4996***
			(0.1166)	(0.1446)
Property		0.0078		0.0139
		(0.0151)		(0.0154)
Age		0.0015**		0.0016**
		(0.0007)		(0.0006)
ROA		−0.1482**		−0.1166*
		(0.0547)		(0.0563)
lnART		0.0070***		0.0103***
		(0.0016)		(0.0019)
Growth		0.0259***		0.0310***
		(0.0054)		(0.0048)
DUA		0.0092**		0.0042
		(0.0034)		(0.0032)
Constant	0.1484***	0.1352***	0.2480***	0.2287***
	(0.0018)	(0.0119)	(0.0103)	(0.0150)
N	21,226	11,642	21,226	11,642
adj. R^2	0.0617	0.0841	0.0726	0.0970

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

data, the original sample data are processed as follows: (1) The sample of ST, ST* and PT firms are excluded from the sample due to the large changes in the information provided over the sample period. (2) Unlisted firms were excluded from this paper. (3) Companies in the financial and insurance industry were excluded. (4) A tailing process removed the 1% and 99% quantiles for continuous type variables eliminates the influence of extreme values on the regression analysis. This leaves a total of 21,226 annual observations from 2007 to 2019.

2.2. Model setup

This paper sets up a panel fixed-effects model to control for unobservable random disturbances that vary over time, or with individuals, and examines the impact of inefficient investment on the level of digital development. Second, this paper adds the cross product term of inefficient investment and financing constraints to construct a moderating effect model;

$$EDL_{it} = \alpha_0 + \alpha_1 Iveffect_{it} + \alpha_2 Controls_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$EDL_{it} = \beta_0 + \beta_1 Iveffect_{it} + \beta_2 SA_{it} + \beta_3 Iveffect_{it} * SA_{it} + \beta_4 Controls_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{4}$$

where i and t denote cities and years. The explanatory variable EDL_{it} is the digitization level of firms; the key explanatory variable $Iveffect_{it}$ is the inefficient investment; $Iveffect_{it}*SA_{it}$ is the cross product term of inefficient investment and financing constraints; $Controls_{it}$ represents the set of control variables; γ_j is the individual fixed effect; λ_t is the time fixed effect; and ε_{it} is the random error term.

Table 3
Results of intermediate effect test.

Variables	(1) *EDL*	(2) *SA*	(3) *EDL*	(4) *EDL*	(5) *SA*	(6) *EDL*
*Iveffect_*	−0.2123***	−0.3917***	−0.2336***	−0.2711***	−0.5579***	−0.3210***
	(0.0411)	(0.0490)	(0.0426)	(0.0517)	(0.0788)	(0.0504)
SA			−0.0791***			−0.0986***
			(0.0040)			(0.0072)
Controls	No	No	No	Yes	Yes	Yes
Constant	0.1484***	1.4290***	0.2625***	0.1352***	1.2870***	0.2618***
	(0.0018)	(0.0023)	(0.0059)	(0.0119)	(0.0127)	(0.0097)
N	21,226	28,224	21,226	11,642	15,422	11,642
adj. R^2	0.0617	0.0666	0.0724	0.0841	0.1625	0.0956

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

Table 4
Results of the nature of firms ownership.

Variables	State-owned firms		Private firms		Foreign-invested firms		Others firms	
	(1) *EDL*	(2) *EDL*	(3) *EDL*	(4) *EDL*	(5) *EDL*	(6) *EDL*	(7) *EDL*	(8) *EDL*
Iveffect	−0.3084**	1.1635*	−0.2424***	0.3546	−0.1918	−1.0509	−0.2573	−0.2513
	(0.1395)	(0.6300)	(0.0484)	(0.2439)	(0.3211)	(1.1860)	(0.2182)	(1.0971)
SA		0.1426***		−0.0859***		−0.1905*		−0.0403
		(0.0401)		(0.0127)		(0.1063)		(0.0464)
Iveffect×SA		−1.0969**		−0.5222***		0.6557		−0.0085
		(0.4381)		(0.1653)		(0.9863)		(0.6957)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0846*	−0.1063	0.1372***	0.2492***	0.0708	0.3255**	0.1567***	0.2092**
	(0.0410)	(0.0617)	(0.0110)	(0.0149)	(0.0511)	(0.1136)	(0.0320)	(0.0738)
N	868	868	10,051	10,051	252	252	469	469
adj. R^2	0.2534	0.2649	0.0918	0.1083	0.1874	0.2070	0.2256	0.2236

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

3. Discussion of empirical test results

3.1. Benchmark regression results

Table 2 reports the results of the benchmark regression of inefficient corporate investment and digital transformation. The empirical results are divided into four columns. As seen in columns 1–2, the coefficient estimates of *Iveffect* are negative and pass the 1% significance level test, indicating that inefficient investment significantly inhibits digitalization. After adding the control variables, for every 1 unit change in inefficient investment, the level of digitization changes by 0.2711 units. The regression results in columns 3–4 show that the regression coefficient of *Iveffect* is positive but insignificant, while the regression coefficient of *Iveffect*SA* is significantly negative at the 10% level, indicating that financing constraints exacerbate the inhibitory effect of inefficient investment on digital development. In conclusion, inefficient investment is detrimental to the development of digitalization, and the degree of financing constraints further worsens this negative effect.

3.2. Mechanistic test of financing constraints

In order to delve further into the mechanism of action between inefficient investment and digital transformation, this paper selects financing constraints for the mediating effect test. The results are shown in Table 3.

Columns 1–3 are the results without the inclusion of control variables, showing that the *Iveffect* and SA coefficients are negative and pass the 1% significance level test, indicating that financing constraint as a mediating variable produces a partial mediating effect. Columns 4–6 show the results with the inclusion of control variables. Again, it can be seen that the *Iveffect* and *SA* coefficients are significantly negative, indicating that the inclusion of control variables increases the negative impact of inefficient investment on digital transformation through financing constraints. In terms of economics, the mediating effect of financing constraints on the impact of inefficient investment on digital transformation is 17.14% after the inclusion of the control variables.

This suggests that financing constraints have a partial mediating effect on the impact of inefficient investment on digital transformation, and the transmission path of inefficient investment, financing constraints and digital transformation is effective. Inefficient investment still has a negative impact on digitalization, even if it can alleviate the financing constraint, perhaps due to the high cost of external financing in a constrained environment, preventing firms from being able to finance good investment opportunities, thereby exacerbating inefficient investment (Myers and Majluf, 1984), which further inhibits digital transformation.

Table 5
Results of different levels of digitization of firms.

Variables	High firm digitization level		Low firm digitization level	
	(1)	(2)	(3)	(4)
	EDL	*EDL*	*EDL*	*EDL*
Iveffect	−0.1449**	0.7989**	−0.0136***	−0.0006
	(0.0603)	(0.2851)	(0.0024)	(0.0066)
SA		−0.1406***		0.0035***
		(0.0116)		(0.0004)
Iveffect×SA		−0.8389***		−0.0090
		(0.2172)		(0.0055)
Controls	Yes	Yes	Yes	Yes
Constant	0.2171***	0.3957***	0.0173***	0.0127***
	(0.0143)	(0.0170)	(0.0005)	(0.0004)
N	5864	5864	5778	5778
adj. R^2	0.1087	0.1379	0.2467	0.2506

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

Table 6
Robustness results using explanatory variables lagged one period.

Variables	(1)	(2)	(3)	(4)
	L_EDL	*L_EDL*	*L_EDL*	*L_EDL*
Iveffect	−0.2947***	−0.3615***	−0.3876**	−0.0384
	(0.0352)	(0.0354)	(0.1484)	(0.1753)
SA			−0.0713***	−0.0655***
			(0.0052)	(0.0075)
Iveffect×SA			0.0503	−0.2925**
			(0.1085)	(0.1275)
Controls	No	Yes	No	Yes
Constant	0.1472***	0.1297***	0.2513***	0.2168***
	(0.0015)	(0.0100)	(0.0076)	(0.0100)
N	18,337	9694	18,337	9694
adj. R^2	0.0618	0.0891	0.0700	0.0975

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

3.3. Heterogeneity analysis

1 Nature of business property

The sample is divided into two categories: state-owned enterprises (SOEs), private, foreign-owned and other types of companies, and the heterogeneous effects of inefficient investment on digital transformation of different ownership models are examined. The regression results are shown in Table 4. Columns 1–2 and 3–4 show the regression results for SOEs and private firms that show that the regression coefficient of *Iveffect* is negative and passes the 5% level of significance test. The regression coefficient of *Iveffect* × *SA* is significantly negative, indicating that the negative impact of inefficient investment on digital transformation will increase as the pressure of financing constraints increases. Columns 5–6 and 7–8 show the regression results for foreign and other firms, where the regression coefficients of both *Iveffect* and *Iveffect* × *SA* are insignificant, indicating that the impact of inefficient investment on digital transformation such companies is small and there is no moderating effect of financing constraints.

1 Digital development level

In cities with different degrees of digital transformation, the impact of inefficient investment on digitalization levels may differ. The median of digitalization is used as the criterion to divide the sample cities into firms with high levels of digitalization and those low firm levels. The regression results are shown in Table 5 in which columns 1–2 are the regression results for the high digitization firms, and columns 3–4 are the regression results for the low digitization firms.

The regression coefficients of *Iveffect* and *Iveffect* × *SA* in columns 1–2 are significantly negative in the case of high digitization, indicating that inefficient investment has a significant negative impact on the digital transformation of companies with high digitization, and the cross-product of inefficient investment and financing constraints also significantly inhibits the increase of digitization levels. Second, in the low-digitization sample, inefficient investment also inhibits digitalization. Moreover, comparing the regression coefficients of *Iveffect*, it is clear that inefficient investment has a stronger inhibitory effect on the digital transformation of firms in the high digitization level sample compared to the low digitization sample.

Table 7
Results of endogeneity problem test.

Variables	(1) Stage 1 *Iveffect*	(2) Stage 2 *EDL*	(3) Stage 1 *Iveffect×SA*	(4) Stage 2 *EDL*
Mean_Iveffect	1.0075***			
	(0.0503)			
Iveffect		−2.7593***	1.2603***	12.3700***
		(0.2655)	(0.0140)	(1.7994)
SA			0.0444***	0.4221***
			(0.0016)	(0.0664)
Mean_Iveffect×SA			0.1910***	
			(0.0204)	
Iveffect×SA				−9.9372***
				(1.3805)
Controls	Yes	Yes	Yes	Yes
Constant	−0.0052	0.4664***	−0.0747***	−0.2771***
	(0.0054)	(0.0276)	(0.0029)	(0.0955)
Observations	11,642	11,642	11,642	11,642
Centered R^2		−0.1332		−0.3955
Kleibergen-Paap rk LM statistic	316.591	316.591	74.446	74.446
Kleibergen-Paap rk Wald F statistic	401.541	401.541	87.936	87.936

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

4. Robustness tests

4.1. Using explanatory variables lagged by one period

This paper uses a one-period lag of the digitization level for the robustness test (Hong et al., 2022), as shown in Table 6. Columns 1–2 show that the coefficient estimate of *Iveffect* is significantly negative, which is consistent with the baseline results. Columns 3–4 are the results of the moderating effect, showing that the coefficient of *Iveffect*SA* is significantly negative after adding the control variables. The above results indicate that the findings, once the one-period lag in the level of digitization is included, are consistent with the previous findings, indicating that the regression results are robust.

4.2. Endogeneity problem test

The endogeneity issue may affect the accuracy of the benchmark regression results. Therefore, to mitigate the effects of unobservable factors, this paper follows Zhou et al. (2020) and uses the industry average investment efficiency (*Mean_Iveffect*) as an instrumental variable and empirically analyzes the model using two-stage least squares (2SLS), as shown in Table 7. Columns 1 and 3 show the results of the first-stage regression. The coefficient estimates of the instrumental variable *Mean_Iveffect* are positive and pass the 1% significance level test, indicating that the two are significantly and positively correlated between inefficient investment and industry average investment efficiency, satisfying the instrumental variable correlation requirement. The values of Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F are greater than the critical value of 10, indicating that there is no weak instrumental variable problem and no unidentifiable problem with instrumental variables. Columns 2 and 4 show the regression results of the second stage, where the regression coefficients of *Iveffect*SA* are significantly negative, which are consistent with the baseline results. The above results indicate that, after solving the endogeneity problem, inefficient investment does inhibit the level of digitization.

5. Conclusions and recommendations

This paper takes Chinese listed companies from 2007 to 2019 as a research sample, and empirically tests the impact of investment efficiency on corporate digital development, and the mediating effect of financing constraints, and the conclusions obtained are as follows:

1 The results show that inefficient investment is detrimental to digitalization; there is a positive relationship between investment efficiency and digitalization, and the higher the financing pressure on a company, the more unfavorable the digital transformation, and financing constraints exacerbates this negative effect.
2 The financing constraint has a more significantly negative moderating effect on the relationship between inefficient investment and digitization levels for state-owned firms, private firms, and firms with higher digitization levels.
3 Companies can alleviate financing pressure to a certain extent through inefficient investment, but it is still fundamentally detrimental to their digital transformation.

Table A1
Results of MLE test.

Variables	(1) *EDL*	(2) *EDL*	(3) *EDL*	(4) *EDL*
Iveffect	−0.2123***	−0.2711***	0.0558	0.3171**
	(0.0327)	(0.0468)	(0.1183)	(0.1574)
SA			−0.0687***	−0.0725***
			(0.0065)	(0.0102)
Iveffect×SA			−0.2114**	−0.4996***
			(0.0830)	(0.1177)
Controls	No	Yes	No	Yes
Constant	0.2439***	0.3141***	0.3397***	0.3896***
	(0.0104)	(0.0176)	(0.0138)	(0.0214)
N	21,226	11,642	21,226	11,642
Log likelihood	255.1430	−414.1270	380.0981	−330.9276

Note: *, **, *** represent 10%, 5%, and 1% significance levels; t-values are reported in parentheses.

CRediT authorship contribution statement

Guiyang Xu: Conceptualization, Methodology, Validation, Supervision, Writing – review & editing, Funding acquisition. **Guanggui Li:** Data curation, Formal analysis, Visualization. **Peibo Sun:** Software, Data curation, Formal analysis. **Dan Peng:** Methodology, Software, Data curation, Validation, Writing – original draft, Funding acquisition.

Declaration of Competing Interest

None.

Data Availability

The authors do not have permission to share data.

Acknowledgments

This work was supported from the General Research Project on Humanities and Social Sciences in Henan Universities (2023HNSKGL160); Research and Practice Project on Higher Education Teaching Reform in Henan Province (2021SJGLX242Y), and the Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX22_0011).

Appendix A. MLE test

Differences in regression methods may affect the robustness of the baseline regression results, so this paper replaces the model regression method and uses maximum likelihood estimation (MLE) for the empirical regression. The results are shown in Table A1. The results in columns 1–2 indicate that inefficient investment has a negative impact on the digitalization level of firms. The results in columns 3–4 show that financing constraints exacerbate the negative impact of inefficient investment on the digitization level of firms. The above results indicate that the baseline regression results are still robust after replacing the estimation method of the model.

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