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EDITED BY
Songyu Jiang,
Rajamangala University of Technology Rattanakosin, Thailand

REVIEWED BY
Xiaojun Ke,
Quanzhou Institute of Information Engineering, China
Yiteng Zhang,
Chengde College of Applied Technology, China
Han Chen,
Shinawatra University, Thailand

*CORRESPONDENCE
Hao Chong
✉ chonghao@njfu.edu.cn

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Digital finance and the agribusiness paradox: insurance-induced credit constraints and the transparency trap in low-marketization regions

Hao Chong* and Hong Wang

College of Economics and Management, Nanjing Forestry University, Jiangsu Province, Nanjing, China

Against the backdrop of digital inclusive finance, how to effectively alleviate financing constraints for agribusinesses not only aligns with the demands of rural revitalization but also facilitates the rational allocation of market resources. Existing research predominantly adopts a borrower-centric perspective, lacking systematic consideration of how digital inclusive finance influences lender behavior. This study, however, adopts a lender-centric approach, integrating the unique characteristics of agribusinesses and accounting for the moderating effect of agricultural insurance to examine the mechanism through which digital inclusive finance impacts financing constraints for these enterprises. Using a sample of Chinese agribusinesses from 2011 to 2022, a Difference-in-Differences (DID) model is established to analyze the roles of Tobin's *Q* and agricultural insurance in the influence process. The findings reveal that digital inclusive finance alleviates financing constraints for agribusinesses, with the impact exhibiting various qualitative aspects. Tobin's *Q* partially obscures the effect of digital inclusive finance on financing constraints, while agricultural insurance suppresses the alleviating role of digital inclusive finance in addressing these constraints.

KEYWORDS

agribusinesses, agricultural insurance, digital financial inclusion, financing constraints, Tobin's *Q*

1 Introduction

As the primary sector, agriculture constitutes China's fundamental material production domain and the bedrock of its national economy, serving as a vital pillar driving nationwide economic development and progress. Against the backdrop of digitalization, to propel further agricultural advancement and meet the demands of the rural revitalization strategy, the report of the 20th CPC National Congress emphasized accelerating the development of the digital economy, promoting its deep integration with the real economy, and fully advancing rural revitalization. In recent years, the Chinese government has successively issued a series of relevant policy guidance documents: the "14th Five-Year Plan for Digital Economy Development" explicitly calls for accelerating the digital transformation of agriculture-related sectors such as crop cultivation, animal husbandry, and fisheries. The "Digital Agriculture and Rural Development Plan (2019–2025)" offers guidance for agribusinesses across multiple domains, including crop cultivation informatization, livestock intelligence, fisheries smartification, seed industry digitization, diversification of

new business models, and end-to-end quality and safety control. This guidance spans all stages from production to operations. Against this backdrop of policy and era, sustainable and high-quality development has become an imperative for agribusinesses. Digital inclusive finance, as a product of deep integration between fintech and inclusive finance principles, enhances transparency, addresses information asymmetry, and reduces financing costs to alleviate corporate funding pressures. This has systemic significance in easing financing constraints for enterprises. However, compared to other businesses, agribusinesses face challenges such as low marketization, weak risk resilience, and relatively low investment value. Additionally, the widespread implementation of agricultural insurance policies may create systemic interdependencies. These characteristics partially limit the effectiveness of digital inclusive finance in alleviating financing constraints for agribusinesses. To further develop these enterprises and promote the synergistic integration of digital technology with rural revitalization, relying solely on technical measures is no longer sufficient. A more systematic analysis of agribusinesses is required to provide foundational financial support for high-quality economic development.

Digital inclusive finance has already attracted attention in the academic community, but existing research has overlooked two key dimensions in the financing process of agribusinesses: first, the behavioral response of lenders: previous studies have mainly focused on borrowers 'capabilities (borrowing capacity, borrowing channels), but have neglected whether digital inclusive finance alters lenders' risk assessment of agricultural assets; second, the regulatory mechanisms at the institutional level: the interaction between digital inclusive finance and market signaling instruments (such as Tobin's *Q*) and risk-sharing mechanisms (such as agricultural insurance) still lacks systematic theoretical analysis. To fill these research gaps, this study employs a multivariate difference-in-differences (DID) approach, using China's data from 2011 to 2022 as a sample, to construct a lender-centered analytical framework. By further analyzing the "masking effect" of Tobin's *Q* and discussing moral hazards arising from agricultural insurance, we reveal the impact mechanism of digital inclusive finance on agricultural enterprise financing. Our findings offer targeted solutions for alleviating agribusiness financing constraints while advancing theoretical understanding of DIF's institutional embeddedness in developing economies. Based on the above analysis, the innovations of this paper are as follows: 1. Focusing on agribusinesses with strong practical significance, this group combines characteristics of agricultural vulnerability and market-oriented management. Their financing constraint mechanisms exhibit significant heterogeneity, which not only meets practical requirements but also holds operational significance. 2. Constructing a multi-stage difference-in-differences (DID) model breaks through the limitations of traditional static analysis. By identifying differences in policy impact points, it accurately captures the dynamic effects of digital inclusive finance development, thereby effectively alleviating endogeneity issues. 3. Empirical research reveals for the first time that agricultural insurance has a significant negative moderating effect on the "digital inclusive finance-finance constraints" relationship. This counterintuitive finding challenges the theoretical assumption that traditional risk mitigation tools inevitably promote financial inclusion. 4. The value dissipation mechanism under marketization degree adjustment. Increased corporate transparency significantly improves the linear perception of financing constraints. The study finds that digital inclusive finance exhibits distinct characteristics in low-market regions.

2 Literature review and problem statement

2.1 Research status on financing constraints

Financing constraints refer to excessively high external investment costs resulting from underdeveloped financial markets, directly impacting enterprises' ability to secure sufficient capital to meet internal financing needs. This prevents enterprises from achieving optimal financing levels (Farre-Mensa and Ljungqvist, 2016). According to the pecking order theory, enterprises should prioritize internal financing (Myers and Majluf, 1984). However, most enterprises cannot generate sufficiently high profits to meet internal financing demands, necessitating external financing (Denis and Sibilkov, 2010). For China, most companies remain under significant financing constraints (Zhuo et al., 2020). As a prominent example, agribusinesses face unstable internal cash flow due to high volatility in agricultural product prices and low profit margins (averaging 4–6 percentage points lower than manufacturing), making it difficult to fund technological upgrades or production expansion through retained earnings (Zhang and Jin, 2025). Whether financing constraints arise depends on the borrower's perspective—analyzing whether firms lack financing channels or methods—and the lender's perspective—assessing whether firms are worthy investments, including investment risks, profits, and firm value. Thus, resolving corporate financing constraints can be achieved through expanding market financing (Cornaggia et al., 2015), utilizing internet finance (Hau et al., 2024), reducing information asymmetry between parties, and enhancing corporate transparency (Chen et al., 2011; Menkhoff et al., 2012). However, there are many problems in external financing for agriculture-related enterprises.

2.2 Current state of research on digital inclusive finance issues

Duoguang Bei define digital inclusive finance as a model capable of achieving broad financial coverage, reducing service costs, and maintaining long-term sustainability. They emphasize that by reducing barriers to financial service access, stimulating price discovery mechanisms, and enhancing information flow, digital inclusive finance effectively addresses the "last mile" challenge in financial services. Furthermore, tailored to China's national context, the "Peking University Inclusive Finance Index" has been developed. Aligned with the characteristics of finance in the new era, this digital inclusive finance index better captures trends in China's digital inclusive finance landscape (Guo et al., 2020). Using the cash-cash flow sensitivity model (Fazzari et al., 1988), research indicates that inclusive financial innovations can

effectively alleviate financing constraints for SMEs (Demirgüç-Kunt et al., 2017). These innovations impact SME financing constraints across multiple dimensions of digital inclusive finance.

Agribusinesses, constrained by factors like land and products, struggle to form group-based risk mitigation strategies. Their low profit margins and slow return on investment further deter investors. The inherent nature of agriculture makes agribusinesses more susceptible to obstacles in risk management and product sales. Even leading enterprises in the agricultural sector may encounter financing difficulties during critical phases of technological upgrades in cultivation and breeding, or new product development (Deng et al., 2025).And because of the constraints of various objective factors, the difficulty of agricultural risk prediction increases, and the information asymmetry is aggravated (Alli, 2025). Therefore, analyzing the financing constraints of agribusinesses requires not only a focus on digital inclusive finance but also guidance and support from public policy.

2.3 Current research status of policy-based agricultural insurance

Policy-based agricultural insurance serves not only as a vital tool for safeguarding corporate interests but also as a significant national support policy. As a crucial means of agricultural risk management, it acts as an important lever for advancing agricultural development (Tang and Zhang, 2020). By transferring risks, it enhances total factor productivity and boosts agricultural economic growth (Karlan et al., 2014). At the same time, agricultural insurance faces significant information asymmetry issues such as adverse selection and moral hazard, which may distort the behavior of market participants in the agricultural insurance sector (Liao et al., 2023). This information asymmetry, as the root cause of adverse selection and moral hazard, increases the likelihood of farmers engaging in passive loss prevention, lax damage mitigation, or insurance fraud (Clarke, 2016). So, when the research focus shifts to agribusinesses, what impact does digital inclusive finance have on them? What mechanisms underlie this impact? Are there regional or equity-based heterogeneities? These are the key issues we should focus on.

2.4 Research gaps and theoretical questions

Through reviewing existing literature, this study identifies gaps in research on financing constraints for agribusinesses. Most studies lack targeted analysis of agribusinesses—such as their low marketization and high risk levels—and rarely examine the combined effects with policy-based agricultural insurance.

Therefore, this paper utilizes provincial-level digital inclusive finance data from 2011 to 2022 and data on agriculture-related enterprises listed on the NEEQ. Insurance data is calculated based on the China Insurance Yearbook and regional statistical yearbooks. A two-way fixed effects model is constructed to examine the relationship between digital inclusive finance and financing constraints of agriculture-related enterprises. A multi-period DID model is further employed to measure the impact at the inclusive finance policy level. While using Tobin's Q as an mediating variable, the study introduces policy-based agricultural insurance as a moderator variable and conducts heterogeneity analysis across dimensions such as ownership structure, enterprise location, and investment efficiency.

3 Model construction and mechanism analysis

3.1 Impact of digital inclusive finance on financing constraints of agribusinesses

Existing literature indicates that most Chinese enterprises face financing constraints, which can be analyzed from both borrowers' and lenders' perspectives. From the enterprise's standpoint, factors such as equity structure, scale, and ability to obtain investor information influence financing channels (Allen et al., 2005). Limited financing opportunities and high financing costs increase the difficulty of external financing. Combined with low profits and insufficient internal financing among agribusinesses, this creates financing constraints (Berger and Udell, 1998). From the perspective of lenders, imperfect market mechanisms create significant information asymmetry and moral hazard issues (Giné and Karlan, 2014), Under incomplete information, lenders may restrict the number of participants in high-credit-rated markets and require full collateral to curb the pretense of low-risk borrowers. This market mechanism's imperfection makes credit rationing a primary tool for adverse selection management, yet it may also displace high-quality borrowers (Cable and Turner, 2021). Simultaneously, the value and growth potential of investee companies are key considerations for investors. The combined impact of these factors within traditional financial markets—which are often inefficient and lack liquidity—results in low financing efficiency, corporate funding difficulties, and widespread misallocation of resources under conventional financial models.

The continuous advancement of innovative technologies like big data and the internet has propelled inclusive finance to a new level, breaking through numerous constraints of traditional finance and creating a financing platform better suited to serve the "long tail" population (Suri, 2025). This has brought marginal borrowing groups excluded by traditional financial models closer while expanding diversified investment options for household investors (Berg et al., 2020) and enhancing capital circulation efficiency. The emergence of digital inclusive finance alleviates financing constraints by enhancing funding efficiency, reducing financing costs, and broadening financing channels. Furthermore, it significantly eases corporate financing constraints by reducing information asymmetry between transaction parties (Berg et al., 2020) and improving corporate transparency (Tian et al., 2022). The operational characteristics of agribusinesses make it difficult for them to establish credit. Coupled with the high risks inherent in agricultural production, even enterprises that pass credit institution reviews often face substantial interest burdens. These factors collectively exacerbate financing constraints for agribusinesses. Digital inclusive finance holds promise in alleviating these

financing constraints to some extent, leading to the first hypothesis of this paper.

Hypothesis 1: digital inclusive financial policies can alleviate financing constraints for agribusinesses.

3.2 Mechanism pathways through which digital inclusive finance influences financing constraints

Digital inclusive finance not only enhances information transparency and reduces information asymmetry, but also helps enterprises more accurately grasp market operations and policy changes (Obschonka and Audretsch, 2020), influence corporate value, and improve credit efficiency (Huang et al., 2018). As shown in Figure 1, on one hand, innovations in digital inclusive finance have revolutionized traditional financial sectors. They not only expand the coverage of financial services and create broader platforms but also enhance corporate financing channels while effectively reducing information asymmetry between lenders and borrowers. On the other hand, they effectively attract numerous small-scale investors in financial markets, helping to expand the investment demand of the "long-tail" group in stock and bond markets. Simultaneously, by reducing information asymmetry between enterprises and investors, as well as among enterprises themselves, search costs are correspondingly lowered. Enterprises' operational and profit conditions become more directly exposed to investors. From this perspective, transparency in high-value enterprises would attract more investment interest from lenders.

As shown in Figure 2, at this level, increased transparency in less market-oriented enterprises reduces enterprise value (Ma and Meng, 2015), the increase of transparency of enterprises with low market value will make investors lose interest in investment, thereby diminishing investors' willingness to invest. Most rural areas are in the low marketization stage, and the marketization degree of agriculture-related enterprises is relatively low (Ding and Fan, 2024).For instance, in the "Western Dairy Companies 'Biological Asset Revaluation Case," a dairy farming listed company disclosed the valuation model for transitioning from the cost method to fair value measurement for biological assets (cows) as required by accounting standards. The audit report revealed that disease risks caused annual fluctuations in cow fair value reaching 35% (compared to just 5% under the cost method). Banks deemed the valuation too uncertain, reducing the collateral ratio from 60% to 40% and cutting the credit line by 120 million yuan (based on Accounting Standard for Business Enterprises No.5—Biological Assets and the bank's internal risk control documents). Meanwhile, this paper categorizes enterprises based on marketization data into three groups: agriculture-related enterprises, comparison enterprises, and total enterprises.

The annual marketization index is averaged as shown in Figure 3. It is evident that agricultural enterprises (agribusinesses) exhibit inherently low marketization levels, whether compared to other comparison enterprises or the overall enterprise average. Enterprises with higher growth and investment value attract more investor capital. Tobin's *Q* serves as a crucial metric for assessing corporate value and growth potential (Tobin, 1969). It also measures investment decision-making tendencies, making it a key indicator investors consider when making investment decisions, leading to the second hypothesis.

Hypothesis 2: Tobin's *Q* partially masks the impact of digital inclusive finance on financing constraints for agribusinesses.

3.3 The regulatory role of agricultural insurance

Nowadays, the climate change is strong, which has a great degree of damage to the stability of agricultural production (Musa, 2025). Agricultural insurance can guide farmers in adjusting production structures, helping enhance agribusinesses' risk resilience and improve agricultural output quality. It serves not only as a vital tool for agricultural risk management but also as a key national support policy for the agricultural sector, enhancing enterprise development stability and increasing risk-bearing capacity (Walters and Preston, 2017). However, agricultural insurance also faces significant issues of information asymmetry, including adverse selection and moral hazard (Le et al., 2020). While these problems are not unique to agricultural insurance, the challenge lies in the higher costs associated with obtaining agricultural production information and conducting oversight, making it difficult for insurers to reduce the probability of adverse selection and moral hazard behaviors. It is highly probable that the existence of agricultural insurance further increases the probability of moral hazard, which was originally reduced by digital inclusive finance. Studies have found that insured farmers tend to reduce field management inputs (e.g., a 12% decrease in fertilization frequency and a 25% increase in delayed pest and disease control rates), and these behaviors significantly increase loan default risks (Rosalia, 2023). After lenders detected such behaviors through satellite remote sensing technology, the agricultural loan disbursements in high-risk areas were reduced by 30%.Moreover, due to its inherent characteristics, agriculture typically faces systemic risks. Once disasters occur, such as typhoons or droughts, they often result in excessive scale and severity, rendering insurance ineffective (Miranda and Glauber, 1997). Under these circumstances, investors may reassess their investment decisions in agribusinesses located in regions with robust agricultural insurance coverage, reducing investments to avoid associated risks. Thus, the implementation of agricultural insurance may partially undermine the role of digital inclusive finance in alleviating corporate financing constraints (as illustrated in Figure 1, leading to the third hypothesis.

Hypothesis 3: agricultural insurance reduces the financing constraint-alleviating effect of digital inclusive finance.

3.4 Digital inclusive finance exhibits heterogeneous effects on financing constraints for agribusinesses

From the perspective of ownership structure, China's banking system is predominantly composed of state-owned banks, leading to a greater propensity for banks to favor state-owned enterprises

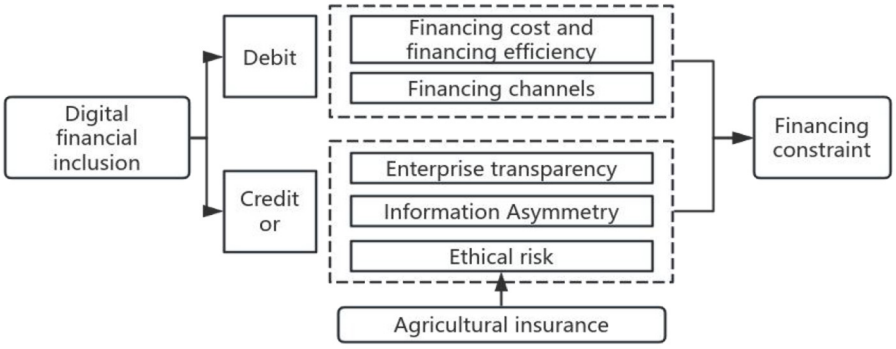


FIGURE 1
Adjustment effect of agricultural insurance.

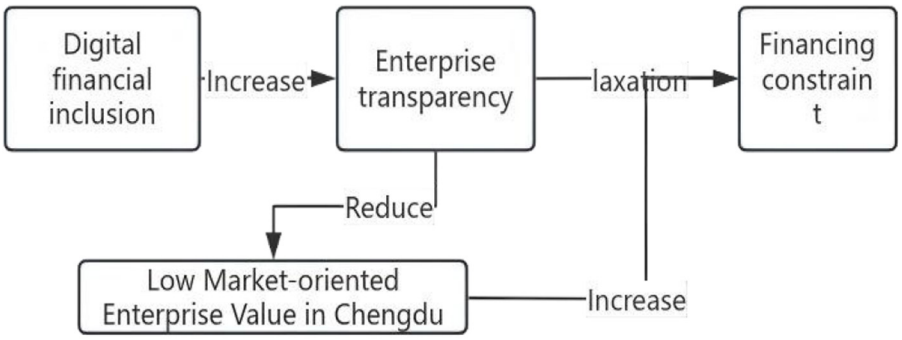
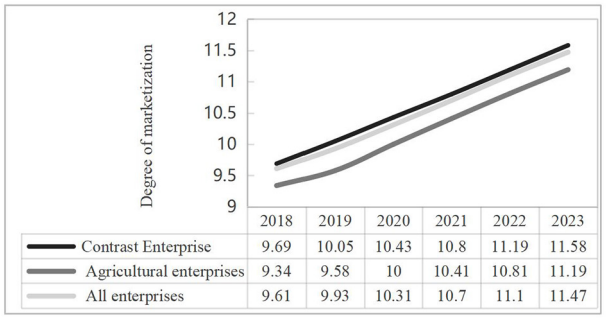


FIGURE 2
The masking effect of Tobin's *Q*.

in financing. Consequently, banks are more inclined to provide credit support to state-owned enterprises, while private enterprises often face "financial discrimination" (Allen et al., 2005). Regarding financing through alternative channels, SOEs also frequently receive "preferential treatment" from securities regulators (Luo et al., 2025). Consequently, SOEs face fewer financing constraints than private enterprises. Thus, SOEs are less responsive to digital inclusive finance, making private enterprises—which face greater financing difficulties—the primary beneficiaries of its impact.

Geographically, while some scholars argue that inclusive finance exists to bridge gaps in areas underserved by traditional finance, the Matthew Effect suggests that digital inclusive finance yields more pronounced results in regions where traditional digital finance is already well-developed. Remote areas, hindered by immature infrastructure and technology, now face a wider gap with advanced regions despite greater digital maturity. This exacerbates the financing difficulties of the "long-tail" population to some extent.



	2018	2019	2020	2021	2022	2023
Contrast Enterprise	9.69	10.05	10.43	10.8	11.19	11.58
Agricultural enterprises	9.34	9.58	10	10.41	10.81	11.19
All enterprises	9.61	9.93	10.31	10.7	11.1	11.47

FIGURE 3
Comparison of marketization levels among enterprises.

Regarding corporate investment efficiency, inefficient corporate investments can be broadly categorized into overinvestment and underinvestment. Depending on cash flow utilization, overinvesting firms often exhibit an "empire-building" mentality, favoring aggressive investment strategies. Underinvesting firms, typically driven by prudence, may forgo investment opportunities due to reluctance to bear excessive risk (Balakrishnan et al., 2016). As vulnerable enterprises, agribusinesses struggle to bear the costs of overly aggressive strategies. With fixed technologies and limited transformation capabilities, they require relatively prudent investment approaches. Investors, predominantly risk-averse, may be more inclined to

finance underinvesting enterprises under digital inclusive finance conditions, leading to the fourth hypothesis.

> **Hypothesis 4:** the impact of digital inclusive finance on financing constraints for agribusinesses exhibits heterogeneity across ownership structures, regions, and investment conditions.

4 Model analysis

4.1 Data sources

This study references the China Securities Regulatory Commission's Guidelines for Industry Classification of Listed Companies and the Specialized Statistical System for Agriculture-Related Loans. The scope of agriculture-related industries includes agriculture, forestry, animal husbandry, and fisheries, as well as enterprises in the manufacturing sector such as agricultural and sideline food processing, food manufacturing, alcoholic beverages, beverages, and refined tea manufacturing, and wood processing. The study focuses on agriculture-related enterprises from 2011 to 2022, with data sourced from the Guotai An Database (CSMAR), Peking University Digital Inclusive Finance Index, China Insurance Yearbook, and regional statistical yearbooks. Sample selection criteria are as follows: exclusion of enterprises with incomplete data; exclusion of enterprises under ST or PT status during the sample period, as well as those newly listed or listed during the year. Ultimately, 1,585 agribusinesses were selected for observation, with data processing conducted using STATA 17.0.

Concurrently, this study employs a multi-period DID analysis of digital inclusive finance policies implemented in Lankao County, Henan Province (2016), Ningbo City, Zhejiang Province, and Ningde City and Longyan City, Fujian Province (both 2019). The policy selection is appropriate: first, the policies were implemented in staggered phases (2016 vs. 2019), meeting the requirements for a multi-period DID design. Second, the policies cover representative regions at different development levels—from a national pilot zone (Lankao) to eastern coastal areas (Ningbo) and revolutionary base areas (Ningde, Longyan)—combining regional diversity with relevance to agriculture-related enterprises. Finally, while all policies centered on digital inclusive finance, their specific focuses—such as Lankao's "county-level poverty alleviation," Ningbo's "micro and small enterprises," and Fujian's "poverty eradication"—closely aligned with the research theme. This alignment enables precise identification of their heterogeneous impacts on financing constraints for agribusinesses, providing a reliable exogenous policy shock for causal inference. Municipal-level digital inclusive finance policies (Lankao County, Henan in 2016; Ningbo City, Zhejiang and Ningde City/Longyan City, Fujian in 2019) represent provincial-level impacts. This is primarily because these pilot zones required provincial government approval and support, with their outcomes directly serving provincial inclusive finance development goals.

4.2 Variable descriptions

4.2.1 Explained variable

Given the mutual influence between financing constraints and financial variables such as cash flow and corporate leverage, this study adopts a model for measuring the degree of corporate financing constraints, drawing on Hadlock and Pierce (2010), Gu et al. (2020), and Chen et al. (2020), to avoid potential endogeneity issues:

$$P(QUFC = 1or\,0Z_{i,t}) = \frac{e^{Z_{i,t}}}{1+e^{Z_{i,t}}}$$

$$Z_{i,t} = b_0 + b_1 size_{i,t} + b_2 lev_{i,t} + b_3\left(\frac{Cash\ Div}{ta}\right)_{i,t} + b_4 MB_{i,t} + b_5\left(\frac{NWC}{ta}\right)_{i,t} + b_6\left(\frac{EBIT}{ta}\right)_{i,t} \quad (1)$$

Size, lev, Cash Div, MB, NWC, EBIT, and*ta* represent firm asset size, financial leverage ratio, cash dividends, price-to-book ratio, net working capital, earnings before interest and taxes, and total assets, respectively.

These variables are processed annually and standardized using three variables: company size, company age, and cash dividend payout ratio ($y_i = \frac{x_i-\bar{x}}{s}$, where$\bar{x} = \frac{1}{n}\sum_n^1 x_i$ and$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\bar{x})^2}$). By sorting the mean values of standardized variables for listed companies in ascending order and using the data's quantile points as thresholds for financing constraints, we determined the dummy variable QUFC for financing constraints. Specifically, listed companies above the 66th percentile were classified into the low financing constraint group, assigned QUFC = 0; those below the 33rd percentile were categorized into the high financing constraint group, assigned QUFC = 1. We fitted the probability P using a Logit regression model and named it FC. Analysis revealed that higher values of FC indicate more severe financing constraints for firms. Unlike the SA index, which is based solely on a company's size and age: $SA = 0.737 \times Size + 0.043 \times Size^2 - 0.040\times$ Age. Potential challenges include the non-linear relationship between agricultural enterprise scale and financing capacity (e.g., large farms may face liquidity traps due to heavy asset burdens), and the inability of age to reflect technological iteration shocks (e.g., young vertical agribusinesses may have greater financing advantages). The FC Index addresses the core issue of agribusinesses 'financing constraints, which stem from cash flow shortages that cannot meet investment demands. It directly captures the tension between an enterprise's endogenous financing capacity (operating cash flow) and investment impulses (capital expenditures), aligning with the agricultural sector's "high-risk-low-cash-flow" characteristics.

4.2.2 Explanatory variables

This paper employs the annual provincial Digital Inclusive Finance Index (Index) to assess the development status of digital inclusive finance across different regions. The provincial level serves as the core unit for financial regulation and policy implementation. The development of digital inclusive finance is directly influenced by provincial policies (e.g., financial reform

plans). Utilizing provincial data allows for the most accurate measurement of the macro policy and regulatory environment in which enterprises operate. Simultaneously, it ensures data robustness by effectively smoothing out micro-level fluctuations at the municipal and county levels (e.g., isolated events in specific cities), thereby providing a more stable and reliable metric for regional digital financial development. This approach also more effectively mitigates endogeneity issues, rendering the model estimation results more robust and reliable.

The benefits of digital inclusive finance should encompass broad coverage of financial services (Coverage), which measures the accessibility and scope of digital financial services; depth of utilization (Usage), reflecting the activity level and depth of users' actual engagement with digital financial services, including payments, credit, insurance, credit scoring, investments, money market funds, and other services—this dimension is directly linked to enterprises' financing capacity; and the degree of digitalization (Digitize), which focuses on the convenience and cost controllability of financial services, such as mobile usage and actual financing costs. This dimension directly relates to the accessibility and cost of financing. Therefore, this paper introduces indicators for these three sub-dimensions to conduct an in-depth analysis of the specific aspects impacted by digital inclusive finance.

4.2.3 Control variables

The following financial indicators were selected for analysis:

(1) Total Investment (Ti) (2) Leverage Ratio (Lev), calculated as: Leverage Ratio = Total Liabilities/Total Assets (3) Firm age (Age), defined as the number of years since the company's listing as of 2022; (4) Asset size (Size), represented by the natural logarithm of year-end total assets; (5) Stock yield (Yield), the annual individual stock return rate considering reinvestment of cash dividends; (6) Financing cost (Cost), calculated as the proportion of corporate financial expenses to total liabilities at the end of the period.

4.2.4 Mediating variable

Tobin's Q is selected as the mediating variable. Calculation formula: Tobin's Q = Market Value/Total Assets; Market Value = RMB Ordinary A-shares × Current Closing Price × End-of-Period Value + Domestic-listed Foreign B-shares × Current Closing Price × End-of-Period Value × Daily Exchange Rate + (Total Shares - RMB Ordinary A-shares - Domestic-listed Foreign B-shares) × (Total Shareholders' Equity at Period-End/Paid-in Capital at Period-End) + Total Liabilities at Period-End.

4.2.5 Adjusting variables

By utilizing provincial agricultural insurance indicators, we analyze regional risk protection environments and examine two channels influencing corporate financing: 1. Policy support in high-insurance-density regions shapes lenders' risk expectations for local enterprises; 2. Increased regional insurance coverage may amplify free-riding behavior (e.g., uninsured firms relaxing risk management when neighboring farms receive compensation). Individual enterprise insurance status (participation status) directly modulates their risk structure.The following indicators are selected:Agricultural Insurance Penetration (x): agricultural insurance premiums/Gross Value Added of Primary Industry; Agricultural Insurance Density (y): agricultural insurance premiums/Number of Primary Industry Workers; Agricultural Insurance Scale (z): agricultural insurance premium income/Property insurance premium income.

4.3 Empirical model

$$FC_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 Controls_{i,t} + f_i + y_t + \varepsilon_1 \quad (2)$$

$$FC_{i,t} = b_0 + b_1 Index_{i,t} + b_2 Controls_{i,t} + f_i + y_t + \varepsilon_2 \quad (3)$$

$$Tobin's\ Q_{i,t} = \delta_0 + \delta_1 Index_{i,t} + \delta_2 Controls_{i,t} + f_i + y_t + \varepsilon_3 \quad (4)$$

$$FC_{i,t} = \gamma_0 + \gamma_1 Index_{i,t} + \gamma_2 Tobin's\ Q_{i,t} + \gamma_3 Controls_{i,t} + f_i + y_t + \varepsilon_4 \quad (5)$$

$$FC_{i,t} = \beta_0 + \beta_1 Tj_{i,t,d} + \beta_2 Index_{i,t} + \beta_3 Insurance_{i,t,d} + f_i + y_t + \varepsilon_5 \quad (6)$$

$$FC_{i,t} = c_0 + c_1 Tobin's\ Q_{i,t} + c_2 Tobin's\ Q_{i,t}^{\ 2} + c_3 Controls_{i,t} + f_i + y_t + \varepsilon_6 \quad (7)$$

Where subscripts i and t denote individual and year, respectively, and d represents different agricultural insurance indicators; $FC_{i,t}$ represents the financing constraint for firm i in year t; $DID_{i,t}$ is the product of the treatment group dummy variable (treatment group = 1, control group = 0) and the policy timing dummy variable (post-policy = 1, pre-policy = 0);α_0, b_0, c_0, β_0, δ_0, and γ_1 are the intercept terms; $Index_{i,t}$ is the inclusive finance index for firm i in year t; $Tobin's\ Q_{i,t}$ denotes the Tobin's Q ratio for firm i in year t; $Controls_{i,t}$ represents the above series of control variables; $Insurance_{i,t,d}$ denotes a series of agricultural insurance indicators; $\beta_1\ Tj_{i,t,d}$ represents the product of different *Insurance* indicators and *Index*; f_i, y_t respectively represent individual fixed effects and time fixed effects; ε_1, ε_2, ε_3, ε_4, ε_5, ε_6 are random error terms.

5 Empirical results and analysis

5.1 Benchmark regression

The benchmark model employed in this study is a two-way fixed effects model, simultaneously accounting for time and firm-level fixed effects. The results are presented in Table 1. Column (1) reveals that digital inclusive finance significantly alleviates financing constraints for enterprises. The coefficient for the overall index (Index) is −0.002 and is statistically significant at the 1% level, indicating that agribusinesses in cities with higher levels of digital inclusive finance development face relatively fewer financing constraints. In other words, digital inclusive finance helps alleviate corporate financing constraints. Further analysis of the digital inclusive finance index in columns (2), (3), and (4) reveals that,

TABLE 1 Benchmark regression results.

	Index regression	Coverage regression	Usage regression	Digitize regression	DID
	FC	FC	FC	FC	FC
Index/DID	−0.002***				−0.041***
Coverage		−0.001			
Usage			−0.000		
Digitize	(0.001)	(0.001)	(0.000)	−0.001*** (0.000)	
Ti	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Lev	−0.410*** (0.032)	−0.412*** (0.032)	−0.407*** (0.032)	−0.413*** (0.032)	−0.406*** (0.032)
Age	0.050*** (0.013)	0.027** (0.013)	0.016** (0.006)	0.024*** (0.005)	0.008*** (0.001)
Size	−0.165*** (0.010)	−0.165*** (0.010)	−0.166*** (0.010)	−0.165*** (0.010)	−0.167*** (0.010)
Yield	−0.026*** (0.006)	−0.026*** (0.006)	−0.026*** (0.006)	−0.026*** (0.006)	−0.028*** (0.006)
Cost	0.182 (0.140)	0.178 (0.141)	0.173 (0.141)	0.165 (0.140)	0.148 (0.141)
_cons	4.057*** (0.222)	4.135*** (0.222)	4.185*** (0.218)	4.119*** (0.218)	4.216*** (0.217)
N	1,585.000	1,585.000	1,585.000	1,585.000	1,585.000
r2	0.398	0.394	0.394	0.398	0.397
r2_a	0.294	0.290	0.290	0.295	0.294
id	√	√	√	√	√
Time	√	√	√	√	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

compared to the depth and breadth of digital inclusive finance, the level of convenience provided to customers is the indicator most likely to influence corporate financing constraints. Its coefficient is −0.001, significant at the 1% level. This may be because, for agribusinesses—the "long-tail" segment of the investment market—the depth and breadth of digital adoption are less effective than more convenient usage methods in reducing investors' costs, boosting their interest, and thereby easing financing constraints for these enterprises. Column 5 shows that after controlling for individual and time fixed effects, the average effect coefficient of policy implementation (DID) is −0.041, significantly negative. This indicates that, on average, the outcome variable Y for individuals exposed to the policy treatment decreased by 0.041 units compared to unexposed individuals, thus confirming Hypothesis 1.

5.2 Parallel trend test and placebo test

5.2.1 Parallel trend test

Figure 4 illustrates the dynamic effects of the policy intervention. The horizontal axis represents time relative to the policy implementation, while the vertical axis shows the estimated coefficient of the treatment effect and its confidence interval. It can be observed that prior to the policy implementation, the estimated coefficients fluctuated around zero and were statistically insignificant, consistent with the parallel trends assumption. After policy implementation, the treatment effect begins to emerge: it is significant in the implementation period (period = 0); subsequently, the effect is significant in periods 1 and 2, this means that digital inclusive finance can significantly ease corporate financing constraints. But becomes insignificant in period 3 after implementation. This may be due to policy iteration costs or the inability to fully observe the complete policy cycle at the 2022 data node, rather than a model error. This indicates that the policy effect exhibits a clear implementation effect without significant lag.

5.2.2 Placebo test

To validate the robustness of the benchmark regression results, a placebo test was conducted. As shown in Figure 5, after randomly assigning the treatment variable, the kernel density distribution of the estimated coefficient for the "spurious treatment effect" is highly concentrated around zero. The estimated value of the true treatment effect (at the vertical dashed line) lies far from this spurious distribution range. This indicates that the observed treatment effect in the benchmark regression is not driven by

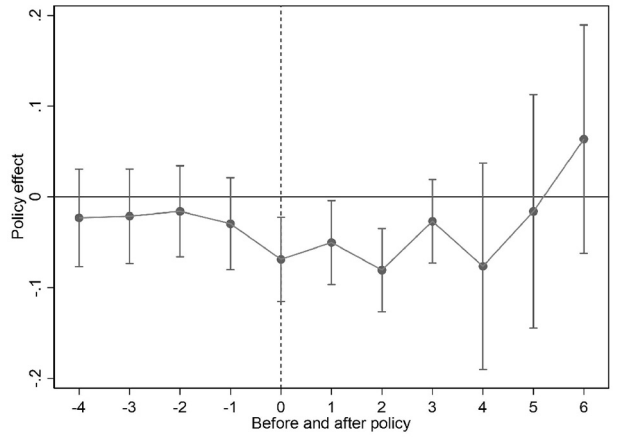


FIGURE 4
Parallel trend test.

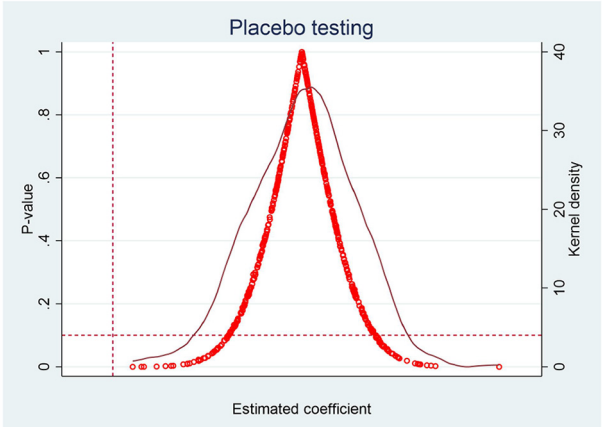


FIGURE 5
Placebo test.

unobserved confounding factors or random error, but rather by the causal impact of the "treatment" itself, further supporting the reliability of the core conclusions of this paper.

5.3 Testing the influence mechanism

5.3.1 Mediating effect of Tobin's Q

Building upon the three-step approach referenced in studies by Wen and Ye (2014), Chen et al. (2014), and Zhang and Kang (2016), this paper employs Sobel and Bootstrap tests to examine indirect effects. This rigorous methodology provides a more scientific demonstration of Tobin's *Q* influencing financing constraints within digital inclusive finance. The empirical analysis results are presented in Table 2. Under the three-step method, the estimated coefficients for α_1, γ_1 and γ_2 are −0.002, −0.002, and −0.016 respectively, all significant at the 1% level. Due to potential multicollinearity in the three-step method, the standard errors of the coefficient estimates increase (Jiang, 2022).

TABLE 2 Masking effect analysis.

	The first step	The second step	The third step	Robustness test
	FC	Tobin's *Q*	FC	FC
Index	−0.002*** (0.001)	−0.006 (0.005)	−0.002*** (0.001)	−0.002*** (0.001)
Tobin's *Q*			−0.016*** (0.003)	
Sobel test	0.00003198***	Intermediate variable (Tobin's Q) Mechanism effectiveness		
Bootstrap test	0.0000271***		0.0000316***	
$\lvert\delta_1{}^*\gamma_1\rvert/\gamma_2$	0.0016875***			
_cons	4.057*** (0.222)	5.479*** (1.811)	4.146*** (0.221)	4.383*** (0.245)
N	1,585.000	1,585.000	1,585.000	1,311.000
r2	0.324	0.346	0.332	0.417
r2_a	0.208	0.234	0.217	0.296
id	√	√	√	√
Time	√	√	√	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

Therefore, to further explore the mechanism of influence, this study conducted a Sobel test on the data based on the three-step method. Given uncertainties in the data distribution, a Bootstrap test was applied with 500 resamples to calculate the value of $\lvert\delta_1{}^*\gamma_1\rvert/\gamma_2$, thereby further validating the masking effect of Tobin's *Q*. Under both methods, the indirect effects were 0.00003198 and 0.0000271 respectively, both significantly positive at the 1% level. Meanwhile, was negative at −0.016. The indirect effects mitigated the direct effects, reducing the total effect and indicating a degree of masking effect. Empirical results indicate that under both tests, Tobin's *Q* partially masks the impact of digital inclusive finance on financing constraints for agribusinesses, thus supporting Hypothesis 2. To validate the findings, we further screened agricultural enterprises with positive cash flows and found that the results in the "Robustness Test" column in Table 2 remain valid. This demonstrates that even well-performing agricultural enterprises may still be constrained by their market value when viewed from the perspective of the credit side of capital.

Without considering the interaction effects with digital inclusive finance. To further investigate the impact mechanism of Tobin Q on corporate financing constraints, this paper conducts an in-depth analysis of its operational framework and establishes Model (7). The empirical findings are presented in the Table 3 below. Empirical findings demonstrate that corporate financing constraints follow a positive U-shaped pattern—initially easing then intensifying as market value (Tobin's Q) increases. This reveals the dual function of Tobin's Q in agricultural financing: the ascending left segment shows how rising Q releases positive signals, attracting investor attention and easing constraints.

TABLE 3 Analysis of the influence of Tobin's *Q*.

	The influence of Tobin's Q.
	FC
Tobin's *Q*]	−0.050*** (0.009)
Tobin's Q^2	0.004***
_cons	4.448*** (0.218)
N	1,585.000
r2	0.411
r2_a	0.309
Id	√
Time	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

The ascending right segment reveals that when Q exceeds a critical threshold, corporate asset characteristics and institutional flaws trigger a "value skepticism mechanism." Higher Q values intensify investor doubts about valuation authenticity, ultimately exacerbating financing constraints.

5.3.2 The regulatory role of agricultural insurance

This study obtained basic insurance data for agribusinesses from the China Insurance Yearbook and regional statistical yearbooks. Calculations yielded the following metrics: agricultural Insurance Penetration (*x*): agricultural insurance premiums/Gross Value Added of Primary Industry; Agricultural Insurance Density (*y*): agricultural insurance premiums/Number of Primary Industry Workers; Agricultural Insurance Scale (z): agricultural insurance revenue/Property insurance premium income. As shown in Table 4, empirical results indicate that the three interaction terms *Tj* are significant at different levels of significance, with coefficients of 0.003, 0.011, and 0.000 respectively. Their direction of effect is opposite to that of Index, proving that the inclusion of agricultural insurance reduces the mitigating effect of digital inclusive finance on financing constraints for agribusinesses. That is, when enterprises are located in regions with higher levels of agricultural insurance, the mitigating effect of digital inclusive finance on financing constraints for agribusinesses is diminished, confirming Hypothesis 3.

5.4 Heterogeneity analysis

As shown in Table 5's empirical results, digital inclusive finance demonstrates more pronounced effects for enterprises facing underinvestment. Typically, agribusinesses carry higher inherent risks, leading investors to favor underfunded enterprises that tend to adopt relatively conservative operational approaches. A key objective of digital inclusive finance is to bridge resource gaps for the long-tail population, thereby increasing investment opportunities for small household investors traditionally excluded from formal financial systems. This demographic prioritizes stable and sustainable investment products, meaning overly aggressive enterprises may not be significantly impacted by digital inclusive finance.

TABLE 4 Moderating effect of agricultural insurance.

	Benchmark	The first adjustment	The second adjustment	The third adjustment
	FC	FC	FC	FC
Index	−0.002*** (0.001)	−0.001** (0.001)	−0.003*** (0.001)	−0.002*** (0.001)
z		−0.866*** (0.307)		
x			−3.774** (1.648)	
y				−0.000* (0.000)
Tj_x, Tj_y, Tj_z		0.003*** (0.001)	0.011*** (0.004)	0.000** (0.000)
_cons	4.057*** (0.222)	4.110*** (0.222)	3.902*** (0.226)	3.916*** (0.228)
N	1,585.000	1,585.000	1,585.000	1,585.000
r2	0.398	0.402	0.403	0.401
r2_a	0.294	0.298	0.299	0.297
id	√	√	√	√
Time	√	√	√	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

Secondly, state-owned enterprises (SOEs), benefiting from ample capital chains and facing relatively low financing pressures, may experience less pronounced impacts from financial model reforms. While private enterprises prioritize profit maximization, SOEs shoulder social responsibilities such as maintaining employment stability, promoting public welfare, and ensuring food security. Consequently, SOEs often receive greater resources and preferential treatment from central banks and financial institutions. Private enterprises, particularly those in agriculture, inherently possess weaker corporate characteristics. Lacking financial market favor while needing external financing, these entities are precisely the focus of digital inclusive finance policies.

Finally, as shown in Table 5, digital inclusive finance proves more effective in regions with stronger traditional economic development. Agriculture-related enterprises, which already enjoy easier access to financing, may secure even greater capital through digitalization. We categorize enterprises by region based on GDP, such as the eastern region encompassing cities like Liaoning Province and Beijing, which collectively account for ∼60% of China's GDP. Heterogeneity analysis by region indicates that digital inclusive finance has the most pronounced effect on enterprises in the more developed eastern region,

TABLE 5 Heterogeneity analysis.

	Limitations	Excessive	Non-state-owned enterprises	State-owned enterprises	Eastern	Central	Western
	FC	FC	FC	FC	FC	FC	FC
Index	−0.002** (0.001)	−0.001 (0.001)	−0.003*** (0.001)	−0.000 (0.001)	−0.002*** (0.001)	0.002 (0.002)	0.001 (0.001)
Ti	0.000** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Lev	−0.427*** (0.042)	−0.497*** (0.056)	−0.302*** (0.040)	−0.560*** (0.049)	−0.383*** (0.038)	−0.488*** (0.093)	−0.454*** (0.075)
Age	0.044*** (0.017)	0.031 (0.025)	0.077*** (0.019)	0.016 (0.018)	0.058*** (0.019)	−0.029 (0.036)	−0.007 (0.032)
Size	−0.174*** (0.014)	−0.150*** (0.017)	−0.159*** (0.014)	−0.148*** (0.015)	−0.176*** (0.014)	−0.148*** (0.022)	−0.149*** (0.023)
Yield	−0.028*** (0.009)	−0.023** (0.010)	−0.019** (0.008)	−0.041*** (0.009)	−0.023*** (0.008)	−0.046*** (0.015)	−0.031** (0.015)
Cost	0.213 (0.183)	0.328 (0.243)	−0.134 (0.165)	1.028*** (0.263)	0.084 (0.159)	0.633 (0.532)	0.225 (0.362)
_cons	4.263*** (0.312)	3.855*** (0.358)	4.083*** (0.293)	3.739*** (0.348)	4.384*** (0.298)	4.009*** (0.518)	3.838*** (0.521)
N	1,006.000	579.000	989.000	596.000	1,031.000	244.000	310.000
r2	0.379	0.479	0.391	0.485	0.375	0.453	0.534
r2_a	0.212	0.203	0.263	0.399	0.259	0.322	0.430
id	√	√	√	√	√	√	√
Time	√	√	√	√	√	√	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

with a coefficient of −0.002, significant at the 1% level. The development of digital inclusive finance exhibits a "Matthew effect." agribusinesses in less economically developed regions may struggle to compete for financing with other industries due to sector-specific characteristics, even when digital inclusive finance is implemented. Thus, Hypothesis 4 is confirmed.

5.5 Robustness tests

The robustness analysis in this paper is broadly categorized into three approaches: (1) altering the dependent variable; (2) modifying the fixed-effects model by upgrading from individual-level to industry-level fixed effects; (3) excluding enterprises with relatively limited agricultural involvement, such as those in food processing, catering, textiles, and apparel. As shown in Table 6, Column (1) demonstrates that after replacing the dependent variable FC with another financing constraint indicator SA, the mitigating effect of digital inclusive finance persists, with a coefficient of −0.000 that is significant at the 5% level. Column (2) indicates that to avoid industry bias inherent in individual-level fixed effects, industry-level fixed effects were employed, revealing that the results remain robust and significant at the 1% level. Column (3), after refining the sample, yields a coefficient of −0.003 that is significant at the 1% level. This not only demonstrates the robustness of the findings but also underscores the critical relevance of this study's focus on agricultural analysis.

TABLE 6 Robustness tests.

	Adjust the dependent variable	Change regression model	Exclude samples
	SA	FC	FC
Index	−0.000** (0.000)	−0.002*** (0.001)	−0.003*** (0.001)
_cons	−3.538*** (0.066)	3.969*** (0.227)	4.025*** (0.333)
N	1,585.000	1,585.000	838.000
r2	0.950	0.401	0.379
r2_a	0.942	0.294	0.269
ID/Industry	id√	Industry√	√
Time	√	√	√

* indicates a *p*-value less than 0.1 (10% significance level), representing marginal significance; ** indicate a *p*-value less than 0.05 (5% significance level), indicating statistical significance of the result; *** indicate a *p*-value less than 0.01 (1% significance level), representing high significance.

6 Empirical results and analysis

Rural revitalization hinges on the development of agribusinesses. Against the backdrop of digital inclusive finance, our primary focus is on how to leverage digital tools more effectively to foster the growth of these enterprises. Building on this foundation, this paper employs both theoretical and empirical

analysis to explore the multifaceted impact of digital inclusive finance on the financing constraints of agribusinesses, enriching the understanding of the influencing mechanisms from the lender's perspective: (1) Digital inclusive finance significantly alleviates financing constraints for agribusinesses. This study analyzes the causes of financing constraints from both borrower and lender perspectives, suggesting that lender investors' willingness to invest significantly influences agribusiness financing constraints based on enterprise characteristics. (2) Tobin's *Q* partially masks. The impact of digital inclusive finance on financing constraints for agribusinesses, as validated through Bootstrap tests. (3) The presence of agricultural insurance dampens the alleviating effect of digital inclusive finance on financing constraints for agribusinesses. This is likely because insurance increases moral hazard among agribusinesses and reduces operational transparency. Additionally, agricultural insurance cannot perfectly absorb the substantial systemic risks inherent in agriculture, leading to insurance failure. Consequently, enterprises in regions with higher agricultural insurance usage may paradoxically lose investor favor. (4) The presence of digital inclusive finance causes agribusiness financing constraints to vary across different investment behaviors, equity structures, and regions.

This study, based on a sample of Chinese agribusinesses, reveals the mitigating effects of digital inclusive finance on financing constraints and the moderating role of agricultural insurance. Its conclusions hold significant implications for developing economies globally. In the context of accelerating digital economy penetration, agricultural sectors in emerging markets commonly face challenges such as credit rationing, collateral insufficiency, and information asymmetry. The empirical framework of this study—multi-period Difference-in-Differences (DID) modeling and mechanism analysis—provides methodological references for evaluating the inclusivity of digital financial tools, particularly in nations with underdeveloped agricultural insurance systems or low marketization levels. Critically, the findings caution that moral hazard risks associated with insurance mechanisms might undermine the benefits of fintech innovations. Therefore, an insurance-based compensation option should be implemented: enterprises can only qualify for loan interest subsidies after demonstrating investment in disaster prevention facilities (e.g., IoT sensor verification), thereby curbing moral hazards. A dynamic agricultural asset valuation platform should be established, integrating satellite remote sensing (land quality), blockchain (supply chain data), and climate models (disaster risk) to replace the static book valuation method of traditional Tobin's *Q*. This approach will resolve information distortion issues and enhance investors' confidence in lending.The conclusions are generalizable to agricultural-dominant economies in Southeast Asia, Latin America, and Sub-Saharan Africa, offering theoretical foundations for designing integrated rural financial reform strategies that combine digital platforms, insurance mechanisms, and land institutional innovation. This approach aligns with global agendas for rural revitalization and inclusive growth, emphasizing the urgency of cross-sectoral policy coordination to unlock trapped capital in agrarian value chains.

In summary, this paper examines the impact mechanism of digital inclusive finance on agricultural development from the lender's perspective of financing constraints in agribusinesses. It employs agricultural insurance to conduct targeted analysis on the causes of financing constraints in agribusinesses, offering new insights for accelerating their development. First, the state should continuously promote the development of digital inclusive finance, organically integrating traditional financial models with digitalization. While expanding financing platforms and channels for agribusinesses, it is also crucial to enhance platform accessibility to attract investors, addressing issues from both the supply and demand sides of capital. Simultaneously, strengthening the review of policy-based agricultural insurance is essential. Establishing scientific agricultural risk classifications and premium rates forms the foundation for ensuring the healthy and sustainable development of agricultural insurance, thereby reducing adverse selection and moral hazard issues in its operation. Second, agribusinesses should proactively disclose corporate information to reduce information asymmetry between lenders and borrowers. By leveraging agricultural insurance and digital technologies, they can secure more financing opportunities and channels while actively innovating. Investing in new technologies will attract greater capital inflows and strengthen internal oversight for sound investment practices. At the management level, leaders should proactively integrate traditional agribusinesses with emerging tech sectors favored by investors. This approach enhances market competitiveness and expands financing avenues. Finally, financial markets should strive to eliminate industry biases, adhere to the original intent of digital inclusive finance, and genuinely aggregate the "long-tail" groups marginalized by traditional finance. This will more effectively assist agribusinesses in broadening financing channels and strengthening their capabilities, thereby promoting the implementation of the rural revitalization strategy.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CH: Methodology, Validation, Formal analysis, Project administration, Data curation, Supervision, Investigation, Software, Conceptualization, Visualization, Funding acquisition, Writing – original draft, Resources, Writing – review & editing. HW: Methodology, Supervision, Resources, Writing – review & editing.

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