How does Financial Misallocation Affect Enterprise Transformation and Upgrading based on the Perspective of Digital Transformation

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Abstract. Financial misallocation deviates capital factors from prices which should be determined by market supply and demand. Not only does it exacerbate economic instability at the macro level, but also reduces the operating efficiency of enterprises at the micro level. Using China A-share listed enterprises from 2008 to 2020 as the original research sample, this paper empirically investigates the impact of financial misallocation on the digital transformation of enterprises and its mechanism of action, and conducts heterogeneity analysis based on enterprise characteristics. Findings demonstrate that: (1) Financial misallocation significantly inhibits the digital transformation of enterprises; (2) Financial misallocation decelerates the transformation process by obstructing the innovation capability of enterprises; (3) The inhibitory effect of financial misallocation on digitalizations of non-SOEs and SMEs is far more evident. This study provides a meaningful empirical basis and policy enlightenment for financial resources to effectively empower the real economy and promote the high-quality development of China's economy.

Keywords: Financial Misallocation; Enterprise Digitalization; Innovation Input; Innovation Output; Innovation Efficiency.

1. Introduction

It is emphasized by the 20th Party Congress, that "China will continue to put the focus of economic development on the real economy. China intends to accelerate the development of the digital economy, promote the deep integration of the digital economy and the real economy, and establish internationally competitive digital industry clusters". In other words, leveraging digital technology to upgrade industry has become a critical path to facilitate the high-quality growth of China's economy (especially micro enterprises). However, according to the Accenture China Digital Transformation Index 2022, only 17% of the 574 sample companies were ranked among the leaders of digital transformation of Chinese enterprises (subsequently abbreviated as DIGI) in 2022, which is basically the same as 16% in 2021. There is a gigantic disparity between the current status of DIGI and the development requirement. How to narrow that gap and accelerate DIGI has become a crucial challenge for China's economic growth nowadays.

DIGI has a strong demand for high-quality financial supply (Hicks, 1973). However, there are always being structural misallocation problems when conventional finance serves the real economy. It tends to loan to enterprises with a certain scale, high profitability (Tang et al., 2020), relatively easy access to information (Ding et al., 2022), and low default risk (Zhen and Luo, 2019), which results in scale discrimination and ownership discrimination in the financial market (Li and Lu, 2020). In terms of scale discrimination, in general, large enterprises (subsequently abbreviated as LEs) have been in business steadily for a longer period of time than SMEs (Small and Medium-sized Enterprises). They have technically well-built information systems and integrated information disclosure. It is less costly for banks to obtain their information. By contrast, SMEs with shorter operating times have higher risks of uncertainty regarding future operating cash flows and lack historical data for reference. Given the default risk and information cost (Caggese, 2019), banks are more apprehensive in lending to SMEs. With regard to ownership discrimination, the Chinese financial system is dominated by the government and commercial banks, and the government can determine the pricing and allocation of financial factors (Liu, 2014). Since SOEs (State Owned Enterprises) and the government are inherently and naturally associated, as well as for political purposes, the government may inject funds into SOEs through direct tax incentives, fiscal subsidies and indirect interventions in banks and other financial institutions to grant loans into SOEs (Xiong and Wei, 2023). In addition, undertaking a great deal of social responsibilities, SOEs predominantly pursue robust and steady business operations, and the government is always there to provide them with critical assistance when necessary. Therefore, SOEs have lower default risk than non-SOEs and are more prone to being favored by capital. Reasons above would lead to financial misallocations (subsequently abbreviated as FM) that can cause a crowding-out effect on SMEs and non-SOEs with DIGI demands, reducing the efficiency of financial services for the real economy.

Most of the existing literatures have explored factors influencing DIGI from political, economic, technological, market, and enterprise perspectives. Rarely have literatures addressed the financial perspective, and they principally concentrate on digital finance (Liu and Hua, 2022; Xiao and Yang, 2022), financial asset allocation (Chen and Yang, 2022), financial aggregation (Li et al., 2022) and financing methods (Zhang, 2022), etc. There is a lack of studies that directly connect FM with DIGI.

Based on this, applying the data of China A-share listed companies from 2008 to 2020 as the research sample, this paper explores the influence of FM on DIGI, which is measured by the relevant eigenvalue word frequency. Subsequently, from two dimensions of innovation input and innovation efficiency, this essay explores the intrinsic mechanism of FM in DIGI. In addition, via using the nature of property right and enterprise size as grouping criteria, this paper also analyzes distinctions in the impact of FM on DIGI of different types of enterprises.

Chief contributions of this paper are: First, this paper empirically tests the inhibitory effect of FM on DIGI, enriching the research related to FM and DIGI. Second, this essay expands the research on the impact factors of DIGI. Third, group regressions of this paper further reveal the heterogeneous impact of FM under different conditions, providing meaningful empirical evidence and political insights for optimizing the allocation of financial resources and accelerating the process of DIGI in China.

2. Theoretical Analysis and Hypothesis Formulation

DIGI requires deep integration of enterprise institutional arrangements with digital technology, which is characterized by high-risk, high-investment, long-cycle and slow-payoff. Sustainable low-cost financial support is an essential assurance for DIGI (Xiao and Yang, 2022). Therefore, whether the problem of financial sources can be addressed is crucial to determine whether enterprises can successfully transform (Wen and Huang, 2022). However, problems of information asymmetry, supply and demand imbalance and high proportion of indirect financing in China's financial market make banks have apparent financial discriminations, resulting in FM (Liu and Hua, 2022), which does not achieve the Pareto optimum (Eisfeldt and Rampini, 2008). FM to a large extent reduces the efficiency of finance serving the real economy and hinders the transformation activities of enterprises.

From the perspective of the source of innovation, on the one hand, FM can crowd out companies' innovation inputs. FM empowers companies with advantageous access to capital to engage in shadow banking by virtue of low-interest borrowings and to earn high-spread returns. Financial leakages and rent-seeking behavior prolong the chain of credit intermediation. They will result in a substantial increase in financing costs for companies at the end of the discrimination chain (Guo et al., 2019), crowding out R&D investment of innovative entities and making it difficult for them to take advantage of investment opportunities (Zhang and Li, 2018). On the other hand, FM can reduce firms' willingness to invest in innovation. For firms with fewer investment opportunities but excess financial resources, a stable production and operation environment tends to lead them to be content with the status quo (Zhang and Li, 2018) and unwilling to carry out digital reforms. In addition, since the disparity in loan costs creates arbitrage space in the market, enterprises possessing superior access to capital have an incentive to abandon part of their principal businesses and high-investment and high-risk digital innovation activities to pursue rent-seeking activities that can generate high returns in the short run (Ding et al., 2022). For firms that have prospective investment opportunities but are constrained by financing, firstly, a tight capital chain increases their liquidity risk and thus they are more inclined to invest their capital in small-scale, short-cycle and fast-impact projects (Zhen and Luo, 2019). However, innovation is characterized by high-investment, long-cycle, high-risk and strong-externalities (Holmstrom, 1989), so firms will scale back or even abandon digital innovation investment. Secondly, FM reduces the risk of innovation undertaken by firms shared by financial markets. The increase in operating risks will lessen their own expectations for future development. Corporate executives tend to adopt more conservative strategic initiatives and pay less attention to innovation transformation (Sung et al., 2019), correspondingly reducing innovation investment. Finally, under the situation of severe FM and augmenting barriers to external financing, substantial rent-seeking costs reduce the innovation benefits of enterprises. When the cost of capital employed is higher than the private rate of return for innovative agents, firms' incentive to innovate will be dampened (Hall and Lerner, 2010), which undoubtedly reduces R&D and digital production facilities investment. As a result, FM can further inhibit DIGI by curtailing firms' innovation inputs.

From the perspective of the whole innovation process, the inability of capital factors to follow the market law to flow into the productive sectors with high marginal rates of return greatly reduces capital utilization efficiency and innovation efficiency, which hinders China's DIGI. FM enables some inefficient SOEs and LEs lacking growth to have priority access to credit resources even at a cost lower than the market interest rate, while SMEs and non-SOEs with higher innovation and production efficiency (Ayyagari et al., 2010) have to obtain financial resources necessary for innovation at a higher cost due to credit discriminations (Zhang and Li, 2018). Moreover, FM spawns financial leakage phenomena and rent-seeking activities (Ding et al., 2022). Rent-seeking brings mostly short-term loans to firms and cannot help them obtain stable long-term loans (Xiong and Wei, 2023). Digital innovation, by contrast, is a long-cycle process that requires adequate financial support throughout. In order to cover R&D demands, innovative entities in a disadvantageous financing position have to toss and turn between multiple rent-seeking activities and engage in games with banks and financial institutions (Li and Lu, 2020). These would distract enterprises from regular innovation activities, and lead to impaired innovation efficiency (Whited and Zhao, 2021; Hottenrott and Peters, 2012). Therefore, FM can reduce R&D efficiency and restrain DIGI.

Consequently, this paper proposes the following two research hypotheses:

H1: FM inhibits DIGI.

H2: FM can suppress DIGI by shrinking innovation input and reducing innovation efficiency.

3. Research Design

3.1 Sample Selection and Data Sources

In this research, listed companies in Shanghai and Shenzhen A-shares from 2008 to 2020 are selected as the initial research sample. Raw data are processed as follows: (1) exclude the samples of ST, *ST and financial companies; (2) exclude samples with missing data; (3) winsorize the upper and lower 1% of all continuous variables. After the above processing, 27,383 observations are finally obtained. All research data in this paper is acquired from the CSMAR and Wind database.

3.2 Variable Settings

3.2.1 Explained Variable - DIGI

Referring to Wu et al. (2021), annual reports of China A-share listed companies from 2008-2020, which are collated through the Python crawler function, are used as the data pool in this study. According to five categories, artificial intelligence technology, big data technology, cloud computing technology, block chain technology and digital technology application, figure words are searched and matched. Then, record word frequencies and sum them up to obtain the index system of DIGI.

Furthermore, indicators are logarithmically processed to eliminate the right--skewed feature of the data, and DIGI is eventually obtained.

3.2.2 Explanatory Variables - FM

Referring to Shao (2010), this essay uses the difference between the firm's cost of capital employed and the industry average cost of capital employed to measure FM. In this case, the firm's cost of capital employed is calculated by dividing interest expenses by total liabilities having deducted accounts payable. Specific main variable definitions are presented in Table 1.

Table 1. Main variable definition and descriptive statistics

Variables	*Definition of variables*	*Mean*	*Std.dev.*	*Medium*	*Min*	*Max*
DIGI	Assessment index is constructed based on the keyword word frequency of Wu Fei et al. (2021)	0.585	0.589	0.527	0.000	1.778
FM	[Interest expense / (liabilities - accounts payable) - industry average interest rate] / Industry average interest rate	-0.026	0.710	-0.081	-1.000	2.513

3.2.3 Control Variables

In this study, firm size (Size), nature of ownership (State), years in operation (Age), board size (Board), percentage of independent directors (Independ), percentage of shares held by top 10 shareholders (Top10), Tobin Q value (Tobinq), return on equity (ROE), leverage ratio (Lev), industry (Ind) and year (Year) dummy variables are selected as control variables.

3.3 Model Setting

To test the impact of FM on DIGI, the model shown below is constructed:

$$\mathrm{DIGI}_{it} = \beta_0 + \beta_1 \mathrm{FM}_{it} + \rho X_{it} + \mathrm{Year} + \mathrm{Ind} + \varepsilon_{it} \quad (1)$$

where, i represents enterprise; t represents time; DIGI represents the digital transformation of enterprise; FM represents the financial misallocation; X represents control variables; Year and Ind represent year and industry fixed effects, respectively; and ε represents random error terms.

4. Empirical Result Analysis

4.1 Baseline Regression: FM – DIGI

Table 2 reports regression results of FM on DIGI. Column (1) does not include control variables, and does not control year and industry fixed effects. Column (2) includes control variables, but does not control year and industry fixed effects. Column (3) includes control variables, and controls year and industry fixed effects. Among three columns, coefficients of FM are all significantly negative at the 1% level, supporting the H1 of this paper. Plausible reasons are that, on the one hand, FM limits the necessary factor input required for DIGI. On the other hand, FM expands the risk exposure suffered by transitioning subjects and makes them less willing to transform, thus inhibiting DIGI.

4.2 Robustness Tests and Endogenous Issues

First, replace the explanatory variable. Referring to Yuan et al. (2021), this paper remeasures the degree of DIGI employing the frequency of DIGI-related terms appearing in the MD&A section of corporate annual reports after adjusting for text length of that section. To ensure the observability of regression coefficients, this research amplifies the new DIGI by a factor of 1000. Column (4) of Table 2 shows regression results after superseding the explanatory variable. The regression coefficient of FM is negative at the 1% significance level, which indicates that FM suppresses DIGI.

Second, exclude part of the sample. Considering the impact of financial crisis in 2008 and COVID-19 in 2020 on the development of Chinese enterprises (Ding et al., 2022; Li et al., 2022), this study removes samples in 2008 and 2020, and then reperforms the regression. Results are exhibited in column (5) of Table 2, where FM has a significant negative effect on DIGI at the 1% level.

Third, exogenous problems. Given that there would still be some unnoticeable factors affecting regression consequences, the propensity score matching (PSM) is further employed to mitigate the interference of endogenous problems brought by omitted variables. Samples whose FM are greater than the median is selected to form the treatment group, and samples whose FM are less than the median form the control group, controlling variables consistent with the baseline regression. Results are listed in column (6) of Table 2. The regression coefficient of FM is significantly negative at the 1% level, also illustrating that FM dampens DIGI.

Table 2. Baseline Regression and robustness test

	(1)	(2)	(3)	(4)	(5)	(6)
	DIGI	*DIGI*	*DIGI*	*DIGI*	*DIGI*	*DIGI*
FM	-0.026***	-0.028***	-0.023***	-0.033**	-0.024***	-0.028***
	(-2.842)	(-3.037)	(-3.351)	(-1.991)	(-3.351)	(-2.859)
Size		0.101***	0.059***	0.057***	0.059***	0.055***
		(13.183)	(9.008)	(4.991)	(8.820)	(6.662)
State		-0.213***	-0.119***	-0.174***	-0.123***	-0.158***
		(-11.047)	(-7.217)	(-5.227)	(-7.234)	(-7.630)
Age		0.016***	0.0000	0.0020	0.0000	-0.0010
		(10.519)	(0.128)	(0.586)	(0.172)	(-0.349)
Board		-0.189***	0.0080	-0.0200	0.0050	0.0280
		(-4.010)	(0.200)	(-0.253)	(0.117)	(0.579)
Independ		0.286*	0.368***	0.688**	0.370***	0.357**
		(1.771)	(2.874)	(2.345)	(2.800)	(2.194)
Top10		-0.001**	0.0000	-0.002*	0.0000	0.0000
		(-2.056)	(-0.983)	(-1.655)	(-0.801)	(0.418)
Tobinq		-0.027**	0.0090	0.0210	0.0100	0.0150
		(-2.188)	(0.965)	(1.080)	(1.052)	(1.181)
ROE		-0.215***	0.064*	0.140*	0.078**	0.0500
		(-5.091)	(1.764)	(1.922)	(2.041)	(0.797)
Lev		-0.385***	-0.110***	-0.205***	-0.107***	-0.0320
		(-8.707)	(-2.882)	(-2.767)	(-2.734)	(-0.608)
Year	No	No	Yes	Yes	Yes	Yes
Industry	No	No	Yes	Yes	Yes	Yes
N	27,383	27,383	24,584	24,472	23,616	6,538
adj.R²	0.001	0.089	0.370	0.315	0.360	0.375

Note: *, ** and *** indicate significant at the 10%, 5% and 1% levels respectively; t-values adjusted for firm-level clustering are in parentheses. Same as below.

5. Mechanism Analysis

According to the preceding theoretical analysis in this essay, FM may handicap DIGI through two channels: shrinking innovation input and reducing innovation efficiency. Based on this, with reference to the study by Zhong et al. (2014), mediation models shown below are constructed for further empirical testing.

$$\mathrm{Mechanism_{it}} = \theta_0 + \theta_1 \mathrm{FM_{it}} + \rho \mathrm{X_{it}} + \mathrm{Year} + \mathrm{Ind} + \varepsilon_{it} \tag{2}$$

$$\mathrm{DIGI_{it}} = \sigma_0 + \sigma_1 \mathrm{FM_{it}} + \sigma_2 \mathrm{Mechanism_{it}} + \rho \mathrm{X_{it}} + \mathrm{Year} + \mathrm{Ind} + \varepsilon_{it} \tag{3}$$

where, Mechanism represents mediating variables, including innovation input (RD) and innovation efficiency (InnoEff). All other variables are defined in the same way as model (1).

With reference to the study by Li and Li (2022), RD is measured using the ratio of company's annual R&D expenditure to operating revenue to better reflect R&D activities matching the size of the firm. Patents can be divided into three categories: invention patents, utility model patents and design patents, in descending order of application difficulty and innovation content (Zhong and Wang, 2017). Synthesizing previous studies (Li et al., 2020; Yang and Li, 2023), InnoEff is gauged by the number of patent applications per unit of R&D investment, and is calculated by [ln (1 + the weighted average total patent applications) / ln (1 + R&D expenditure)]. In this context, the weighted average total patent applications are the sum of invention, utility model and design patents applications gained by taking the weights of 3:2:1.

Columns (1) and (2) of Table 3 demonstrate regression results of the mechanism of RD effect. The coefficient of FM in column (1) is significantly negative, which indicates that FM considerably reduces RD of enterprises. The coefficient of RD in column (2) is positive, revealing that RD can extensively accelerate digital technology upgrading and promote DIGI. After considering the effect of RD, the regression coefficient of FM remains negative at the 1% level, supporting part of the mediating effect of curtailing RD.

Columns (3) and (4) of Table 3 present regression consequences for the mechanism of InnoEff effect. The coefficient of FM in column (3) is significantly negative, implying that FM can cause tremendous disruptions in innovation activities and reduce InnoEff. The coefficient of InnoEff in column (4) is significantly positive, which indicates that InnoEff can significantly contribute to DIGI. After considering the effect of InnoEff, the regression coefficient of FM is still negative at the 1% level, supporting the partial mediating effect of degrading InnoEff.

Table 3. Results of the mechanism test for the effect of FM on DIGI

	R&D input		*R&D efficiency*	
	(1)	(2)	(3)	(4)
	RD	*DIGI*	*InnoEff*	*DIGI*
FM	-0.003^{***}	-0.019^{***}	-0.006^{***}	-0.021^{***}
	(-4.649)	(-2.798)	(-4.741)	(-2.625)
RD		1.452^{***}		
		(5.481)		
InnoEff				0.690^{***}
				(9.982)
Control variables	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	24,584	24,584	19,565	19,565
adj.R²	0.329	0.378	0.267	0.368

6. Further Analysis

Traditional credit discriminations in China give SOEs and LEs preferential access to bank loans at lower interest rates, while non-SOEs and SMEs at the developing stage and with higher growth potential withstand financing constraints. To further investigate whether the effect of FM on DIGI varies by companies' characteristics, two variables, nature of ownership and size, are selected for group regressions.

6.1 Nature of Enterprise Property Rights

In this research, dummy variables are introduced to categorize the sample based on the nature of enterprise property rights. SOEs are assigned a value of 1, and non-SOEs are assigned a value of 0. As illustrated in Table 4, the coefficient of FM is not significant in the SOE setting, but significant at the 1% level in the non-SOE setting. This indicates that FM would have a remarkable inhibitory effect on non-SOEs compared to SOEs. Reasons may be that SOEs are intrinsically backed by the government and objectively have an advanced accessibility of capital elements required for DIGI compared to non-SOEs. The government can not only alleviate financing constraints of SOEs through tax incentives and financial subsidies, but also intervene in banks and other financial institutions directly or indirectly to skew financial resources to them. As a consequence, these impose a crowding-out effect on non-SOEs, which have already lacked financial resource support. Thus, FM exacerbates financing constraints confronted by non-SOEs, and impedes DIGI to a severe extent.

Table 4. Heterogeneity tests

	(1)	(2)	(1)	(2)
	SOEs	*non-SOEs*	*LEs*	*SMEs*
	DIGI	*DIGI*	*DIGI*	*DIGI*
FM	-0.015	-0.028***	-0.0100	-0.034***
	(-1.236)	(-3.345)	(-0.869)	(-4.331)
Control variables	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	9,915	14,669	12,000.	12,584
adj.R²	0.366	0.359	0.372	0.372

6.2 Enterprise Size

In terms of the median enterprise size, sample enterprises are divided into two groups, LEs and SMEs. LEs variables are assigned a value of 1, and SMEs are assigned a value of 0. As reported in Table 4, FM does not significantly affect DIGI of LEs, but suppresses DIGI of SMEs at the 1% significance level. The possible reason is that conventional indirect financial institutions tend to assess credit criteria based on corporate profitability, risk exposure and collateral value, leaving SMEs at a disadvantage. Because of the high availability of information and operational and financial soundness of LEs, it is easy for them to obtain bank credits and loans. Nevertheless, SMEs have not yet reached the stage of stable operation, are less risk-resistant and can provide less collateral value than LEs. Therefore, it is difficult for them to obtain the favor of capital. Meanwhile, DIGI also has scale effect, LEs have the advantages of comprehensive industrial chain and resource allocation, which reduce the degree of FM influence on their DIGI.

7. Conclusion and Suggestions

Using China A-share listed enterprises from 2008 to 2020 as the original research sample, this paper draws the following conclusions: first, FM significantly inhibits DIGI; second, in terms of the mechanism path, FM can slow down the DIGI process by scaling back innovation inputs and reducing innovation efficiency; third, heterogeneity analysis based on the property rights nature and enterprise size ascertains that FM has a profound impact on DIGI for non-SOEs and SMEs, but does not affect SOEs and LEs significantly.

Based on the above findings, this essay makes the following recommendations:

First, continue to deepen financial market-oriented reforms. Reduce government's interventions in the allocation of financial resources and decrease tiltings to SOEs. By enabling the financial market supply and demand to determine the prices of financial factors, the optimal allocation of financial resources would be realized, flowing to the definitely efficient enterprises, and the DIGI process will be facilitated.

Second, improve the supervision and management system. Rigorously crack down on government-enterprise collusion and rent-seeking corruption, and create an appreciative financial market environment to ease the financing constraints confronted by non-SOEs and SMEs in the DIGI process. Enterprises themselves should also be law-abiding, which means that they are supposed to acquire financial resources through formal and legal channels, and focus on operating activities.

Third, banks and financial institutions should implement multi-layered and differentiated credit provisions for distinctive enterprises to broaden financing channels for non-SOEs and SMEs. By this means, the rational allocation of financial resources will improve the quality of financial services to the real economy and promote DIGI.

Fourth, enterprises are supposed to raise awarenesses about the importance of innovation to DIGI. They should increase innovation investment and promote innovation output transformation, as well as integrate resources throughout the process to improve innovation efficiency. Achieving a virtuous circle is conducive to the in-depth development of DIGI.

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