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Mechanisms of Digital Financial Inclusion on New Quality Productivity in Agriculture

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Abstract: Digital financial inclusion is an important tool to promote new quality productivity in agriculture and a strong agricultural country. To investigate how digital inclusive finance empowers new quality productivity in agriculture. First, on the basis of theoretical analysis, the entropy value method is applied to measure the indicators of new agricultural productivity in 31 Chinese provinces excluding Hong Kong, Macao, and Taiwan from 2012 to 2023; Second, the fixed effect model, the media tion effect model and the threshold effect model are applied to study the paths and mechanisms of digital inclusive finance empowering agricultural new quality productivity. The study finds that digital inclusive finance significantly p romotes the development of new quality productivity in agriculture. Heterogeneity analysis shows that digital financial inclusion has a facilitating effect on new agricultural productivity in the eastern, western, and northeastern regions, while it has a d ampening effect in the central region. The mechanism analysis shows that digital inclusive finance empowers the development of agricultural new quality productivity by promoting the level of traditional financial development and the development of regi onal innovation capacity. The results of the threshold test indicate that there is a double threshold for digital financial inclus ion and that it shows a marginal incremental boost to new quality productivity in agriculture. Accordingly, It is advisable to imp rove the construction of digital infrastructure and cultivate professionals; To promote the balanced development of digital inclusive finance in each region according to local conditions; To give full play to the complementary advantages of digital inclusi ve finance and traditional finance; And to strengthen regional technological innovation to release the potential of digital incl usive finance.

Keywords: Digital financial inclusion, new quality productivity in agriculture, traditional financial development, regional innovation.

1. Introduction

Against the backdrop of today's global digital revolution, digital inclusive finance—as an innovative financial service model—is gradually permeating all economic sectors. Agriculture, as the foundation of the national economy, is also experiencing unprecedented opportunities for transformation. New quality productivity in agriculture(ANQP) represent a novel, more dynamic, and promising form of productivity within the agricultural sector. Integrating modern technology, innovative concepts, and advanced management models, they serve as a pivotal force in advancing agricultural modernization and realizing the rural revitalization strategy. Therefore, delving into the impact of digital inclusive finance on ANQP holds not only profound theoretical value but also significant practical implications.

ANQP constitute the vivid embodiment of Chinese-style modernization in the rural and agricultural sphere and the pivotal underpinning for attaining common prosperity. Relevant research primarily focuses on three aspects: First, conceptual delineation: the “new” dimension refers to labourers characterised by knowledge, innovation and autonomy (You et al., 2024), means of production featuring digital-intelligent and informational “new media”, and objects of labour exhibiting “new materials” such as emerging industries and green development (Wang et al., 2024), while the “quality” dimension denotes high quality, multi-quality attributes and dual-quality efficiency (Jiang Yongmu, 2024). Second, regarding the construction of evaluation indicators, Song Zhenjiang et al. (2024) adopted scientific and technological productivity, green productivity, and digital productivity as entry points; Wei et al. (2024) employed the E-CRITIC weighting method from the perspectives of output level and output efficiency to construct indicators, revealing that China's ANQP have shown a sustained overall upward trend, diminishing from east to west. Third, empirical validation: Yang et al. (2024) employed entropy values and the Super-SBM model to measure the upward trend of ANQP in the Yangtze River Economic Belt, demonstrating its significant promotion of ecological efficiency in cultivated land utilization. Yang (2025) revealed that ANQP substantially drives rural consumption upgrades with marginal increasing effects. Chen et al. (2025) found that ANQP can suppress agricultural carbon emission intensity by enhancing rural labor productivity and agricultural land productivity.

Although extant studies have examined the nexus between digital inclusive finance and ANQP, corroborating transmission channels such as agricultural technology adoption and household consumption upgrading (Zhou et al., 2024; Jia et al., 2024), the underlying mechanisms remain under-specified. Consequently, the theoretical scaffolding is drawn from the literature linking digital inclusive finance to high-quality agricultural development. Digital inclusive finance amplifies economies of scale, facilitates the upgrading of employment structures, catalyses green technology innovation (Tan et al., 2023), rationalises intra- and inter-sectoral configurations of agriculture (Hua J et al., 2024), and accelerates land circulation (Wang et al., 2022), thereby propelling agriculture toward high-quality development while exhibiting self-referential threshold effects (Lu et al., 2022). Some studies also indicate that digital

inclusive finance exhibits a positive spatial correlation, promoting rural industrial integration (Zhang et al., 2022) and agricultural economic resilience (Li et al., 2024). However, other scholars have found that in China, digital inclusive finance boosts the green total factor productivity of agriculture within a province but exerts a suppressing effect on neighboring provinces (Zhang et al., 2022).

In summary, research on ANQP is currently in its early stages, with limited exploration of the mechanism through which digital inclusive finance influences these forces. Given this, this study attempts to further explore the topic from three perspectives: First, it constructs an indicator system for ANQP using the entropy method, based on laborers, labor objects, and means of labor, to investigate the relationship between ANQP and digital inclusive finance. Second, it examines the mediating effect of digital inclusive finance on ANQP, using the level of traditional financial development and regional innovation capacity as entry points. Third, it examines the threshold effect of digital inclusive finance itself within ANQP.

2. Theoretical Analysis and Research Hypotheses

2.1. Direct Effect Analysis

Digital inclusive finance empowers ANQP primarily through three channels: For laborers, it not only alleviates credit constraints and enhances social trust to promote farmer entrepreneurship (He et al., 2019), but also increases farmers' income (Liu et al., 2021). Regarding means of production, it drives upgrades in agricultural technology and equipment, accelerates rural infrastructure development, and optimizes agricultural resource allocation. For labor objects, it expands the scope and improves the quality of labor objects, facilitating agricultural transformation and upgrading (Tian, et al., 2020) and driving agriculture toward higher value-added directions. In summary, we propose the following hypothesis:

H1: Digital inclusive finance can promote the development of ANQP.

2.2. Mediational Effect Analysis

First, the level of traditional financial development. Currently, agriculture-related enterprises face severe financing constraints in the rural revitalization strategy (Guo et al., 2022). Digital inclusive finance, integrated with cutting-edge financial technology, effectively reduces banks' operational costs (Zhang et al., 2018) and enhances their credit risk-bearing capacity (Wang et al., 2023), thereby increasing their willingness to support rural revitalization. Moreover, through technological empowerment, digital inclusive finance can drive banks to pursue technological innovation (Al-DMOUR et al., 2020), thereby improving the efficiency and service reach of traditional finance and strengthening its support for ANQP.

Second, regional innovation capacity. Digital inclusive finance alleviates credit constraints, improves financial efficiency, and boosts income to foster innovation and entrepreneurship (Du et al., 2023). Simultaneously, it lowers financial service barriers for entrepreneurs and provides diversified financial services (Deng et al., 2019), facilitating the transformation of innovative achievements into commercial projects. The enhancement of regional innovation capacity, in turn, promotes improvements in agricultural total factor productivity (Zhu et al., 2019), farmers' income (Zhao et al., 2018), and industrial structure (Zhou et al., 2001), thereby driving the development of ANQP. Therefore, we propose the following hypothesis:

H2: Regional innovation capacity and traditional financial development levels mediate the relationship between digital inclusive finance and ANQP.

2.3. Threshold Effect Analysis

The threshold effect of digital inclusive finance on ANQP primarily stems from its uneven development. Significant disparities in the advancement of digital inclusive finance result in varying impacts on ANQP across regions. Specifically, due to disparities in economic development levels, infrastructure construction, talent distribution, and government support across Chinese regions, digital inclusive finance exhibits an east-strong-west-weak distribution pattern where the strong get stronger (Jin et al., 2022). This results in heterogeneous impacts on ANQP. Therefore, we propose the following hypothesis:

H3: The promotional effect of digital inclusive finance on ANQP exhibits nonlinear characteristics.

3. Research Design

3.1. Data Sources

This study utilizes panel data from 2012 to 2023 covering 31 provinces in China (excluding Hong Kong, Macau, and Taiwan). The data sources include the National Bureau of Statistics, provincial statistical yearbooks, the China Statistical Yearbook, the China Rural Statistical Yearbook, the China Science and Technology Statistical Yearbook, and the Digital Finance Research Center at Peking University. Due to missing data for Taobao villages in 2023, linear interpolation was employed to complete the dataset.

3.2. Variable Descriptions

3.2.1. Dependent Variable

The dependent variable in this study is ANQP. Drawing upon the research of Cui (2025), Chen (2025), and Zhu (2024), a comprehensive evaluation was conducted using the entropy method from the perspectives of laborers, objects of labor, and means of labor (see Table 1).

Table 1. System of indicators of new quality productivity in agriculture

Primary Indicators	Secondary Indicators	Tertiary Indicators	Measurement Method	Attribute
New quality productivity in agriculture (ANQP)	Labourer	Labourer Skill	Rural education-culture-entertainment spending per capita	+
			Education expenditure × (Gross output value of agriculture, forestry, animal husbandry and fishery / Regional GDP) / General budgetary expenditure	+
		Labourer Efficiency	Per capita gross value of agricultural output	+
			Disposable Income of Rural Residents	+
			Gross Agricultural Output per Hectare of Cropped Area	+
	Object of Labour	Agricultural Green Development	Pesticide Application Intensity per Unit of Sown Area	-
			Rural Electricity Consumption per Capita	-
			Forest Coverage Rate	+
		Agricultural Industrial Structure Optimization	Number of Taobao Villages	+
			Gross Output Value of Agricultural Services to Total Gross Output Value of Agriculture, Forestry, Animal Husbandry and Fishery	+
	Means of Labour	Agricultural Infrastructure	Rural Broadband Internet Penetration Rate	+
			Optical Cable Length per Square Kilometer	+
			Rural Road Mileage per Capita	+
		Agricultural Science and Technology Input	Total Power of Agricultural Machinery	+
			Personnel Engaged in Agricultural Scientific and Technological Activities	+
			Expenditure on Agricultural Scientific and Technological Activities	+

Notation: "+" signifies positive indicators and "—" signifies negative indicators. Irrespective of sign, an increase in the magnitude of the indicator is associated with an enhancement of agricultural new quality productive forces.

3.2.2. Explanatory Variable

The explanatory variable in this study is Digital Inclusive Finance (DIF), measured by the Peking University Digital Inclusive Finance Index.

3.2.3. Control Variable

Urbanization absorbs surplus agricultural labor, facilitates large-scale agricultural operations, and enables the feedback of technology and human capital to the agricultural sector. Environmental regulations increase production costs, inhibiting productivity enhancement in the short run. Foreign trade stimulates production and technological upgrading in related industries. Land productivity directly reflects the level of agricultural modernization and intensive cultivation. Industrial structure optimization can improve production efficiency and product value-added. Accordingly, this study selects urbanization level (URB), environmental policy (Gov), degree of openness to the outside world (Open), land productivity (Land), and industrial structure (IS) as control variables. Specifically, urbanization level is measured by the proportion of urban population to total regional population; environmental policy is proxied by the ratio of environmental protection fiscal expenditure to total public fiscal expenditure; degree of openness is captured by the ratio of total import and export trade volume to regional GDP; land productivity is calculated as the ratio of gross agricultural output value to sown area of crops; and industrial structure is measured by the Theil Index (Gan et al., 2011), with its computation method specified in Equation (1):

$$T=\sum_{j=1}^{3}\left(\frac{Y_{i,j}}{Y}\right)\ln\left(\frac{Y_{i,j}}{L_{i,j}}/\frac{Y}{L}\right) \quad (1)$$

In Equation (1): T denotes the Theil Index; i represents region (i = 1, 2, ..., n); j denotes industry sector (j = 1, 2, 3); Y indicates output value; and L represents employment.

3.2.4. Mediating Variable

Traditional Financial Development Level (Fin). The ratio of total RMB deposits and loans of financial institutions at year-end to GDP is employed to proxy traditional financial development. Regional Innovation Capacity (Inno). The logarithm of the number of invention patents is adopted to measure regional innovation capacity (Yang et al., 2022).

3.3. Model Specification

To investigate the impact of DIF on ANQP, we specify the following benchmark econometric model:

$$Y_{ANQP_{i,t}}=\alpha_0+\alpha_1 X_{DIF_{i,t}}+\alpha_2 C_{i,t}+\mu_i+\varphi_t+\varepsilon_{i,t} \quad (2)$$

To further examine the mediating effect of DIF on ANQP, the following mediation model is specified:

$$M_{i,t}=\beta_0+\beta_1 X_{DIF_{i,t}}+\beta_2 C_{i,t}+\mu_i+\varphi_t+\varepsilon_{i,t} \quad (3)$$

$$Y_{ANQP_{i,t}}=\gamma_0+\gamma_1 X_{DIF_{i,t}}+\gamma_2 M_{i,t}+\gamma_3 C_{i,t}+\mu_i+\varphi_t+\varepsilon_{i,t} \quad (4)$$

In Equations (2) through (4), the variables are defined as follows: $Y_{ANQP_{i,t}}$ is the dependent variable measuring agricultural new quality productive forces for province i in year t; $X_{DIF_{i,t}}$ is the key explanatory variable of digital inclusive finance; $C_{i,t}$ is a vector of control variables; $M_{i,t}$ is the mediator; μ_i captures province-specific fixed effects; φ_t captures time-specific fixed effects; and $\varepsilon_{i,t}$ is the idiosyncratic error term.

To test for potential nonlinearities and regime-dependent effects of DIF on ANQP, we adopt the panel threshold regression model developed by Hansen (1999). The empirical specification is given by:

$$\begin{aligned} Y_{ANQP_{i,t}}=&\rho_0+\rho_1 X_{DIF_{i,t}} I(X_{DIF_{i,t}}\le\lambda_1)+\rho_2 X_{DIF_{i,t}} I(\lambda_1<X_{DIF_{i,t}}\le\lambda_2)\\ &+\cdots+\rho_n X_{DIF_{i,t}} I(\lambda_{n-1}<X_{DIF_{i,t}}\le\lambda_n)\\ &+\rho_{n+1} X_{DIF_{i,t}} I(X_{DIF_{i,t}}>\lambda_n)+\rho_4 C_{i,t}+\mu_i+\varphi_t+\varepsilon_{i,t} \end{aligned} \quad (5)$$

In Equation (5): $X_{DIF_{i,t}}$ denotes the threshold variable; ρ denotes the coefficient vector; λ denotes the threshold value; and I(·) denotes the indicator function (where I equals 1 if the condition in parentheses is true, and 0 otherwise).

3.4. Descriptive Statistics

Table 2 reveals that ANQP displays a standard deviation of merely 0.086, implying limited cross-provincial heterogeneity. This convergence likely reflects homogeneous agricultural endowments and relatively equitable policy implementation nationwide. Conversely, the DIF demonstrates pronounced variability, as evidenced by its substantial standard deviation and wide range between extreme values. This regional divergence can be ascribed to heterogeneous levels of economic development and uneven penetration of financial knowledge among rural populations across provinces.

Table 2. Descriptive statistics

Variable	Obs.	Mean	Std.	Min.	Max.
Y_{ANQP}	372	0.173	0.086	0.054	0.613
X_{DIF}	372	272.351	96.109	61.470	473.834
M_{Fin}	372	3.496	1.234	0.876	8.164
M_{Inno}	372	8.380	1.614	3.497	11.872
C_{URB}	372	0.598	0.128	0.222	0.942
C_{Gov}	372	0.342	0.157	0.095	1.073
C_{Open}	372	0.240	0.254	0.007	1.543
C_{Land}	372	0.505	0.330	0.161	2.146
C_{Is}	372	0.170	0.127	0.007	0.776

4. Empirical Analysis and Tests

4.1. Baseline Regression

Table 3. Benchmark regression results

Variable Name	Y_{ANQP}	
X_{DIF}	0.0005***	0.0003***
	(24.69)	(8.36)
C_{URB}		0.3384***
		(4.32)
C_{Gov}		-0.0462***
		(-2.64)
C_{Open}		0.0571***
		(3.23)
C_{Land}		0.0924***
		(6.22)
C_{Is}		0.1964***
		(5.880)
_c	0.0439***	-0.2007***
	7.96	(-4.94)
Individual FE	YES	YES
Time FE	YES	YES
N	372	372
R^2	0.6419	0.7307

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; values in parentheses are t-statistics. The same applies below.

To ensure model appropriateness, we employ the Hausman specification test to discriminate between fixed and random effects estimators. The test statistic of 30.40 ($p < 0.001$) strongly rejects the null hypothesis that unobserved individual effects are uncorrelated with regressors, thereby justifying the adoption of the fixed effects (FE) estimator. Table 3 presents the FE estimation results.

The coefficient on DIF is consistently positive and statistically significant at the 1% significance level across all specifications, with and without control variables. This result suggests that DIF exerts a significant promoting effect on ANQP, operating through mechanisms such as mitigating credit constraints, enhancing resource allocation efficiency, and stimulating technological innovation. H1 is thus empirically validated.

4.2. Endogeneity Issues

Although the baseline estimates establish a positive association between DIF and ANQP, reverse causality remains a concern: the development of ANQP may simultaneously foster the penetration of DIF. To mitigate this simultaneity bias, we instrument contemporary DIF with its first lag (L_DIF) and estimate the model via two-stage least squares (2SLS). Table 4 reports the estimation results.

The first-stage coefficient on the lagged instrument is positive and highly significant ($p<0.01$). Diagnostic tests confirm instrument validity: the Kleibergen-Paap rk LM statistic rejects underidentification ($p<0.01$), while the Kleibergen-Paap rk Wald F-statistic of 634.839 comfortably exceeds the Stock-Yogo weak IV critical value of 16.38, alleviating concerns about weak instrument bias. The second-stage estimate of DIF remains positive and statistically significant at the 1% level, corroborating that the baseline conclusion is robust to endogeneity correction.

Table 4. Endogeneity test results

	X_{DIF}	Y_{ANQP}
X_{DIF}		0.0023***
		(4.09)
X_{L_DIF}	0.7746***	
	(25.20)	
Control Variable	YES	YES
Individual FE	YES	YES
Time FE	YES	YES
N	341	341
R^2	0.9548	0.7808
Kleibergen-Paap rk LM statistic	16.264***	
Wald F statistic	634.839	

4.3. Robustness Checks

To verify the robustness of our baseline findings, we implement three complementary strategies: alternative variable specifications, outlier removal, and exclusion of developed provinces. Table 5 reports the estimation results. First, we decompose the digital inclusive finance index into its three constituent dimensions—coverage breadth (BR), usage depth (DE), and digitalization support (DI)—and re-estimate the model using each sub-index. All three dimensions exhibit positive and statistically significant coefficients at the 1% level, corroborating the main results. Second, we address potential outliers by winsorizing all continuous variables at the 1st and 99th percentiles. Third, we exclude five economically advanced provinces (Beijing, Shanghai, Guangdong, Jiangsu, and Zhejiang) where digital

inclusive finance is most developed, thereby ensuring that our findings are not driven by regional outliers. The coefficient of interest remains positive and significant at the 1% level in all robustness specifications. H1 thus passes all robustness checks.

Table 5. Robustness test results

Variable	Y_{ANQP}				
	alternative variable specifications			outlier removal	exclusion of developed provinces
X_{BR}	0.0003***				
	(7.74)				
X_{DE}		0.0003***			
		(7.74)			
X_{DI}			0.0002***		
			(7.18)		
X_{DIF}				0.0003***	0.0003***
				(8.81)	(8.52)
_c	-0.1793***	-0.2618***	-0.3292***	-0.2011***	- 0.0735***
	(-4.12)	(-6.59)	(-9.17)	(-5.17)	(-2.65)
Control Variable	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
N	372	372	372	372	312
R^2	0.7239	0.7131	0.7179	0.7590	0.8309

4.4. Eterogeneity Analysis

Table 6. Heterogeneity test results

Variable	Y_{ANQP}			
	eastern region	central region	western region	northeastern region
X_{DIF}	0.0006***	-0.0002*	0.0001***	0.0002***
	(6.32)	(-1.71)	(5.24)	(7.65)
C_{URB}	0.7309***	0.8500***	0.1751***	-0.0525
	(4.77)	(4.79)	(3.70)	(-0.61)
C_{Gov}	-0.0202	-0.1154***	-0.0013	-0.0107
	(-0.69)	(-4.01)	(-0.12)	(-0.81)
C_{Open}	0.1614***	0.0053	0.1070***	0.1069**
	(2.96)	(0.55)	(5.72)	(2.59)
CLand	0.0122	0.2276***	0.1526***	0.1598***
	(0.57)	(3.97)	(9.42)	(5.25)
C_{Is}	0.2144	-0.2266***	0.0636***	-0.0684**
	(0.81)	(-4.17)	(5.45)	(-2.13)
_c	-0.5466***	-0.2623***	-0.0853***	0.0710
	(-5.98)	(-3.26)	(-4.44)	(1.24)
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
N	120	72	144	36
R^2	0.8277	0.9298	0.9482	0.9457

To investigate the regional heterogeneity of digital inclusive finance, this study partitions the 31 provincial-level regions (excluding Hong Kong, Macao, and Taiwan) into four economic zones according to the classification of the State Council: eastern region, central region, western region, and northeastern region. The subsample regression results are reported in Table 6.

The results indicate that digital inclusive finance significantly promotes agricultural new quality productive forces in all regions except the central region. The coefficient is highest in the eastern region and lowest in the western region. This pattern can be attributed to the following factors: the eastern region possesses a robust economic foundation, leading financial technology development, well-established infrastructure, and abundant human capital, which collectively enable more efficient support for agricultural technological innovation and industrial upgrading. Conversely, the western region exhibits relatively weak economic fundamentals, lagging development of digital inclusive finance, insufficient infrastructure, and shortage of skilled labor, resulting in less pronounced promoting effects.

Notably, digital inclusive finance appears to inhibit the

development of agricultural new quality productive forces in the central region, albeit with lower statistical significance. According to data from the National Bureau of Statistics, the output value share of secondary and tertiary industries in the central region has exceeded 90% over the past five years, leading to capital scarcity in the agricultural sector. Additionally, the central region lags behind the eastern region in terms of economic development level and urbanization degree (Li et al., 2023). Furthermore, with respect to education expenditure as a component of agricultural new quality productive forces, the western region (0.03) surpassed the central region (0.02) in 2023. In summary, industrial structural bias and limited financial literacy among rural households constrain the effectiveness of digital inclusive finance in the central region.

5. Further Analysis

5.1. Mechanism Analysis

Based on Equations (2) and (3), this study employs traditional financial development level (Fin) and regional innovation capacity (Inno) as mediating variables to investigate the mechanisms through which digital inclusive finance (DIF) affects agricultural new quality productive forces (ANQP). The estimation results are presented in Table 7. Columns 1 and 3 report the regressions of DIF on the two mediators, respectively. The results reveal that DIF exerts a positive and statistically significant effect on both Fin and Inno at the 1% level, indicating that DIF enhances both mediators.

Columns 2 and 4 present the joint effects of DIF and the mediators on agricultural new quality productive forces. All three variables—DIF, Fin, and Inno—remain positive and statistically significant at the 1% level. This finding can be attributed to the following mechanisms: digital inclusive finance leverages fintech instruments to broaden financial service channels and reduce service costs, thereby improving the efficiency and coverage of traditional finance and enabling more precise support for innovation and upgrading in the agricultural sector. Simultaneously, through big data and cloud computing technologies, digital inclusive finance provides funding support and information platforms for regional innovation, fostering agricultural technological innovation and industrial integration. The enhancement of traditional financial development and regional innovation capacity collectively provides robust momentum for the advancement of agricultural new quality productive forces, driving the transformation of agriculture toward intelligentization and high efficiency.

In summary, DIF influences ANQP through the channels of Fin and Inno. H2 is thus empirically validated.

Table 7. Impact mechanism test

	M_{Fin}	Y_{ANQP}	M_{Inno}	Y_{ANQP}
X_{DIF}	0.0040***	0.0002***	0.0048***	0.0003***
	(9.48)	(5.20)	(15.63)	(4.70)
M_{Fin}		0.0282***		
		(5.53)		
M_{Inno}				0.0189***
				(2.64)
_c	3.1127***	-0.2885***	5.6857***	-0.3083***
	(7.46)	(-6.86)	(18.57)	(-5.38)
Control Variable	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
N	372	372	372	372
R^2	0.5044	0.7533	0.8626	0.7362

5.2. Threshold Effect Analysis

Given the complexity and heterogeneity of DIF, its impact on ANQP may exhibit nonlinear threshold characteristics. Accordingly, we employ Equation (5) for empirical testing. To determine the number of thresholds and estimate the threshold values, we implement the Bootstrap method with 300 replications. The test results are reported in Table 8.

Digital inclusive finance passes both the single-threshold test and the double-threshold test at the 1% significance level, whereas the triple-threshold test is statistically insignificant. This indicates the existence of double threshold effects, with estimated threshold values of 375.3539 and 411.3299, respectively.

Table 8. Threshold effect test results

Threshold Variable	Threshold Type	F-Statistic	P-Value	F Critical Value		
				1%	5%	10%
X_{DIF}	single-threshold	98.59	0.0000	47.2018	28.3465	20.6978
	double-threshold	30.93	0.0033	22.9022	15.4063	12.2528
	triple-threshold	13.82	0.3800	65.3903	50.3594	33.6360

We further conduct threshold regression analysis, with the estimation results reported in Table 9. The impact of DIF on ANQP is positive and statistically significant at the 1% level across all threshold intervals. Specifically, when DIF is no higher than 375.3539, a one-unit increase in DIF is associated with an average increase of 0.0002 units in ANQP. When DIF falls within the range of 375.3539 to 411.3299, the marginal effect rises to 0.0003 units. When DIF exceeds 411.3299, the promoting effect is further strengthened, with the coefficient reaching 0.0004.

In summary, as the level of digital inclusive finance continuously improves, its promoting effect on agricultural new quality productive forces exhibits a marginal increasing trend. This pattern arises because higher levels of digital inclusive finance enable more precise capital allocation, lower financing costs, and stronger support for agricultural technological innovation and industrial upgrading, thereby more powerfully facilitating the development of agricultural new quality productive forces. H3 is thus empirically validated.

Table 9. Threshold regression results

Variable	Y_{ANQP}
X_{DIF} (X_{DIF}≤375.3539)	0.0002***
	(3.46)
X_{DIF} (375.3539<X_{DIF}≤411.3299)	0.0003***
	(4.92)
X_{DIF}(X_{DIF}>411.3299)	0.0004***
	(4.62)
C_{URB}	0.3624***
	(4.28)
C_{Gov}	0.0137
	(0.53)
C_{Open}	0.0638**
	(2.26)
C_{Land}	0.0727**
	(2.05)
C_{Is}	0..1051**
	(2.45)
_c	-0.1782***
	(-2.91)
N	372
R^2	0.8041

6. Conclusions and Policy Implications

Based on the theoretical analysis of the mechanisms through which digital inclusive finance enables agricultural new quality productive forces, this study utilizes panel data covering 31 Chinese provinces (excluding Hong Kong, Macao, and Taiwan) from 2012 to 2023 to explore the impact of digital inclusive finance on agricultural new quality productive forces. The main conclusions are as follows: First, digital inclusive finance significantly enhances agricultural new quality productive forces. Second, the effect of digital inclusive finance on agricultural new quality productive forces varies across regions: it significantly promotes development in the eastern, northeastern, and western regions, while exerting an inhibiting effect in the central region. Third, digital inclusive finance fosters agricultural new quality productive forces by improving traditional financial development and regional innovation capacity. Fourth, there exist double threshold effects in the relationship between digital inclusive finance and agricultural new quality productive forces, exhibiting a marginal increasing trend. Based on these findings, the following policy recommendations are formulated:

First, improve infrastructure construction and cultivate professional talent to unleash the promoting effect of digital inclusive finance. Accelerate the coverage of broadband and fiber-optic networks through fiscal subsidies and tax incentives, with particular emphasis on remote areas, to ensure efficient penetration of digital inclusive financial services. Provide targeted fiscal subsidies to telecom operators to expedite rural information infrastructure development. Simultaneously, establish collaborative mechanisms among government, enterprises, and educational institutions to cultivate agricultural digital talent. Implement incentive measures such as tax reductions and housing subsidies to attract interdisciplinary professionals. Leverage distance education platforms to deliver digital skills training for farmers, creating a "talent attraction + talent cultivation" dual-wheel drive mechanism to provide human capital support for digital agriculture development.

Second, adopt region-specific strategies to promote balanced development of digital inclusive finance across regions. For the eastern region, capitalize on its leading advantage in fintech development by prioritizing agricultural technology venture capital funds and supporting the application of artificial intelligence and blockchain in precision agriculture. For the northeastern region, given its characteristics of vast land with sparse population and prominent large-scale agriculture, intensify financial support for mechanization and digital transformation of agricultural machinery, develop exclusive products such as "Smart Farm Loans", and establish agricultural remote sensing monitoring and financial service platforms covering the entire region. For the western region, strengthen fiscal investment in digital infrastructure, promote inclusive services such as mobile payments and supply chain finance, and conduct "digital skills + financial literacy" outreach training programs. For the central region, establish targeted agricultural credit allocation mechanisms, guide capital to agriculture through fiscal interest subsidies, and build "digital agriculture industry-education integration demonstration zones" based on county-level characteristic industries.

Third, promote deep collaboration between digital inclusive finance and traditional financial institutions. Leverage the extensive network coverage and strong credibility of traditional financial institutions, combined with the efficiency and convenience of digital technology, to construct an integrated "offline services + online platforms" model. Focus on developing digital credit products oriented toward agricultural technological innovation, utilize big data for precise profiling to lower financing barriers, and enhance service efficiency through intelligent risk control systems to achieve precise drip irrigation of financial resources.

Fourth, enhance regional technological innovation to unlock the potential of digital inclusive finance. Establish specialized credit facilities for smart agriculture, providing interest-subsidized loans and risk compensation mechanisms for projects involving agricultural big data and intelligent equipment. Concurrently, optimize fiscal incentive structures by granting agricultural technology enterprises additional tax credits for digital transformation, supplementing the existing super-deduction for research and development expenditures. Furthermore, leverage agricultural technology parks as anchors for developing digital inclusive financial service centers, and design specialized financial instruments such as "scientific and technological achievement transformation loans" to lower financing thresholds and accelerate the diffusion of precision agriculture technologies.

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