

Research on the Impact of Digital Transformation on Enterprise Investment Efficiency

Fubo Zheng^a

Capital University of Economics and Business, Beijing 100071, China

^a2482024716@qq.com

Abstract

Against the backdrop of the rapid development of the digital economy, enterprise digitalization has become a key approach to improving resource allocation efficiency. However, low investment efficiency remains a major obstacle to achieving high-quality development. Based on sample data of Chinese A-share listed companies from 2008 to 2022, this study constructs an enterprise digitalization index through text mining and uses the Richardson expected investment model to evaluate the issue of low investment efficiency. The study further provides empirical evidence on how digital transformation affects enterprise investment efficiency and the underlying mechanisms through which this effect operates. The empirical results show that digital transformation significantly reduces the phenomenon of low investment efficiency, mainly by curbing over-investment. In the basic model, the mitigating effect of digital transformation on under-investment does not reach statistical significance, but this effect becomes evident when using instrumental variable estimation and longer lag periods. The core mechanism by which digital transformation inhibits over-investment is alleviating financing constraints. For private enterprises, the improvement in investment efficiency brought about by digital transformation is particularly significant. This study confirms how digital transformation optimizes enterprise resource allocation at the enterprise level and provides policy insights for differentially promoting the digital strategies of various types of enterprises and deepening the governance reform of state-owned enterprises.

Keywords

Digital Transformation; Investment Efficiency; Over-investment; Under-investment; Financing Constraints; Nature of Property Rights.

1. Introduction

With the in-depth development and penetration of artificial intelligence, big data, cloud computing and other digital technologies, digital transformation has become the core strategic choice for enterprises to reshape their competitive advantages and achieve high-quality development. The report of the 20th National Congress of the Communist Party of China clearly put forward "accelerate the construction of Digital China", and the "14th Five-Year Plan for Digital Economic Development" further emphasized promoting the deep integration of digital technology with the real economy. At the micro level, digital transformation not only changes the production organization mode and business model of enterprises, but also profoundly reshapes the information processing mechanism, internal governance structure, and resource allocation logic of enterprises. Among them, whether the efficiency of investment decisions can be systematically enhanced through digital means, and how exactly to enhance investment efficiency, have become key issues with both theoretical value and urgent practical significance. The core role of digital transformation in driving technological and industrial revolutions has attracted widespread attention from the international academic community. Some studies have

expounded the mechanism of digitalization from three dimensions: technology, organization, and strategy. According to the research of Mohsin et al.[1], digitalization enables enterprises to conduct real-time data processing and integrate the most advanced technologies, thereby providing real-time digital support to decision-makers and helping them improve strategic response efficiency during economic or political turmoil. Vial [2]proposed a dynamic capability theoretical framework, stating that digitalization can help enterprises build sustainable competitive advantages through three dynamic capabilities: identifying opportunities, seizing opportunities, and reconfiguring resources.Domestic researchers such as He and Liu [3]have also explored the integration path between the real economy and digitalization, pointing out that digitalization provides strong support for the transformation and upgrading of Chinese real enterprises. The "Research Report on the Development of China's Digital Economy (2023)" shows that the proportion of industrial digitalization is as high as 81.7%. Scholars have discussed the digitalization process in different industries, with the manufacturing industry focusing on intelligent manufacturing[4] and the financial industry focusing on data-driven development[5]. However, there is limited empirical research on how digitalization affects enterprise investment efficiency, especially whether it has different impacts on over-investment and under-investment. In addition, few empirical studies explicitly evaluate how digital transformation, as a broad technological transformation, affects investment efficiency. In China's institutional environment, how the type of ownership moderates the relationship between digitalization and investment efficiency requires systematic empirical research.

In short, this study aims to make contributions in three aspects: first, directly study the impact of digitalization on investment efficiency, considering over-investment and under-investment respectively; second, enhance causal inference through instrumental variable methods and a series of robustness tests; third, study the mediating channel of financing constraints and reveal the moderating role of ownership type.

2. Theoretical Analysis and Research Hypotheses

2.1. How Digitalization Affects Enterprise Investment Efficiency

Enterprise investment efficiency is a core issue in the field of corporate finance. In the neoclassical framework, the Modigliani-Miller theorem[6] states that the investment decisions of enterprises depend only on available investment opportunities. However, in reality, the existence of information asymmetry and agency problems leads enterprise investment deviate from the optimal level, manifested as over-investment or under-investment[7]. As a process in which enterprises comprehensively apply digital technology to reshape business processes, organizational structure and business models, digital transformation may affect investment efficiency through the following mechanisms.

Firstly, reduce information asymmetry. Digital technology enables enterprises to collect, process and analyze internal and external information more efficiently[8], thereby facilitating more effective investment activities. At the same time, digitization enables enterprises to disclose their information more transparently, enhancing external investors' understanding of the company's development status and reducing the information costs of external financing[9], which helps to obtain external financing and alleviate the problem of insufficient investment. Secondly, digital transformation can reduce agency costs. Management may engage in excessive investment for their own interests, such as expanding the enterprise scale or pursuing short-term performance[10]. Digitalization limits such behaviors by strengthening internal control and improving supervision mechanisms: Digital systems make business processes more transparent and standardized, reducing the opportunities for management to manipulate information; Real-time data monitoring enables the board of directors and shareholders to promptly detect abnormal investment activities[11], thereby reducing the agency costs of the

management and improving the investment efficiency of the enterprise. Thirdly, alleviate financing constraints. The disclosure of the enterprise data help to narrow the information gap between financial institutions and enterprises, make enterprises easier access to credit[12]; In addition, digitalization itself can demonstrate the strength of the enterprise, convey the enterprise's forward-looking vision and technical capabilities to financial institutions and the capital market, helping the enterprise build a good reputation and expand financing channels. Also, financing constraints are usually regarded as a key factor leading to insufficient investment[13]. Underinvestment occurs when firms identify investment projects with positive NPV but cannot obtain sufficient investment funds due to financing difficulties. After alleviating financing constraints, enterprises have sufficient funds to support the transformation of investment opportunities into actual investments, thereby reducing the problem of insufficient investment and improving the efficiency of enterprise investment.

Drawing upon the preceding discussion, the research formulates the hypotheses presented below:

H1: Other things being equal, the higher the degree of digital transformation, the higher the enterprise investment efficiency, that is, the lower the degree of inefficient investment.

2.2. Heterogeneous Effects of Digital Transformation on Over-investment and Under-investment

Although theoretically, digitization is expected to enhance overall investment efficiency, when analyzed in terms of its specific effects, it may have different impacts on excessive investment and insufficient investment.

Over-investment mainly stems from agency conflicts[10]. Digital transformation can directly restrict the self-serving behavior of management through the aforementioned mechanisms of strengthening supervision and process transparency, and the improvement of this governance effect is usually reflected in a relatively short period of time. In contrast, under-investment is more due to structural financing constraints and macro-environmental uncertainty[14]. Even if digitalization improves the information environment, enterprises may still find it difficult to obtain sufficient financing due to factors such as insufficient collateral and unclear industry prospects. The mitigating effect of digital transformation on these deep-seated obstacles is relatively indirect and limited. In addition, alleviating financing constraints requires the support and cooperation of external entities such as banks, and it may take a longer time to convert digital signals into actual credit resources. Based on these reasons, this study proposes the following hypothesis:

H2: The inhibitory effect of digitalization on over-investment is more significant than its mitigating effect on under-investment.

3. Research Design

3.1. Sample Selection

We begin with an initial sample of China's A-share listed firms covering the years 2008 to 2022. Data on financials, corporate governance, and industry classifications are sourced from the CSMAR (Guotai'an) database. The main word-frequency indicators capturing the degree of digital transformation were derived from the text of listed companies' annual reports, which were obtained through Python web crawling. Basic information such as listing date and nature of actual controller is also obtained from CSMAR.

The initial sample is processed as follows: (1) We refine the initial dataset through the steps outlined below: first, financial-sector firms (with industry codes beginning with J) are removed (2) exclude samples with special treatment (ST, *ST, PT); (3) retain observations with relevant financial data for at least two consecutive years to calculate lag variables and investment

efficiency indicators; (4) We further drop firm-year records for which the core variables are unavailable; (5) With the exception of the investment efficiency residual, we winsorized all continuous variables at the 1% and 99% percentiles; however, due to the presence of significant outliers in the investment efficiency residual, a stricter censoring approach using the 2% and 98% quantiles was employed to mitigate their impact.

After applying the filtering criteria detailed above, we obtain an unbalanced panel of 1,954 listed firms, totaling 10,637 firm-year records.

3.2. Definitions and Measurement of Variables

3.2.1. Degree of Inefficient Investment

Following the framework of Wang Dan et al.[15] and Richardson (2006)[16], we first estimate a baseline equation to capture firms' normal investment levels, and then take the absolute residuals from this regression as a measure of investment inefficiency. The expected investment model is specified as:

$$Inv_{i,t} = \beta_0 + \beta_1 Inv_{i,t-1} + \beta_2 Q_{i,t-1} + \beta_3 Cash_{i,t-1} + \beta_4 Size_{i,t-1} + \beta_5 Lev_{i,t-1} + \beta_6 Age_{i,t-1} + \sum Industry + \sum Year + \varepsilon_{i,t} \quad (1)$$

In this specification, $Inv_{i,t}$ denotes firm i 's net investment expenditure during year t , calculated as the ratio of capital spending to total assets at the beginning of the year. To construct the expected investment model, we use as regressors the following firm characteristics: Tobin's Q , cash holdings, leverage, firm size, and listing age, represented respectively by Q , $Cash$, Lev , $Size$, and Age .

The disturbance term, denoted $\varepsilon_{i,t}$, captures the discrepancy between a firm's actual investment expenditure and its expected level. A positive residual signals overinvestment (OverInv), whereas for a negative residual, its absolute magnitude corresponds to underinvestment (UnderInv). To assess investment efficiency comprehensively, overall inefficiency is measured by $Inveff_abs_{i,t} = |\varepsilon_{i,t}|$, with larger absolute values indicating lower efficiency.

3.2.2. Digitalization Index

Following the approach of Wu et al.[17], we characterize corporate digitalization along multiple dimensions-including artificial intelligence, blockchain, cloud computing, big data, and the application of digital technologies-and quantify the degree of digital transformation by first summing the relevant word counts and then applying a logarithmic transformation. To mitigate simultaneity and potential reverse causation, the baseline specification uses the one-period lag of the digitalization variable, denoted as $L.Digital$. In robustness checks, an additional binary indicator, $high_dig$, is constructed based on the industry-year median: it equals one when a firm's digitalization level surpasses the contemporaneous industry median, and zero otherwise.

3.2.3. Mediating Variable: Financing Constraints (SA)

Drawing on Hadlock and Pierce[18], we gauge firms' financing constraints using the SA index:

$$SA_{i,t} = -0.737 \times Size_{i,t} + 0.043 \times Size_{i,t}^2 - 0.04 \times Age_{i,t}$$

In this setup, $Size_{i,t}$ is the natural log of the firm's total assets, while $Age_{i,t}$ gives the number of years it has been publicly traded. A larger absolute SA index denotes tighter financial constraints.

The study includes the following control variables to account for possible confounding effects on investment efficiency: firm size (Size, measured as the natural log of total assets), leverage (Lev), return on assets (ROA), cash holdings (Cash_ratio), firm age (Age_ln), the natural log of listing years plus one), and ownership concentration (Top1, the percentage of shares held by the largest shareholder). In addition, every specification contains industry dummies (ind_num, built according to the CSRC 2012 industry classification) and year fixed effects (Year).

4. Analysis of Empirical Evidence

4.1. Baseline Regression Analysis

To assess the effect of digitalization on corporate investment efficiency, we adopt a two-way fixed effects specification that includes industry and year dummies, and we compute standard errors clustered at the firm level.

$$\begin{aligned} Inveff_abs_{i,t} &= \alpha_0 + \alpha_1 L.Digital_{i,t} + \alpha X_{i,t} + \mu_{ind} + \lambda_t + \varepsilon_{i,t} \\ OverInv_{i,t} &= \beta_0 + \beta_1 L.Digital_{i,t} + \beta X_{i,t} + \mu_{ind} + \lambda_t + \varepsilon_{i,t} \\ UnderInv_{i,t} &= \theta_0 + \theta_1 L.Digital_{i,t} + \theta X_{i,t} + \mu_{ind} + \lambda_t + \varepsilon_{i,t} \end{aligned}$$

In this notation, "i" and "t" represent the company and the year respectively. The dependent variables- $Inveff_abs_{i,t}$, $OverInv_{i,t}$, and $UnderInv_{i,t}$ -are measures of overall inefficient investment, overinvestment, and underinvestment derived from Model (1).

Table 1. Regression results of the benchmark model

	(1)	(2)	(3)
	Inveff_abs	OverInv	UnderInv
L_Digital	-0.00113**	-0.00261***	-0.000257
	(0.000455)	(0.000999)	(0.000347)
Size	-0.000363	0.00208*	-0.00332***
	(0.000534)	(0.00119)	(0.000396)
Lev	0.00387	0.0142**	-0.00227
	(0.00244)	(0.00673)	(0.00201)
ROA	0.00496	0.0278**	-0.00455*
	(0.00395)	(0.0139)	(0.00269)
Cash_ratio	-0.0104***	-0.0181**	-0.00240
	(0.00364)	(0.00797)	(0.00319)
Age_ln	-0.0133***	-0.0224***	-0.00787***
	(0.00127)	(0.00269)	(0.000904)
Top1	-0.0000765**	-0.000145*	-0.00000107
	(0.0000359)	(0.0000765)	(0.0000266)
_cons	0.0724***	0.0444	0.120***
	(0.0121)	(0.0273)	(0.0102)
N	10621	4179	6442
r2	0.0898	0.119	0.139

Note: Values in parentheses represent the robust standard error of clustering at the company level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; the values in parentheses are the standard errors of clustering at the firm level. All regressions controlled for industry fixed effects and annual fixed effects as shown in the table below.

The core explanatory variable is the first-order lag term of corporate digital transformation intensity. The control variables include enterprise size (Size), leverage ratio (Lev), asset return rate (ROA), cash ratio (Cashratio), logarithm of the number of years since establishment of the enterprise (Age_{ln}), and equity concentration (Top1). Appropriate variable control is applied to account for industry and annual fixed effects. To address potential heteroscedasticity and internal serial correlation within enterprises, standard errors are clustered at the enterprise level and estimated using robust variance estimation methods.

As shown in the (1) column of the table, the coefficient of L.Digital is statistically significant at the 5% level and is consistent with the hypothesis H1, that is, digital transformation generally improves the efficiency of enterprise investment. When inefficient investment is decomposed into two directional components, the L. digital coefficient for the over-investment regression in the second column is statistically significant at the 1% level, indicating that digitalization effectively curbs over-investment. In contrast, the coefficient corresponding to the non-investment regression in the third column does not reach statistical significance. This suggests that the improvement in investment efficiency brought about by digital transformation mainly manifests in the aspect of curbing over-investment, while its alleviation effect on the investment deficiency issue in the base model is not yet clear, supporting hypothesis H2.

4.2. Robustness Tests

Table 2. Robustness Test 1

	(1)	(2)	(3)
	Inveff_abs	OverInv	UnderInv
high_dig	-0.00222**	-0.00624***	-0.00121*
	(0.000921)	(0.00213)	(0.000693)
Size	-0.00128**	0.00275**	-0.00454***
	(0.000573)	(0.00122)	(0.000488)
Lev	0.00563**	0.0124**	-0.00231
	(0.00267)	(0.00628)	(0.00237)
ROA	0.00606	0.0104	-0.00836
	(0.00372)	(0.00634)	(0.00517)
Cash_ratio	-0.00695*	-0.0196**	0.00203
	(0.00397)	(0.00892)	(0.00352)
Age_ln	-0.0128***	-0.0267***	-0.00768***
	(0.00134)	(0.00310)	(0.00101)
Top1	-0.0000614*	-0.000162*	0.0000297
	(0.0000370)	(0.0000857)	(0.0000276)
_cons	0.0897***	0.0324	0.146***
	(0.0130)	(0.0302)	(0.0122)
N	10621	4072	6549
r2	0.0857	0.118	0.153

To assess the consistency of benchmark results, a series of robustness tests were conducted. Firstly, we replaced the continuous digital indicators with binary variables and constructed a dummy variable named "high_dig": when the enterprise's digitalization level was higher than the median of the industry year, the variable took the value of 1, otherwise it was 0, to replace the original continuous variable L.Digital. As shown in Table 2, the inefficient investment in the high-digitalization level group was significantly lower than that in the low-digitalization level group, and the absolute value of the coefficient was larger. This might imply that there is a certain threshold feature in the impact of digital transformation on investment efficiency: when the digitalization level exceeds the industry median, its inhibitory effect on inefficient investment becomes more obvious. This effect is consistent with the results of the benchmark regression, and this test enhances the robustness of our research conclusion.

This paper also takes into account the time dynamic factors and uses the digital transformation variable L2. Digital, which is lagged by two periods, as the key regression variable for another robustness test. Table 3 shows that the estimated coefficients of L2.Digital are all negative and statistically significant, and their absolute values are all higher than the values of the first-order lagged variable in the benchmark results. This result indicates that the efficiency improvement effect brought by digitalization is persistent and cumulative, and is more fully manifested over a longer time period.

At the same time, this result also further alleviates concerns about the reverse causal relationship.

Table 3. Robustness Test 2

	(1)	(2)	(3)
	Inveff_abs	OverInv	UnderInv
L2_Digital	-0.00202***	-0.00360***	-0.000816*
	(0.000599)	(0.00137)	(0.000465)
Size	-0.00121*	0.00309**	-0.00543***
	(0.000682)	(0.00128)	(0.000599)
Lev	0.00416	0.00486	0.0000733
	(0.00298)	(0.00522)	(0.00295)
ROA	0.00774*	0.00638	0.00305
	(0.00408)	(0.00427)	(0.00618)
Cash_ratio	0.00172	-0.00214	0.00565
	(0.00504)	(0.00910)	(0.00469)
Age_ln	-0.00988***	-0.0214***	-0.00571***
	(0.00216)	(0.00460)	(0.00175)
Top1	-0.0000799*	-0.000121	0.000000718
	(0.0000463)	(0.000106)	(0.0000332)
_cons	0.0884***	0.0385	0.160***
	(0.0153)	(0.0324)	(0.0144)
N	6543	2598	3945
r2	0.0973	0.143	0.176

4.3. Addressing Endogeneity: Instrumental Variable Method

Although our baseline model controls for industry and year fixed effects and uses the one-period lag of digitalization to mitigate reverse causality, omitted variables and measurement errors may still lead to endogeneity issues. Based on existing studies that use lagged independent variables as instrumental variables[19], this study further uses the third-order lag variable of digital transformation (L3.Digital) as an instrumental variable and performs two-stage least squares estimation (2SLS). The instrumental variable we selected satisfies the relevance condition: the digital intensity of enterprises three periods ago is closely related to the current digital level, but it is unlikely to have a direct impact on the contemporaneous investment efficiency residual. Table 4 presents the estimated results of the second stage.

The first-stage F-statistic values for the three regressions (1266.8, 763.5, and 795.2) all far exceeding the 10% critical value of 16.38 in the Stock-Yogo weak identification test, thus eliminating concerns about weak instrumental variables. Also, our second-stage results confirm that the instrumental variable is significantly correlated with Inveff_abs, OverInv, and UnderInv. Compared to the benchmark OLS model, the absolute values of the IV estimation coefficients approximately double, indicating that the OLS estimation has an upward bias; therefore, the true efficiency-enhancing effect of digitalization is underestimated, and endogeneity leads to attenuation of the estimation results. Notably, the IV estimation further indicates that digital transformation significantly alleviates underinvestment, suggesting that after properly addressing endogeneity issues, The comprehensive promotion effect of digitalization on investment efficiency is increasingly obvious, which further proves that digitalization has a persistent and cumulative effect on the improvement of enterprise investment efficiency, and also proves hypothesis H1

Table 4. Instrumental Variable Estimation Results

	(1)	(2)	(3)
	Inveff_abs	OverInv	UnderInv
L3.Digital	-0.00390***	-0.00551***	-0.00171**
	(0.00104)	(0.00214)	(0.000839)
Size	-0.000975	0.00323**	-0.00528***
	(0.000718)	(0.00131)	(0.000658)
Lev	0.00249	0.00328	-0.00106
	(0.00315)	(0.00484)	(0.00348)
ROA	0.00410	0.00329	-0.0000312
	(0.00334)	(0.00389)	(0.00728)
Cash_ratio	0.00653	-0.0000113	0.00858
	(0.00559)	(0.00966)	(0.00524)
Age_ln	-0.00933***	-0.0178***	-0.00733***
	(0.00328)	(0.00674)	(0.00260)
Top1	-0.0000735	-0.0000798	-0.00000348
	(0.0000534)	(0.000118)	(0.0000389)
N	5026	2059	2967
Phase 1 F-value	1266.8	763.5	795.2

4.4. Heterogeneous Effects of Ownership Type

The preceding analysis has confirmed that digital transformation exerts an overall positive effect on investment efficiency; however, this impact may be heterogeneous across firms with different ownership structures. Table 5 reports the regression results grouped by the nature of the actual controller. Within the private firm subsample, the coefficients of L.Digital on Inveff_abs, OverInv and UnderInv are all significantly negative; while in the state-owned enterprise subsample, the coefficients of L.Digital all fail to pass the significance test. This indicates that the improvement effect of digital transformation on investment efficiency is mainly concentrated in non-state-owned enterprises

The possible reasons for this disparity could be that state-owned enterprises are influenced by policies, and their investment decisions are often affected by various non-market factors[20]. Additionally, the budget constraints of state-owned enterprises are relatively loose, and the role of digitalization in alleviating their financing constraints is not obvious. Furthermore, the development paths of managers in state-owned enterprises are closely related to political goals[21], so the information and governance advantages brought by digitalization cannot fully exert their marginal effects; In contrast, non-state-owned enterprises face more intense market competition. Digital transformation can more directly alleviate financing constraints and reduce agency costs, thereby significantly optimizing investment behavior.

Table 5. Heterogeneous Effects by Ownership Type

	(1)	(2)	(3)	(4)	(5)	(6)
	Inveff_abs	Inveff_abs	OverInv	OverInv	UnderInv	UnderInv
L_Digital	0.00144	-0.00161***	0.00413	-0.00321***	0.00114	-0.000784**
	(0.00195)	(0.000497)	(0.00462)	(0.00116)	(0.00157)	(0.000379)
Size	-0.00302	-0.00118*	-0.0149*	0.00301**	-0.00242	-0.00475***
	(0.00242)	(0.000616)	(0.00809)	(0.00130)	(0.00172)	(0.000526)
Lev	-0.0116	0.00759***	-0.0114	0.0137**	-0.0242*	-0.000160
	(0.0155)	(0.00285)	(0.0493)	(0.00671)	(0.0127)	(0.00251)
ROA	0.0810	0.00743*	0.208	0.0124*	-0.00705	-0.00694
	(0.0591)	(0.00407)	(0.207)	(0.00739)	(0.0329)	(0.00530)
Cash_ratio	-0.0154	-0.00572	-0.0205	-0.0190**	0.00733	0.00229
	(0.0193)	(0.00412)	(0.0415)	(0.00929)	(0.0152)	(0.00371)
Age_ln	-0.00932	-0.0129***	0.0130	-0.0271***	-0.0116**	-0.00761***
	(0.00654)	(0.00142)	(0.0265)	(0.00325)	(0.00500)	(0.00108)
Top1	-0.0000547	-0.0000692*	0.000861	-0.000176**	-0.000191	0.0000323
	(0.000181)	(0.0000386)	(0.000516)	(0.0000878)	(0.000129)	(0.0000296)
_cons	0.111**	0.0870***	0.475***	0.0250	0.103***	0.150***
	(0.0478)	(0.0139)	(0.152)	(0.0313)	(0.0372)	(0.0130)
N	418	9861	137	3816	281	6045
r2	0.289	0.0848	0.481	0.118	0.395	0.152

4.5. Testing the Mediating Role of Financing Constraints

Information asymmetry is the root cause of financing constraints[22], and financing constraints are the direct trigger for insufficient investment[13]. The essential feature of digital transformation lies in reducing information asymmetry through the integration and sharing of data elements. Therefore, examining this intermediary path of alleviating financing constraints can directly capture the core function of digitalization. We take the SA index as the proxy variable for financing constraints and use the Bootstep method to test its mediating effect[23]; The results are shown in Table 6.

This paper eliminates the fixed effects by conducting industry-year-wise group mean removal for all variables, and performs 1000 company-level clustering Bootstrap sampling to obtain the bias-corrected confidence interval for the indirect effect. The results show that, only in the overinvestment equation, the mediating effect of financing constraints is significant at the 5% level.

The above results indicate that financing constraints are an auxiliary transmission path for digitalization to suppress overinvestment, but have a limited improvement effect on investment deficiency. The improvement of investment efficiency by digital transformation mainly relies on the reduction of agency costs and the optimization of internal governance. The alleviation of investment deficiency may require a more substantial improvement in the financing environment, and only enterprise-level digitalization efforts are not sufficient to completely resolve the issue.

Table 6. Bootstrap Mediation Analysis

Dependent Variable	Indirect Effect	95% Bias-Corrected CI	Significance
Inveff_abs	-0.0000154	[-0.0000627, 0.00000414]	No
OverInv	0.0000566	[0.0000223, 0.0001646]	Yes
UnderInv	-0.0000551	[-0.0001123, 0.0000401]	No

5. Conclusion and Policy Recommendations

In summary, our analysis leads to the following four core conclusions. First, enterprise digitalization significantly improves the overall investment efficiency. Second, when the investment efficiency is decomposed into two directional components, the main effect of digitalization lies in curbing excessive investment; in the baseline model, the alleviation effect of digitalization on insufficient investment is not statistically significant, but it becomes obvious in the instrumental variable estimation and the test using a longer lag period of the digital transformation degree variable, indicating that the impact of digitalization on investment efficiency has a time lag and functions through different governance paths. Third, digital transformation inhibits overinvestment mainly by easing financing constraints. Fourth, compared with state-owned enterprises, digitization plays a more significant role in improving the investment efficiency of private enterprises. Meanwhile, this paper still has several limitations. First, this paper uses the frequency of MD&A words in annual reports as the proxy indicator for digitalization. Although this method is widely used in the literature, the word frequency statistics may not fully reflect the depth of digitalization throughout the entire production and operation process of the enterprise. In the future, data such as digital capital investment and digital patents can be combined to construct a more comprehensive measurement system for research. Second, this paper uses A-share listed companies as the sample. The conclusion's application to small and medium-sized enterprises and non-listed enterprises requires careful consideration. Small and medium-sized enterprises face more

prominent constraints in their digital transformation, and the relationship between their digitalization and investment efficiency may exhibit different characteristics. Future research will focus on enterprises in regional equity markets. Third, although lagged variable instrumental variables and various robustness tests have been employed, it is still difficult to completely eliminate the potential influence of time-varying omitted variables. Certain enterprise characteristics that change over time and are unobservable may simultaneously affect digital transformation and investment efficiency, resulting in certain biases in the estimation results. Future research can attempt to use more exogenous policy shocks or geographical characteristics as instrumental variables to further alleviate the endogeneity bias. Based on these findings, we put forward the following suggestions: first, enterprises should regard digital transformation as the core part of its development strategy. Digital transformation provides important opportunities for enterprises to reconstruct management systems and optimize governance mechanisms. At the same time, it must be recognized that improving investment efficiency through digitalization is a gradual and slow process that requires continuous investment and long-term commitment.

Second, when implementing digital economy policies, the government should adopt differentiated guiding strategies. For private enterprises, further utilization of tax incentives and special subsidies can be employed to reduce their costs in digital transformation and promote the implementation of digital transformation in private enterprises. For state-owned enterprises, promoting digitalization should be closely integrated with deepening the reform of state-owned enterprises, establishing a more market-oriented investment and financing framework and management evaluation system, so that digitalization can better enhance the resource allocation efficiency of state-owned enterprises.

Thirdly, the digital information transmission capabilities should be fully utilized to narrow the information gap between financial institutions and enterprises. Financial service institutions should attach importance to the signal role of enterprises' digital maturity in credit decision-making, and strive to incorporate digitalization levels into the credit allocation model. They should provide financing convenience for enterprises with actual growth potential but facing short-term capital constraints, fundamentally solving the problem of low investment caused by insufficient funds for some enterprises.

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