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Going Global in the Digital Era:
How Digital Finance Affects Chinese OFDI

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ABSTRACT

This study investigates the effect of digital finance on Chinese OFDI using Probit and Logit models on A-share-listed Chinese enterprises and representative OFDI data from 2011 to 2020. It shows that digital finance has a heterogeneous impact on Chinese OFDI both in probability and scale depending on the enterprise digitalization level. That is, digital finance has a positive (negative) effect on the OFDI of high (low) digital enterprises. Mechanism analysis reveals that the digital divide, which causes credit resources to be squeezed and increased financing constraints for these enterprises, is the main cause of the negative impact of digital finance on the OFDI of low-digital enterprises while the negative impact of digital finance on the OFDI of low-digital enterprises is limited to greenfield investments and highly competitive industries. The findings highlight the importance of encouraging enterprise digital transformation when developing digital finance policies to effectively leverage the potential of digital finance to drive Chinese firms' OFDI.

KEYWORDS

Chinese OFDI, Digital Divide, Digital Finance, Digital Inequality

1. INTRODUCTION

Outward FDI (OFDI) is an effective way for developing countries to engage in global cooperation, acquire advanced technologies, and undergo industrial transformation (Jiang et al., 2020). China, the world's largest developing country, has experienced sizeable growth in OFDI since the implementation of the "Go Global" strategy at the turn of new millennium, becoming a major source of OFDI worldwide. According to the Statistical Bulletin of China's Outward Foreign Direct Investment, China's nonfinancial OFDI has increased approximately 55-fold in 20 years, from $2.7 billion in 2002 to $152.02 billion in 2021, making it the second-largest global outbound investor[1]. This signifies the

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historic transition of Chinese corporations from global manufacturers to global investors. However, the rapid development of the digital economy, particularly in digital finance, has presented both opportunities and challenges for Chinese enterprises expanding globally (Feng & Chen, 2022). While digital technologies open up new avenues for Chinese enterprises to participate in global markets, they also present challenges, such as lack of innovation capacity and modest technological advantages when compared to developed counterparts (Huang and Khan, 2022). This divide is becoming increasingly apparent, with only 17% of enterprises achieving high digital transformation by 2022[2]. This gap limits Chinese enterprises' long-term ability to enhance their global competitiveness, increase productivity, and maximize the benefits of OFDI (Deng et al., 2022). Therefore, bridging the digital divide is critical for Chinese enterprises to remail competitive in the global marketplace. This can be achieved by increasing their capacity for innovation, technological advancements, and operational efficiency, allowing them to maintain competitiveness, increase productivity, and maximize the benefits of their OFDI (Jiang et al., 2023).

The Chinese government has been actively encouraging Chinese enterprises to expand internationally in recent years, and has offered them strong support for their overseas endeavors. This support has manifested itself in a variety of policies aimed at encouraging and facilitating international investment, particularly in the digital economy (Li et al., 2023). A significant policy example was the Guidelines for Foreign Investment Cooperation in Digital Economy, which were published by the Chinese Ministry of Commerce in 2021. These guidelines underscore the significance of actively participating in the global industry chain of digital economy, and optimizing the "Go Global" strategic layout, as well as emphasizing the importance of digital technology in promoting firms' digital transformation and establishing globally competitive digital enterprises (Ge et al., 2022). In this light, studying the relationship between digital finance and China's OFDI can provide valuable insights into the nuanced mechanisms through which digital finance has influenced and shaped the patterns of outbound investment Chinese enterprises. This would help policymakers, researchers, and market participants understand the dynamics of China's international investment landscape. It will also aid policymakers in developing supportive policies and initiatives to encourage and facilitate digitalization among businesses, specifically targeting those with low digitization levels.

Digital finance is an important aspect of the digital economy that uses digital information technology to overcome the time and space constraints of traditional financial services (Cao et al., 2022). It has the potential to improve the efficiency of financial services while lowering associated costs (Gomber et al., 2017; Sun et al., 2023). It may play an important role in easing the financing constraints faced by multinational enterprises and their OFDI (Wang et al., 2022). However, on the flip side of the coin, such digital financial services are available and benefiting to firms that have already digitalized (Zeng et al., 2022). Consequently, firms that have a low level of digitalization (or those lacking digital production and operation practices) are likely to experience digital inequality because of digital divide (Selwyn, 2004; Mayer, 2018). As a result, the impact of digital finance on OFDI is proportional to the digitalization level of enterprises. Due to the high cost, lengthy cycle time, and difficulty of digital transformation projects the digital transformation of enterprises is unfortunately ongoing and expensive (Wen et al., 2022). While a large number of (particularly Chinese) enterprises have a low level of digitalization due to their high tax burden (Chen et al., 2023).

A considerable amount of empirical work has been conducted to assess the determinants of Chinese OFDI. These studies have considered a variety of factors such as human mobility (Gao et al., 2013), exchange rate (Liu & Deseatnicov, 2016), traditional financial supply (Yan et al., 2018), minimum wage (Fan et al., 2018), the Belt and Road Initiative (Du & Zhang, 2018), environmental regulation (Dong et al., 2021), public participation (Li et al., 2022) and so forth. However, the literature on the impact of digital finance on OFDI in the digital age is scarce. While most studies on the economic consequences of digital finance have overlooked the notion of digital divide or digital inequality. The majority of the existing literature only discussed the digital divide theoretically (Robinson, 2015; Lythreatis, 2022) with little empirical research on the topic. While some research demonstrates the economic effects of the digital divide on different countries (van Dijk, 2006; James, 2009), regions (Forman et al., 2012;), or households (Wang et al., 2023). However, there has been little research at the firm level. In this light, it critical to consider digitalization differences between enterprises while exploring the impact of digital finance on OFDI.

This study aims to examine the impact of digital finance on China's OFDI and to identify its underlying causes and mechanisms. We do so by establishing Probit and Tobit models and using data from Chinese A-share listed firms from 2011-2020, as well as regional-level Peking University Digital Finance Index data and representative OFDI data manually collected from the fDi Markets Database and Zephry Database. We also obtain greenfield investment data from the former database and get M&A data from the latter database, both of which are highly authoritative and frequently used to study international investment issues (Bollaert & Delanghe, 2015; Rasciute & Downward, 2017; Castellani, 2022). While the enterprise OFDI decision and OFDI amount are mainly used to depict the OFDI behavior of firms. In addition, we employ a variety of methods to address potential endogeneity issues. Furthermore, we provide a comprehensive discussion of the rationales and plausible mechanisms underlying impacts.

We reached the following main results. First, we find that digital finance reduces Chinese enterprises' overall OFDI, regardless of their OFDI decisions or scales[3]. Second, we discover that the impact of digital finance on OFDI varies with firms' digitalization levels: digital finance has a positive (negative) impact on the OFDI of high-digital (low-digital) firms. These finding imply that the digital divide among Chinese firms causes digital inequality in their OFDI activities. Third, our findings demonstrate that the digital divide impedes the OFDI behaviors of enterprises with low digitalization levels by limiting their access to credit and increasing their financial constraints. Finally, we document that greenfield investments and highly competitive industries are more likely to experience negative adverse effect from digital finance in the context of OFDI.

This study contributes to the existing body of knowledge in the following major ways. First, to our knowledge, this is the first study to examine the effect of digital finance on Chinese OFDI using comprehensive data from Chinese A-share listed firms from 2011 to 2020. By offering updated estimates, it contributes to research on the determinants of OFDI in developing countries. Second, this is the first study of its kind to provide empirical evidence on the digital divide at the firm level, offering a novel perspective on the impact of digital inequality on China's outbound investment patterns. This novel perspective adds to broader discussions about digital transformation and the need to address digital inequality in enterprises, particularly in developing economies. Finally, the results of this study hold significant policy implications for (typically developing) countries seeking to accelerate their digital transformation and reduce digital inequality among enterprises. This research provides insights into the challenges and potential strategies for bridging the digital divide by exploring the phenomenon of digital divide at the enterprise level and discussing its ramifications through the lens of OFDI. It provides valuable guidance for policymakers in developing effective policies to promote digital inclusion and increase enterprise participation in global investment activities.

The rest of this study is organized as follows: Section 2 presents the theoretical analysis and hypothesis. Section 3 introduces the data, variables, and model specifications. The empirical results of the baseline regression, endogeneity discussion, and robustness tests are presented in Section 4. While Section 5 explores the potential mechanisms and heterogeneous effects. Section 6 summarizes the conclusions.

2. THEORETICAL ANALYSIS AND HYPOTHESIS

OFDI is a business behavior with a clearer "financial threshold" when compared to other economic behaviors of enterprises, and financial services play a more important role in firms' OFDI behavior (Olivier et al., 2023). The "Relative Access to Credit Hypothesis" (proposed by Klein et al., 2002) suggests that poor financial development discourages OFDI. In addition, a considerable amount of literature has demonstrated that a region's or a country's financial development heavily influences its OFDI level (Buchak et al., 2018; Jiang et al., 2020; Wang & Anwar, 2022). In this light, we can conclude that financial services could alleviate the enterprises' financing constraints and thus promote their overall OFDI. While the emergence of digital finance has disrupted the traditional financing and credit system, digital finance platforms have provided new financing channels for corporate credit through new technologies, effectively replacing traditional banks in the credit market (Buchak et al., 2018). Therefore, the impact of digital finance on corporate OFDI cannot be equated with the impact of traditional finance on corporate OFDI.

Digital finance has altered the operational mode of traditional financial intermediaries by utilizing information technologies such as big data, cloud computing and artificial intelligence. It also introduced new dynamics into the finance and credit markets, which will inevitably reduce enterprises financing constraints and promote their OFDI. Access to traditional financial services was hampered by information asymmetry and the high financing costs, two of the major barriers (Razzaq & Yang, 2023). However, digital finance can enable new business models by using intelligent algorithms (such as cloud computing) as well as effectively reduce the cost of financial services through economies of scale (Merler et al., 2018). In addition, digital finance can alleviate the information asymmetry problem between banks and enterprises using advanced information technology such as big data and artificial intelligence, which provides a new financing channel for corporate credit (Buchak et al., 2018; Fuster et al., 2019).

Apart from this, as a form of digital innovation, digital finance can expedite the processing of loan applications by using big data to improve the operational efficiency of credit processes (Fuster et al., 2019). Digital finance platforms can also alleviate enterprises' financing constraints by providing more efficient financial services, which in turn promotes their OFDI. However, enterprises must have a high digital level in order to utilize digital finance to alleviate their financing constraints. Due to the fact that digital finance platforms rely on the big data information left by enterprises on the internet for credit management, only enterprises with a history of digital production and operation behavior may become potential customers of digital finance. Accordingly, we propose the following:

Hypothesis 1: Digital finance can promote OFDI in highly digitalized enterprises.

With the deepening of the process of digital industrialization and industrial digitalization, the digital level of different industries and different firms begins to show obvious differences (Barnett et al., 2017). According to the definition of the "digital divide" proposed by van Dijk (2006), the "digital divide" consists of two dimensions "access divide" and "usage divide". Therefore, we can attribute the "digital divide" caused by varying levels of digitization to a new form of inequality. This "digital divide" caused by digital differences is gradually emerging, with a small number of high-digital enterprises fully utilizing digital information technology to rapidly expand their production scale and seize the leading position in the industry (Barnett et al., 2017). In contrast, low-digital enterprises are unable or unwilling to engage in digital production and operation, resulting in their inability to reap the benefits if the digital economy or even the crowding out of resources that they might have had access to. This issue can also be examined using the equilibrium model.

Suppose that the credit resources faced by enterprises are certain in the economy and that enterprises are divided into two types: high-digital firms and low-digital firms. We define the two types of firms as financial services consumers. In addition, there are also two types of financial services producers: traditional banks and digital finance platforms. To conduct OFDI, both types of firms need to use financial services to ease their financing constraints. When high-digital firms fully utilize of digital finance for credit transactions, low-digital firms will inevitably be crowded out of any credit resources they may have. The equilibrium is that high-digital firms face low financing constraints and low-digital firms face high financing constraints, and the greater financing constraints faced by low-digital firms will undoubtedly lead to a negative effect on their OFDI (Buch et al., 2014). We thus propose the following hypothesis:

Hypothesis 2: Digital finance will hinder the OFDI of enterprises with low levels of digitalization.

The preceding analysis shows that the impact of digital finance on OFDI is dependent on the level of enterprise digitalization. With the advent of digital finance, high-digital enterprises can leverage the benefits of digitalization to ease their financing constraints. However, low-digital enterprises may not only be unable to use digital finance, but they may also face greater financing constraints due to the crowding-out effect. Therefore, the overall impact of digital finance on Chinese OFDI is the effect of digital finance on the OFDI of high-digital enterprises superimposed on OFDI of low-digital firms. Therefore, the following hypothesis is proposed.

Hypothesis 3: The overall impact of digital finance on Chinese OFDI is dependent on the relative magnitude of the positive and negative effects.

3. DATA AND METHODOLOGY

3.1. Data and Sample

We use Chinese A-share listed companies as our sample. Their financial information is obtained from the China Stock Market and Accounting Research Database (CSMAR). The OFDI data include both greenfield investment and cross-border M&As. The former is retrieved from the fDi Markets Database, and the latter from is obtained from the BvD Zephry Database. In addition, we also collect province-level digital finance data from the Peking University Digital Finance Index, which is widely used to study digital finance (Sun et al., 2023).

We further cleaned the samples as follows: (1) we excluded samples that were listed for less than one year or were delisted during the sample period; (2) we excluded samples where the key variables were missing or clearly not complying with the accounting criteria; (3) we excluded samples with Special Treatment (ST) or Particular Transfer (PT) and those in the financial sector; (4) we only kept the investment samples that were more than or equal to 1 million RMB; (5) we excluded OFDI transactions whose destinations are in "tax havens" such as Cayman Islands, Bermuda and British Virgin Islands; and (6) all continuous variables are winsorized at 1% and 99%.

The matching procedures of the database used in our study are as follows: First, we use the listed firms' English names provided by the fDi Markets Database and stock codes provided by the Zephry Database to match the financial information. Second, we aggregated greenfield investment and cross-border M&A data at the firm-year level. Third, we use the obtained enterprise samples to match the regional digital finance index year by year.

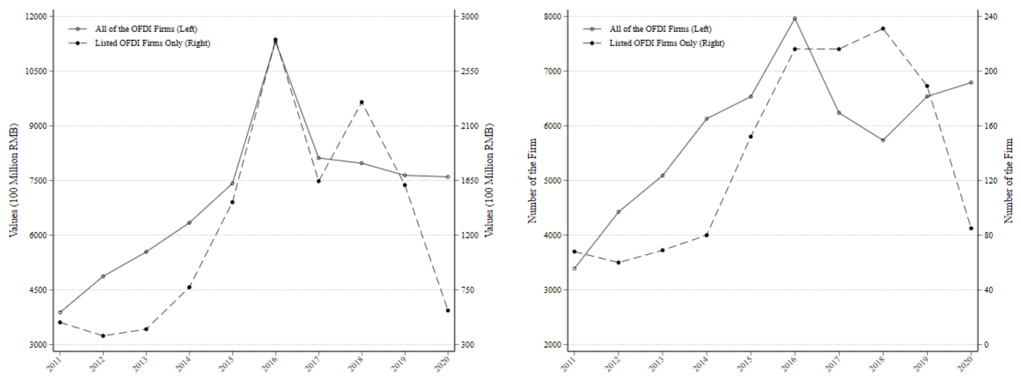
Finally, we obtain a database of 21710 firm-year observations for 3344 firms from 2011 to 2020, including 1366 investment records for 744 OFDI firms. Figure 1 shows that the sample used in our study can reflect the overall development trend of Chinese OFDI to some extent. For the fluctuations after 2016, we conduct a robustness test to examine their potential impact on our conclusions.

3.2. Models and Variables

To analyze the impact of digital finance on OFDI, we portray firms' OFDI behavior from two aspects: OFDI decision and OFDI amount. The dummy variable (Decision) represents whether

Figure 1. The trend of Chinese non-financial OFDI from 2011 to 2020

Notes: Figure 1 shows the trend of both the OFDI samples used in this paper and the over Chinese OFDI in the amount of OFDI (left) and the number of OFDI enterprises (right).



the firm has an OFDI record or not, and the continuous variable (Amount) is the logarithmic value of the total OFDI amount (millions RMB) of an enterprise. The Probit model and Tobit model are used to explore the impact of digital finance on OFDI decisions and the amount of OFDI respectively. Furthermore, we also use the number of OFDI records (Number), the amount per OFDI records (Aamount), the number of the destinations of enterprises' OFDI (Breadth), and the average number of OFDI records per destination (Depth) in a given year to conduct a robustness test.

$$Prob\left(Decision_{it} = 1\right) = \Phi\left(\alpha_0 + \alpha_1 * Dfinance_{ipt} + \mathbf{X}\pm + \delta_p + \delta_j + \delta_t + \varepsilon_{it}\right) \tag{1}$$

$$Amount_{it} = \begin{cases} \beta_0 + \beta_1 * Dfinance_{ipt} + \mathbf{X}^{2} + \delta_p + \delta_j + \delta_t + \mu_{it} \ , y^* > 0 \\ 0 \ , \ y^* = 0 \end{cases} \tag{2}$$

where $Decision_{it}$=1 denotes that firm *i* made OFDI in year *t*. $Amount_{it}$ represents the level of OFDI made by firm *i* in year *t*. $Dfinance_{ipt}$ is the logarithmic value of the digital finance index at year *t* for province *p* where enterprise *i* is located. In addition, δ_p, δ_j and δ_t denote province, industry and time fixed effects respectively and ε_{it} is the residual term. ***X*** is a set of firm-level control variables: total factor productivity (TFP), Firm size (Size), Leverage ratio (Lev), Return on assets (ROA), Type of ownership (SOE), Firm age (FirmAge), Firm growth (Growth), Capital density (Capital), Firm transparency (Big4), Two jobs in one (Dual). The detailed definition of all the variables is shown in Table A1 in the Appendix.

3.3. Descriptive Statistics

Table 1 reports the summary statistics of the main variables from the full sample and the sample of OFDI firms.

Table 1. Descriptive statistics

	Full Sample					OFDI Sample Only				
	Mean	sd	Min	Max	N	Mean	sd	Min	Max	N
Decision	0.063	0.243	0	1	21,710	1	0	1	1	1,366
Amount	0.319	1.323	0	10.323	21,710	5.067	1.938	0.802	10.323	1,366
Number	0.094	0.460	0	17	21,710	1.496	1.125	1	17	1,366
Aamount	0.097	0.388	0	2.389	21,710	1.546	0.396	0.426	2.389	1,366
Breadth	0.084	0.388	0	14	21,710	1.329	0.858	1	14	1,366
Depth	0.070	0.287	0	8	21,710	1.115	0.380	1	8	1,366
Dfinance	5.479	0.517	2.846	6.071	21,710	5.532	0.479	2.962	6.071	1,366
TFP	7.503	0.900	5.541	10.073	21,710	7.885	0.953	5.701	10.073	1,366
Size	7.774	1.185	5.273	11.281	21,710	8.483	1.367	5.273	11.281	1,366
Lev	41.197	19.855	3.200	88.416	21,710	46.539	18.802	3.200	88.416	1,366
ROA	3.567	6.776	-51.895	21.421	21,710	4.557	5.672	-41.834	20.489	1,366
SOE	0.312	0.463	0	1	21,710	0.267	0.443	0	1	1,366
FirmAge	2.861	0.335	1.386	3.555	21,710	2.842	0.348	1.386	3.555	1,366
Growth	0.162	0.379	-0.572	3.705	21,710	0.213	0.367	-0.489	3.273	1,366
Capital	3.366	0.972	0.638	6.171	21,710	3.336	0.907	0.738	6.171	1,366
Big4	0.053	0.224	0	1	21,710	0.142	0.349	0	1	1,366
Dual	0.291	0.454	0	1	21,710	0.335	0.472	0	1	1,366

4. EMPIRICAL ANALYSIS

4.1. Baseline Regression

We investigate the real effect of digital finance on firms' OFDI decision and amount using the Probit and Tobit models, and the results are presented in Table 2. Columns (1) and (2) contain the regression results of Eq. (1), while columns (3) and (4) contains the regression results of Eq. (2). The estimated coefficient of α_1 is significantly negative at the 5% level, when only controlling for the region, industry, and time fixed effects (Column 1). After controlling for the firm-level control variables, the estimated coefficient of α_1 is -0.0508 and still significant at the 5% level (Column 2). Similarly, the estimated coefficient of β_1 is also significantly negative at the 5% level in column (3) when only controlling for the region, industry, and time fixed effects. In addition, the estimated coefficient of β_1 is -0.2454 and significant at 5% level when controlling for the firm-level control variables in column (4). The results suggest that digital finance hinders Chinese OFDI overall, whether in terms of probability or amount. It means that the positive effect of digital finance on high-digital firms' OFDI is smaller than the negative effect of digital finance on low-digital firms' OFDI. Therefore, we can preliminarily assume that there is a digital divide between high-digital and low-digital firms. Due to the lack of ability to utilize digital finance, the low-digital enterprises are deprived of the financial resources originally belong to them, which may lead to an increase of financing constrains.

4.2. Endogeneity Discussion

Although we have controlled as many firm-level variables as possible in our empirical model, there is still a possible problem of omitted variables. For example, regional macro variables that affect both

Table 2. Baseline results: digital finance and Chinese OFDI

	(1)	(2)	(3)	(4)
	Decision	**Decision**	**Amount**	**Amount**
Dfinance	-0.0523**	-0.0508**	-0.2603**	-0.2454**
	(0.0217)	(0.0209)	(0.1165)	(0.1094)
TFP		0.0188***		0.1028***
		(0.0027)		(0.0141)
Size		0.0237***		0.1263***
		(0.0018)		(0.0097)
Lev		0.0003***		0.0016***
		(0.0001)		(0.0006)
ROA		0.0010***		0.0050***
		(0.0003)		(0.0017)
SOE		-0.0437***		-0.2285***
		(0.0044)		(0.0232)
FirmAge		-0.0133**		-0.0749***
		(0.0055)		(0.0290)
Growth		0.0005		0.0035
		(0.0040)		(0.0210)
Capital		-0.0064***		-0.0323***
		(0.0022)		(0.0116)
Big4		0.0252***		0.1289***
		(0.0062)		(0.0317)
Dual		0.0148***		0.0788***
		(0.0036)		(0.0186)
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	21,710	21,710	21,710	21,710
Pseudo R^2	0.0483	0.1200	0.0296	0.0748

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively.

firm OFDI and regional digital finance can be omitted. To mitigate concerns over potential omitted variables in the baseline regression, we first add as many regional-level control variables as possible to the original models (1) and (2). Based on the new model, we further use an instrumental method to completely exclude the possible interference of the empirical results caused by omitted variables. We include the additional control variables as follow: (1) Traditional financial development (Trfinance); (2) Open degree (Open); (3) Economic development (GDP). (4) Industrial structure (Indstructure) and (5) Internet development degree (Net)[4]. The regression results are shown in Table 3 (columns 1 and 2). We find that the estimated coefficients of α_1 and β_1 are still significantly negative after adding the control variables that may affect both digital finance and corporate OFDI at the regional level.

Following the method of Chen & Zhang (2021), we take the historical post and telecommunications business volume of the region where the enterprise is located at as the instrumental variable for digital finance. Specifically, we use each region's post and telecommunications business volume (million RMB) in 1988 as their instrumental variable for the development of digital finance. In addition, refer to the setting method of Nunn & Qian (2014), we interact it with the mean value of digital finance in other regions of the country except this region to obtain a new instrumental variable that changes with both region and time. Finally, the ivProbit and ivTobit estimation are conducted, and the regression results are shown as columns (3)-(6) in Table 3. Columns (3) and (5) of Table 3 report the first-stage regression results of ivProbit and ivTobit. We find that the estimated coefficients of the instrumental variables are significantly positive, indicating that regions with historically high post and telecommunications business volume also have higher digital finance today. Therefore, the correlation of the instrumental variables is satisfied. The second-stage estimates reported in columns (2) and (4) of Table 3 show that the estimated coefficients of digital finance are also significantly negative, indicating that the baseline regression results hold after fully considering the possible endogeneity of the model.

Table 3. Endogeneity discussion: Additional controls and instrumental method

	(1)	(2)	(3)	(4)	(5)	(6)
	Decision	**Amount**	**Dfinance**	**Decision**	**Dfinance**	**Amount**
Dfinance	-0.0524**	-0.2638**		-0.1020**		-0.3998*
	(0.0239)	(0.1249)		(0.0442)		(0.2355)
IV			1.2199***		1.2200***	
			(0.0254)		(0.0254)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	21,710	21,710	21,710	21,710	21,710	21,710
Pseudo R^2	0.1204	0.0749				

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. Pseudo R^2 are not reported in columns (3)-(6) when using instrumental method.

4.3. Robustness Tests

We conduct a series of additional tests to check the robustness of our baseline results. First, we replace the dependent variables by the number of OFDI records (Number), the average amount of each OFDI record (Aamount), the number of the destinations of enterprises' OFDI (Breadth), and the average number of OFDI records per destination (Depth). All the estimated results are shown in Table A2. Second, following Fan et al. (2018), we re-estimate Eq. (1) and Eq. (2) by using the complementary log-log model and Poisson pseudo-maximum likelihood estimation (PPML) method to address the "rare events" and zero-truncated problems. The results are shown in Table A3. Third, we restrict the sample period to 2011-2019 and 2011-2016, and re-estimate Eq. (1) and Eq. (2). The results are shown in Table A4. Forth, following Li et al. (2022), we exclude the OFDI records whose destinations are Hong Kong, Macau and Taiwan and the regression results are shown in Table A5. Fifth, excluding the impact of continuous investments on regression results, we only use the samples with no OFDI record in year t-1 but with OFDI record in year t to estimate the results. Furtherly, we also restrict the samples to those who have no OFDI record in year t-3 but have OFDI record in year t. Both of the estimated results are shown in Table A6. Sixth, addressing the potential omitted variable problems, we add the industry-time joint fixed effect and firm fixed effect to the models and the estimated results are shown in Table A7. It can be found that the findings of this study still hold after considering the above potential problems.

5. FURTHER ANALYSIS

5.1 Mechanism Analysis: Why Is the Overall Effect Negative?

In this section, we will explore the reason why digital finance has an overall negative effect on Chinese OFDI. Specifically, we will check whether digital finance depresses low-digital enterprises' OFDI but promotes high-digital enterprises' OFDI and analyze the plausible mechanisms.

5.1.1 The Existence of the Digital Divide

Is the overall negative effect of digital finance on Chinese OFDI caused by the existence of a digital divide between firms? Considering that firms' digitalization level reflects their participation degree in the digital economy and the extent to which it uses digital media for production and transactions, it is rational to divide them into high-digital and low-digital groups by their digitalization level. And it can also reflect whether there is a digital divide between different companies facing digital finance. Therefore, we construct a digital level indicator at the firm level and divide the sample into high-digital and low-digital groups according to their digitalization level. We furtherly re-estimate Eq. (1) and Eq. (2) using the sample of high-digital and low-digital enterprises.

Following Jiang et al. (2023), we use data on firms' digitization-related intangible assets to calculate their digitization level. First, we regard the intangible assets that are related to the development of the digital economy as digital intangible assets, such as "software", "network", "client", "management system", and "intelligent platform". Second, we sum up the identified digital intangible assets at the firm-year level to obtain the total amount of digital intangible assets of the enterprise every year. Third, we take the total amount of digital intangible assets over the total amount of intangible assets of the enterprises as their digitization level each year. Finally, we rank the enterprises according to their average digitization level and define the samples in the 90%, 80% and 70% quartiles as high digitalization enterprises, while the latter samples are defined as low digitalization enterprises.

We further re-estimate Eq. (1) and Eq. (2) by using the high-digital samples and low-digital samples, and the regression results are shown in Table 4. Columns (1) and (3) are the regression results using the high-digital samples and columns (2) and (4) are the regression results using the low-digital samples. When the sample is divided into high-digital and low-digital firms according to whether they are in the 90% quartile (Panel A), the estimated coefficients of digital finance on firms' OFDI decision and OFDI amount are both significantly positive in the high-digital samples, while they are both significantly negative in the low-digital samples. This indicates that digital finance can facilitate high-digital firms' OFDI while discouraging low-digital firms' OFDI. While the estimated coefficients of digital finance on high-digital firms' OFDI are not significant when the sample is divided into high-digital and low-digital firms according to whether they are in the 80% quantile (Panel B) or 70% quantile (Panel C), the estimated coefficients of digital finance on low-digital firms' OFDI are significantly negative. This suggests that the negative impact of digital finance on OFDI in the baseline results appears to be driven primarily by low-digital firms experiencing a digital divide. Possibly digital finance negatively affects low-digital firms' OFDI because the digital divide crowds out their original opportunities and resources.

In addition, to mitigate concerns over the potential error of the measurement of firms' digitalization level, we also use the textual information of listed enterprises' annual reports to calculate

Table 4. The existence of digital divide

	(1)	(2)	(3)	(4)	(5)	(6)
	Decision		**Amount**		**FC**	
	Digital-H	**Digital-L**	**Digital-H**	**Digital-L**	**Digital-H**	**Digital-L**
Panel A:(90)						
Dfinance	0.8004**	-0.0568***	3.9270**	-0.2808**	-0.0721	0.0317***
	(0.3237)	(0.0214)	(1.5504)	(0.1127)	(0.0586)	(0.0121)
N	1,712	19,998	1,712	19,998	1,709	19,998
Pseudo R^2	0.2018	0.1207	0.1347	0.0747	0.7102	0.7438
Panel B:(80)						
Dfinance	-0.0624	-0.0573***	-0.2999	-0.2816**	-0.0471	0.0358***
	(0.0820)	(0.0219)	(0.4135)	(0.1154)	(0.0397)	(0.0125)
N	3,645	18,065	3,645	18,065	3,645	18,065
Pseudo R^2	0.1658	0.1235	0.1045	0.0766	0.7143	0.7478
Panel C:(70)						
Dfinance	-0.0785	-0.0513**	-0.3577	-0.2530**	-0.0270	0.0391***
	(0.1897)	(0.0223)	(0.3092)	(0.1169)	(0.0292)	(0.0128)
N	5,631	16,079	5,631	16,079	5,631	16,079
Pseudo R^2	0.1558	0.1233	0.0958	0.0772	0.7207	0.7499
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

their digitalization level. Specifically, we follow Zeng et al. (2022) and Sun et al. (2022) to regard the frequency of digitalization-related terms disclosed in the annual reports of listed enterprises as their digitalization level. We repeat the process in the previous part and find that the findings of the study still hold. The detailed results are shown in Table A8.

5.1.2 Plausible Mechanism

The previous results suggest that digital finance has a negative impact on the OFDI of low-digital firms because of the existence of the digital divide. In this section, we will analyze what exactly depresses low-digital firms' OFDI. Is it truly the existence of the digital divide that crowds out the potential opportunities and resources for low-digital firms? Considering that financing constraints are the key factor that determines OFDI, digital finance has the most significant impact on the financing constraints of firms. Therefore, we suppose that the digital divide leads to the crowding out of potential credit resources for low-digital firms, which results in higher financing constraints of low-digital firms when facing digital finance.

To test this hypothesis, we calculate the financing constraints index (FC) of firms by following Hadlock & Pierce (2010) and analyze the impact of digital finance on the financing constraints of high-digital firms and low-digital firm. The results are shown as columns (5) and (6) in Table 4.

The estimated coefficients of digital finance in low-digital samples are all significantly positive, indicating that digital finance does increase the financing constraints of low-digital firms. In contrast, the estimated coefficients of digital finance in high-digital samples are significantly negative at 15% level, indicating that digital finance can reduce financing constraints of high-digital firms to some extent. Therefore, it can be argued that the digital divide makes low-digital firms' access to credit resources crowded out when they face the development of digital finance, which leads to an increase in their own financing constraints. The increase in financing constraints directly leads to a decrease in OFDI by low-digital firms.

We also use the digitalization index calculated by the textual information of listed enterprises' annual reports to conduct a robustness test. The findings above still hold and the detailed results are shown as columns (5) and (6) in Table A8.

5.2 Heterogeneity Analysis: Which Subsample Is More Likely to Lose the OFDI Chance?

In this section, we will conduct heterogeneity analysis from the perspective of OFDI types and industry competition to examine which subsample is more likely to be deprived of OFDI chances due to the existence of the digital divide.

5.2.1 Heterogeneous Effects Across OFDI Types

To examine the heterogeneous effects of digital finance on different types of OFDI of low-digital enterprises, we divide the low-digital samples into Greenfield OFDI samples and cross-border M&A samples. In addition, we further use the two subsamples to re-estimate Eq. (1) and Eq. (2), and the results are shown in Table 5. Columns (1) and (2) are the regression results using the Greenfield OFDI samples and columns (3) and (4) are the regression results using the cross-border M&A samples. The estimated coefficients of digital finance in columns (1) and (2) are both significantly negative, while the estimated coefficients in columns (3) and (4) are almost insignificant. This suggests that the negative impact of digital finance on the OFDI of low-digital firms facing the digital divide mainly occurs in the Greenfield OFDI samples.

The heterogeneous effects of digital finance on low-digital enterprises' OFDI can be explored by analyzing the specific processes of greenfield OFDI and cross-border M&As OFDI. To be specific, the investment process of greenfield OFDI is complex and often requires a large amount of cash flow, which is more likely to be influenced by enterprises' financing constraints. In contrast, cross-border M&As mainly involve partial or full transfer of firms' ownership, and their demand for cash flow is relatively limited. Therefore, the impact of financing constraints on cross-border M&As is not significant, which means that the negative effect of digital finance on low-digital enterprises only exist in greenfield OFDI samples.

5.2.2 Heterogeneous Effects Across Industry Competition

To examine the heterogeneous effects across industry competition groups, we divide the low-digital enterprises into high-competitive samples and low-competitive samples according to the Herfindahl-Hirschman Index (HHI) of the industry to which the enterprises belong. Specifically, we regard the firms whose HHI is in the 50% quantile as low-competitive industry firms (Competitive-L) and otherwise as high-competitive industry firms (Competitive-H). In addition, we re-estimate Eq. (1) and Eq. (2) and the results are shown in Table 6. Columns (1) and (2) are the regression results using the high-competitive samples and columns (3) and (4) are the regression results using the low-competitive samples. The estimated coefficients of digital finance are significantly negative for the sample of highly competitive industry firms. The estimated coefficients of digital finance in the low-competitive industry samples are not significant. This suggests that the negative impact of digital finance on the OFDI of low-digital firms facing the digital divide mainly occurs in the highly competitive industry firms.

Table 5. Heterogeneous effects: OFDI types

	(1)	(2)	(3)	(4)
	Greenfield		M&A	
	Decision	Amount	Decision	Amount
Panel A:(90)				
Dfinance	-0.0344**	-0.1711*	-0.0262	-0.1235
	(0.0152)	(0.0970)	(0.0176)	(0.0894)
N	19,998	19,998	19,998	19,998
Pseudo R^2	0.2256	0.1465	0.0825	0.0526
Panel B:(80)				
Dfinance	-0.0313**	-0.1552***	-0.0298*	-0.1410
	(0.0157)	(0.0539)	(0.0180)	(0.0910)
N	18,065	18,065	18,065	18,065
Pseudo R^2	0.2327	0.1510	0.0834	0.0532
Panel C:(70)				
Dfinance	-0.0309**	-0.1548**	-0.0254	-0.1228
	(0.0157)	(0.0670)	(0.0185)	(0.0923)
N	16,079	16,079	16,079	16,079
Pseudo R^2	0.2519	0.1642	0.0791	0.0505
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

By analyzing the different degrees of resource constraints faced by firms form high-competitive and low-competitive industries, we can uncover the underlying mechanisms of the finding mentioned above. As the competitive nature of the market determines that firms in highly competitive industries face greater pressure from competitors in the same industry, it is in line with economic logic. When they are at a digital disadvantage, their potential credit resources are more likely to be crowded out by their competitors in the same industry, leading to an increase in the degree of financing constraints. Therefore, the negative impact of digital finance on low-digital enterprises' OFDI is mainly significant in the highly competitive industry firms.

6. DISCUSSION

6.1 Conclusion

This study investigates the impact of digital finance on Chinese OFDI using data from Chinese A-share listed firms from 2011-2020, as well as matching regional-level Peking University Digital Finance Index data and representative OFDI data manually collected from the fDi Markets Database and Zephry Database. The empirical exercise of our study yielded the following main results. We documented that digital finance decreases the overall decisions and scales of Chinese OFDI. In

Table 6. Heterogeneous effects: Industry competition

	(1)	(2)	(3)	(4)
	Competitive-H		Competitive-L	
	Decision	Amount	Decision	Amount
Panel A:(90)				
Dfinance	-0.0814***	-0.4010***	0.0150	0.0549
	(0.0248)	(0.1309)	(0.0421)	(0.2114)
N	15,326	15,326	4,672	4,672
Pseudo R^2	0.1343	0.0825	0.1122	0.0705
Panel B:(80)				
Dfinance	-0.0849***	-0.4155***	0.0207	0.0823
	(0.0256)	(0.1352)	(0.0415)	(0.2080)
N	13,566	13,566	4,499	4,499
Pseudo R^2	0.1403	0.0862	0.1130	0.0708
Panel C:(70)				
Dfinance	-0.0853***	-0.4233***	0.0502	0.2308
	(0.0263)	(0.1388)	(0.0435)	(0.2142)
N	11,793	11,793	4,286	4,286
Pseudo R^2	0.1456	0.0901	0.1080	0.0679
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

addition, we discovered that the impact of digital finance on OFDI varies with firms' digitalization levels: digital finance has a positive (negative) impact on the OFDI of high-digital (low-digital) firms. These findings imply that the digital divide among Chinese firms causes digital inequality in their OFDI process. While mechanism analysis revealed that the digital divide impedes the OFDI behaviors for enterprises with low digitalization levels by limiting their credit access and increasing financial constraints. Finally, heterogeneity analysis demonstrated that the greenfield investments and industries with high levels of competition are more likely to experience negative adverse effects.

6.2 Policy Implications

As the digital divide may deprive low-digital companies of the opportunity to "go global", more attention should be paid to the coverage and availability of digital financial services when promoting the development of digital finance. Digital inequality in developing countries needs to be addressed more closely in order to ensure that every enterprise can benefit from the digital economy's dividends. It is essential for governments to make efforts to minimize the digital divide caused by differences in firms' digitization to prevent unequal opportunities and outcomes. Bridging the digital divide of Chinese enterprises is essential for their OFDI endeavors. In an increasingly digitalized global economy, Chinese companies must embrace digital technologies to remain competitive. By narrowing the digital gap, these enterprises can enhance their productivity, operational efficiency, and ultimately maximize the benefits of their OFDI. Additionally, bridging the digital divide enables Chinese companies to effectively expand their presence in foreign markets by leveraging tools such as e-commerce platforms, data analytics, and cloud computing. This digital transformation allows for improved market adaptation, enhanced products and services, and a better customer experience. Moreover, bridging the digital divide facilitates seamless communication and collaboration between Chinese enterprises, local partners, and subsidiaries overseas, fostering knowledge transfer and innovation. Lastly, investing in digital infrastructure can contribute to the sustainable and inclusive growth of host countries' digital economies, benefiting the local population and creating a conducive environment for Chinese OFDI activities.

6.3 Limitations and Future Research

This study recognizes several limitations that can serve as avenues for future research. First, we used the Peking University Digital Finance Index to estimate firms' digital finance. This index, however, may have limitations. Future research could focus on developing more precise and appropriate indicators to capture the various aspects of digital finance for a more comprehensive analysis. Second, our analysis only included publicly traded Chinese enterprises, which may limit the findings' applicability to unlisted firms. Inclusion of unlisted firms in the sample in the future research would provide a more complete understanding of the relationship between digital finance and OFDI in the broader business landscape. Finally, to understand how digital finance affects firms' OFDI, a comprehensive and unified theoretical framework is required. Because of the evolving nature of digital finance, there is a scarcity of well-developed theoretical frameworks capable of fully capturing its impact on firms' OFDI. In order to strengthen the digital finance literature, future studies could attempt to establish a theoretical model that elucidates the underlying mechanisms and economic effects of digital finance in the context of outward FDI.

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ENDNOTES

1. Data were accessed at http://fec.mofcom.gov.cn/article/tjsj/tjgb/ [23/05/2023]
2. Accenture Enterprise Digital Transformation Index 2022.
3. The decisions represent whether the firm has an OFDI record or not and the scales represents the total OFDI amount (millions RMB) of an enterprise.
4. The detailed measurement of the variables is shown in Table A1 in the Appendix.

APPENDIX

Table A1. Variable definitions

Variable	Definition
Decision	Dummy variable equals 1 if a firm has an OFDI record in a given year, and otherwise 0
Amount	Scale of the firm's OFDI in that year and it equals to the logarithmic value of the total OFDI amount (millions RMB)
Numbers	Number of OFDI records for a company in a given year
Aamount	Logarithmic value of average amount per OFDI record
Breadth	Number of OFDI host countries for a company in a given year
Depth	the average number of OFDI records invested per host country
Dfinance	the logarithmic value of the digital finance index
TFP	Total factor productivity, it is calculated using LP method
Size	Firm size, the natural logarithm of the total number of employees
Lev	Leverage ratio, total debts over total assets
Roa	Return on assets, the net profit over total assets
SOE	Dummy variable equals 1 if a firm is state-owned, and otherwise 0
FirmAge	Firm age, the number of years the firm has been in existence
Growth	The growth rate of operating income
Capital	Dummy variable equals 1 if a firm is capital-intensive, and otherwise 0
Big4	Dummy variable 1 if the firm's auditor is from one of the big four accounting firms
Dual	Dummy variable equal to 1 if the firm's actual controller is the chairman or the general manager.
SA	Financing constraints, it is calculated using the method provided by Hadlock and Pierce (2010)
Trfinance	Traditional financial development and it equals to the natural logarithm of the total number of financial industry employees
Open	Open degree and it equals to the natural logarithm of the total amount of regional imports and exports
GDP	Economic development and it equals to the natural logarithm of regional GDP
Indstructure	Industrial structure and it equals to the second industry output value over GDP
Net	Internet development degree and it equals to the regional internet penetration rate

Table A2. Robustness tests: Key variables' measurement

	(1)	(2)	(3)	(4)
	Number	**Amount**	**Breadth**	**Depth**
Dfinance	-0.0797**	-0.0757**	-0.0719**	-0.0585**
	(0.0347)	(0.0337)	(0.0305)	(0.0241)
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	21,710	21,710	21,710	21,710
Pseudo R^2	0.0960	0.0862	0.0984	0.0930

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

Table A3. Robustness tests: Models' setting form

	(1)	(2)
	Decision	Amount
Dfinance	-0.0543**	-0.2168*
	(0.0211)	(0.1136)
Control	Yes	Yes
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	21,710	21,640
Pseudo R^2		0.1627

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

Table A4. Robustness tests: Special periods

	(1)	(2)	(3)	(4)
	Decision	Amount	Decision	Amount
Dfinance	-0.0561**	-0.2748**	-0.0481**	-0.2409**
	(0.0226)	(0.1197)	(0.0221)	(0.1169)
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	18,646	18,646	10,514	10,514
Pseudo R^2	0.1115	0.0688	0.1353	0.0838

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

Table A5. Robustness tests: Special samples

	(1)	(2)
	Decision	Amount
Dfinance	-0.0517***	-0.2510***
	(0.0188)	(0.0974)
Control	Yes	Yes
Province	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
N	21,710	21,710
Pseudo R^2	0.1310	0.0834

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

Table A6. Robustness tests: continuous investments

	(1)	(2)	(3)	(4)
	Decision	**Amount**	**Decision**	**Amount**
Dfinance	-0.0378**	-0.1809**	-0.0344**	-0.1634**
	(0.0173)	(0.0876)	(0.0148)	(0.0729)
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	21,337	21,337	21,150	21,150
Pseudo R^2	0.0788	0.0504	0.0671	0.0434

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

Table A7. Robustness tests: multiple fixed-effects

	(1)	(2)	(3)	(4)
	Decision	**Amount**	**Decision**	**Amount**
Dfinance	-0.0617**	-0.3015***	-0.0674***	-0.2682**
	(0.0270)	(0.1102)	(0.0213)	(0.1118)
Control	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Industry	No	No	No	No
Year	No	No	No	No
Industry-Year	Yes	Yes	Yes	Yes
Firm	No	No	Yes	Yes
N	21,710	21,710	21,447	21,447
Pseudo R^2	0.1391	0.0866	0.3351	0.3657

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints. The results in Columns (3) and (4) are estimated using the linear probability model (LPM), so some samples are lost.

Table A8. The existence of digital divide: measurement of firms' digitalization level

	(1)	(2)	(3)	(4)	(5)	(6)
	Decision		Amount		FC	
	Digital-H	Digital-L	Digital-H	Digital-L	Digital-H	Digital-L
Panel A:(90)						
Dfinance	0.4679*	-0.0585***	2.2509*	-0.2931***	0.0778	0.0249**
	(0.2484)	(0.0211)	(1.1488)	(0.1119)	(0.0581)	(0.0121)
N	1,885	19,825	1,885	19,825	1,884	19,825
Pseudo R^2	0.2579	0.1147	0.1593	0.0716	0.7475	0.7429
Panel B:(80)						
Dfinance	0.0515	-0.0554**	0.3175	-0.2798**	0.0317	0.0218*
	(0.0968)	(0.0216)	(0.4625)	(0.1151)	(0.0415)	(0.0125)
N	3,849	17,861	3,849	17,861	3,848	17,861
Pseudo R^2	0.1796	0.1216	0.1123	0.0758	0.7423	0.7441
Panel C:(70)						
Dfinance	-0.0455	-0.0494**	-0.2053	-0.2449**	0.0312	0.0193
	(0.0666)	(0.0222)	(0.3333)	(0.1177)	(0.0361)	(0.0127)
N	5,858	15,852	5,858	15,852	5,858	15,852
Pseudo R^2	0.1483	0.1240	0.0921	0.0773	0.7197	0.7531
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are in the parentheses. Province, Industry and Year represent the province, industry and year fixed effects, respectively. The results of control variables are not reported due to space constraints.

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