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Analyses of Topical Policy Issues

The impact of financial deepening on agricultural production: A household-level analysis of BigTech finance

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The relationship between financial deepening and agricultural production remains ambiguous. Previous literature has demonstrated that financial depth can alleviate poverty among rural households by facilitating self-employment in non-agricultural sectors or migration to urban areas, but its impact on rural households engaged in the agriculture sector has not been discussed. This paper utilizes the usage of financial services provided by a leading BigTech company in China and household survey data to analyze how financial deepening affects rural households' agricultural production. The findings demonstrate the efficacy of BigTech finance in augmenting agricultural income for rural households. Mechanism analysis reveals that this impact is only observed among financially constrained rural households or those affected by climate disasters, thereby facilitating an expansion in the agricultural production inputs and enhancing efficiency. Furthermore, the distributional analysis underscores that BigTech finance primarily benefits rural households with limited access to traditional financial services, suggesting its complementary role to traditional finance in bolstering agricultural production amidst financial deepening endeavors.

1. Introduction

The literature on the outcomes of financial development documents that financial deepening fosters economic growth and reduces income inequality by helping the poor (Levine, 2005; Beck, Levine, & Levkov, 2010; Bruhn & Love, 2014). In particular, Ayyagari et al. (2020) finds that financial deepening reduces poverty of rural households through self-employment in non-agricultural sectors in rural areas or through migration to the tertiary sector in urban areas. However, there is a lack of direct evidence on the effect of financial deepening on the households who remained in the agricultural sector in rural areas.

Rural credit programs rolled out in many developing countries aim to alleviate poverty. However, the outcomes of these programs are questionable. Subsidized government-driven rural credit programs often face rent-seeking problems (Hoff & Stiglitz, 1990). Recent studies on microfinance programs struggle to provide solid evidence that they indeed raise income (Banerjee et al., 2015). These findings raise an important question on whether financial deepening can benefit rural households in the agricultural sector.

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The recent rise of financial technology has revolutionized the provision of financial services globally (Allen et al., 2021). By leveraging big data and machine learning techniques, financial technology is thought to better overcome monitoring problems and provide more efficient financial services (Phlippon, 2019). Among the countries at the forefront of financial technology, China has emerged as a leading player in FinTech and BigTech lending (Cornelli et al., 2020). BigTech companies are technology firms that have a well-established presence in the market for digital services and possess distinct advantages that are difficult for traditional financial intermediaries to replicate (Stulz, 2019; Vives, 2019). This study aims to investigate the impact of financial deepening initiated by BigTech companies on rural households in the agricultural sector.

Why is financial deepening initiated by BigTech companies important to agricultural production? On the one hand, rural households face financial constraints to expand production and enhance productivity, which is especially pronounced in rural China as land market frictions limit farmers to borrow from traditional financial intermediaries. The emergence of financial services provided by BigTech companies has the potential to better assess the creditworthiness of rural households and provide tailored financial products and services (Frost et al., 2019; Hau et al., 2021). On the other hand, the nature of agricultural production is risky due to factors like natural disaster shocks. BigTech companies can provide financial instruments on their platform for risk management, such as insurance products, which help farmers to reduce the impact of adverse events.

Our study utilizes a county-level financial deepening index (hereafter BigTech finance usage) based on data from Ant Financial Services Group, one of the largest BigTech Companies in China, to measure the household utilization of BigTech financial services.[1] Combining with rural household information from China Family Panel Studies (CFPS) survey, we find a positive correlation between BigTech finance usage and household agricultural income in rural areas after controlling for household fixed effects. The impact is economically significant, as a 1-unit standard deviation increase in BigTech finance usage is associated with an average increase of 24.86 % in household agricultural income.

One of the major challenges of our study is identifying the causal effects of BigTech finance usage on household agricultural income. The first concern is that BigTech finance usage improves household agricultural income through increasing the probability of rural households' self-selection into agricultural production. To mitigate the sample selection issue, we use Heckman selection model and find that the positive effect of BigTech finance usage on household remains robust. The second concern is that left censoring (zero values of agricultural income) in the data may bias the OLS estimation. To address this issue, we use Tobit regression, and the results remain consistent. The third concern is reverse causality and unobservable omitted variables. We employ a two-stage least square (2SLS) approach to address this issue. Our instrumental variable is the number of post offices per million people in prefecture-level cities in 1984, which represents the historical foundation of a city's information communication and may correlate with the present information communication infrastructure and the usage of BigTech finance. The 2SLS results are consistent with the OLS estimates, providing further support for the causal effect of BigTech finance usage on household agricultural income.

Our paper explores the potential mechanisms through which BigTech finance usage affects household agricultural income. On the one hand, our results show that the effect of BigTech finance on agricultural income is more pronounced among households denied access to traditional financial services and those experiencing financial vulnerability. This finding suggests that BigTech finance helps alleviate financial constraints faced by these households. On the other hand, we find that the impact of BigTech finance on agricultural income is more significant when households face natural disasters, particularly among financially vulnerable households. This finding indicates that BigTech finance enhances households' ability to cope with risks and shocks. Furthermore, our analysis reveals that by helping rural households who are financially constrained or who have experienced climate disasters, BigTech finance usage leads to increased investments in agricultural materials and land leases. These investments help alleviate resource misallocation in agricultural production, ultimately enhancing productivity.

Finally, we discuss the distributional effect of BigTech finance. The reward of BigTech finance usage is unequally distributed among different income groups. We find that only households with lowest income (0-20 % total income group) significantly benefit from the usage of BigTech finance. The impact of one-unit standard deviation increase in BigTech finance on agricultural income would lead to 63.2 % in total income for the average household in the lowest income group, suggesting the potential of reducing poverty and income inequality within rural areas. We also identify the marginal households who benefit from BigTech finance usage. We find that households with ages from 40 to 50 and education level of secondary school benefit most from BigTech finance usage. These households are on the margin who possess certain ability and knowledge, yet are excluded from traditional financial services due to various constraints. Furthermore, BigTech finance usage has a stronger effect on the household agricultural income in areas with low coverage of agricultural banking institutions and low agriculture-related loans. The effects of BigTech finance usage on agricultural income are more pronounced among households who are less exposed to traditional financial services with no bank loans or less bank loan amount. All the evidence suggests that, in terms of the impact of financial deepening on agricultural production, financial services provided by BigTech companies are pro-poor and play a complementary role to traditional finance.

Our paper is related to two broader strands of literature. The first strand examines the impact of financial development on household well-being. While numerous studies have documented the positive effect of financial development on economic growth (Levine, 2005), researchers have focused on investigating the influence of financial development on individuals, particularly in terms of income equality. Prior research has provided both cross-country and within-country evidence on the role of financial development in reducing poverty and income inequality (Beck et al., 2007; Demirgüç-Kunt & Levine, 2009; Beck et al., 2010; Bruhn & Love, 2014). Moreover, scholars have sought to determine whether financial development specifically increases the income of the poor. Burgess &

[1] This index is developed by the Institute of Digital Finance at Peking University and Ant Financial Services Group. (https://en.idf.pku.edu.cn/)

Pandes (2005) exploit the expansion of rural bank branches in India and find that financial development reduced rural poverty by stimulating non-agricultural output, but not agricultural output. Using survey data of Chinese rural households, Beck et al. (2015) show that access to external finance is positively associated with the decision to become an entrepreneur and the sales growth of microenterprises. Considerable research efforts have been devoted to evaluating the effectiveness of microfinance programs, typically in the form of group lending. However, demonstrating that these programs genuinely lead to income improvement remains a challenge (Banerjee et al., 2015; Banerjee et al., 2021).

Recently, attention has shifted towards studying the impact of financial technology (FinTech). Studies have shown that FinTech adoption improves household risk-taking (Hong et al., 2022), increases household consumption, reduces consumption inequality (Yang & Zhang, 2022; Zhou et al., 2023), and raises rural households' subsistence consumption levels (Yang et al., 2022). However, research on the impact of FinTech on income inequality remains relatively scarce (Karlan et al., 2016). Notable exceptions include Demir et al. (2022) and Hodula (2023), who use country-level FinTech indices and find that financial inclusion significantly reduces income inequality. Furthermore, Lee et al. (2023) show that province-level digital finance development alleviates poverty in China. However, due to limitations of country and province level data, these papers face identification issues (Demirgüç-Kunt et al., 2017). Wang and Fu (2022) is closely related to our study, as they find that FinTech adoption can mitigate rural households' vulnerability to poverty, but their mechanism analysis emphasizes the importance of non-agricultural employment.

The second strand of literature investigates the impact of digital technology on the agricultural sector (Goldfarb and Tucker, 2019). Prior research reveals a positive influence, particularly when digital platforms connect farmers directly with markets. The adoption of mobile phones has been found to improve market efficiency, reduce price dispersion, and increase farmers' profits (Jensen, 2007; Goyal, 2010). In China, the development of rural e-commerce helps farmers sell agricultural products, promotes off-farm employment, and increases farmers' revenue (Zhang et al., 2023; Chen et al., 2023; Li and He, 2024). Taobao villages, e-commerce clusters at the village level, have been shown to increase farmers' income, promote entrepreneurship, and foster industrial prosperity (Gao et al., 2024). The expansion of e-commerce to rural villages has led to a significant increase in household consumption (Couture et al., 2021). In contrast to previous research, we emphasize the role of financial deepening in assisting farmers.

Our paper contributes to the existing literature by bridging these two strands of research to study how the usage of BigTech finance affects rural households' agricultural income, shedding light on its potential to alleviate poverty and address income inequality for rural households in the agricultural sector. We acknowledge the endogeneity challenge inherent in studying BigTech finance and take the necessary steps to address this issue. Furthermore, we provide comprehensive evidence on the mechanisms through which BigTech finance usage impacts agricultural income, complementing existing findings.

Our paper is organized as follows: Section 2 introduces the background of this study and and the development of the hypothesis. Section 3 introduces the data used in this paper. Section 4 establishes the causal impact of BigTech finance on household agricultural income. Section 5 analyzes the mechanisms. Section 6 discusses the distributional effect of BigTech finance; Section 7 concludes the paper.

2. Background and hypothesis development

2.1. Frictions in rural China

Despite China's remarkable economic growth, the increasing income inequality serves as a reminder that the benefits of economic reform are not evenly distributed. Both the urban-rural divide and the disparities within rural areas play significant roles in contributing to this income inequality (Piketty et al., 2019; Zhang, 2021). The low agricultural productivity stands out as a major factor driving the significant income gap between urban and rural areas, as well as the inequalities within rural regions. Many scholars believe that certain frictions pose significant obstacles to the development of agricultural production.

The most prominent one is land ownership. Under present land system in rural China, agricultural land remains collectively owned (usually by the village or a lower-level unit), while the rights to use the land were distributed to rural households. In theory, households had the right to rent or transfer their land use rights to other households, but in practice, land rental is uncommon due to various concerns (Brandt et al., 2002). Furthermore, the absence of land ownership prevented households from using it as collateral for borrowing. Adamopoulos et al. (2022) have documented significant misallocation of land and capital in rural China, resulting in substantial welfare losses for rural households.

Besides institutional friction in rural China, the support for rural households from the formal financial system is limited. The Chinese government has made great efforts to improve the access to credit in rural areas. According to the Report on Rural Financial Services in China conducted by the People's Bank of China (PBOC), the amount of agricultural-related loans outstanding reached 23.6 trillion RMB in 2014, accounting for 28.1 % of total loans outstanding. While the government implemented preferential monetary policies towards agricultural-related loans and rural financial institutions, credit rationing remains a severe issue in rural China. Li et al. (2013) find that 61.5 % Chinese rural households were rationed in the credit market, causing a 15.7 % net income loss. According to CFPS 2014, only 6.55 % rural households obtained loans from banks and other financial institutions.[2] For those excluded by the formal financial institutions, some resort to informal finance. For example, 16.37 % rural households obtained loans from friends and relatives.

[2] This number is similar to the finding in other studies. Specifically, the China Household Finance Survey data revealed that only 7.37% of rural households had access to regular credit loans for productive purposes in 2015 (Fu and Huang, 2018).

Rural households in China have faced limited insurance coverage. Significant progress has been made in addressing these gaps. Since 2007, the government has actively promoted and subsidized agricultural insurance to protect farmers' livelihoods against various risks. Additionally, the introduction of the New Rural Pension Program (NRPP) in 2009, a fully funded defined contribution plan with substantial government subsidies, aims to provide old-age support for rural elderly. According to CFPS 2014, approximately 76.75 % rural households have enrolled in the New Rural Pension Program. Moreover, since 2002, China has initiated the implementation of the New Cooperative Medical System (NCMS) in rural areas, which is a medical mutual aid system with a specific focus on severe ailments and achieved coverage exceeding 80 % of rural areas by 2010. Although the government-initiated insurance plan caters to the basic needs of rural households, it falls short in addressing their re-invest requirements in production which necessitates supplementation from commercial insurance. However, limited access to commercial insurance persists due to the prevailing low education levels and income among rural households.

2.2. FinTech, BigTech, and formal financial system in China

The Chinese financial system is dominated by the banking sector. The government has implemented a moderate level of financial repression, which involves regulating credit amounts and interest rates to ensure that limited financial resources are allocated to firms and sectors favored by the state. State-owned enterprises (SOEs) enjoy easy access to formal financial services, while small businesses and individuals face higher capital costs and often find themselves excluded from the formal financial system. As a result, they often turn to informal finance as an alternative (Liu, 2016; Allen et al., 2017). When compared to other BRICS countries[3], Chinese individuals have limited access to formal credit, with only 7 % being able to avail themselves of such services. Moreover, their access to alternative informal credit is also relatively low (Fungáčová & Weill, 2015). This creates an opportunity for FinTech and BigTech platforms to step in and provide financial services.

While FinTech and BigTech platforms offer similar online financial services, their business models differ significantly. FinTech credit firms, typically referring to P2P lending firms, were initially built on decentralized platforms where individual lenders selected borrowers or projects within a market framework. In contrast, BigTech firms own diverse business lines and leverage their extensive user base obtained from non-financial activities to extract valuable user information and provide financial services (Stulz, 2019; Vives, 2019; Mester, 2021). According to a recent cross-country database on FinTech and BigTech credit, China is the largest market for both types of credit (Cornelli et al., 2020). In 2018, BigTech companies provided loans amounting to USD 363 billion, which increased to USD 516 billion in 2019. We exclude FinTech credit from our analysis as the P2P platforms ceased to operate in China by the end of 2020 due to stringent regulatory measures.

BigTech companies in China usually refer to BAT (Baidu, Alibaba, and Tencent). Unlike Baidu and Tencent, Alibaba owns the largest online shopping platforms, including Alibaba (B2B), Tmall (B2C), and Taobao (C2C). Alipay was launched in 2004 to improve online payments through escrow accounts that greatly alleviates the concern on the reliability of online counterparties and facilitates online transactions. Using big data from the online shopping platform and machine learning techniques, Alipay started to grant credit to small and micro-enterprises that sell on their platforms either through collaborations with banks or through their online bank. In 2015, Alipay was re-branded as Ant Financial Services Group, the financial subsidiary of Alibaba, which is an all-in-one ecosystem providing various forms of financial services, including payment (Alipay), investment (money market fund Yu'e Bao), online bank (MYbank), and insurance. According to the prospectus of Ant Group, Alipay App boasts a user base of over 1 billion active users, with a remarkable total payment transaction volume of 118 trillion RMB. Through its platform, it has facilitated significant consumer credit and credit balances for micro and small businesses, amounting to 1.7 trillion RMB and 0.4 trillion RMB respectively. Furthermore, it has played a crucial role in facilitating asset management with a scale of 4.1 trillion RMB, as well as handling insurance premiums and shared amounts totaling 51.8 billion RMB.[4]

2.3. Hypotheses development

The emergence of BigTech finance has the potential to transform the financial landscape in rural area, where households have traditionally faced significant barriers to using formal financial services. The limited access to formal financial services in rural areas has been a persistent challenge (Li et al., 2013; Fungáčová & Weill, 2015). Moreover, traditional financial institutions often face high costs and information asymmetries when serving remote and dispersed populations, leading to a reliance on informal financial channels that can be unreliable and expensive (Ayyagari et al., 2010; Turvey et al., 2013).

However, BigTech finance, leveraging the vast digital footprints and data analytics capabilities of large technology companies, offer a viable solution to this problem by reducing information asymmetries and transaction costs (Gambacorta et al., 2019; Jagtiani & Lemieux, 2018). Furthermore, BigTech platforms has the ability to offer customized financial products and services based on the specific needs and circumstances (Hau et al., 2021), which further enhance the scale and productivity of agricultural production, and hence, the agricultural income of rural households. Drawing upon these arguments, we propose the first hypothesis:

Hypothesis 1. The usage of BigTech finance is positively associated with agricultural income among rural households.

We propose the mechanisms behind Hypothesis 1 that BigTech finance holds the potential to effectively augment rural household's

[3] BRICS countries include Brazil, Russia, India, China, and South Africa.
[4] All the data statistics in the prospectus cover a 12-month period up until June 30, 2020.

agricultural production inputs through easing financial constraints and managing risks, thereby fostering a substantial increase in agricultural productivity and agricultural income. Therefore, we can check such mechanisms as the following steps.

Firstly, BigTech finance can ease financial constraints. Rural households face challenges of low income and limited education, leading to a high Engel coefficient and inadequate financial resources for agricultural production (Yu, 2018; Dong et al., 2012). Furthermore, the illiquidity of land and real estate exacerbates their exclusion from traditional financial systems, hindering their ability to secure credit necessary for productive activities (Bu and Liao, 2022; Jiang et al., 2020). Conversely, BigTech finance offers a diverse range of micro-consumption and production loans for households, which do not necessitate collateralized assets or stable income streams for loan acquisition; instead, they are based on users' consumption records and credit history from their big data. According to a research report on rural online consumption in China for 2022, BigTech financial services have been utilized by 97.2 % of rural residents, with installment consumption and credit consumption services being used by 38 % and 24.1 % respectively.[5] Moreover, during 2012 to 2016, Ant Financial has disbursed loans exceeding 700 billion yuan to small and micro enterprises, with more than one-third of these loans being specifically allocated for agricultural purposes.[6]

We argue that the benefits of BigTech finance will be particularly salient for households that have been excluded from the formal financial system due to limited collateral or credit histories (Frost et al., 2019; Jagtiani & Lemieux, 2018). By leveraging alternative data sources and credit assessment methods, BigTech companies can extend financial services to these underserved households, potentially unlocking significant gains in agricultural productivity and income (Björkegren & Grissen, 2018; Gambacorta et al., 2019). Hence we propose the following hypothesis:

Hypothesis 2. The positive impact of BigTech finance on agricultural income is more pronounced for households with limited access to traditional financial credit.

Financially vulnerable households, characterized by limited capacity to afford unforeseen expenses, may stand to benefit more from BigTech finance than their more financially stable counterparts (Demirgüç-Kunt et al., 2017). Access to credit and other financial services through BigTech platforms may enable these households to smooth consumption, and invest in agricultural production, potentially leading to stronger improvements in income (Suri et al., 2021; Karlan et al., 2014). Hence we propose the following hypothesis:

Hypothesis 3. The positive impact of BigTech finance on agricultural income is more pronounced for financially vulnerable households.

Secondly, BigTech finance can help rural households managing risks. In agricultural production, households face lots of natural risks, such as climate-related shocks (Chatterjee et al., 2020; Farrin & Miranda, 2015). In China, the average annual crop disaster rate over the past 15 years stands at approximately 30 %, as reported by the China Statistical Yearbook. Limited access to commercial insurance due to low levels of education and income results in increased precautionary savings for potential shocks, which indirectly restricts financial resources available for agricultural production materials (Suri et al., 2021; Karlan et al., 2014). Additionally, coupled with the exclusion of loans from traditional financial systems, this results in a lack of capacity to reinvest in production when exposed to external shocks.

However, leveraging BigTech platform's scale advantage and the information superiority of big data, BigTech finance effectively mitigates barriers faced by rural families in accessing commercial insurance. For example, leveraging its technological and informational advantages, Ant Financial collaborates with traditional commercial insurance companies to extend insurance services nationwide to rural users in agricultural production and the rural user base of their insurance service reached 130 million in 2016.[7] Moreover, the 2022 report on rural online consumption in China reveals that the number of users for online insurance in rural areas reaches 45.449 million, with a majority (78.6 %) falling within the age range of 26–45 years old, while users aged over 46 years old constitute a proportion of 11.7 %.[8]

We argue that BigTech finance can play a crucial role in helping rural households cope with natural disasters such as droughts or floods, which can have devastating effects on agricultural production and income (Chatterjee et al., 2020; Farrin & Miranda, 2015). By providing access to insurance products and emergency loans, BigTech finance help households to overcome financial difficulties in these shocks and recover their agricultural productivity (Cole et al., 2017; Karlan et al., 2014). Therefore, we propose Hypotheses 4 as evidence that BigTech finance can help rural households managing risks.

Hypothesis 4. The impact of BigTech finance on agricultural income becomes more pronounced when households experience natural disaster shocks, particularly among financially vulnerable households.

Finally, by alleviating financial constraints and effectively managing risks, BigTech finance can facilitate the expansion of household production scale through increased inputs, thereby enhancing overall production efficiency. Therefore, we have the final hypothesis:

Hypothesis 5. BigTech finance plays a pivotal role in enabling households to expand their agricultural inputs and enhance

[5] The 2022 report on rural online consumption in China: https://trendinsight.oceanengine.com/arithmetic-report/detail/801

[6] https://www.36kr.com/p/1721299845121

[7] https://www.36kr.com/p/1721299845121

[8] The 2022 report on rural online consumption in China: https://trendinsight.oceanengine.com/arithmetic-report/detail/801

production efficiency.

3. Data

In Section 2.2, we discussed how Ant Group, a prominent BigTech company, plays a leading role in providing extensive financial services in China. Based on data from Ant Group, the Research Center for Digital Finance at Peking University developed an index system characterizing the financial services provided by Ant Group. [9] This index system combines transaction and account-level data from Ant Group to assess three dimensions of financial service adoption provided by BigTech companies: breadth of coverage, depth of usage, and level of digitalization. These indices cover 31 provinces (2011-2018), 337 cities (2011-2018), and approximately 2,800 counties (2014-2018) across mainland China. The breadth of coverage index measures the regional penetration of BigTech finance, while the level of digitalization index reflects the accessibility of digital financial services. Furthermore, the depth of usage index evaluates the extent to which BigTech financial services are utilized, including payment services, monetary fund services, credit services, insurance services, investment services, and credit investigation services.[10]

In this paper, we employ the county-level depth of usage index to assess the adoption of BigTech finance among households within a given county. Our primary focus is on the actual utilization of BigTech finance rather than its mere availability, which is indicated by the breadth of coverage and the level of digitalization. We justify this focus on the depth of usage for two reasons: First, during the years 2016-2018, which account for two-thirds of the panel data used in our main regression analysis, the coverage rate was consistently high. Second, there was minimal variation in the level of digitalization across regions (see Appendix Fig. A1 for more details). This limited variability makes it difficult to study differences in coverage. To emphasize the role of BigTech companies in our analysis, we replace the term "depth of usage index" with "BigTech finance usage" throughout the remainder of this paper.

Fig. 1 depicts the progression and fluctuations in the utilization of BigTech finance in China. The left side of the figure showcases the average BigTech finance usage at the province level over time. It reveals a substantial and rapid increase in BigTech finance usage from 2014 to 2017. On the right side, the figure illustrates the divergent patterns of BigTech finance usage across different counties throughout the sample period, indicating significant variations across China. To facilitate the interpretation of our regression analysis and eliminate the time trend from this index, we standardized BigTech finance usage at the national level for each year.[11]

The rural households included in our analysis are drawn from the China Family Panel Studies (CFPS). The CFPS is a biennial longitudinal survey conducted by the Institute of Social Science Survey (ISSS) at Peking University.[12] Launched in 2010, it aims to gather nationally representative data on Chinese communities, families, and individuals. The survey collects longitudinal information at the individual, family, and community levels, focusing on various aspects of well-being in contemporary China. Topics covered include economic activities, education outcomes, family dynamics, migration, and health. The survey encompasses 25 provinces, municipalities, and autonomous regions, with all family members in the sample households being included in the study. Currently, the publicly available CFPS data encompasses biennial waves from 2010 to 2020. After matching the CFPS data with county-level BigTech finance data (2014-2018), we obtain household information from the 2014, 2016, and 2018 waves of CFPS.

As our research specifically focuses on agriculture, we excluded urban samples and concentrated on rural households. Our analysis focuses on the household income derived from agricultural and sideline products in the CFPS household survey, using the logarithm of this variable as our primary outcome variable. Alongside the key explanatory variables of BigTech finance usage, control variables in regressions include the family size (Num), the proportion of males (Male), the mean of schooling years (Eduy), average age (Age) and age square (Age2), the marriage status of highest income member (Marriage), the average health status (Health), family dependency ratio (FDR), the internet application (Internet), basic pension plan (Pension) and commercial insurance (CommInsur). Moreover, the net value of house assets (House) and social trust variable (SocialTrust) are controlled to measure family wealth and social capital. Additionally, we control for potential omitted variables, such as economic development measured by GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and traditional financial development as proxied by agriculture-related loans (AgrLoans).[13]

Table 1 presents summary statistics of the main variables, providing insights into the characteristics of the rural households in our sample: (1) 74.2 % of rural households in our sample are engaged in agricultural production; (2) The number of observations for variable HasAgr is more than that of variable AgrOut, indicating that agricultural income is missing for households not engaged in agricultural production; (3) Household agricultural incomes exhibit significant variability across the sample, with the average agriculture income being 11,633.61 RMB, and a standard deviation of 35,562.56.

We also observe distinct patterns of BigTech finance usage in our sample. After standardization, the BigTech finance usage (BigTech) is -0.359, indicating that the BigTech finance usage in rural areas is 0.359 standard deviations lower than the national average. This finding is consistent with the relatively lower levels of financial development typically observed in rural areas, attributable to limited infrastructure and economic growth. Moreover, the standard deviation and range of values demonstrate significant variation in BigTech finance usage in our sample, providing the necessary conditions for analyzing the impact of BigTech finance.

[9] https://en.idf.pku.edu.cn/

[10] The specific indicators used in depth of usage are shown in Appendix Table A1.

[11] The standardized formula is $BigTech_{ct} = \frac{Usage_{ct} - Mean_t}{StDev_t}$, where $Mean_t$ is the nationwide mean of BigTech finance usage index in year t and $StDev_t$ is the corresponding standard deviation.

[12] http://www.isss.pku.edu.cn/cfps/en/index.htm

[13] The definitions of the main variables used in this paper could be found in Appendix Table A2.

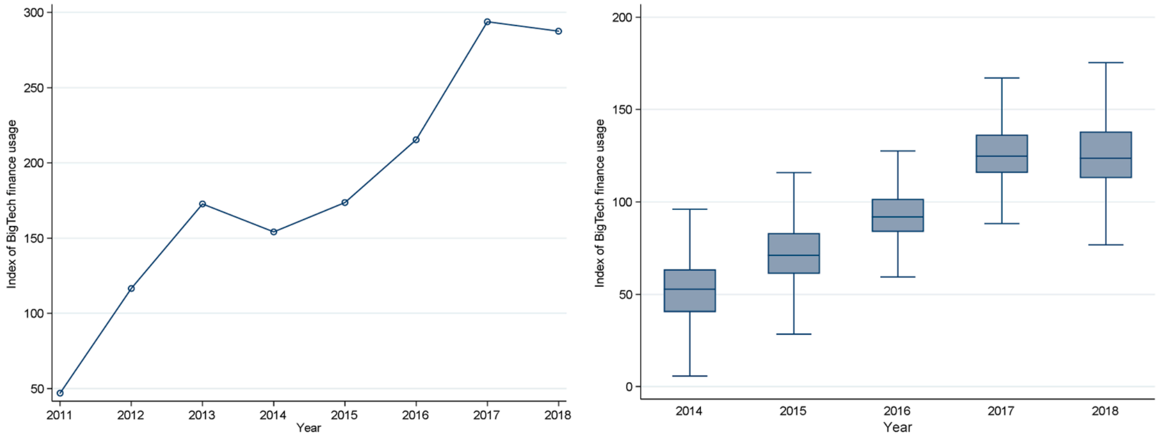

Fig. 1. BigTech finance usage in China.
The left figure shows the time series of average BigTech finance usage aggregated by the province-level index. The right figure shows the variations of BigTech finance usage across counties illustrated by the county-level index. In the right figure, the line within the box is the median value of the index, the upper and lower hinge of the box is 75th and 25th percentile index, respectively. The adjacent line above the upper hinge indicates the upper adjacent value (which is calculated by 75the percentile value+1.5*interquartile range, and interquartile range equals to the difference between the upper hinge and the lower hinge). The adjacent line below the lower hinge indicates the lower adjacent value (which is calculated by 25the percentile value-1.5*interquartile range).

Table 1
Summary statistics.
This table reports the summary statistics. HasAgr is a dummy variable that equals to one when the household is engaged in agricultural production. Log(AgrOut) is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the annual standardized measure of BigTech finance usage, adjusted with the national mean and standard deviation. Control variables are: family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. See Appendix Table A2 for detailed variable definitions.

Variable name	Obs.	Mean	Std.	Min.	Max.
HasAgr	17677	.742	.438	0	1
Log(AgrOut)	13109	6.415	4.094	0	14.286
BigTech	17677	-.359	.934	-2.990	3.034
Num	17449	3.461	1.899	1	17
Age	15390	43.680	9.720	16	64
Age2	15390	20.024	8.687	2.560	40.960
FDR	17449	38.495	32.174	0	100
Eduy	14537	6.589	3.671	0	19
Male	15390	.502	.271	0	1
Health	17449	.644	.358	0	1
Pension	15484	.794	.404	0	1
CommInsur	17408	.972	.164	0	1
Marriage	16766	.811	.392	0	1
Internet	17066	.483	.500	0	1
House	17267	19.310	93.206	-7992	5017
SocialTrust	17021	1.946	1.719	0	10
log(GDP)	16610	10.117	.634	8.600	12.619
Light	17402	1.301	1.889	.198	41.039
log(AgrLoans)	17677	27.569	.499	25.783	28.900

4. The impact BigTech finance on household agricultural income

To empirically test Hypothesis 1, which posits that increased utilization of BigTech finance enhances agricultural income for rural households, this section employs a three-step approach. First, we obtain baseline results using a double fixed effect model in panel data. Second, we discuss the challenges in identifying the causal effect, such as sample selection and left-censored data. Finally, we utilize instrumental variables to establish the robustness and validity of the causal relationship.

4.1. Baseline results

We begin by studying the correlation between BigTech finance usage and household agricultural income. Specifically, we run the baseline regression model as follows:

$$\log(AgrOut_{ict}) = \alpha BigTech_{ct} + X_{ict}\gamma + \lambda_t + \mu_i + \varepsilon_{it} \tag{1}$$

where the dependent variable,$AgrOut_{cit}$, is the agricultural income of household i in county c at year t; our key explanatory variable, $BigTech_{ct}$, is the standardized index of BigTech finance uage of county c at year t. X represents a set of control variables, including family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), brightness of lights (Light), and agriculture-related loans (AgrLoans). We report the OLS estimations of Model (1) and robust standard errors in Table 2. Column 1 only considers the relationship between BigTech finance and household agricultural income, and columns 2 to 5 add control variables, year fixed effects, county fixed effects and household fixed effects successively.

The results in columns 1-3 show a negative correlation between BigTech finance usage and household agricultural income when excluding county and household fixed effects (columns 1-3). However, this negative relationship becomes significantly positive when county and household fixed effects are incorporated (columns 4-5). The possible explanation is that the coefficients of BigTech finance usage in columns 1-3 are biased due to omitted variables in county c. In some counties, agricultural income constitutes only a small portion of total household income and is relatively low. Meanwhile, these counties may tend to have more comprehensive infrastructure, more developed economic condition and rapid BigTech growth. Therefore, we observe a negative relationship between BigTech finance usage and household agricultural income in columns 1-3. When we incorporate county and household fixed effects to address this bias, the negative relationship disappears and the positive effect emerges in columns 4-5. The coefficient estimated in column 5 suggests that, with every 1-unit standard deviation increase in BigTech finance usage, household agricultural income increases by 24.86 % (exp(0.222)-1 = 0.2486) on average. This finding is both statistically and economically significant, suggesting a noteworthy and impactful improvement of BigTech finance usage on agricultural income.

4.2. Sample selection

There is a potential sample selection problem in Table 2, as only households engaged in agricultural production entered the baseline regressions. Specifically, the results in columns 4 and 5 of Table 2 could potentially be attributed to sample selection rather than a causal effect. Given that agricultural output is heavily influenced by natural conditions, BigTech finance usage helps households to better withstand risks and consequently increases their likelihood of participating in agricultural production. Suppose BigTech finance usage facilitates the transition of rural households with high productivity from non-agricultural production to agricultural production. In that case, even if BigTech finance usage has no direct causal effect on the agricultural production process, we would observe a significant positive correlation between BigTech finance usage and agricultural income based on the sample of Table 2.

To address this concern, we first verify whether BigTech finance usage indeed increases the likelihood of households engaging in agricultural production. The results are presented in columns 1 and 2 of Table 3, showing that with every 1-unit standard deviation increase in the BigTech finance, there is a significant 1.7 percentage point increase in the probability of households participating in agricultural production.[14] This suggests the existence of a sample selection issue. The question then arises as to whether this sample selection issue compromises the causal relation observed in Table 2. To address this, we employ the Heckman selection model, and the result is presented in column 3 of Table 3. It shows that the coefficient of BigTech finance usage is still significantly positive and its magnitude is close to that in column 5 of Table 2. Moreover, we exclude households with records of changing from non-agricultural production to agricultural production in column 4 and the result is robust. Therefore, both columns 3 and 4 suggest that the sample selection issue does not threaten the causal relationship in Table 2.

4.3. Left-censored data

As shown in Table 1, the minimum value of household agricultural income is zero, and these zero values account for 27.3 % (3579 in 13109) of the samples with agricultural production. This indicates our data has a left-censored problem in the agricultural income variable. If the reason for left censoring is related to BigTech finance usage, for example rural households switch to non-agricultural sector as BigTech finance develops, the estimations in Table 2 could be biased. We use the Tobit model to address the left-censoring problem, and the result is presented in column 5 of Table 3.[15] It shows that the positive effect of BigTech finance usage on agricultural

[14] The marginal effect of BigTech with household fixed effect remains positive; however, it loses statistical significance in column 2 of Table 3. This can be attributed to the fact that a substantial number of observations are dropped due to all-zero or all-one outcomes, as most households have not altered their participation in agricultural production.

[15] We only control county fixed effects in Tobit model in column 5 of Table 3. Tobit model uses maximum likelihood estimation to estimate coefficients, making it difficult to converge when there are too many fixed effects. This is the reason why we do not control household fixed effects in the Tobit model.

Table 2
The impact of BigTech finance usage on household agricultural income.
This table reports the panel regression estimates of county-level BigTech finance usage on household agricultural income. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. We include year fixed effects, county fixed effects, and household fixed effects as indicated. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses. See Appendix Table A2 for detailed variable definitions.

	log(AgrOut)				
	(1)	(2)	(3)	(4)	(5)
BigTech	-.082*	-.134**	-.293***	.237**	.222**
	(.043)	(.060)	(.065)	(.111)	(.107)
Num		.088***	.089***	.060**	.020
		(.029)	(.028)	(.027)	(.051)
Age		.017	.019	.048	.086
		(.039)	(.039)	(.036)	(.062)
Age2		-.011	-.004	-.033	-.099
		(.044)	(.044)	(.041)	(.071)
Eduy		.057***	.055***	.014	-.003
		(.013)	(.013)	(.013)	(.035)
Male		.475**	.525***	.367**	.555**
		(.185)	(.185)	(.167)	(.264)
FDR		-.009***	-.007***	-.005***	.002
		(.002)	(.002)	(.002)	(.003)
Marriage		.458***	.417***	.137	-.118
		(.120)	(.119)	(.109)	(.157)
Health		1.037***	1.016***	.418***	-.018
		(.133)	(.133)	(.123)	(.174)
Pension		.011	.046	.236**	.161
		(.115)	(.115)	(.105)	(.136)
CommInsur		1.297***	1.264***	1.122***	.651
		(.359)	(.355)	(.330)	(.433)
House		-.001	-.001	.000	.001**
		(.001)	(.001)	(.000)	(.001)
SocialTrust		-.044*	-.033	.041*	.026
		(.026)	(.026)	(.024)	(.032)
Internet		.000	.174*	.058	.023
		(.092)	(.094)	(.086)	(.114)
log(GDP)		1.401***	1.393***	1.397***	.899**
		(.091)	(.090)	(.354)	(.353)
Light		-1.024***	-.909***	-.495**	-.452**
		(.070)	(.070)	(.231)	(.223)
log(AgrLoans)		-.079	.228**	1.616***	1.642***
		(.099)	(.109)	(.610)	(.567)
Year FEs	No	No	Yes	Yes	Yes
County FEs	No	No	No	Yes	No
Household FEs	No	No	No	No	Yes
Observations	13109	9712	9712	9711	8297
R2	.000	.064	.071	.285	.675

income remains robust, implying that the left-censored data does not compromise the relationship in Table 2.

4.4. Instrumental variable

Although the estimates in Table 2 remain robust after considering sample selection and left-censored data, there could still be omitted variables or reverse causality that we have not taken into account, which may still threaten the inference of causality of the baseline result in Table 2. To address the potential endogeneity issue, we employ the instrumental variable methodology.

The instrumental variable we chose is the number of post offices per million people in prefecture-level cities in 1984 (N_post). This historical variable of information and communication construction, dating back 30 years ago prior to China's rapid economic development, has become inconsequential in light of the transformative changes witnessed across all regions of China following the reform and opening up policies as well as trade liberalization. Consequently, the current economic status of different regions of China exhibits minimal correlation with this particular historical variable (Gao et al., 2022; Tao et al., 2022). However, this variable partially captures the historical foundation of a city's information communication and exhibits a certain degree of correlation with subsequent network infrastructure development in the city, thereby influencing the advancement of BigTech finance (Jiang et al., 2021; Luo et al., 2023; Li et al., 2024).

Given that N_post is a cross-sectional variable and the endogenous variable BigTech in our benchmark regression is a panel variable, certain adjustments need to be made to N_post in order for it to serve as an effective instrumental variable in the fixed effect model. We multiply N_post by the year dummy variable to generate panel variables N_post2016 and N_post2018, which, in conjunction

Table 3
Sample selection and left-censored data.
This table presents regressions to address problems of sample selection and left-censored data in the panel regression estimates in Table 2. In columns 1 and 2, the dependent variable is HasAgr, a dummy variable that equals to 1 when the household is engaged in agricultural production. In columns 3 to 5, the dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. Controls are: family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, county fixed effects, household fixed effects and the inverse Mills ratio in the Heckman selection model as indicated. The sample in columns 1 and 2 includes all households in rural China and the sample in columns 3 to 5 comprises only rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. We exclude households with records of changing from non-agricultural production to agricultural production in column 4. In columns 1 and 2, marginal effects from logistic regression are presented. For columns 3, 4, and 5, we report coefficients from Heckman selection model, ordinary least square estimation, and Tobit model, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	HasAgr		log(AgrOut)		
	(1) Logit	(2) Logit	(3) Heckman	(4) OLS	(5) Tobit
BigTech	.017*	.021	.259**	.221**	.277*
	(.010)	(.229)	(.109)	(.111)	(.149)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	No	No	No	Yes
Household FEs	No	Yes	Yes	Yes	No
Inverse Mills ratio	No	No	Yes	No	No
Observations	12040	1901	8295	7539	9712
R2/ Pseudo R2	.201	.049	.676	.664	

with N_post, are subsequently employed as instrumental variables for BigTech. Thus, it can be inferred that the impact of N_post on BigTech varies across different years.

After integrating the instrumental variables into the survey data based on city codes, we use two stage least square (2SLS) to estimate the instrumental variable regression. The first stage regression result in column 1 of Table 4 demonstrates a positive and strengthening effect over time, indicating that the density of post offices per million people in prefecture-level cities in 1984 is associated with increased usage of BigTech finance.[16] The second stage regression result in column 2 reaffirms the positive impact of BigTech finance usage on household agricultural income. Furthermore, the instrumental variable test indicates that these instruments do not suffer from weak instrument problems.

It is important to note that the IV estimates of BigTech finance usage in Table 4 are considerably larger compared to the baseline estimates in Table 2. There are two possible explanations. First, the corrective endogeneity is very likely the case here (Jiang, 2017). Since we consider a regression of BigTech finance usage on household agricultural income, it may dramatically underestimate the benefit of BigTech finance because it might have more usage in areas with lower agricultural income as shown in the first three columns in Table 2. Second, the IV estimates provide local average treatment effects (LATEs) specific to the IV. The total samples can be classified into three types based on their responses to the exogenous shock: takers, never-takers, and compliers. Compliers are those households who increase their usage of BigTech finance influenced by the shock. Takers refer to those households that increase their usage of the BigTech finance regardless of whether the shock exists or not, such as those with higher education, and willingness to accept new things. Never-takers refer to households that do not use BigTech finance or increase their usage regardless of the shock, such as those with the lowest education and a particular resistance to new things. We assume there are no antagonists, the group of households that use the BigTech finance when it is not affected by the shock, but do not use the BigTech finance when it is affected by the shock (generally speaking, this group is relatively small). The instrumental variable method estimates the average effect on compliers. This effect is often not equal to the average treatment effect because the average treatment effect comes from not only compliers but also takers. Therefore, if the influence of BigTech finance usage is greater among compliers, the IV estimates will be higher than the average treatment effect.

5. How BigTech finance affects agricultural production

In this section, we investigate how BigTech finance affect agricultural production. As outlined in our hypotheses (Section 2.3), we posit that BigTech finance provides financial services to those rural households who are financially constrained or who have experienced climate disasters, enabling them to expand their production inputs and improve production efficiency. In the following

[16] It is worth noting that the coefficient of N_post in the first stage regression is estimated using a fixed effect regression model. Out of all households, only 5 (accounting for 0.066%) have changed their counties, resulting in an insignificant estimation due to the limited number of observations.

Table 4
Instrumental variable regression, 2SLS.
This table reports the 2SLS estimation. Column 1 presents the first stage estimations of 2SLS regressions, where the dependent variable is the standardized index of BigTech finance usage. Column 2 presents the second stage estimations of 2SLS regressions, where the dependent variable is household agricultural income subjected to a natural logarithmic transformation after adding one. N_post is the instrumental variable, which is the number of post offices per million people in prefecture-level cities in 1984. N_post2016 is the product of N_post and the dummy of year 2016 and N_post2018 is the product of N_post and the dummy of year 2018, which are designed so that N_post that do not change over time and takes on panel data characteristics. Controls are: family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	BigTech (1)	log(AgrOut) (2)
N_post	.029	
	(.040)	
N_post2016	.009***	
	(.001)	
N_post2018	.005***	
	(.001)	
BigTech		1.555**
		(.740)
Controls	Yes	Yes
Year FEs	Yes	Yes
Household FEs	Yes	Yes
Observations	7048	5600
R2	.898	
Weak IV F-test		38.907

analysis, we systematically examine these mechanisms by testing Hypotheses 2-5.

Hypothesis 2. We explore whether the impact of BigTech finance on household agricultural income is particularly pronounced among households with limited access to traditional financial credit. Given the absence of information regarding banks' rejection of household loan applications in CFPS, we turn to alternative survey data, the China Household Finance Survey in 2015 (CHFS2015)[17], for information on whether a household's loan application was rejected by a bank. Consequently, we evaluate Hypothesis 2 based on CHFS2015. The results are shown in columns 1 and 2 of Table 5. Due to the cross-sectional nature of the data, household fixed effects are not controlled in the regressions. Columns 1 and 2 reveal a significant impact of BigTech finance on household agricultural income only among households that have been denied access to bank credit. This finding remains robust regardless of whether we control for households' credit demand or not.

Hypothesis 3. In CFPS, we employ the margin of safety as an indicator to assess a household's financial vulnerability in terms of their capacity to bear extraordinary expenditures. Specifically, it can be calculated as follows:

$$\begin{aligned} &margin\ of\ safety = \frac{total\ income - breakeven\ income}{total\ income} \\ &where\quad breakeven\ income = \frac{household\ regular\ expenditures}{net\ income/total\ income} \end{aligned} \tag{2}$$

To calculate the margin of safety (MS) for each household, we follow a two-step process. First, we determine the break-even income, which is obtained by dividing a household's regular expenditure (including clothing, food, transportation, rental expenses, and

[17] China Household Finance Survey (CHFS) is a nationwide sample survey project conducted by China Household Finance Survey and Research Center, aiming to collect relevant information on the micro level of household finance. Since 2011, six rounds of the survey have been successfully conducted, with samples distributed in 29 provinces, 355 counties (districts and county-level cities), and 1,428 communities. Covering 40,011 households and 127,000 individuals; It is representative of national, provincial and sub-provincial cities (https://chfs.swufe.edu.cn/dczx/dczx.htm). However, variables related to rural household's lending from financial institutions were only reported in the 2015 survey. Therefore, only CHFS2015 data is used here.

Table 5
Financial constraints.
This table reports regression results for **Hypothesis 2 and 3**. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is a dummy variable indicating whether the household use BigTech financial service in column 1-2 and is the standardized index of BigTech finance usage in column 3. Rejected is a dummy variable, indicating that the household was denied loan applications by banks. FinVln is a dummy variable indicating the household with financial vulnerability. CreditNeed is a dummy variable indicating that the household has the demand for agricultural loans. Controls are: family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample in columns 1 and 2 comes from CHFS2015. The sample in column 3 comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	log(AgrOut)		
	(1)	(2)	(3)
BigTech	.193	.299	.105
	(.859)	(.859)	(.114)
BigTech*Rejected	4.335***	4.296***	
	(1.192)	(1.198)	
Rejected	.373*	-.723**	
	(.201)	(.315)	
BigTech*FinVln			.274**
			(.125)
FinVln			-.384***
			(.125)
CreditNeed		1.203***	
		(.264)	
Controls	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Household FEs	No	No	Yes
Observations	5547	5547	8101
R2	.031	.035	.679

mortgage payments) by the ratio of net income (total income minus total expenditure) to total income. This break-even income represents the minimum income required to cover the household's regular expenses. Next, we compute the MS by calculating the ratio of the difference between the total income and break-even income to the total income. This ratio provides an indication of the household's financial buffer against unexpected or extraordinary expenses. Typically, a ratio larger than 20 % suggests the household has a relatively safe margin of safety to handle such expenditures. Thus, we divide the sample based on the 20 % threshold and create a dummy variable, denoted as FinVln (MS < 20 %), which identifies households with financial vulnerability.

Given their limited capacity to cover regular expenses, financially vulnerable households naturally exhibit financial constraints. However, these households often face insolvency according to conventional banking standards, which poses challenges in accessing loans and subsequently restricts their ability to invest in agricultural production. This is supported by the coefficient of FinVln in column 3 of Table 5, indicating that financial vulnerability significantly reduces agricultural income. Nevertheless, the coefficient of BigTech*FinVln demonstrates a significant positive effect, suggesting that increased utilization of BigTech finance can mitigate the adverse impact of financial vulnerability on agricultural production. Thus, Hypothesis 3 is confirmed.

Hypothesis 4. It is widely recognized that rural households face lower incomes due to the high volatility associated with agricultural production and limited access to credit or insurance products for risk mitigation. However, by utilizing BigTech finance usage, rural households can gain convenient access to credit and insurance that enables them to recover from natural disasters that disrupt the agricultural production process. This, in turn, can result in an overall increase in their income levels. To examine this, we expect that the impact of BigTech finance on agricultural income becomes more pronounced when households face the repercussions of natural disasters, particularly among financially vulnerable households.

We utilize the annual count of natural disasters in prefecture-level cities obtained from the CSMAR database to gauge the climate risk faced by rural households. By dividing the sample into high-risk and low-risk groups based on the number of disasters in their cities per year, we create a dummy variable (referred to as HighDisaster) that identifies whether a rural household belongs to the high-risk group in a given year. The results presented in Table 6 provide empirical support for Hypothesis 4: In column 1, we observe a significantly positive coefficient of BigTech*HighDisaster, indicating that the impact of BigTech finance on agricultural income is more pronounced among households facing a higher frequency of natural disasters. Furthermore, the magnitude of the significant coefficient of BigTech*HighDisaster in column 2 surpasses that in column 3, suggesting that BigTech finance plays a greater role in mitigating natural risk among financially vulnerable households.

Hypothesis 5. First, we explore whether they choose to invest in additional production materials, acquire more land, or employ more labor. Table 7 displays the effects of BigTech finance usage on household agricultural inputs. The results indicate that a 1-unit standard deviation increase in BigTech finance usage corresponds to a substantial 5.55 % (exp(0.054)-1 = 0.0555) increase in agricultural materials and a 10.96 % (exp(0.104)-1 = 0.1096) increase in land lease. However, no significant relationship is observed between BigTech finance usage and labor costs or machinery lease.

By increasing the inputs of materials and land in agricultural production, rural households have the potential to scale up their operations and improve the efficiency of their agricultural practices. To test this, we employ two methods to assess the efficiency of agricultural production within households. The first method involves measuring household technology efficiency using stochastic frontier analysis (SFA). SFA takes into account various factors such as the costs of agricultural materials, labor, machinery leasing, other expenses, and the total value of the household's agricultural and sideline products. The second method calculates the ratio of total income to total costs in agricultural production. Both columns 1 and 2 in Table 8 show significant positive association between BigTech finance usage and agricultural production efficiency. This suggests that the utilization of digital financial services plays a role in improving the efficiency of agricultural production within rural households. So far, Table 7 and 8 provide supporting empirical evidence for Hypothesis 5.

6. The distributional effect of BigTech finance

Rural households in China, particularly those who are impoverished, have faced limited access to finance through traditional financial institutions. The emergence of BigTech finance in rural areas raises an important question regarding whether every household equally benefits from this recent advancement. We examine this distributional effect to shed light on whether BigTech finance is welfare-enhancing.

We contend that the distribution of income benefits resulting from the utilization of BigTech finance is not equitably distributed among households. As a result, we raise pertinent questions: Which households benefit the most from the progress of BigTech finance? Who are the marginal households that use BigTech finance? Does the utilization of BigTech finance contribute to the overall welfare of our society? To examine the distributional impact of BigTech finance usage on rural households, we conduct heterogeneity analysis across three dimensions: total income, age, and education.

First, we divide our sample into five groups based on the household's total income quintiles within counties in 2014 and conduct our analysis on the households within each income group. The results, as shown in Table 9, reveal that the estimated coefficient in column 1 is statistically significant at the 1 % confidence level. This suggests that only households with the lowest income (0-20 % total income group) demonstrate a significant impact of BigTech finance usage on household agricultural income, implying an asymmetric impact of BigTech finance usage on income improvement.

To quantify the income improvement for the lowest income groups, we calculate the marginal effects of BigTech finance usage on average total income within each group. Referring to column 1 in Table 9, the estimated coefficient is 1.068. This value indicates that a one-unit standard deviation increase in BigTech finance usage would result in an average household agricultural income improvement of 190.96 % (exp(1.068)-1 = 1.9096). For the lowest income group, this translates to a 63.2 % increase in household total income

Table 6
Risk management.
This table reports regression results for **Hypothesis 4**. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. MS is the margin of safety and MS < 20 % indicates that the household is financially vulnerable. HighDisaster is a dummy variable, taking the value of 1 if the household lives in a city that experienced more natural disasters. Controls are: family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet uage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors are in the parentheses.

	log(AgrOut)		
	(1) All	(2) MS<20%	(3) MS>=20%
BigTech	-.055	.109	-.261
	(.139)	(.369)	(.181)
BigTech*HighDisaster	.358***	.677**	.337**
	(.119)	(.318)	(.155)
HighDisaster	.081	.140	-.001
	(.108)	(.314)	(.142)
Controls	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes
Observations	8297	1241	4781
R2	.676	.718	.707

Table 7
The effect of BigTech finance usage on household agricultural inputs.
This table reports the panel estimations of county-level BigTech finance usage on households' agricultural inputs. Materials refers to the cost of materials used in agricultural production. HiringCost refers to labor employment costs in agricultural production. MachineryLease refers to machinery rental costs in agricultural production. LandLease refers to land lease costs in agricultural production. They all undergo a natural logarithmic transformation after being incremented by one in regressions. "HasAgriculturalMachinery" is a dummy variable taking the value of 1 if the household possesses agricultural machinery; "HasLandLease" is also a dummy variable taking the value of 1 if the household has leased land from others. BigTech is the standardized index of BigTech finance usage. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust(SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, county fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependents:	log(Materials)	log(HiringCost)	log(Machinery Lease)	HasAgriculturalMachinery	HasLandLease	Log(Land Lease)
BigTech	.054*	.037	.002	-.017	.016	.104*
	(.031)	(.085)	(.084)	(.013)	(.011)	(.061)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8297	8297	8297	8297	8297	8297
R2	.738	.620	.665	.656	.647	.688

Table 8
The effect of BigTech finance usage on agricultural production efficiency.
This table reports the panel estimations of county-level BigTech finance usage on households' agricultural production efficiency. Efficiency1 is the technology efficiency calculated by the Stochastic Frontier Model (SFA) based on the cost of farm materials, labor, machinery leasing, other costs, and the total value of the household agricultural and sideline products; Efficiency2 is the ratio of total agricultural income over total agricultural input cost. BigTech is the standardized index of BigTech finance usage. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust(SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include household controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	(1)	(2)
	Efficiency1	Efficiency2
BigTech	.001***	.163*
	(.000)	(.094)
Controls	Yes	Yes
Year FEs	Yes	Yes
Household FEs	Yes	Yes
Observations	8297	8240
R2	.996	.412

($4705.81*1.9096/14218.05 = 0.6320$) on average. Consequently, this income improvement for the lowest income households suggests that BigTech finance has the potential to aid the poor and mitigate income inequality.

Second, we divide the sample based on the average age of the household labor force into three groups: the young group (below 35 years old), the middle-aged group (35-50 years old), and the elderly group (above 50 years old). This division allows us to assess the impact of BigTech finance on agricultural income across different age groups. The results in columns 1-3 of Table 10 indicate that the middle-aged group of households is the most influenced by BigTech finance usage. We observe a significantly positive coefficient for BigTech finance usage only in the middle-aged group, while no significant effect is found for either young or elderly households. Several factors contribute to this pattern. Middle-aged households, compared to conservative elderly households, are more receptive to new technologies, have higher internet usage rates, and benefit more from the convenience of utilizing BigTech finance. Additionally, middle-aged households, as opposed to young households with greater future potential, are more likely to face exclusion from traditional finance, leading them to rely on BigTech finance for support in agricultural production. By considering the heterogeneity

Table 9

The heterogeneous impact in different percentile groups of household total income.

This table shows the heterogeneous impact of BigTech finance on household agricultural income in groups of different total income. We divide the households into five groups using the 2014 percentile of household total income within counties. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), the average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust(SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses. After regressions, we calculate the increase in total income resulting from the impact of a 1-unit standard deviation increase in BigTech finance usage on agricultural income by using the following equation: average household agricultural income * (exp(α)-1) /agerage household total income * 100.

	log(AgrOut)				
	(1)	(2)	(3)	(4)	(5)
Percentiles of total income	0-20%	20-40%	40−60%	60−80%	80−100%
BigTech	1.068***	.098	-.239	.190	.372
	(.318)	(.250)	(.237)	(.212)	(.243)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes
Observations	1071	1549	1632	1766	1755
R2	.667	.672	.666	.711	.667
Average household agricultural income, RMB	4,705.81	8,467.45	10,401.84	13,060.85	22,506.37
Average household total income, RMB	14,218.05	33,326.68	54,702.63	80,087.66	155,013.40
Increase in total income due to the impact of BigTech finance on agricultural income, %	63.20	2.62	-4.04	3.41	6.54

Table 10

Heterogeneity analysis from the perspectives of age and education.

This table illustrates the heterogenous impact of BigTech finance on household agricultural income across different age and education groups. We categorize the households based on the average age of household labor force. Column 1 represents young age group, column 2 denotes the middle-aged group, and column 3 denotes the elderly group. Columns 4 to 6 are subsamples divided by the average years of schooling of household labor force. Column 4, 5, and 6 presents primary school and below, middle school, and high school and above, respectively. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage with the national mean and the national standard deviation. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), the average health status (Health), family dependency ratio (FDR), internet application (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

Dependent:	log(AgrOut)					
Grouping basis:	Age of labor force			Education of labor force		
Groups:	Young Age<35	Middle-aged 35<=Age<=50	Elderly Age>50	Primary school and below	Middle school	High school and above
	(1)	(2)	(3)	(4)	(5)	(6)
BigTech	.220	.266*	-.120	.023	.722***	.196
	(.402)	(.141)	(.330)	(.152)	(.218)	(.363)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532	4802	1092	3593	2443	974
R2	.774	.684	.684	.686	.685	.688

across age groups, we gain valuable insights into the differential impacts of BigTech finance on agricultural income.

Finally, we conduct an analysis based on the average years of education of the household labor force, dividing the samples into three groups: primary school and below, middle school, and high school and above. This division allows us to examine the heterogeneous impact of BigTech finance usage on agricultural income across different education levels. The results presented in columns 4-6 of Table 10 indicate that for households with a middle school education level, the estimated coefficient of BigTech finance usage is positive and statistically significant at the 1 % confidence level. However, for households with an average education level of primary school or below, as well as those with a high school education level or above, the influence of BigTech finance usage on household agricultural income is not statistically significant. In other words, households that possess some capacity to learn but face limitations in accessing traditional finance benefit the most from BigTech finance. These households can leverage BigTech finance to improve their agricultural income and overcome the constraints they encounter within the traditional financial system.

Furthermore, we explore the effect of BigTech finance under different level of traditional financial development, so as to shed light on the relation between BigTech finance and traditional finance. We first look at the heterogenous effect of BigTech finance in regions with different levels of financial development on agricultural production to determine the marginal households who benefit most from BigTech finance usage. Then we directly investigate how households borrowing behavior change with the development of BigTech finance usage.

In order to assess the level of traditional financial development on agricultural production in rural areas of China, we face several challenges due to the limited availability of accurate macro data specifically focused on agricultural production in rural areas. To address this issue, we adopt two different approaches: The first approach focuses on the number of banking institutions providing financial services specific to agricultural production that operate in a specific county annually. This includes institutions such as the Agricultural Bank of China, rural credit cooperatives, and rural commercial banks. By considering the presence of these institutions, we gain further insights into the availability of traditional financial services for agricultural production in rural areas. The second approach considers the amount of agriculture-related loans granted in a province annually. The data at the county level is not available, thus analyzing the province-level amount of agriculture-related loans provides a valuable perspective on the degree of traditional financial development on agricultural production. By employing multiple measurements, we aim to capture a more comprehensive understanding of the level of traditional financial development on agricultural production in rural areas.

We conduct the analysis on subsamples divided according to the measures of financial development on agricultural production. The findings presented in Table 11 consistently show a clear pattern: the significant impact of BigTech finance usage is observed in regions with low levels of traditional financial development in agricultural production in rural areas, while there is no significant effect in areas with high levels of traditional financial development. This implies that, in rural regions where traditional financial services are underdeveloped, BigTech finance plays a crucial role in providing financial services for rural households and improves their agricultural income.

In addition, we use household observations to investigate the heterogenous effects of BigTech finance. In CFPS, we can directly observe households' use of bank loans and informal loans (e.g., loans from friends and relatives). Therefore, we could compare the effect of BigTech finance usage on individuals with and without bank loans. Specifically, we include the interaction term of BigTech finance usage and whether the household possesses a bank loan (HasBankLoans) or the amount of the bank loan (BankLoans) in the baseline regression. Results are shown in column 1 of Table 12. The coefficient of BigTech finance usage is significantly positive, while the coefficient of the interaction term of BigTech finance usage and HasBankLoans is significantly negative. This implies that the impact of BigTech finance usage is particularly pronounced among households unable to access loans from banks. The results in column 2 exhibit a similar pattern to those in column 1, with the coefficient of the interaction remaining negative and being on the margin of significance.

We also compare the effect of BigTech finance usage on individuals with and without informal loans. In particular, we use loans from relatives and friends. Results in columns 3 and 4 of Table 12 reveal significantly positive coefficients for BigTech finance usage, indicating its significant influence on agricultural income. However, the interaction terms of BigTech finance usage and loans from relatives and friends do not exhibit a significant impact on household agricultural income. These findings suggest that the utilization of

Table 11

The heterogenous impact of BigTech finance usage on agricultural income across different levels of traditional financial development.

The table shows how the impact of BigTech finance on household agricultural income varies with the development level of traditional finance. First, we categorize the sample based on the number of county-level agricultural banking institutions in columns 1 and 2. Column 3 and 4 represent results of groups based on amount of province-level agricultural-related loans. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust(SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

Dependent:	log(AgrOut)			
Grouping basis:	Number of agricultural banking institutions		Amount of agriculture-related loans	
Groups:	Low	High	Low	High
	(1)	(2)	(3)	(4)
BigTech	.359*	.162	.318**	.181
	(.213)	(.128)	(.137)	(.200)
Controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes
Observations	2741	5283	4546	3384
R2	.649	.691	.654	.714

Table 12
BigTech finance usage and traditional household finance.
This table employs the interaction term to investigate whether BigTech finance usage exerts a different influence for households with varied borrowing status. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the standardized index of BigTech finance usage. HasBankLoans is a dummy variable taking the value of 1 if the household has bank loans. BankLoans is the amount of bank loans the household borrowed, which is subjected to a natural logarithmic transformation after adding one. HasFRLoads is a dummy variable taking the value of 1 if the household has loans borrowed from friends and relatives. FRLoans is the amount of loans the household borrows from friends and relatives, which is subjected to a natural logarithmic transformation after adding one. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage), average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust(SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light), and agriculture-related loans (AgrLoans) as proxies for traditional financial development. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	log(AgrOut)			
	(1)	(2)	(3)	(4)
BigTech	.268**	.257**	.226**	.225**
	(.108)	(.108)	(.110)	(.110)
BigTech × HasBankLoans	-.416**			
	(.203)			
HasBankLoans	-.137			
	(.227)			
BigTech × log(BankLoans)		-.031		
		(.020)		
log(BankLoans)		-.009		
		(.022)		
BigTech × HasFRLoads			-.028	
			(.155)	
HasFRLoads			-.053	
			(.143)	
BigTech × log(FRLoans)				-.003
				(.016)
log(FRLoans)				-.005
				(.015)
Controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes
Observations	8293	8281	8280	8280
R2	.676	.676	.676	.676

BigTech finance is particularly beneficial for households underserved by traditional financial institutions, while exhibiting no association with social capital.

In summary, the impact of BigTech finance is most pronounced for marginal households —those with low income, a moderate level of ability and knowledge, but limited access to traditional finance. These households derive significant benefits from BigTech finance, as it serves as a bridge, filling the gap and providing them with the necessary financial services. By leveraging the advantages of technology and innovative financial solutions, BigTech finance plays a vital role in empowering these households and enabling them to overcome the financial barriers they face.

There are disagreements on whether financial services innovations have positive impacts on individuals, especially the poor (Karlan et al., 2016). Hodula (2023) utilizes a panel of 78 countries over the 2013–2019 period and shows that the impact of FinTech and BigTech credit on income inequality emerges only in countries with an already high level of financial inclusion. This seems to suggest that BigTech finance is only effective in regions where traditional finance has already been well-established. However, our findings pose a different picture that BigTech finance is more beneficial in areas with less traditional financial development. High financial exclusion of rural households provides the opportunity for BigTech companies to offer low-cost, low-barrier, and unsecured financial services. We can gain insights into the nature of their interaction and the role played by BigTech companies in the financial landscape of rural China.

This paper has thus far substantiated the usage of BigTech finance, which has effectively facilitated enhanced agricultural income for rural households previously excluded from traditional financial services. Does this imply that BigTech finance holds greater significance than traditional finance in the context of rural household agricultural production in China? To address this pivotal inquiry, we conduct a horse-race comparison of the effects of BigTech finance and traditional finance on household agricultural production. We employ the agriculture-related loans (AgrLoans) as proxies for traditional financial development and standardize all control variables in regressions to ensure comparability of coefficients between BigTech and AgrLoans. The results in Table 13 demonstrate that traditional finance and BigTech finance serve different segments of rural households. Traditional finance primarily caters to higher-income families with substantial income sources and assets, who are typically not excluded by conventional financial institutions. In contrast, BigTech finance mainly targets low-income families who lack sufficient income or assets to access financial services from traditional institutions. This finding highlights the role of BigTech finance in financial deepening, as it increases the usage of financial services among previously underserved households.

7. Conclusion

Our paper investigates the causal impact and underlying mechanism of BigTech finance usage on household agricultural income. By utilizing an index of BigTech finance usage and household survey data from the China Family Panel Studies (CFPS), we find a positive and economically significant relationship between BigTech finance usage and household agricultural income in rural areas. Our findings demonstrate that a 1-unit standard deviation increase in BigTech finance usage leads to an average rise of 24.86 % in household agricultural income. We address potential endogeneity issues by considering sample selection and left censoring. Additionally, we employ instrumental variable approaches to address any remaining endogeneity concerns. Through these robustness checks, we confirm the causal relationship between BigTech finance usage and household agricultural income.

Our analysis uncovers the underlying mechanisms driving the impact of BigTech finance usage on household agricultural production. Notably, BigTech finance exhibits a significant positive impact on agricultural income among households that lack access to conventional financial services, those grappling with financial vulnerability, and those confronted with natural disasters. By providing assistance to financially constrained rural households and those affected by climate-related shocks, BigTech finance usage leads to increased investments in agricultural materials and land leases, ultimately enhancing agricultural productivity.

Finally, we discuss the distributional effect of BigTech finance. We find that the effect of BigTech finance usage on agricultural income is particularly strong for households in the lowest-quintile of total income, while traditional finance mainly benefits households with middle-level of total income. This asymmetric impact suggests that BigTech finance has the potential to bridge the income inequality gap in rural areas. Our findings also reveal that the influence of BigTech finance predominantly originates from households on the margin—those with a moderate level of ability and knowledge and limited exposure to traditional financial services.

The findings of this study have important policy implications. First, policymakers should recognize the potential of BigTech finance in promoting financial deepening and reducing income inequality in rural areas. Our results suggest that BigTech finance can serve as a beneficial complement to traditional bank loans, particularly in the context of financial repression. This is in line with the findings of Frost et al. (2019), who show that BigTech lenders have an information advantage in credit assessment relative to traditional credit bureaus, and firms that accessed BigTech credit expanded their product offerings. By extending financial services to underserved rural households, BigTech finance can help alleviate financial constraints and enhance risk resilience among marginalized households. Policies that support the development and adoption of BigTech financial services in rural regions could further amplify these benefits.

Second, the complementary role of BigTech finance to traditional finance highlights the importance of fostering a diverse and competitive financial ecosystem. While some studies suggest that FinTech lending serves as a substitute for bank lending by catering to inframarginal borrowers (Tang, 2019; Cornaggia et al., 2018; Balyuk et al., 2022), our findings provide evidence of a complementary relationship between BigTech finance and bank services in rural areas of China. This underscores the potential for BigTech finance to fill the gaps left by traditional financial institutions and promote financial depth in underserved regions. Policymakers should encourage collaboration and healthy competition between BigTech companies and traditional financial institutions to ensure that rural households have access to a wide range of financial products and services tailored to their needs. By fostering a diverse and competitive financial system, policymakers can help ensure that rural households have access to the financial tools they need to improve their livelihoods and contribute to the overall economic development of their communities.

CRediT authorship contribution statement

Hong Zhang: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yuejing Wang:** Visualization, Validation, Formal analysis, Data curation, Methodology, Investigation. **Xiaoquan Wang:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Conceptualization.

Appendix

Fig. A1 and Tables A1 and A2

Table 13

Comparative analysis of the impact of digital finance and traditional finance on household agricultural income.

This table aims to compare the impacts of digital finance and traditional finance on household agricultural income. The dependent variable is household agricultural income, which is subjected to a natural logarithmic transformation after adding one. BigTech is the index of BigTech finance usage. AgrLoans represents agriculture-related loans as proxies for traditional financial development. Controls include family size (Num), the proportion of males (Male), average years of schooling (Eduy), average age (Age) and age squared (Age2), the marital status of the highest income member (Marriage),average health status (Health), family dependency ratio (FDR), internet usage (Internet), basic pension plan (Pension), commercial insurance (CommInsur), the net value of house assets (House), social trust (SocialTrust), GDP per capita (GDP), urbanization development measured by the brightness of lights (Light). The control variables in the regression are standardized to ensure comparability of the two coefficients. We include controls, year fixed effects, and household fixed effects. The sample comprises rural households engaged in agricultural production, drawn from the CFPS 2014, 2016, and 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are in the parentheses.

	log(AgrOut)				
	(1)	(2)	(3)	(4)	(5)
percentiles of total income:	0–20%	20–40%	40–60%	60–80%	80–100%
BigTech	.837***	.198	-.204	.150	.362
	(.310)	(.249)	(.236)	(.216)	(.246)
AgrLoans	.945	.303	-.040	1.953**	-.858
	(1.298)	(.910)	(.930)	(.872)	(.940)
Controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Household FEs	Yes	Yes	Yes	Yes	Yes
Observations	1061	1526	1632	1749	1743
R2	.662	.675	.667	.706	.673

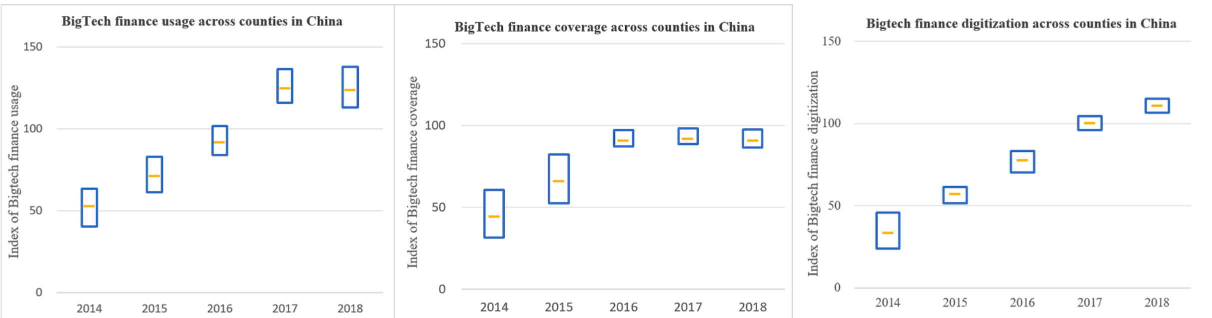

Fig. A1. BigTech finance index across counties and years.

The figure shows the variations of BigTech finance usage, coverage, and digitization across counties and years in China, illustrated by the county-level index. The yellow line within the box is the median value of the index; the upper and lower hinges of the box represent the 75th and 25th percentiles, respectively. The graph indicates that the majority of the variance in the BigTech Finance Index stems from the usage index, particularly during the period of 2016-2018. In subsequent years, there is a near-universal coverage with a median coverage index close to 100, resulting in minimal regional disparities. On the other hand, when examining the Digitization Index, it becomes evident that the variability of the index primarily stems from temporal factors rather than geographical disparities, indicating that it predominantly serves as a metric for assessing the overall digital advancement of a nation, with minimal variation observed across counties.

Table A1

Specific indicators of sub-indices of BigTech finance usage.

This table lists the specific indicators used to construct each sub-index. Source: Guo et al. (2020); Yang & Zhang (2022).

	Specific indicators
Payment	Number of payments per capita
	Amount of payments per capita
	Proportion of number of high-frequency active users (50 times or more each year) to number of users with a frequency at least once each year
Money Funds	Number of Yu'ebao purchases per capita
	Amount of Yu'ebao purchases per capita
	Number of people who have purchased Yu'ebao per 10,000 Alipay users
Credit	Number of users with an internet loan for consumption per 10,000 adult Alipay users
	Number of loans per capita
	Total amount of loans per capita
	Number of users with an internet loan for small & micro businesses per 10,000 adult Alipay users
	Number of loans per small & micro business
	Average amount of loans among small & micro businesses
Insurance	Number of insured users per 10,000 Alipay users
	Insurance coverage per capita
	Insurance amount per capita

(continued on next page)

Table A1 (*continued*)

	Specific indicators
Investment	Number of people engaged in internet investment and money management per 10,000 Alipay users
	Number of investments per capita
	Investment amount per capita
Credit	Number of credit investigations by natural persons per capita
Investigation	Number of users with access to credit-based livelihood services (including finance, accommodations, mobility, social contacts, etc.) per 10,000 Alipay users

Table A2
Variable definitions.
This table describes definitions for the main variables used in this paper.

Variable name	Definitions
HasAgr	Dummy variable, 1 indicating that the household is engaged in farming
Log(AgrOut)	Logarithmic household income from agricultural and sideline products
BigTech	Standardized index of depth of BigTech finance usage
Num	Family population
Age	Average age in the household's labor force
Age2	Square of Age variable (Ageˆ2/100)
Eduy	Average years of schooling years in the household's labor force
Male	Proportion of males in the household's labor force
FDR	Family dependency ratio ((elders+children)/laborforce*100)
Health	Average self-rated health status of all family members
Pension	Dummy variable, 1 indicating the household have any pension
CommInsur	Dummy variable, 1 indicating the household have any commercial insurance
Marriage	Dummy variable, 1 indicating the member of the household with the highest income is married
Internet	Dummy variable, 1 indicating members of the household use their phones or computers to access the Internet
House	Net house assset in the househould, total house assset value minus total house mortgage
SocialTrust	The average trust level in strangers of family members, 0 for no trust, 10 for full trust
log(GDP)	Logarithmic GDP per capita calculated using the county-level registered population
Light	The average county-level brightness of lights
log(AgrLoans)	Logarithmic amount of agriculture-related loans at province level

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