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Who Benefits from the Internet? The Impact of Internet Technology on Farmers' Agricultural Sales Performance and Its Heterogeneity

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Abstract

Smallholder farmers in developing countries often face barriers to market participation due to information asymmetry and limited access to marketing channels. This study investigates the impact of internet technology on farmers' agricultural sales and its heterogeneity, using data from the China Family Panel Studies (CFPS) covering 14,577 agricultural households. Propensity score matching and unconditional quantile regression are employed for empirical analysis. The results show that (1) internet adoption significantly improves agricultural sales performance, increasing average sales output by 4680 CNY (Chinese Yuan, the official currency of China); (2) the effects of internet adoption are heterogeneous across industry types, education level, income level, social ties, and internet access devices; (3) the marginal impact of internet use grows with higher sales levels, with the strongest effect observed at the 95% quantile. This study highlights the impact of rural internet technology on increasing market transaction efficiency.

Keywords: smallholder farmers; internet technology; agricultural sales performance; market participation; inclusiveness



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1. Introduction

Smallholder farmers' limited market participation has long been a major barrier to income growth in developing countries [1,2]. Due to the small scale of operations, low degree of organization, and asymmetric information, smallholder farmers have long been at the lower end of the agricultural value chain and have faced the challenge of “producing, selling, but failing to secure good prices” [3,4]. On the one hand, smallholders rely on traditional offline sales channels, which are constrained by spatial distance and information barriers [4,5]. Consequently, they often enter the market with outdated information and limited market access, since market information is often monopolized by intermediaries—leading to a significant squeeze on sale performance [6,7]. On the other hand, their market participation is highly blind, lacking effective supply–demand matching mechanisms and market feedback channels, which can easily lead to the stagnation, underpricing, or even waste of agricultural products [1,4]. This not only weakens farmers' ability to participate in the market on a sustained basis and reduces their income, but also indirectly affects the stability of agricultural production and supply.

In recent years, Information and Communication Technology (ICT) has developed rapidly worldwide and has become a key driver of socioeconomic transformation [8,9].

In rural areas of developing countries, ICT has injected modern elements into traditional agriculture and offered solutions to information isolation and market disconnection [9]. In the production process, ICT enables farmers to access more advanced production technologies and adopt adaptive behaviors to cope with adverse climatic conditions [10]. On the marketing side, ICT can reduce information search costs and improve access to information—including available services, farming techniques, processing options, prices, and market opportunities [1,11]. The process of technology adoption can be theoretically informed by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [12]. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of individuals' willingness to adopt new technologies, while UTAUT extends this framework by incorporating additional factors such as social influence and facilitating conditions. Accordingly, among various ICT tools, internet technology is the most widely adopted and influential, owing to its openness, interactivity, and accessibility [13,14]. It has sharply reduced the cost of accessing critical data, including market dynamics, price trends, and supply–demand conditions. As one of the core forms of digital technology application in rural areas, the internet is evolving from an information acquisition tool to a transaction aggregation platform [15,16]. Through social media, e-commerce platforms, short-video live streaming, and other formats, farmers can actively engage in product marketing, customer matchmaking, and brand building—thereby breaking the traditional constraints of information asymmetry, limited channels, and low returns. The adoption of internet technology provides a viable pathway for smallholders to overcome sales bottlenecks and integrate into the modern market system [4,8].

Some studies confirm that internet technology helps enhance smallholders' market participation by improving information accessibility, reducing transaction costs, and expanding market boundaries [5]. Meanwhile, some scholars have questioned the universality and sustainability of internet technology's effects. They thought that smallholders still face multiple barriers in accessing and utilizing the internet [17]. Moreover, the digital divide may polarize the benefits of the internet among different types of farmers, further exacerbating income inequality across regions and groups [18]. These controversies in existing studies also indicate that the literature generally overlooks the heterogeneous impacts of internet technologies. In addition to internet technology, another brand of literature examines the impact of rural e-commerce on farmers' agricultural product sales, incomes within the context of rural e-commerce development. Existing studies also report two contrasting findings regarding its effects on farmers' sales and incomes, while a smaller body of research further highlights significant heterogeneity impacts across different households and products. For example, Couture et al. [19] showed that e-commerce has had a limited impact on the income growth of rural producers and workers, with benefits primarily manifesting as a lower cost of living for a small number of rural households—those that are younger, wealthier, and located in more remote markets.

This study has two main objectives. First, we seek to examine the impact of internet technology adoption on farmers' agricultural sales performance in the Chinese context. To measure sales performance, we draw on data from the China Family Panel Studies (CFPS)—organized and implemented by the China Center for Social Science Surveys at Peking University—and use agricultural product sales as the dependent variable, with the commercialization rate of agricultural product sales employed as a robustness test. Second, we further investigate the heterogeneous effects of internet adoption across different groups of farmers, distinguished by education level, social networks, income groups, and industry types. In addition, we apply unconditional quantile regression to capture the impact across different marketing scales. By doing so, we aim to provide new explanations for the

controversies surrounding ICTs in the literature and to clarify whether internet technology promotes digital inclusion or results in elite capture.

Our study contributes to the existing literature in two important ways. We extend research on ICT adoption by focusing on marketing performance, providing new evidence for farmers' market participation. While some studies, such as Fan and Salas [20], analyze how internet adoption affects farmers' participation, few explore its role in marketing performance, particularly in the Chinese context, where agricultural production is highly decentralized and small-scale, and traditional information channels remain costly and inefficient. Second, we highlight the heterogeneous effects of internet adoption across farmers with different education levels, social networks, and income, as well as differences in their ability and willingness to adopt digital technologies. In addition, we distinguish the impacts of different internet access devices (i.e., mobile devices versus computers). Our findings offer actionable policy insights for promoting equitable and effective diffusion of internet technologies, thereby improving smallholders' market participation and incomes in rural areas.

2. Literature Review

2.1. Agricultural Market Participation

Farmers' market participation can be defined as the behavior and process which they bring their products into the market for transactions. Agricultural product sales represent the most direct form of market participation: through sales, farmers realize the value transformation of their agricultural products, which serves as the primary source of agricultural income and a key mechanism for integrating into the market system [9]. In developed countries, farmers' market participation is highly organized, relying on cooperatives to generate scale effects and reduce costs through unified standards and centralized bargaining [3]. In contrast, the main issues with farmers' market participation in developing countries include low levels of farmers' organization [4,21], the fragmentation of smallholders, low cooperative coverage (e.g., only 20% in Vietnam) [16], and an even lower probability of non-members participating in contract farming [21]. This low-organized marketing model also gives rise to multiple challenges in agricultural product marketing, including higher transaction costs, information asymmetry, and limited marketing channels [6,22–24]. As a result, farmers often lack autonomy in selling their agricultural products.

2.2. Impact of the Internet on Agricultural Marketing

2.2.1. Internet Technology and Agricultural Product Sales

The development of digital infrastructure has been identified as an effective pathway for the adoption of internet technology in developing countries [25]. Internet technology can transcend multiple constraints, playing a key role in alleviating smallholders' market participation barriers and enabling easier access to sales markets [20,26]. For example, it reduces information asymmetry and transaction costs [27–29], which are major constraints on smallholders' agricultural product marketing [26]. Consequently, internet technology exerts a positive spillover effect on farmers' market participation.

From the perspective of product sales, existing studies have confirmed the positive impact of internet use on product sales. For instance, Fan and Salas [20] found that internet use boosted smallholder farmers' domestic market sales volume in Peru by 6.2%. Zhang [2] verified the internet's positive effects across dimensions like online turnover and sales volume. Katherine [30] also confirmed that higher internet penetration effectively improves agricultural product output. Additionally, Liu and Wang [31] noted that the popularity of WeChat e-commerce significantly enhances farmers' sales performance—an effect more pronounced when social networks are strong. On the other hand, studies emphasize that

farmers can use the internet to access more agricultural sales information, expanding their information sources and positively influencing sales [1,18,32].

2.2.2. The Impact of Internet Use on Income

Beyond direct product sales, existing studies have also explored the impact of internet use on factors closely linked to agricultural sales—such as income and the rural economy. In terms of income, the internet-driven online sales model has opened up new revenue opportunities for farmers [33,34]. Additionally, Aditya and Ashok [35] noted that farms with internet access are more likely to increase their income share. Hailan Qiu [36] argued that internet technology strengthens social networks and boosts agricultural product income levels. Zou and Mishra [37] showed that the internet can also help rural households improve their profitability by facilitating social network expansion and supporting business activities. The popularization of internet technology has brought about a substantial increase in profits for farmers. Pesci et al. [8] demonstrated that the use of internet technology by California direct-marketing farmers helps to increase profits. Wang and He [38] further noted that the internet enables farmers to adapt to online sales channels, thereby reducing supply risks and increasing unit profits. Specifically, for every 1 percentage point increase in the proportion of online sales, unit profits can rise by 1.12 CNY (CNY is the ISO 4217 currency code for the Chinese Yuan (Renminbi, RMB), the official currency of China). In addition, several countries and regions have implemented internet-based programs to explore its effects on the rural economy, including agricultural productivity and agricultural resource utilization [24,26,38–42].

However, the potential risks of internet technology should not be overlooked. Over-reliance on such technology may lead to the transfer of agricultural labor to non-agricultural sectors, while the digital divide may exacerbate sales fragmentation and information overload, thereby reducing decision-making efficiency [39]. Moreover, the upfront investment, ongoing expenses, and packaging and distribution costs associated with online sales may also reduce farmers' incomes [8]. Nichols et al. [43] also found that some producers struggle to establish or optimize online sales channels due to limited technical capacity and insufficient family labor, potentially resulting in counterproductive outcomes.

2.2.3. Heterogeneous Effects of Internet Technology

The heterogeneous impact of the internet on agricultural marketing has also been discussed, particularly across regional and demographic dimensions. Regionally, the positive impact of the internet is likely to be greater, particularly for disadvantaged groups in remote or rural areas [4,44,45]. For example, O'Hara and Low [44], using USDA data, found that farms in remote rural areas were more likely to have online markets. These markets provided rural farms with more opportunities to sell their agricultural products and were more conducive to increasing their income. Pesci et al. [8] showed that despite relatively weak internet infrastructure in remote rural counties, 64% of farmers have established online markets. This phenomenon stems from the strategic reliance of remote-area farmers on online channels, as well as farmers' need to overcome geographical constraints to reach urban consumers via tools such as social media and online platforms [15]. As a result, internet use plays a more significant role in promoting agricultural sales in rural areas than in urban areas [18].

In terms of population characteristics, the effects of internet use are moderated by individual farmer characteristics, including education, age, gender, household size, and non-farm work experience [8,20,46]. For instance, Li [16] argued that farmers with higher educational attainment are better able to benefit from internet use. Pesci et al. [8] found that younger farmers are more receptive to digital tools (68% vs. 60%), as they possess

stronger digital literacy and adapt more readily to online marketing, resulting in greater income gains. Furthermore, female farmers are more likely than male farmers to engage in online sales (49% vs. 43%), thereby securing a larger share of sales through digital channels [44]. Farmers in poor health experience limited productivity gains from internet use due to reduced participation in marketing activities [47]. Xie et al. [18] also noted that single farmers achieve higher income levels. Moreover, subgroup analyses demonstrate that farmers with higher education, younger age, non-farm employment experience, and moderate household size are more likely to benefit from digital technology [48].

2.3. Literature Synthesis and Research Gaps

In summary, existing studies have explored the value of the internet in agriculture, but most of these studies focus on income and agricultural economic dimensions. Research on the impact of internet use on farmers' agricultural product sales is still limited, with a lack of in-depth exploration into the relationship between the internet and agricultural product sales performance. Moreover, the existing literature mostly focuses on the impact of e-commerce as a specific form, treating it as the primary internet-based technology affecting agricultural sales, while research on internet technology itself in relation to agricultural sales has limitations. Finally, existing research has not addressed the heterogeneous impacts of digital technologies on agricultural sales, nor has it effectively answered whether internet adoption fosters digital inclusion or reinforces elite capture.

3. Methodology

3.1. Theoretical Framework

Assume that farmers are rational economic agents whose goal is to maximize the utility derived from agricultural product sales. Given that the total output of agricultural products is (q_0), which is determined by farmers' own resource endowments (such as land, capital, and other characteristics), farmers need to allocate this output between sales (q_s) and self-consumption (q_c), i.e., $q_0 = q_s + q_c$, where $q_s \geq 0, q_c \geq 0$. The farmers' utility function is assumed to consist of two components: the monetary utility brought by sales revenue and the living utility brought by the consumption of their own food:

$$U = U(p \cdot q_s - C_2(q_s)) + V(q_c) \quad (1)$$

p denotes the unit selling price of agricultural products, and $C_2(q)$ represents the transaction costs incurred in the process of selling agricultural products, including costs associated with information search, negotiation, and transportation. Sales costs increase with the volume of sales, with $C'(q) > 0, C''(q) > 0$.

The impact of internet technology (I) on farmers' agricultural product sales operates through two channels: first, internet use expands the sales scope of farmers' agricultural products and enhances their bargaining power, thereby increasing the sales price of agricultural products, i.e., $\frac{dp}{dI} > 0$; second, the internet can reduce transaction costs in the transaction process, i.e., $\frac{dC_2}{dI} < 0$. The utility function is expressed as:

$$U = U(p(I) \cdot q_s - C_2(q_s, I)) + V(q_c) \quad (2)$$

The first-order condition for utility maximization is as follows:

$$\frac{dU}{dq_s} = U'(p(I) \cdot q_s - C_2(q_s, I)) \left(p(I) - \frac{dC_2(q_s, I)}{dq_s} \right) = V'(q_0 - q_s) \quad (3)$$

Assume that farmers are price takers, so $\frac{dp}{dq} = 0$. The equilibrium condition for the optimal sales decision is that the utility derived from selling one unit of agricultural products equals the utility loss incurred from forgoing self-consumption, thereby determining the optimal sales volume q_s^* . Meanwhile, the adoption of internet technology increases the marginal utility of agricultural product sales by raising the sales price and reducing transaction costs. This leads to a reallocation of more products from self-consumption to sales, thereby boosting agricultural product sales. Based on the above optimal conditions, a decision-making function for farmers' agricultural product sales can be constructed.

$$q^* = x(p, I, q_0, Z) \quad (4)$$

Z represents other variables influencing farmers' sales decisions, including household characteristics and individual farmer attributes.

To empirically estimate Equation (4), drawing on the research of Liu et al. [5], a multiple linear regression model is constructed to empirically analyze the impact of internet technology adoption on agricultural product sales, expressed as follows:

$$Sale_i = \alpha_0 + \alpha_1 I_i + \sum \beta_j Z_{ji} + \gamma + \omega + \varepsilon_i \quad (5)$$

$Sale_i$ denotes the agricultural product sales performance of household i , reflecting the final outcome of agricultural product sales decisions. I_i is the internet technology adoption variable, set as a dummy variable: it takes the value of 1 if internet technology is adopted, and 0 otherwise. Z_{ji} represents other household-level control variables. According to Liu et al. [15] and Nguyen et al. [47], the basic characteristics of the household heads include gender, education level, marital status, non-agricultural employment experience, and health status. In addition, we incorporate household-level characteristics that may intervene in the estimation of the causal relationship between internet technology adoption and agricultural product sales, such as government subsidies, land rental, and the level of agricultural mechanization [49]. α , and β are the estimated coefficients of the variables. γ and ω denote unobserved regional and time fixed effects, and ε_i is the error term.

3.2. Empirical Strategy

First, the ordinary least squares (OLS) method is employed to estimate Equation (6). However, OLS estimation faces two key challenges: first, the farmers' decision to adopt internet technology is subject to self-selection, which may give rise to bias and thereby lead to endogeneity issues; second, in practice, it is impossible to simultaneously observe the agricultural product sales performance of the same farmer under both scenarios of adopting and not adopting internet technology. This, combined with potential interference from unobservable other random factors, may result in biases in the OLS estimation results.

To mitigate the impact of other random factors and sample self-selection bias on the estimation results, two solutions are employed: one is the instrumental variable (IV) method, which selects variables correlated with internet technology adoption but uncorrelated with farmers' agricultural product sales to conduct two-stage least squares (2SLS) estimation; the other is to further use propensity score matching (PSM) for estimation after matching samples from the treatment group and the control group. This method is based on the logic of randomized natural experiments, defining households that have adopted internet technology as the treatment group and those that have not as the control group. By constructing a counterfactual analysis framework, it compares differences in agricultural product sales performance between the two groups. Three sets of comparative data are thus obtained: first, for the treatment group, the difference in agricultural product sales performance is estimated under the counterfactual scenario where households that adopted

internet technology switch to non-adoption—this is the Average Treatment Effect on the Treated (ATT), expressed as

$$\tau^{ATT} = E[Y_i(1) - Y_i(0) | Z_i = 1] \quad (6)$$

Second, for the control group, the difference in agricultural product sales performance is estimated under the counterfactual scenario where households that have not adopted internet technology switch to adoption—this is the Average Treatment Effect on the Controls (ATC), expressed as

$$\tau^{ATC} = E[Y_i(1) - Y_i(0) | Z_i = 0] \quad (7)$$

Third, let $E(Y_i = 1)$ represent the average agricultural product sales performance of all households when they adopt internet technology, and $E(Y_i = 0)$ represent the average agricultural product sales performance of all households under the counterfactual scenario where they do not adopt it. The difference in agricultural product sales performance across all households is then compared, expressed as

$$\tau^{ATE} = E[Y_i(1) - Y_i(0)] = E[Y_i(1)] - E[Y_i(0)] \quad (8)$$

Since Propensity Score Matching (PSM) only estimates the average treatment effect of internet technology adoption on agricultural product sales performance, unconditional quantile regression (UQR) is subsequently employed to assess the heterogeneous impact of internet adoption on agricultural product sales values across different quantiles. Koenker and Bassett [50] proposed the conditional quantile regression (CQR) method. Its estimation results are confined to the conditional distribution of the dependent variable given the covariates, relying on specific covariate configurations. It struggles to reveal the impact of marginal changes in explanatory variables on the overall distribution of the dependent variable (particularly quantiles) and may be constrained by the selection of control variables in high-dimensional settings.

Firpo et al. [51] introduced unconditional quantile regression to analyze the impact of marginal changes in the distribution of the explanatory variable X on the τ -th quantile of the unconditional distribution of Y , which is expressed as

$$RIF(q_\tau, y, F_y) = q_\tau + \frac{\tau - 1(y \leq q_\tau)}{f_y(q_\tau)} \quad (9)$$

$RIF(q_\tau, y, F_y)$ denotes the recentered influence function corresponding to the τ -th quantile of F_y , q_τ is the unconditional quantile of y , satisfying $f_y(q_\tau) = \tau$, where $f_y(\cdot)$ is the density function of y . By treating the RIF value as the dependent variable and taking internet adoption and other control variables as explanatory variables, estimation can be performed using methods such as OLS or generalized linear regression, expressed as

$$E[RIF(q_\tau, y, F_y) | X] = \alpha_0 + \alpha_1 I_i + \sum \beta_j Z_{ji} + \varepsilon_i \quad (10)$$

α_1 denotes the estimated unconditional marginal effect of internet adoption on sales performance at the τ -th quantile, reflecting the heterogeneous role of internet technology across different sales levels. The current unconditional quantile estimation does not account for sample self-selection bias. Drawing on the study by Bitler et al. [52], we first use propensity score matching to estimate the propensity score. We then weigh each observation by its inverse propensity-score weight ($1/\hat{p}$ for the treatment group and $1/(1 - \hat{p})$ for the control group) and employ inverse probability weighting to obtain unconditional quantile estimates at different quantile points.

3.3. Data Collection and Variable Selection

The data utilized in this study are derived from the China Family Panel Studies (CFPS), organized and implemented by the Institute of Social Science Survey, Peking University. Three waves of data from 2018, 2020, and 2022 are selected, with the samples exhibiting good comparability and representativeness. Given the focus on agricultural product sales, only samples of households engaged in agricultural production are retained, resulting in a final dataset containing 14,577 observations.

The dependent variable, agricultural product sales performance, is measured using the question “In the past 12 months, how much money did your family get from selling the agricultural products produced by yourselves (total output value of agricultural product sales (unit: ten thousand CNY))?” To control for the impact of the household’s agricultural production scale, the ratio of the total sales value of agricultural and sideline products to the total production value is used as a substitute dependent variable for robustness testing. Additionally, this study conducts a robustness test using the proportion of household self-produced food in total household food consumption. The rationale is that if farmers achieve high sales performance, they will sell more of their self-produced agricultural products and purchase a greater variety of externally sourced agricultural products for household consumption, thereby increasing dietary diversification.

The core explanatory variable is the adoption of internet technology, which is comprehensively measured based on whether the household’s agricultural production decision-maker accesses the internet via mobile devices (question number QU201) and computers (question number QU202). In cases where the household’s agricultural production decision-maker is missing or cannot be matched, supplementary matching is conducted using the household head or the household financial manager.

The definitions and descriptive statistical characteristics of other household-level control variables and individual farmer characteristic variables are presented in Table 1.

Table 1. Descriptive Statistical Analysis.

Variable	Definition	Unit	Mean	Std. Dev.
Agricultural sales performance	Output value of agricultural sales	10,000 CNY	1.377	4.562
Internet use	1 = Uses the internet; 0 = Does not use the internet	--	0.497	0.500
Age	Age of the household head	Years	48.451	13.504
Gender	1 = Male; 0 = Female	--	0.716	0.451
Education level	Total number of years of formal schooling successfully completed (Total number of years of formal schooling successfully completed: primary level (1–6 years), junior high level (7–9 years), senior high level (10–12 years) or tertiary level (13–16 years)).	Years	6.772	4.425
Health status	1 = Very healthy; 2 = Quite healthy; 3 = Relatively healthy; 4 = Fair; 5 = Unhealthy	--	2.948	1.245
Marital status	1 = Married; 0 = Other	--	0.794	0.405
Non-agricultural employment experience	1 = Has non-agricultural employment experience; 0 = No experience	--	0.107	0.309
Agricultural mechanization level	Total value of agricultural machinery owned by the household	10,000 CNY	0.434	1.798
Land leasing-in	1 = Leases additional land; 0 = Does not lease land	--	0.145	0.352
Government subsidies	Amount of government subsidies received	10,000 CNY	0.145	0.839

Note: Source: Authors’ calculation based on China Family Panel Studies (2018, 2020, 2022) (applicable to all tables in this paper).

4. Results and Discussion

Table 2 presents the benchmark regression results concerning the impact of internet technology adoption on farmers' agricultural product sales performance. Without controlling for other variables, the estimated coefficient of internet technology adoption is 0.714, significant at the 1% level. This indicates that, compared with non-adoption of internet technology, the adoption of internet technology increases the average output value of agricultural product sales by 7140 CNY. After controlling for other household and household head characteristics, the estimated coefficient of internet technology adoption decreases to 0.407, remaining significant at the 1% level. This suggests that the adoption of internet technology can significantly enhance farmers' agricultural product sales performance. This is consistent with our theoretical expectations, as the adoption of internet technology may enhance agricultural product sales performance by increasing sales prices and reducing search costs, even though our analysis primarily examines the impact of internet technology on sales prices and search costs. As Liu et al. [5] noted, due to high transport costs and the lack of reliable market information, farmers in developing countries who sell agricultural products are often exploited by intermediaries, ICT tool could help farmers cut out intermediaries and sell agricultural products to consumers directly. This conclusion is consistent with the findings of Fan and Salas [20] in Peru, who also found that internet technology significantly enhances farmers' market participation. In addition, this result is consistent with studies on rural e-commerce. For instance, Liu et al. [5] showed that the adoption of e-commerce technology helps increase farmers' sales prices and total income, though its role in reducing transaction costs during the sales process is limited.

Table 2. Benchmark Regression Results.

Variables	(1)	(2)	(3)	(4)
Internet use	0.685 *** (0.075)	0.0679 *** (0.119)	0.500 *** (0.139)	0.407 *** (0.118)
Age			−0.003 (0.004)	0.001 (0.004)
Gender			0.460 *** (0.088)	0.317 *** (0.085)
Education level			0.008 (0.010)	0.012 (0.009)
Health status			−0.052 (0.041)	−0.045 (0.039)
Marital status			0.360 *** (0.092)	0.315 *** (0.083)
Non-agricultural employment experience			−0.186 ** (0.149)	−0.207 * (0.112)
Agricultural mechanization level				0.479 *** (0.097)
Land leasing-in				1.936 *** (0.211)
Government subsidies				0.166 (0.119)
Constant	1.037 *** (0.053)	1.040 *** (0.059)	0.782 *** (0.211)	0.222 (0.201)
Individual Fixed effects	No	Yes	Yes	Yes
Time Fixed effects	No	Yes	Yes	Yes
Adjusted R ²	0.005	0.020	0.022	0.089
Observations	14,577	14,517	14,517	14,448

Notes: 1. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 2. Models 2–4 control for provincial fixed effects; 3. Standard errors are adjusted for clustering at the provincial level.

Regarding control variables, among household characteristics, both the level of agricultural mechanization and land rental significantly enhance agricultural product sales performance. As core technical and scale-related inputs in household agricultural production, machinery and land exert significant positive effects on agricultural product sales. Agricultural modernization emphasizes that the adoption of advanced machinery reduces labor intensity and improves production efficiency. Larger and more mechanized farms are better able to access markets, reduce per-unit marketing and transportation costs, and enhance bargaining power in the market. The impact of government subsidies on household agricultural product sales revenue is insignificant, potentially due to the structure of such subsidies. For instance, current agricultural subsidies are primarily allocated to food crops—which have relatively low product value—rather than cash crops. Thus, subsidies do not necessarily directly boost the output value of farmers' agricultural product sales.

Building on the benchmark regression, further robustness tests were conducted (Table 3). Given that a certain proportion of agricultural product sales values are zero (i.e., no agricultural products are sold to the external market), first, observations with a zero value for the dependent variable were excluded from the sample for re-estimation. The results show that the impact coefficient of internet technology adoption on the output value of agricultural product sales is 0.683, significant at the 1% level. In addition, considering that zero values may result in a left-censored distribution of the data, the Tobit model was employed for estimation, with an estimated coefficient of 0.474, significant at the 1% level. The core independent variable “internet technology adoption” was replaced with “internet usage duration” for model estimation, with an estimated coefficient of 0.060, significant at the 1% level. This further confirms that the use of internet technology can effectively increase the output value of agricultural product sales. Finally, the dependent variable was replaced for model estimation. (1) The commercialization rate of agricultural product sales was constructed to analyze the impact of internet technology adoption on agricultural product sales performance. The estimated coefficient is 0.018, significant at the 1% level, indicating that internet technology adoption can significantly increase the commercialization rate of agricultural products. (2) The food self-sufficiency rate was constructed. The results show that internet technology adoption reduces the self-sufficiency rate of self-produced agricultural products—specifically, it decreases the proportion of self-consumed food from one's own production and increases the proportion of externally purchased food. This also indirectly indicates that internet technology adoption can increase the sales rate of self-produced food and enhance agricultural product sales performance.

Table 3. Robustness Tests.

Variables	(1)	(2)	(3)	(4)	(5)
Internet use	0.583 *** (0.203)	0.474 *** (0.175)	0.060 *** (0.036)	0.018 *** (0.005)	−0.025 *** (0.003)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	9504	14,448	14,448	9504	14353
Adjusted R ²	0.116	--	0.075	0.160	0.087

Notes: 1. The dependent variables in models (1), (2), (4), and (5) are sequentially the output value of agricultural product sales, the output value of agricultural product sales, the commercialization rate of agricultural products, and the self-sufficiency rate of self-produced food. Among them, model (1) is estimated after excluding samples with zero values, and model (2) is estimated using the Tobit model (considering the left-censored distribution characteristic of the dependent variable). 2. The independent variable in model (3) is the duration of internet usage. 3. Models 1–3 control for provincial fixed effects. 4. Standard errors are adjusted for clustering at the provincial level. 5. *** $p < 0.01$.

There may be mutual causation between the adoption of internet technology and agricultural product sales. Therefore, this study uses watching short videos as an instrumental variable for internet technology adoption and employs the two-stage least squares method for analysis. The rationale for selecting this instrumental variable is that watching short videos is correlated with farmers' internet use, yet it has no direct relationship with the output value of farmers' agricultural product sales. Table 4 presents the estimation results of the endogeneity test. The results show that the estimated coefficient of internet use on the output value of agricultural product sales is 0.441, significant at the 1% level. In addition, internet use still has a significant impact on the commercialization rate and the self-sufficiency rate of self-produced food, consistent with the estimation results in Table 3. This indicates that the adoption of internet technology has a significantly positive effect on agricultural product sales performance.

Table 4. Endogeneity Test.

Variables	Output Value of Agricultural Product Sales	Commercialization Rate	Self-Sufficiency Rate of Self-Produced Food
Internet use	0.441 *** (0.183)	0.022 *** (0.007)	−0.021 *** (0.009)
Fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	7795	5172	7735
Adjusted R ²	0.090	0.019	0.022

Note: *** $p < 0.01$.

To avoid biases in model estimation caused by sample self-selection, this study further employs Propensity Score Matching (PSM) for estimation, with the output value of agricultural product sales as the dependent variable. First, to ensure the model's matching quality and result accuracy, a balance test is conducted on the control variables of the treatment and control groups, which—together with the propensity scores—supports the hypothesis testing. Once the hypotheses are satisfied, the average treatment effect is estimated. Table 5 presents the average treatment effects after matching via three methods—nearest neighbor matching, radius matching, and kernel matching—with relatively robust estimation results. Taking nearest neighbor matching as an example, for households that have not adopted internet technology, the agricultural product sales output value will increase by 0.374 ten thousand CNY after they adopt the technology. For households that have already adopted internet technology, if they had not done so, their agricultural product sales output value would have decreased by 0.445 ten thousand CNY. The overall average treatment effect between the treatment and control groups is 0.409, with all coefficients significant at the 1% level.

Table 5. Estimation Results of Propensity Score Matching.

Variables	Nearest Neighbor Matching	Radius Matching	Kernel Matching
ATU	0.374 *** (0.110)	0.340 *** (0.102)	0.376 *** (0.100)
ATT	0.445 *** (0.110)	0.361 *** (0.091)	0.349 *** (0.079)
ATE	0.409 *** (0.098)	0.351 *** (0.078)	0.362 *** (0.095)
Observations	14,508	14,508	14,508

Note: 1. ATU = Average Treatment Effect on the Untreated; ATT = Average Treatment Effect on the Treated; ATE = Average Treatment Effect. 2. *** $p < 0.01$.

Given the significant differences between planting industry and animal husbandry and fishery, a heterogeneity test was conducted according to industrial classification. Table 6 presents the estimation results for OLS and PSM, respectively. For the planting industry, the estimated coefficient of internet technology adoption on farmers' agricultural product sales output value is 0.367 (PSM), which is significant at the 1% level, indicating that internet technology adoption increases the sales output value of planting products by 0.367 ten thousand CNY. For animal husbandry and fishery, the impact coefficient of internet technology adoption is 0.477, meaning that internet technology adoption increases the sales output value of animal husbandry and fishery products by 0.477 ten thousand CNY. Compared with the planting industry, internet technology adoption has a greater impact on the agricultural product sales performance of households engaged in animal husbandry and fishery. This may be because animal husbandry and fishery themselves have higher industrial economic value than the planting industry and are more susceptible to market fluctuations. Sectors with higher value-added products typically require stronger information support and market integration to achieve optimal returns. Moreover, compared with staple crops that often face relatively stable demand and government-regulated prices, animal husbandry and fishery products are more market-oriented and price-sensitive [53]. In such sectors, the ability to access accurate market and price information through the internet significantly reduces uncertainty and enhances bargaining power in transactions. Internet technology enables farmers to obtain market and price information more quickly and timely, thereby enhancing agricultural product sales performance.

Table 6. Industrial Heterogeneity.

Variables	Planting Industry	Planting Industry	Animal Husbandry and Fishery	Animal Husbandry and Fishery
	OLS	PSM	OLS	PSM
Internet use	0.411 *** (0.092)	0.367 *** (0.105)	0.598 *** (0.194)	0.477 *** (0.142)
Adjusted R ²	0.102	--	0.069	--
Observations	13,945	13,945	7096	7096

Note: *** $p < 0.01$.

To further explore differences in how internet use impacts the agricultural product sales performance of farmers with distinct characteristics, this study conducts a heterogeneity analysis of farmer groups across three dimensions—educational attainment, social networks, and income level—to clarify the actual effect of internet technology in empowering agricultural product sales. Specifically, farmers are classified according to the following criteria: (1) educational attainment is divided into two groups—junior high school and below, and above junior high school; (2) income level is grouped based on an annual household income threshold of 40,000 CNY (the median value); and (3) social networks are distinguished by a social relationship score, with farmers scoring above 6 points (out of 10) categorized as having stronger networks. The results are presented in Tables 7–9.

Table 7. The heterogeneous impacts of Internet use across education levels.

Variables	High Education Level	High Education Level	Low Education Level	Low Education Level
	OLS	PSM	OLS	PSM
Internet use	0.134 (0.149)	0.294 (0.277)	0.443 ** (0.126)	0.324 ** (0.131)
Observations	2400	2400	12,046	12,046

Note: ** $p < 0.05$.

Table 8. The heterogeneous impacts of Internet use across social networks.

Variables	Strong Social Networks	Strong Social Networks	Weak Social Networks	Weak Social Networks
	OLS	PSM	OLS	PSM
Internet use	0.367 ** (0.139)	0.323 ** (0.144)	0.585 *** (0.133)	0.659 *** (0.137)
Observations	9329	9329	3559	3559

Note: ** $p < 0.05$, *** $p < 0.01$.**Table 9.** The heterogeneous impacts of Internet use across income levels.

Variables	High Income Level	High Income Level	Low Income Level	Low Income Level
	OLS	PSM	OLS	PSM
Internet use	0.445 ** (0.210)	0.374 *** (0.143)	0.075 ** (0.047)	0.032 (0.044)
Observations	7437	7437	6652	6652

Note: ** $p < 0.05$, *** $p < 0.01$.

In terms of educational attainment, for households with a higher level of education, the adoption of internet technology has a positive but statistically insignificant impact on farmers' agricultural product sales performance. However, for households with a lower level of education, the adoption of internet technology significantly improves their agricultural product sales performance with a significantly positive impact, and the estimated coefficient is 0.324. This indicates that the impact of internet technology on the output value of agricultural product sales is greater for farm households with the lowest educational attainment than for those with a higher level of education. This is consistent with the findings of Fabregas et al. [53] regarding Africa and India. Farmers with lower educational attainment have relatively limited channels for obtaining agricultural product sales information and are more willing to adopt easily accessible and structured information channels. Consequently, the transmission effect of agricultural information via mobile phone-based internet technology is more pronounced. Moreover, less-educated farmers may also exhibit higher responsiveness to timely and concrete information provided digitally because it reduces the search and transaction costs associated with market participation. This is also consistent with the study by Zheng and Ma [10] who found that internet use significantly improved farmers' production and sales profit, with the effect being particularly pronounced among those with lower educational attainment.

From the perspective of social networks (as shown in Table 8), for households with strong social network ties, internet technology exerts a significant impact on the output value of their agricultural product sales, with an estimated coefficient of 0.323; for households with weak social network ties, internet technology has a significant and greater impact on the output value of their agricultural product sales, with an estimated coefficient of 0.659. This indicates that compared with households with strong social network ties, those with weak social network ties can more effectively increase the output value of their agricultural product sales through the adoption of internet technology. It further demonstrates that the rapid development of internet technology in rural areas can more effectively generate industrial inclusiveness effects and promote inclusive development across different types of households. One possible explanation is that farm households with stronger social networks already benefit from established channels for accessing market information and trading opportunities. By contrast, households with weaker networks face higher barriers in accessing reliable and timely information. For them, the internet serves

as an efficient substitute for traditional social capital, providing access to broader market opportunities, reducing information asymmetry, and lowering transaction costs.

From the perspective of income level (as shown in Table 9), farmers with higher household per capita income experience a more significant improvement in their agricultural product sales performance after using the internet. Farmers with higher incomes typically have better infrastructure and larger industrial scales (e.g., smartphones, broadband networks) and are more capable of engaging in activities such as accessing e-commerce platforms and conducting advertising promotions—thereby further amplifying the marginal benefits and industrial development brought by the internet. For households with lower income levels, the impact of internet technology adoption is also positive but insignificant.

To test whether government subsidies help enhance the impact of internet technology on the output value of agricultural product sales, the results are presented in Table 10. For households that received government subsidies, the impact coefficient of internet technology adoption on the output value of their agricultural product sales is 0.146, which is insignificant at the 10% level. For households that did not receive government subsidies, the estimated coefficient of internet technology adoption on the output value of their agricultural product sales is 0.722, which is significant at the 10% level. The findings of this study indicate that government subsidies have not formed a policy synergy with digital technology to promote the development of agricultural product sales. This is correlated with the design and targeting of agricultural subsidies, which are often oriented toward stabilizing production or ensuring food security. As a result, the subsidies may not directly incentivize households to engage in internet-based sales channels, thereby weakening the marginal effect of internet adoption.

Table 10. The heterogeneous impacts of Internet use across government subsidies.

Variables	With Government Subsidies	With Government Subsidies	Without Government Subsidies	Without Government Subsidies
	OLS	PSM	OLS	PSM
Internet use	0.132 ** (0.106)	0.146 (0.120)	0.770 *** (0.215)	0.722 *** (0.176)
Observations	8323	8323	6125	6125

Note: ** $p < 0.05$, *** $p < 0.01$.

Table 11 further presents the estimation results of the unconditional quantile regression. At the 5% quantile, the estimated coefficient for the impact of internet technology adoption on farmers' agricultural product sales output value is positive but insignificant, indicating that internet technology has no significant impact on farmers with relatively low agricultural product sales volumes. From the 25% to the 95% quantile, the impact coefficients of internet technology adoption on farmers' agricultural product sales output value are 0.038, 0.074, 0.206, and 1.904 in sequence, all significant at the 1% level. This indicates that as the output value of agricultural product sales continues to increase, the promotional effect of internet technology adoption on agricultural product sales grows progressively, reflecting a significant heterogeneous impact across the distribution. These findings are consistent with recent research showing that the benefits of digital technologies in agriculture are not evenly distributed. For example, Ma and Zhang [10] found that internet use significantly improves farm household income in rural China, with stronger effects for households that are more market-oriented.

Table 11. Quantile Regression.

	5% Quantile	25% Quantile	50% Quantile	75% Quantile	95% Quantile
Internet use	0.012 (0.015)	0.038 *** (0.021)	0.074 *** (0.036)	0.206 *** (0.069)	1.904 *** (0.456)

Note: *** $p < 0.01$.

In addition, existing studies have also compared the effects of different internet access devices. Fabregas et al. [54] noted that in low-income countries, mobile phones have a higher penetration rate and lower information transmission costs, thus exerting a more direct impact on agricultural market behaviors. Fan and Salas [20] found that while both mobile phones and internet access help improve farmers' market participation, the overall impact of the internet is stronger than that of mobile phones. Building on this, this study further compares the impact of different internet access methods on farmers' agricultural product sales performance. The empirical results are presented in Table 12. Accessing the internet via mobile devices has a significantly positive impact on the output value of agricultural product sales, with a coefficient of 0.379, significant at the 1% level; in contrast, the impact coefficient for internet access via computers is 0.200, insignificant at the 10% level, indicating a relatively weak effect. This may be because mobile devices such as smartphones have a much higher penetration rate in rural China than computers, and smartphones offer greater flexibility in information search and transmission, along with ease of operation—thus playing a more pronounced role in farmers' agricultural product sales.

Table 12. Comparison of Effects between Mobile Phones and Computers.

Variables	Mobile Device	Mobile Device	Computer	Computer
	OLS	PSM	OLS	PSM
Internet use	0.419 *** (0.123)	0.364 *** (0.130)	1.857 (1.631)	0.197 (2.774)
Controls	Yes	Yes	Yes	Yes
Observations	13,020	13,020	7244	7244

Note: *** $p < 0.01$.

5. Conclusions and Policy Implications

The difficulty small-scale farmers face in selling agricultural products is a structural issue that hinders the modernization of agriculture in developing countries. Using data from the China Family Panel Studies (CFPS), this paper systematically examines the impact of internet technology adoption on farmers' agricultural product sales performance and its heterogeneous characteristics. The results show that internet technology adoption has significantly improved farmers' agricultural product sales performance, with the average output value of their agricultural product sales increasing by 4680 CNY. The role of internet technology exhibits significant heterogeneity. At the industry level, the promotional effect of the internet on sales performance is greater for farmers engaged in animal husbandry and fishery than for those engaged in crop farming. At the group level, farmers with lower educational attainment and weaker social networks benefit more significantly from internet technology. This indicates that the internet has alleviated, to a certain extent, the sales disadvantages stemming from insufficient traditional information acquisition capabilities, reflecting the characteristics of technological inclusiveness.

In contrast, high-income farmers experience a relatively greater improvement in sales performance, owing to their stronger ability to apply digital tools and better resource endowments. In addition, the results of the unconditional quantile regression show that as

sales output value increases, the marginal effect of the internet rises, reaching 23,440 CNY at the 95% quantile. This indicates that the internet has a more prominent enabling effect on farmers with larger sales scales. Government subsidies have not formed a synergistic effect with internet technology. Among farmers who received subsidies, the internet's impact on sales performance is insignificant, which may be related to the orientation of subsidy policies (focusing on food crops rather than high-value-added cash crops) and farmers' reliance on subsidies.

The findings of this study have several policy implications for promoting rural information technology and increasing market transaction efficiency. First, the government should strengthen network infrastructure coverage and quality in rural areas, expanding 5G network coverage to remote villages, effectively reducing internet data fees and the cost of using smart devices, and fully leverage the accessibility and convenience of smartphones. By developing dedicated mobile apps or smart mini-programs, farmers can more easily and quickly access market price and transaction information through farmers' smart phones, thereby lowering transaction barriers. Agricultural extension personnel can also include training on mobile app usage to enhance their applicability. Second, efforts should focus on enhancing the income-generating effects of internet applications for low-income farmers. The study confirms that while the income effects of internet technology are generally inclusive in terms of education and social capital, this inclusivity is less evident at the income level. While maintaining the current inclusive effects, the government should strengthen digital technology adoption among low-income groups through measures such as smart device subsidies and skill training. At the same time, digital tools should be designed to be simple and user-friendly for farmers with lower education levels, incorporating features such as voice guidance, WeChat groups, short-video or offline support channels to reduce usage barriers. Finally, the government should actively promote a shift in subsidies from production-oriented approaches to technology-linked strategies. Sales-oriented subsidies, such as smart device grants, logistics and transaction subsidies, or e-commerce sales rewards, can create a mutually reinforcing effect between government support and internet technology, boosting farmers' income.

This study has certain limitations. We do not differentiate the impacts of various internet technology models on agricultural sales performance. With the rapid rise in short-video e-commerce and live-streaming commerce, these emerging platforms may influence farmers in distinct ways. However, due to data constraints, this study was unable to fully capture these effects or the marginal differences. Future research could address this by using more detailed data and focusing on specific internet models.

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