

Article

Social Commerce, Acquaintance Networks, and Smallholder Income: The Case of Pinggu District Peach Farmers

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Abstract

In the context of digital rural development, social commerce has become a low-threshold channel through which smallholders can connect directly with consumers. Yet limited evidence explains how acquaintance-based social networks shape the income effects of social commerce in fresh agricultural-product marketing. Using survey data from 724 peach-farming households in Pinggu District, Beijing, in 2024, this study examines the effect of WeChat-based direct marketing on farmers' per capita net income from peach production. Benchmark regression, propensity score matching, and an instrumental variable approach are used to address selection bias and potential endogeneity. The results show that WeChat-based direct marketing significantly increases farmers' income, with the fully controlled benchmark estimate indicating an increase of 0.287 log points in per capita net income. This finding remains stable after replacing the dependent variable, addressing extreme values, and excluding special samples. Mechanism analysis indicates that the income effect operates mainly through higher average selling prices. Heterogeneity analysis further shows that the effect is stronger among households with higher social expenditure, suggesting that acquaintance-based embeddedness helps transform social relations into market value. Going beyond prior studies that focus mainly on participation, sales performance, or average income effects, this study identifies the selling-price transmission mechanism and shows that acquaintance-network embeddedness amplifies the income gains from WeChat-based direct marketing.

Keywords: WeChat-based direct marketing; social commerce; acquaintance society; smallholders; farmer income; social networks

Academic Editor: Giuseppe Timpanaro

Received: 10 June 2026

Revised: 28 July 2026

Accepted: 28 July 2026

Published: 30 July 2026

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1. Introduction

With the rapid development of the digital economy, agricultural e-commerce has become an important channel for agricultural product circulation and rural market integration [1,2]. Compared with traditional marketing systems centered on wholesale markets and intermediaries, e-commerce provides new opportunities for smallholder farmers to reach broader consumer markets, improve access to market information, and participate more directly in agricultural value chains [3–5]. In China, rural e-commerce has also been regarded as an important policy instrument for promoting agricultural product sales, linking smallholders with modern agriculture, and enabling rural households to share the

benefits of digital development [6–9]. Existing studies suggest that rural e-commerce can reduce transaction costs, expand market access, and contribute to household income growth and inclusive employment opportunities [10–13]. However, these benefits are not automatically accessible to all smallholders. Many farmers still face barriers when entering e-commerce markets, including weak consumer trust in online agricultural products, difficulties in connecting with e-commerce supply chains, mismatches between small-scale production and diversified consumer demand, limited online operation capacity, and insufficient organizational coordination. As a result, smallholders often participate indirectly through intermediaries, enterprises, cooperatives, or other leading actors, remaining primary suppliers rather than independent market actors.

In recent years, the widespread use of mobile internet and social media has promoted the rapid development of social commerce, making it a new form of agricultural e-commerce. Social commerce integrates e-commerce and social networking, in which social interaction, user recommendations, trust mechanisms, and relationship-based communication play important roles in transactions [14–18]. In China, WeChat provides a low-threshold channel for smallholders to conduct online marketing and direct sales [19]. Other rapidly developing social-commerce modes in China include livestream marketing on Douyin, Kuaishou, and Taobao Live, which relies on algorithmic traffic, real-time product demonstrations, and host–viewer interaction to reach broad consumer groups [20,21]. Recent studies have further examined farmers' adoption of agricultural livestreaming e-commerce and the roles of platform support, streamer characteristics, product attributes, and livestreaming scenes in shaping farmer participation and consumer engagement [22,23]. Compared with these livestreaming channels, WeChat-based direct marketing requires less investment in public-traffic acquisition and professional live operation and relies more strongly on private social networks, repeated communication, and pre-existing interpersonal trust, making it particularly suitable for smallholders and motivating this study's specific focus on WeChat. Its distinctive feature lies in the embeddedness of transactions in an acquaintance society. Economic action is not isolated from social relations; market transactions are often embedded in social networks and shaped by trust, information flows, and relational constraints [22–28]. For fresh agricultural products, where quality is difficult to standardize and intrinsic attributes are not easily observed by consumers, information asymmetry is particularly strong [29,30]. WeChat-based direct marketing can transform offline acquaintance relationships into online customer networks, while trust and reputation constraints may reduce perceived quality risks, restrain opportunistic behavior, and support repeated transactions [31–33].

From the consumer perspective, trust is particularly important in social commerce because it reduces perceived quality and transaction risks and strengthens purchase intentions [14,18,31–33]. For fresh agricultural products, acquaintance-based communication, customer feedback, and reputation signals may help consumers evaluate product credibility when quality cannot be fully observed before purchase. A growing body of literature has examined rural e-commerce and farmers' income. One strand of research focuses on how smallholders participate in e-commerce, suggesting that high platform entry costs, weak online operation capacity, limited digital skills, and insufficient supporting services often push smallholders toward indirect participation through enterprises, cooperatives, or e-commerce service providers. Studies on social capital and farmers' e-commerce participation further show that social networks can affect farmers' digital market entry, entrepreneurial behavior, and e-commerce performance [34,35]. Other studies on agricultural digitalization, digital divides, and digital skills suggest that farmers' ability to use digital tools remains an important condition for effective participation in online markets [36–40]. Some studies also show that smallholders can participate directly through social media applications, forming farmer-to-consumer sales channels [41].

Evidence from Africa, South Asia, and Latin America also indicates that mobile communication, digital market information, and internet-based channels can reduce information frictions and improve farmers' market access and price outcomes [42–44]. Another strand examines the income effects of rural e-commerce and finds that e-commerce can increase farmers' income by expanding sales channels, reducing transaction costs, alleviating information asymmetry, improving bargaining power, and increasing the market value of agricultural products. A further strand discusses the practical barriers faced by smallholders in accessing e-commerce markets, including weak product standardization, limited online marketing ability, inadequate logistics conditions, and high costs of connecting with downstream distribution channels. For fresh agricultural products, studies on farmers' markets, short food supply chains, alternative food networks, and local food systems further suggest that direct producer–consumer connections can help communicate product quality, origin, freshness, and local identity, thereby strengthening consumer trust and market value [42–50].

Although these studies provide an important basis for understanding rural e-commerce and farmers' income growth, several issues remain underexplored. First, most existing studies treat rural e-commerce as a general phenomenon or focus mainly on platform-based e-commerce, while WeChat-based social commerce as a smallholder direct-marketing model has received less attention. Second, although many studies examine whether e-commerce increases farmers' income, the selling-price mechanism through which WeChat-based direct marketing promotes income growth remains insufficiently examined. For fresh products such as peaches, income growth depends not only on whether farmers sell online, but also on whether they can obtain higher selling prices by bypassing intermediaries, matching differentiated consumer demand, and enhancing consumer trust. Third, the role of social network embeddedness in shaping heterogeneous income gains from social commerce has not been fully discussed.

To address these gaps, this study examines WeChat-based direct marketing among peach farmers in Pinggu District, Beijing, China. Pinggu peaches (*Prunus persica* (L.) Batsch) are a representative fresh agricultural product with strong regional characteristics, high quality heterogeneity, and high requirements for timely marketing, consumer trust, and logistics fulfillment. Based on field survey data collected from 724 peach-farming households in 2024, this study evaluates whether WeChat-based direct marketing increases smallholder income and further examines its underlying mechanism. Specifically, a benchmark regression model is first used to estimate the effect of WeChat-based direct marketing on farmers' per capita net income from peach production. Propensity score matching and an instrumental variable approach are then employed to address potential selection bias and endogeneity. Several robustness checks are conducted, including replacing the dependent variable, using winsorized regression, and excluding special samples. Finally, this study tests whether WeChat-based direct marketing increases income by raising the average selling price of peaches and examines whether household social expenditure, which reflects farmers' embeddedness in acquaintance society, affects this income effect.

This study contributes to the literature in three ways. First, it shifts the analytical focus from rural e-commerce in general or platform-based e-commerce to WeChat-based social commerce, providing micro-level evidence on a low-threshold direct-marketing model for smallholders. Second, it clarifies the mechanism underlying the income effect of e-commerce by examining whether WeChat-based direct marketing promotes income growth through price premiums. Third, it investigates whether farmers with different levels of embeddedness in acquaintance society benefit differently from WeChat-based direct marketing, thereby providing evidence on the inclusiveness and boundary conditions of social-commerce-based income growth. The remainder of this paper is organized as

follows. Section 2 develops the mechanism analysis and research hypotheses. Section 3 describes the study area, data sources, variable measurement, and empirical strategy. Section 4 presents the empirical results. Section 5 discusses the main findings. Section 6 concludes and proposes policy implications.

2. Mechanism Analysis and Research Hypotheses

2.1. WeChat-Based Direct Marketing as a Social Commerce Model for Smallholders

WeChat (Tencent, Shenzhen, China)-based direct marketing refers to a social-commerce model in which smallholders use WeChat Moments, group chats, private messages, and friend-to-friend referrals to sell agricultural products directly to consumers. Unlike platform-based e-commerce, this model does not mainly depend on formal online stores, paid traffic, or complex platform rules. Instead, it relies on social interaction, acquaintance networks, private traffic, and relationship-based trust. For smallholders with limited digital skills, weak online operation capacity, and insufficient resources for platform-based marketing, WeChat-based direct marketing provides a relatively low-threshold way to enter digital markets [14–19,36–41]. In the case of peach farmers, its operational logic can be understood from the following four aspects. In the case of peach farmers, the operational logic of WeChat-based direct marketing is illustrated in Figure 1 and can be understood from the following four aspects.

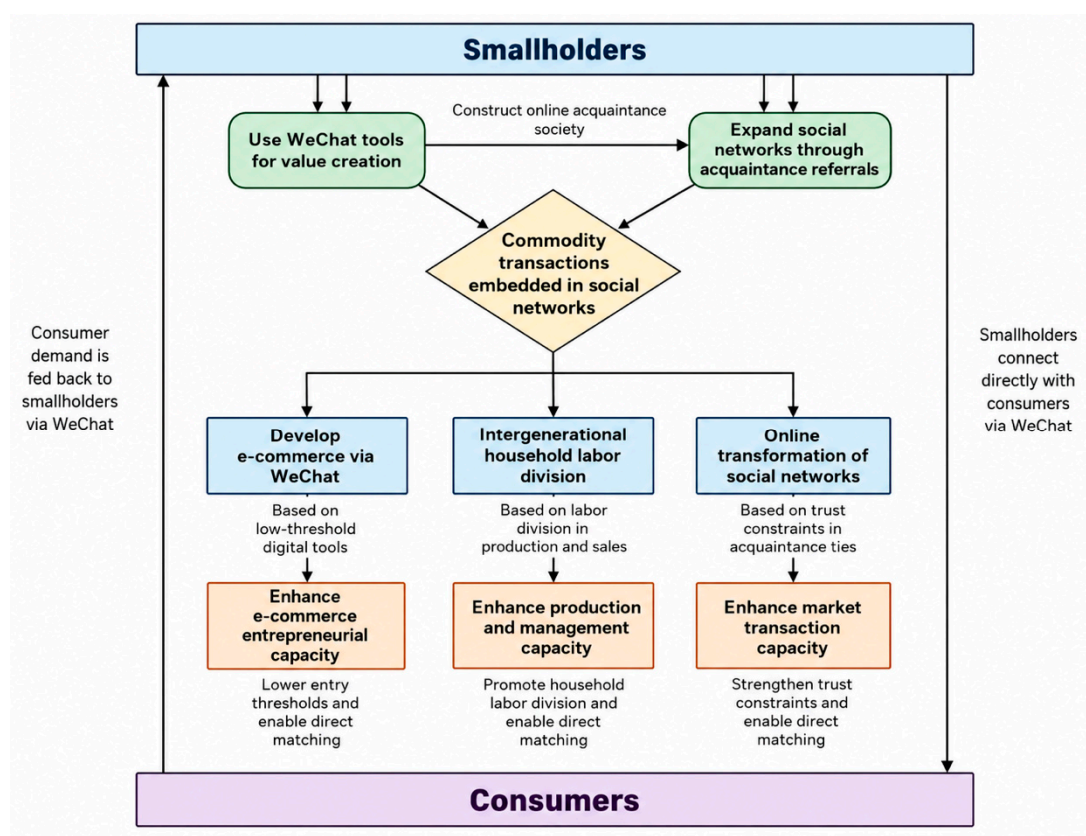


Figure 1. WeChat-based direct marketing model for smallholders.

First, smallholders use WeChat to conduct business activities, thereby improving their e-commerce entrepreneurial capacity. In platform-based e-commerce, farmers often need to register stores, design product pages, purchase traffic, respond to platform rules, and maintain continuous online operations. These requirements may exceed the capacity of many small-scale farmers, especially where rural digital divides and unequal digital skills remain evident [36–40]. By contrast, WeChat-based direct marketing allows farmers

to use familiar social media tools to publish peach information, display product quality, communicate with consumers, receive orders, and arrange delivery. Social media has been shown to provide direct marketers with opportunities to connect farmers and consumers, although lack of time and technical expertise may still constrain farmers' active use of these channels [41]. In this way, farmers can conduct online marketing without fully entering formal e-commerce platforms. This reduces the initial cost of digital marketing and enables smallholders to participate in e-commerce within their familiar social and production environment.

Second, smallholders implement household intergenerational division of labor, thereby improving their production and marketing capacity. Smallholder households are usually organized around family labor. In peach production, older household members are often more familiar with orchard management, fruit thinning, bagging, harvesting, grading, and local trading practices, while younger members are generally more capable of using smartphones, WeChat, mobile payment, online communication, and express delivery services. WeChat-based direct marketing therefore makes it possible for household members to divide tasks between production and marketing. Older members continue to undertake orchard production and quality control, while younger members take responsibility for online promotion, customer communication, order processing, payment collection, and logistics coordination. This intergenerational cooperation helps smallholder households extend from the production stage to the sales stage and strengthens their ability to participate in agricultural value chains. Existing studies also show that agricultural digitalization is reshaping farmers' production practices, information use, and marketing routines, while digital skills can affect farmers' agricultural entrepreneurship by improving access to production credit, modern technologies, and social capital [36–40].

Third, smallholders embed commodity transactions in online acquaintance-based social networks, thereby improving their market transaction capacity. In traditional peach marketing, farmers often sell peaches to intermediaries and have limited direct contact with final consumers. In WeChat-based direct marketing, however, transactions are embedded in networks of relatives, friends, neighbors, classmates, colleagues, and referrals from existing customers. Economic action is therefore closely connected with social relations, trust, information flows, and reputation constraints [22–28,34,35]. This feature is particularly important for fresh agricultural products. Because consumers cannot fully observe the quality, taste, freshness, and production process of peaches before purchase, information asymmetry is strong [29,30]. Short food supply chains and direct marketing channels are often seen as ways to reduce information asymmetry and rebuild consumer trust in food markets [42–50]. Through WeChat Moments, group chats, pictures, videos, customer feedback, and repeated interaction, peach farmers can display production scenes, harvesting processes, product quality, and delivery information. This helps reduce consumers' quality uncertainty and strengthens trust. Evidence on WeChat e-commerce also indicates that social connections between farmers and consumers can enhance smallholder agricultural sales performance [19].

Fourth, government-supported e-commerce public services improve online fulfillment capacity. WeChat-based direct marketing does not end with online communication and order formation. For fresh peaches, effective fulfillment also depends on grading, packaging, express delivery, freshness preservation, and timely transportation. If rural logistics services are weak, online orders may be difficult to transform into completed transactions. Therefore, village-level express delivery services, e-commerce service stations, public logistics facilities, and local government support can improve the feasibility of WeChat-based direct marketing. These services help farmers reduce delivery costs, improve fulfillment efficiency, and expand the geographical scope of peach sales. Studies on agricultural product e-commerce also emphasize that logistics capacity and supporting

services are important conditions for the effective operation of online agricultural product markets. For perishable agricultural products, inefficient logistics and inadequate cold-chain facilities may lead to product loss, higher costs, and weaker market performance, making public logistics support particularly important [51–54].

In summary, WeChat-based direct marketing enables smallholders to use familiar digital tools, organize household labor more effectively, mobilize online acquaintance-based social networks, and rely on public logistics services to complete online transactions. It therefore provides a feasible social-commerce model for smallholders to connect directly with consumers, improve their market participation capacity, and contribute to the economic and social dimensions of sustainable rural development [55,56]. Based on this analysis, this study proposes the following hypothesis:

H1. *WeChat-based direct marketing has a positive effect on smallholder income.*

2.2. Income-Increasing Mechanism of WeChat-Based Direct Marketing

This study constructs an analytical framework for the income-increasing mechanism of WeChat-based direct marketing, as shown in Figure 2. Through WeChat, smallholders can directly connect with consumers, changing the traditional marketing channel from “smallholder–intermediary–consumer” to “smallholder–consumer”. WeChat-based direct marketing promotes smallholder income growth mainly by increasing the selling price of peaches. The specific mechanisms are as follows.

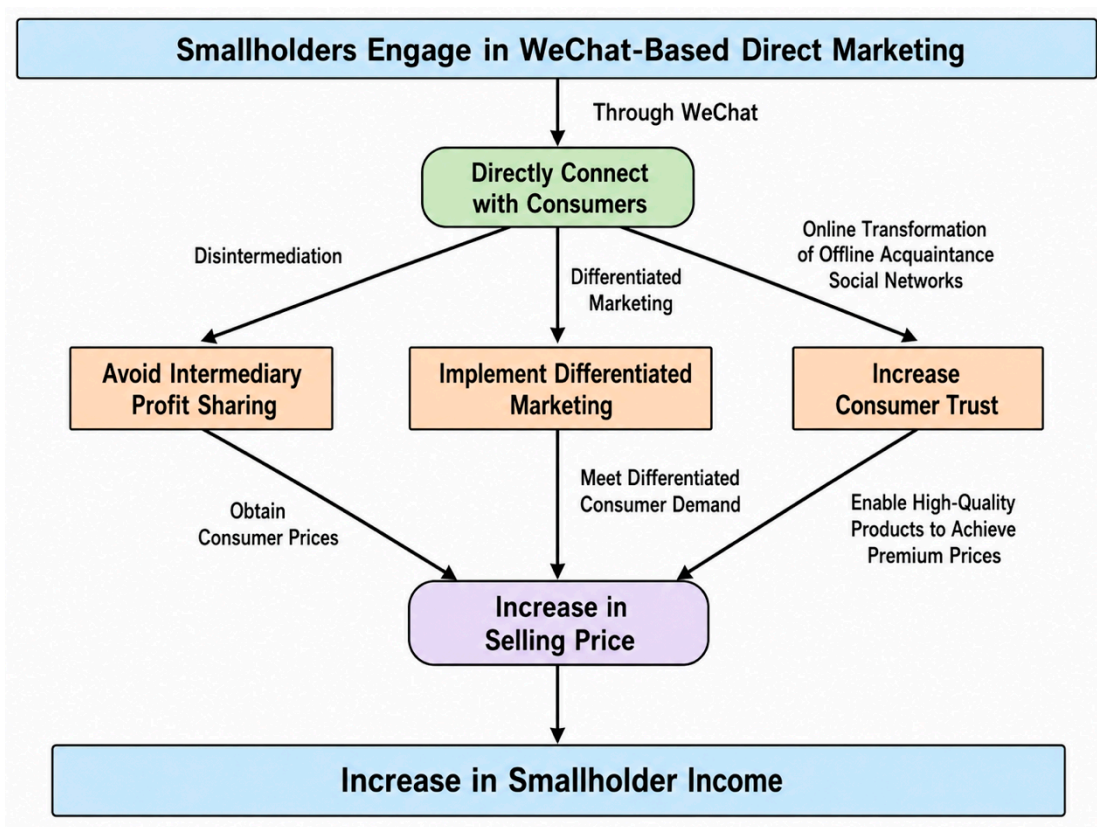


Figure 2. Mechanism through which WeChat-based direct marketing increases smallholder income.

First, WeChat-based direct marketing helps smallholders avoid intermediary profit sharing. In the traditional marketing model, smallholders usually trade only with intermediaries. Because intermediaries have stronger channel advantages, information advantages, and bargaining advantages, they occupy a dominant position in the market. In particular, intermediaries often control downstream sales channels and possess more

information about consumer demand, terminal-market prices, and product preferences, while smallholders have limited access to consumers and market information. WeChat-based direct marketing enables smallholders to communicate directly with consumers, obtain more timely information about market demand and willingness to pay, and gradually establish their own customer networks. This weakens intermediaries' control over market information and sales channels, expands farmers' alternative selling opportunities, and enhances their price-setting capacity and bargaining power. By contrast, smallholders are often in a dependent position. As a result, they can only obtain relatively low producer prices, while a large share of profits is captured by intermediaries. Transaction cost economics suggests that different market arrangements affect transaction costs and the distribution of transaction gains among participants [55–60]. Under WeChat-based direct marketing, smallholders trade directly with consumers and achieve disintermediation. By avoiding intermediary profit sharing, farmers can obtain relatively higher consumer prices, thereby increasing the selling price of peaches and realizing income growth.

Second, WeChat-based direct marketing enables smallholders to obtain differentiation premiums. With rising household income and the upgrading of consumption structure, consumers' personalized, diversified, and high-quality demands have continued to increase. Under WeChat-based direct marketing, smallholders can directly connect with consumers and more accurately match differentiated consumer demand. This makes consumers more willing to pay differentiation premiums for peaches that meet their preferences for quality, freshness, origin, and trust. Studies on short food supply chains and alternative food networks show that direct producer–consumer connections can help communicate product quality, origin, and local characteristics more effectively [42–50]. As a result, farmers can increase the selling price of peaches and achieve income growth.

Third, WeChat-based direct marketing increases consumer trust. The key to smallholders' online direct marketing lies in the online transformation of offline acquaintance-based social networks through WeChat and the embedding of transactions in acquaintance-based social networks. Fresh agricultural products have strong experience-good attributes, and consumers often cannot fully verify product quality before purchase, which creates information asymmetry between producers and consumers [29,30]. From the consumer perspective, such information asymmetry creates perceived quality risk, which may reduce purchase intentions and willingness to pay. In social commerce, product displays, repeated communication, customer feedback, and acquaintance-based reputation provide consumers with informational and relational cues, thereby reducing perceived risk and strengthening trust [31–33]. By reducing perceived quality risk through the trust mechanisms of acquaintance society, WeChat-based direct marketing can increase consumers' confidence in product quality. Research on embeddedness and online shopping also shows that social relations and trust can reduce transaction uncertainty and affect purchase intentions [14–18,22–33]. When consumers have stronger trust in product quality, they are more willing to pay higher prices for high-quality peaches. This promotes the realization of quality-based pricing and ultimately contributes to income growth.

Based on the above analysis, this study proposes the following hypothesis:

H2. *WeChat-based direct marketing promotes smallholder income growth by increasing the selling price of peaches.*

3. Data and Methodology

3.1. Data Sources

The data used in this study were obtained from a field survey conducted by the research team in Pinggu District, Beijing, from July to December 2024. Pinggu District is a well-known peach-producing area in China, and peach production is an important source

of household income for local farmers. The location of the study area and the approximate distribution of the surveyed villages are shown in Figure A1. To ensure sample representativeness, this study adopted a stratified random sampling strategy. First, several representative townships in Pinggu District were selected according to the scale and distribution of peach production. Within each township, multiple peach-producing villages were selected, and farm households were then randomly sampled for face-to-face interviews.

The questionnaire was specifically designed to collect the data required for this study. It consisted of several modules covering household characteristics, peach production and marketing, digital technology use, sales channels, income and costs, social relationships, and local logistics conditions. WeChat-based direct marketing was measured by whether a household sold peaches directly to consumers through WeChat during the survey year, with a value of 1 for participation and 0 otherwise. The dependent variable was the logarithm of per capita net income, calculated by dividing the household's reported annual net income from peach production by the total number of household members, while the selling price was measured using the average actual transaction price of peaches reported by each household.

A total of 738 farmer questionnaires were collected in this survey, including 414 questionnaires from farmers participating in WeChat-based marketing and 324 questionnaires from non-participating farmers. The questionnaires were screened according to a uniform set of data-quality criteria, and two main types of samples were excluded. First, some questionnaires contained missing values for key variables and therefore could not meet the requirements of the subsequent empirical analysis. Second, some questionnaires contained obvious logical inconsistencies among responses concerning household income, sales revenue, output, sales volume, selling prices, or basic household characteristics, which could not be corrected through follow-up verification or cross-checking. Based on these criteria, 14 questionnaires were excluded, including 13 from participating farmers and one from non-participating farmers. A final sample of 724 valid questionnaires was obtained, comprising 401 participating farmers and 323 non-participating farmers. It should be noted that the same screening criteria were applied to both groups.

3.2. Model Specification

3.2.1. Benchmark Regression Model

To estimate the impact of WeChat-based direct marketing on smallholder income, this study constructs a benchmark regression model using household-level cross-sectional survey data. Regression-based empirical strategies are commonly used in farm-household studies to estimate the effects of digital participation, e-commerce participation, and market access on household income or production behavior [61,62]. The benchmark model is specified as follows:

$$\ln Income_i = \alpha_0 + \alpha_1 WeChat_i + \beta X_i + \varepsilon_i$$

where $\ln Income_i$ denotes the logarithm of per capita net income from peach production of household i . $WeChat_i$ is the core explanatory variable, indicating whether household i participates in WeChat-based direct marketing. If the household sells peaches through WeChat, $WeChat_i$ equals 1; otherwise, it equals 0. X_i represents a vector of control variables, including household head characteristics, household characteristics, information infrastructure conditions, and geographical location characteristics. α_0 is the constant term, α_1 measures the effect of WeChat-based direct marketing on smallholder income, β represents the coefficients of the control variables, and ε_i is the random error term.

If α_1 is significantly positive, it indicates that WeChat-based direct marketing has a positive effect on smallholder income.

3.2.2. Mechanism Test Model

The theoretical analysis suggests that WeChat-based direct marketing mainly promotes smallholder income growth by increasing the average selling price of peaches. To test this mechanism, this study follows the causal step approach proposed by Baron and Kenny [63] and constructs the following mechanism test models.

First, the benchmark model specified in equation above is used to estimate the total effect of WeChat-based direct marketing on smallholder income.

Second, the following model is used to examine whether WeChat-based direct marketing affects the mediating variable, namely the average selling price of peaches

$$\ln Price_i = \gamma_0 + \gamma_1 WeChat_i + \delta X_i + \mu_i$$

where $\ln Price_i$ denotes the logarithm of the average selling price of peaches for household i . γ_1 measures the effect of WeChat-based direct marketing on the selling price of peaches, and μ_i is the random error term.

Third, both the core explanatory variable and the mediating variable are included in the income equation

$$\ln Income_i = \lambda_0 + \lambda_1 WeChat_i + \lambda_2 \ln Price_i + \rho X_i + v_i$$

where λ_2 measures the effect of the average selling price of peaches on smallholder income after controlling for WeChat-based direct marketing. If WeChat-based direct marketing significantly increases the selling price of peaches, and the selling price further has a significant positive effect on income, this provides evidence that the selling-price channel is an important mechanism through which WeChat-based direct marketing promotes smallholder income growth.

All statistical analyses were performed using Stata version 17 (StataCorp LLC, College Station, TX, USA).

3.3. Variable Measurement

3.3.1. Dependent Variable

The dependent variable is smallholder income, measured by per capita net income from peach production. Following previous studies, this study calculates this variable by dividing the annual net income of a household from peach production by the total number of household members [7–13,64]. In the empirical analysis, the logarithm of per capita net income is used to reduce the influence of extreme values and improve the interpretability of the regression coefficients.

3.3.2. Core Explanatory Variable

The core explanatory variable is whether the household participates in WeChat-based direct marketing. This variable is a binary variable. It equals 1 if the farmer sells agricultural products through WeChat, and 0 otherwise. Specifically, WeChat-based direct marketing refers to farmers using WeChat group chats, Moments, private messages, and other social functions to promote and sell peaches to relatives, friends, neighbors, acquaintances, and potential consumers. This measurement is consistent with studies that emphasize social commerce, WeChat-based sales, social connections, and digital participation in smallholder agricultural marketing [14–19,36–41].

Field interviews showed that most small-scale farmers in Pinggu District do not directly operate on mainstream e-commerce platforms such as Taobao, JD.com, Douyin, or Kuaishou because of high operating costs and technical barriers related to platform operation, logistics, payment systems, and traffic acquisition. Instead, many farmers choose WeChat as their main channel for social-commerce participation. This sales mode is low-cost and can help farmers establish relatively trusted buyer–seller relationships through

acquaintance networks. This observation is also consistent with studies showing that rural digital divides, limited digital skills, and insufficient platform operation capacity may constrain farmers' participation in formal digital markets [36–40]. Therefore, this study focuses on farmers' actual use of WeChat for agricultural product sales and examines its effect on household income.

3.3.3. Mediating Variable

The mediating variable is the average selling price of peaches. It is measured by the weighted average price received by a household from selling peaches through all offline and WeChat channels during the survey year. Since the theoretical analysis suggests that WeChat-based direct marketing promotes income growth mainly by increasing the selling price of peaches, this variable is used to test the price mechanism. Previous studies on transaction costs, information asymmetry, short food supply chains, and direct producer–consumer connections indicate that direct marketing may reduce intermediary dependence, improve quality information transmission, strengthen consumer trust, and affect the price received by producers [29,30,42–50,55–60].

3.3.4. Control Variables

Following previous studies, this study controls for three categories of variables: household head characteristics, household characteristics, and information infrastructure conditions.

First, household head characteristics include age, health status, years of education, online shopping expenditure, and short-video platform use. These variables reflect the individual endowment, digital exposure, and information acquisition capacity of the household decision-maker. Age, education, and health status are commonly used to capture farmers' human capital and decision-making capacity, while online shopping expenditure and short-video platform use reflect farmers' exposure to digital platforms, online consumption experience, and information acquisition channels [36–40,64,65].

Second, household characteristics include actual peach planting scale, part-time employment status, the number of agricultural laborers, and household social expenditure. These variables capture production conditions, labor allocation, and social network embeddedness [22–28,34,35,66,67].

Third, information infrastructure conditions are measured by the distance from the current residence to the nearest express delivery point and the number of express delivery points within the township. The nearest express delivery point refers to local express service outlets, rural delivery stations, or other facilities that provide parcel delivery and pickup services for farmers, while the number of express delivery points reflects the coverage and availability of local logistics services. Together, these variables capture both farmers' accessibility to express delivery services and the overall logistics-support capacity of the township, which are particularly important for the fulfillment of online fresh-produce orders [51–54,68].

The definitions and descriptive statistics of the main variables are shown in Table 1.

Table 1. Definitions and descriptive statistics of main variables.

Variable	Definition or Assignment	Std. Dev.	Min	Max	Mean
Per capita net income from peach production	Annual net income from peach production divided by the total number of household members, measured in CNY	14,310.8700	1375.0000	117,500.0000	16,172.9000

WeChat-based direct marketing	Binary variable: 1 if the household conducts WeChat-based direct marketing; 0 otherwise	0.4974	0.0000	1.0000	0.5539
Age	Age of the household head	8.7310	19.0000	88.0000	60.4848
Health status	Health status of the household head, measured on a five-point scale: very poor = 1, poor = 2, fair = 3, good = 4, very good = 5	0.9797	1.0000	5.0000	3.8467
Years of education	Converted from the education level of the household head, measured in years	2.2168	2.0000	16.0000	9.4461
Online shopping expenditure	Total amount spent by the household head on online purchases in 2023, measured in CNY	4826.7390	500.0000	50,000.0000	3780.6750
Short-video platform use	Binary variable indicating whether the household head uses short-video platforms, such as Douyin, Kuaishou, Xigua Video, or Xiaohongshu, to obtain information: 1 if yes; 0 otherwise	0.4056	0.0000	1.0000	0.7928
Household social expenditure	Total annual expenditure used by the household to maintain social relations, including gifts for relatives, friends, weddings, funerals, and other social occasions. It reflects the household's embeddedness and social connection intensity in an acquaintance society, measured in CNY	7362.9870	500.0000	60,000.0000	8734.3920
Actual peach planting scale	Actual land area used by the household for peach cultivation, measured in mu	4.0163	1.0000	25.0000	6.3896
Part-time employment status	Binary variable: 1 if the household engages in part-time employment; 0 otherwise	0.3467	0.0000	1.0000	0.8605
Household size	Total number of household members, measured in persons	1.4152	1.0000	9.0000	3.3301
Number of agricultural labors	Total number of household members engaged in agricultural production, measured in persons.	0.8165	1	6	2.1050
Number of express delivery points within the township	Total number of express delivery points within the township where the household is located, measured in units	2.4630	1.0000	10.0000	5.9254
Distance to the nearest express delivery point	Distance from the household's current residence to the nearest express delivery point, including local express outlets, rural delivery stations, or other facilities providing parcel delivery and pickup services, measured in kilometers	0.2963	0.1000	3.0000	0.6781

4. Results

4.1. Benchmark Regression Results

To examine the effect of social-commerce participation on farmers' income growth, this study uses the benchmark regression model for empirical estimation. Before interpreting the regression results, variance inflation factors were calculated to examine potential multicollinearity. The mean VIF was 1.33, and all individual VIF values were below the conventional threshold of 10, indicating that multicollinearity was not a serious concern in the benchmark model. The Breusch–Pagan/Cook–Weisberg test rejected the null hypothesis of constant variance ($\chi^2(1) = 8.69$, $p = 0.0032$). The White test also rejected the null hypothesis of homoskedasticity.

The regression results are reported in Table 2. Columns (1), (2), (3), and (4) present the estimation results after adding different sets of control variables. Specifically, Columns (2), (3), and (4) sequentially include household head characteristics, household characteristics, and information infrastructure variables. Compared with Column (2), Column (3) adds production and labor variables that are more directly related to household income formation. Planting scale captures production capacity, while part-time employment and agricultural labor reflect household labor allocation; these variables explain a substantial share of the cross-household variation in peach-farming income, increasing the R^2 from 0.160 to 0.665, while the coefficient of social-commerce participation remains stable.

The results in Column (4) show that, compared with farmers who do not participate in social commerce, farmers who participate in WeChat-based direct marketing have a 0.287 log point higher per capita net income from peach farming. The result in Column (1) shows that, without adding any control variables, the coefficient of social-commerce participation is positive, indicating that social-commerce participation has a significant positive effect on farmers' income growth. Columns (2), (3), and (4) further show that, after controlling for household head characteristics, household characteristics, and information infrastructure variables, the coefficient of social-commerce participation remains significantly positive. This indicates that, after controlling for relevant variables, social-commerce participation can still significantly improve farmers' income, and this effect is relatively robust.

Table 2. Benchmark regression results.

Variable	Log of per Capita Net Income			
	(1)	(2)	(3)	(4)
Social-commerce participation	0.4964 *** (0.0531)	0.3353 *** (0.0594)	0.2924 * (0.0374)	0.2866 * (0.0386)
Age		0.0089 ** (0.0036)	0.0084 * (0.0022)	0.0084 * (0.0021)
Years of education		0.0252 * (0.0138)	0.0216 (0.0091)	0.0213 (0.0091)
Health status		0.0100 (0.0267)	0.0309 * (0.0179)	0.0323 * (0.0190)
Log of online shopping expenditure		0.1401 *** (0.0300)	0.0712 * (0.0184)	0.0707 * (0.0184)
Short-video platform use		0.2176 *** (0.0645)	0.0751 (0.0458)	0.0728 (0.0457)
Actual peach planting scale			0.0770 * (0.0059)	0.0768 * (0.0061)
Part-time employment status			0.6344 * (0.0578)	0.6341 * (0.0579)

Number of agricultural labors	−0.2561 *	−0.2539 *
	(0.0200)	(0.0200)
Log of household social expenditure	0.1074 *	0.1064 *
	(0.0142)	(0.0141)
Distance to the nearest express delivery point		−0.0476
		(0.0677)
Number of express delivery points within the township		−0.0017
		(0.0083)
Constant	9.1144 ***	7.1423 ***
	(0.0366)	(0.3761)
Observations	724	724
R ²	0.1047	0.1598

Note. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are reported in parentheses. The dependent variable is the logarithm of per capita net income from peach farming.

Therefore, social-commerce participation not only has a positive effect on farmers' income growth in the original model, but also remains significant after considering individual endowments, household characteristics, and information infrastructure conditions. This further verifies the positive role of social-commerce participation in promoting farmers' income growth and supports Hypothesis 1.

4.2. Estimation Based on Propensity Score Matching

Farmers' participation in social commerce may be affected by individual, household, and geographical characteristics, resulting in potential self-selection bias. To reduce selection bias arising from observable characteristics, this study employs propensity score matching (PSM) to further examine the effect of social-commerce participation on farmers' per capita net income [69,70].

Among the 724 sampled households, 401 participated in WeChat-based direct marketing and 323 did not. Before matching, participating farmers had a significantly higher mean log per capita net income than non-participating farmers (9.611 versus 9.114, $p < 0.001$). They were also younger, better educated, and healthier, cultivated larger peach orchards, had more agricultural laborers, spent more on online shopping, and were more likely to use short-video platforms. Significant differences were also observed in the distance to the county seat and the nearest delivery point. These differences indicate that participation was not randomly determined and justify the use of PSM.

Propensity scores were estimated using a logit model based on the control variables included in the benchmark regression. One-to-one nearest-neighbor matching without replacement was then conducted with a caliper of 0.05 and a common-support restriction. Among the 401 participating households, 212 were outside the common-support region. Therefore, 189 participating households were matched with 189 non-participating households, resulting in 378 matched observations. After matching, the mean standardized bias decreased from 42.8% to 3.6%, the pseudo- R^2 declined from 0.266 to 0.010, and the joint significance test became insignificant ($p = 0.917$), indicating satisfactory covariate balance. The propensity-score density distributions before and after matching are presented in Figure A2.

As shown in Table 3, after matching, the estimated average treatment effect on the treated was 0.334 and remained significant at the 1% level. This result is consistent with the benchmark regression coefficient of 0.287, further confirming the positive income effect of social-commerce participation. The distributions of per capita net income and peach selling prices by social-commerce participation are shown in Figure A3.

Table 3. Propensity score matching results.

Variable	(1)	(2)
	Log of per Capita Net Income	Per Capita Net Income
Social-commerce participation (1 vs. 0)	0.3342 *** (0.0678)	4555.1104 *** (1110.6274)
Control variables	Yes	Yes
Observations	378	378

Note. One-to-one nearest-neighbor matching without replacement was conducted with a caliper of 0.05 and a common-support restriction. The ATT was estimated using 189 matched treatment–control pairs. Standard errors are reported in parentheses. The standard errors generated by psmatch2 do not account for the estimation of the propensity scores. *** indicates significance at the 1% level. The dependent variables are the logarithm of per capita net income from peach farming in Column (1) and per capita net income from peach farming in Column (2).

4.3. Estimation Based on the Instrumental Variable Approach

To examine the effect of farmers’ participation in social commerce on income, this study first used propensity score matching (PSM) to address the problem of selection bias. However, PSM cannot fully solve endogeneity problems, especially those caused by unobserved confounding factors. To further improve the accuracy of the estimation, this section adopts an instrumental variable approach to deal with potential endogeneity. Specifically, the distance from the household’s current residence to the county seat is selected as the instrumental variable for social-commerce participation, and two-stage least squares (2SLS) regression is conducted. This variable can affect farmers’ probability of participating in social commerce because commercial services, digital information, e-commerce training, and marketing support are relatively concentrated around the county seat. A greater distance from the county seat increases farmers’ costs of accessing these resources and may therefore reduce their willingness to participate in WeChat-based direct marketing. To reduce concerns that this variable may also reflect local infrastructure, market accessibility, and economic development, the model controls for household characteristics, production and labor conditions, the distance to the nearest express delivery point, and the number of express delivery points within the township. Village fixed effects are also included in an additional specification. Conditional on these variables, distance to the county seat is assumed not to affect peach-farming income directly through channels other than social-commerce participation.

First, to test whether endogeneity exists, this study conducts the Durbin–Wu–Hausman (DWH) test [71–73]. The test results significantly reject the null hypothesis that social-commerce participation is an exogenous variable, indicating that farmers’ participation in social commerce does involve endogeneity. Therefore, the use of the instrumental variable approach is necessary. Second, the first-stage regression results, reported in Table 4, show that distance to the county seat has a significant negative effect on social-commerce participation, indicating a strong correlation between the instrumental variable and the endogenous explanatory variable. The first-stage F-statistics are 13.07 without village fixed effects and 11.35 with village fixed effects. The Kleibergen–Paap rk LM tests also reject the null hypothesis of underidentification at the 1% level. In addition, following the weak-instrument criterion proposed by Stock and Yogo [74], this study further conducts weak-instrument robustness tests. The Anderson–Rubin tests reject the null hypothesis of no income effect in both specifications. These results indicate that the instrument has meaningful explanatory power. The conditional relationship between distance to the county seat and social-commerce participation is illustrated in Figure A4.

After examining the relevance and validity of the instrumental variable, this study further conducts the second-stage regression. The results show that, after controlling for potential endogeneity, social-commerce participation still has a positive effect on farmers' per capita net income at the 5% significance level. The difference suggests that failing to control for potential endogeneity may lead to an underestimation of the income-increasing effect of social-commerce participation for farmers whose participation decisions are affected by their distance from the county seat.

To further examine the exclusion restriction, this study conducts falsification tests using the 323 households that did not participate in WeChat-based direct marketing. The results show that distance to the county seat has no significant effect on their per capita net income, selling price, or sales volume, either with or without village fixed effects.

In summary, the instrumental variable estimation further confirms the causal relationship between the core variables and shows that social-commerce participation plays a significant role in increasing farmers' income.

Table 4. Regression results based on the instrumental variable approach.

Variable	First-Stage Regression		Second-Stage Regression	
	Coef.	SE	Coef.	SE
Social-commerce participation			0.6485 **	0.2905
Distance from the current residence to the county seat	−0.0150 ***	0.0041		
Age	−0.0010	0.0020	0.0087 ***	0.0022
Years of education	0.0127 *	0.0073	0.0170 *	0.0098
Health status	0.0167	0.0181	0.0242	0.0211
Log of online shopping expenditure	0.0768 ***	0.0163	0.0419	0.0297
Short-video platform use	0.3491 ***	0.0400	−0.0515	0.1131
Actual peach planting scale	0.0034	0.0054	0.0760 ***	0.0065
Part-time employment status	−0.0336	0.0509	0.6500 ***	0.0585
Number of agricultural labors	0.0543 **	0.0217	−0.2746 ***	0.0275
Log of household social expenditure	0.0346 ***	0.0097	0.0933 ***	0.0174
Distance to the nearest express delivery point	−0.2783 ***	0.0922	0.0514	0.1050
Number of express delivery points within the township	0.0494 ***	0.0088	−0.0147	0.0133
Constant	−0.6947 ***	0.2548	6.7041 ***	0.3804
Observations			724	

Note. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4. Robustness Checks

To verify the robustness of the empirical results, this study conducts robustness checks using three methods: replacing the dependent variable, applying winsorized regression, and excluding part of the sample. These methods help examine whether the research conclusions remain stable and reliable under different variable measurements and sample selections.

4.4.1. Replacing the Dependent Variable

To verify the robustness of the above results, this study first replaces the dependent variable. In the regression analysis, the logarithm of the annual net income from peach farming is used as the dependent variable instead of the logarithm of per capita net income, and extreme values in the data are excluded. The results in Column (1) of Table 5 show that, after replacing the dependent variable, the positive relationship between

farmers' participation in social commerce and household annual net income remains significant, while the significance of other control variables remains generally unchanged.

Table 5. Robustness checks of the effect of social-commerce participation on farmers' income.

Variable	(1)	(2)	(3)
	Replacing the Dependent Variable	Winsorized Regression	Excluding Assisting e-Commerce Farmers
Social-commerce participation	0.2689 *** (0.0213)	0.2632 *** (0.0372)	0.2785 *** (0.0385)
Other control variables	Yes	Yes	Yes
Observations	724	724	721
R ²	0.8370	0.6450	0.6629

Note. *** indicates significance at the 1% level. Robust standard errors are reported in parentheses. In Column (1), the dependent variable is replaced by the logarithm of household annual net income from peach farming. In Columns (2) and (3), the dependent variable is the logarithm of per capita net income from peach farming.

4.4.2. Winsorized Regression

To further ensure the robustness of the regression results and reduce the potential influence of extreme values, this study winsorizes the dependent variable at the 5th and 95th percentiles. Specifically, observations below the 5th percentile are replaced with the value at the 5th percentile, while observations above the 95th percentile are replaced with the value at the 95th percentile. This treatment limits the influence of unusually high or low income values without deleting observations. As shown in Column (2) of Table 5, the coefficient of social-commerce participation remains positive and statistically significant at the 1% level after winsorization. This result indicates that the positive income effect of social-commerce participation is not driven by extreme income values.

4.4.3. Excluding Part of the Sample

Some farmers who participate in social commerce not only sell their own agricultural products but also help other farmers sell products online. Because these farmers usually have stronger e-commerce capabilities and richer online resources, they may obtain higher sales revenue and face lower operating costs. To exclude the potential interference of these farmers on the empirical results, this study removes them from the sample and re-estimates the regression model. Column (3) of Table 5 reports the regression results after excluding these "assisting e-commerce farmers". The results show that, after excluding these special samples, the coefficient of social-commerce participation changes only slightly, indicating that the income-increasing effect of social commerce remains significant for ordinary farmers. However, the fluctuation of the regression results decreases, suggesting that assisting e-commerce farmers may amplify the estimated effect of social commerce to some extent because of their stronger e-commerce capacity and higher income levels. After removing these farmers, the regression results more accurately reflect the income-increasing effect for ordinary farmers. The benchmark, PSM, instrumental-variable, and robustness estimates are summarized in Table A1.

4.5. Mechanism Test

According to the previous analysis, WeChat-based direct marketing mainly promotes peach farmers' income growth by increasing the selling price of peaches. To empirically verify this transmission path, this study constructs a mediation-effect model in the model specification section to examine the mediating role of peach selling price in the

income-increasing effect of WeChat-based direct marketing. To avoid relying solely on the stepwise regression method, a Bootstrap test with 5000 replications and a Sobel test are further conducted to examine the statistical significance of the indirect effect. The specific estimation results are reported in Table 6.

Column (1) of Table 6 reports the total-effect regression results. After controlling for a series of relevant variables, the coefficient of farmers' social-commerce participation on income is 0.287 and passes the significance test at the 1% level. This indicates that WeChat-based direct marketing has a significant positive effect on smallholder income growth, satisfying the prerequisite for mediation-effect analysis. Column (2) examines the effect of farmers' social-commerce participation on the selling price of peaches. The results show that the coefficient of social-commerce participation is 0.812 and statistically significant, indicating that farmers can effectively increase the selling price of peaches through WeChat-based direct marketing. Column (3) includes both farmers' social-commerce participation and the selling price of peaches in the model to test the direct effect. The results show that the coefficient of social-commerce participation decreases to 0.218 but remains significant at the 1% level, while the coefficient of peach selling price is 0.084 and significant at the 10% level. This indicates that selling price plays a partial mediating role. The estimated indirect effect is 0.070, accounting for approximately 24.1% of the total effect. The Bootstrap test based on 5000 replications reports a standard error of 0.037. The Sobel test also confirms that the indirect effect is statistically significant ($z = 2.250$, $p = 0.024$).

Overall, the mechanism test suggests that WeChat-based direct marketing can increase peach farmers' income by raising the selling price of peaches. This result supports the theoretical analysis that WeChat-based direct marketing helps farmers avoid intermediary profit sharing, obtain differentiation premiums, and increase consumer trust, thereby improving the price received by farmers. Therefore, Hypothesis 2 is supported.

Table 6. Results of mechanism analysis.

Variable	(1)	(2)	(3)
	Log of per Capita Net Income	Log of Selling Price	Log of per Capita Net Income
Social-commerce participation	0.2866 *** (0.0386)	0.8177 *** (0.0388)	0.2175 *** (0.0520)
Log of selling price			0.0844 * (0.0446)
Other control variables	Yes	Yes	Yes
Observations	724	724	724
R ²	0.6653	0.5748	0.6671

Note. *** and * indicate significance at the 1% and 10% levels, respectively. Robust standard errors are reported in parentheses.

4.6. Heterogeneity Analysis Based on Household Social Expenditure

The income-increasing effect of farmers' participation in social commerce may be affected by multiple factors, among which the mechanism of acquaintance society plays a core role. This study uses household social expenditure as a proxy for the intensity of farmers' participation in social interactions and relationship maintenance in acquaintance society. Farmers in the high-social-expenditure group usually have broader social networks, while those in the low-social-expenditure group tend to have relatively limited social connections. To further examine the influence of acquaintance-society mechanisms on the income effect of social commerce, this study divides the sample into high and low groups according to the level of household social expenditure and conducts separate regressions for the two groups. The income differences between the high-social-expenditure

group and the low-social-expenditure group are then analyzed. Table 7 reports the regression coefficients for the two groups after controlling for other variables.

The regression results show that the effect of WeChat-based direct marketing on farmers' income differs significantly between the high-social-expenditure group and the low-social-expenditure group. The estimated coefficient is 0.381 for the high-social-expenditure group, while it is only 0.272 for the low-social-expenditure group. This indicates that the income-increasing effect of WeChat-based direct marketing is substantially stronger among farmers with higher household social expenditure. The corresponding coefficient estimates and 95% confidence intervals are presented in Figure A5. This pattern is closely related to the acquaintance-society mechanism embedded in social commerce. More specifically, the result suggests that digital networks and traditional social networks are complementary rather than fully substitutable. WeChat does not automatically eliminate differences in farmers' social resources; instead, it enables farmers to transfer their existing acquaintance networks, interpersonal trust, and reputational resources into online market advantages.

In the social-commerce model, farmers' income growth is deeply affected by their social networks. Specifically, farmers in the high-social-expenditure group are generally more actively involved in gift exchanges, weddings, funerals, and other social interactions. These frequent interactions may help farmers maintain interpersonal trust and mobilize existing relationship resources. In addition, some farmers have accumulated extensive interpersonal resources through off-farm work. These farmers are often better able to make full use of social capital, establish stronger trust-based connections through WeChat Moments and group chats, and expand their product markets. Their existing social networks provide an initial customer base, trusted referrals, and more effective channels for word-of-mouth diffusion. This reduces the cost of acquiring customers and forming initial trust, while facilitating repeated transactions and the expansion of customer networks. These advantages enable them to obtain more orders, maintain more stable customer groups, and receive price premiums through social commerce, thereby gaining higher income.

By contrast, farmers in the low-social-expenditure group may participate less actively in social exchanges and have fewer readily mobilizable relationship resources. This weakens the income-increasing effect of e-commerce participation. As a result, it is more difficult for them to achieve the same level of income growth as farmers in the high-social-expenditure group. Therefore, the heterogeneity results are more consistent with an amplification effect: WeChat-based direct marketing digitizes and extends farmers' pre-existing social relationships, thereby amplifying the market returns to stronger social embeddedness. This finding also implies that access to digital technology alone may not be sufficient to eliminate the disadvantages faced by farmers with relatively limited social networks.

Table 7. Heterogeneity results by household social expenditure.

Variable	Low-Social-Expenditure Group	High-Social-Expenditure Group
Social-commerce participation	0.2716 *** (0.0519)	0.3810 *** (0.0602)
Control variables	Yes	Yes
Observations	379	345
R ²	0.5367	0.7136

Note. The dependent variable is the logarithm of per capita net income from peach farming. The control variables are consistent with those in the benchmark regression, including household head characteristics, household characteristics, location variables, and information infrastructure variables. *** indicates significance at the 1% level. Robust standard errors are reported in parentheses.

5. Discussion

The positive income effect identified in this study is generally consistent with previous research showing that rural e-commerce participation can increase farmers' income by expanding market access, reducing transaction costs, improving access to information, and strengthening connections with downstream markets [7–13]. Also, the positive income effect identified in this study is broadly consistent with the findings of Yin et al. [11] and Guan et al. [12]. However, the magnitude of the estimated effects differs across studies. These differences may be related to variations in the definition of e-commerce participation, the measurement of household income, regional economic and logistics conditions, product characteristics, and empirical identification strategies.

This study also complements the emerging literature on WeChat-based agricultural marketing and social commerce. Liu and Wang [19] show that WeChat e-commerce and social connections can improve smallholder agricultural sales performance. The present findings are consistent with their emphasis on the economic value of farmer–consumer social connections, but extend this literature in two respects. First, the outcome examined here is farmers' per capita net income rather than sales performance alone. Second, this study distinguishes the selling-price mechanism from the overall income effect. Compared with platform-based e-commerce, WeChat-based direct marketing relies less on formal online stores, paid traffic, algorithmic recommendations, and professional platform operation, and more on private communication, customer referrals, repeated interaction, and pre-existing interpersonal trust. These channel differences may explain why acquaintance-network embeddedness plays a particularly important role in the present study.

The mechanism findings are related to, but differ from, previous studies that explain the income effects of e-commerce mainly through broader market access, lower transaction costs, improved bargaining power, or better information acquisition [3–5,7–13,53–58]. This study finds that the average selling price of peaches serves as a significant partial transmission channel. This result is consistent with social-commerce research showing that trust and social interaction reduce perceived transaction and quality risks and strengthen consumers' purchase intentions [14–18,29–31]. The difference is that the present study directly links these trust-based interactions to the price received by farmers. This price effect may be particularly pronounced for peaches because their quality is difficult to evaluate before consumption, their freshness declines rapidly, and consumers may be willing to pay more when product information and seller credibility are communicated through trusted social relationships.

The heterogeneity results further extend studies on social capital and farmers' e-commerce behavior. Previous research mainly shows that social capital and digital literacy influence farmers' e-commerce entrepreneurship, market entry, and multi-stage participation [32,33]. The present study shifts attention from whether farmers participate to whether farmers with different levels of social embeddedness obtain different economic returns after participation. From the perspectives of social compensation and social enhancement, the larger income effect among households with higher social expenditure is more consistent with an amplification effect: WeChat extends existing acquaintance networks rather than fully compensating for limited social capital [75,76]. Although access to WeChat is widespread, households still differ in their ability to mobilize private networks and convert relational trust into stable customer resources.

Several limitations should be acknowledged. First, the sample is limited to peach farmers in Pinggu District, and caution is therefore needed when generalizing the findings to other regions and agricultural products. Second, the self-reported income data may contain some measurement error. Third, because the IV model is exactly identified, over-identification tests such as the Hansen J test cannot be conducted, limiting the statistical assessment of the exclusion restriction. Finally, the cross-sectional design does not allow

the dynamic effects of WeChat-based direct marketing to be examined. In addition, online shopping expenditure and short-video platform use may also capture some differences in households' digital orientation. Therefore, these variables are included mainly as controls, and their estimated coefficients should be interpreted with caution.

Future research could use panel data or longitudinal surveys to examine the dynamic effects of social-commerce participation and better address potential reverse causality. The analysis could also be extended to less-developed regions and different agricultural products, while combining survey data with transaction or administrative records to reduce measurement errors. In addition, future studies could compare WeChat-based direct marketing with platform-based and livestreaming channels, such as Douyin, Kuaishou, and Taobao Live, to identify the heterogeneous effects of different digital-marketing models.

6. Conclusions and Policy Implications

6.1. Conclusions

Social commerce provides smallholders not only with a low-threshold online sales channel but also with a mechanism for transforming acquaintance-based social relations into market transactions. Based on survey data from 724 peach-farming households in Pinggu District, Beijing, in 2024, this study examines the income effect, selling-price mechanism, and social-network heterogeneity of WeChat-based direct marketing. The main conclusions are as follows.

First, WeChat-based direct marketing provides a social-commerce model that is highly compatible with the production and marketing conditions of smallholders. Unlike platform-based e-commerce, it does not mainly rely on formal online stores, paid traffic, or complex platform rules. Instead, smallholders use familiar digital tools and acquaintance networks to connect directly with consumers. Therefore, WeChat-based direct marketing is not simply a technical channel for online sales but a market-participation model built on private social networks and relationship-based trust.

Second, the income-increasing mechanism of WeChat-based direct marketing is closely related to changes in farmers' market position. In conventional marketing channels, smallholders often face limited access to buyers, incomplete price information, high buyer-search and negotiation costs, and pressure to sell quickly because peaches are highly perishable. These conditions increase their dependence on local intermediaries, reduce their alternative selling opportunities, and weaken their position in price formation. Through WeChat, smallholders can change the traditional transaction chain from "smallholder–intermediary–consumer" to "smallholder–consumer". This direct connection reduces intermediary profit sharing and allows farmers to retain a larger share of the final consumer price. Direct communication with a wider range of consumers also reduces information, search, negotiation, and coordination costs and weakens the informational advantage traditionally held by intermediaries. More importantly, acquaintance-based social networks help farmers communicate product quality, origin, freshness, and production processes to consumers. The selling-price mechanism therefore reflects not only trust-based quality communication but also an improvement in farmers' outside options and bargaining position in the price-formation process.

Third, the empirical results show that participation in WeChat-based direct marketing is positively associated with farmers' per capita net income from peach farming, and this finding remains stable across alternative estimation methods and robustness checks. The mechanism analysis further shows that the average selling price of peaches plays a significant partial mediating role. This finding suggests that farmers can convert reduced transaction costs, stronger consumer trust, and improved market options into price premiums and income gains. Nevertheless, the selling price should be regarded as evidence

consistent with an improved bargaining position rather than as a direct measure of bargaining power.

Fourth, the income effect of WeChat-based direct marketing is larger among households with higher social expenditure. This finding indicates that acquaintance-network embeddedness amplifies the economic benefits of social commerce, because farmers with broader social connections are better able to obtain initial customers, generate trusted referrals, maintain repeated transactions, and transform relational trust into market value.

6.2. Policy Implications

The findings suggest that policies supporting agricultural e-commerce should not treat WeChat-based direct marketing merely as a low-cost online sales channel. More attention should be paid to the social mechanism behind this model, especially the role of acquaintance networks, trust formation, reputation constraints, and repeated transactions [22–28,34,35].

First, local governments should support WeChat-based direct marketing as a trust-based social-commerce model. Compared with platform-based e-commerce, WeChat-based direct marketing is more suitable for smallholders with limited digital skills and weak platform operation capacity [19,36–40]. Local governments can promote demonstration households, organize experience-sharing activities, and encourage farmers to use WeChat Moments, group chats, and customer referrals to build direct links with consumers. Policy support should focus not only on helping farmers “sell online”, but also on helping them build stable, trust-based customer relationships.

Second, public services should help farmers transform private acquaintance networks into more stable market networks. The heterogeneity results show that farmers with stronger social embeddedness benefit more from WeChat-based direct marketing. This implies that farmers with weaker social networks may be disadvantaged in social commerce. To improve inclusiveness, local governments, cooperatives, and village organizations can build public marketing channels, such as village-level WeChat accounts, cooperative group-buying channels, regional public brands, and collective promotion platforms. These tools can help farmers with weaker personal networks share public customer resources and reduce excessive dependence on individual acquaintance networks.

Third, the public e-commerce service system should be strengthened to support trust-based transactions and the fulfillment of small, time-sensitive online orders. For fresh peaches, consumer trust depends not only on social relationships but also on stable product quality and reliable delivery. Local governments can therefore support village- or township-level shared logistics service hubs that provide rapid sorting, grading, standardized packaging, consolidated collection, and coordination with cold-chain and express-delivery services. Regional branding, quality certification, traceability information, and after-sales services should also be improved. These measures can transform interpersonal trust into more institutionalized market trust and support the sustainable development of WeChat-based direct marketing [51–54].

Fourth, public training programs should incorporate social-commerce digital literacy rather than focusing only on basic smartphone use. Training should cover practical skills such as product presentation, customer communication, WeChat group operation, image and short-video production, online payment, after-sales service, and customer relationship maintenance. Particular attention should be paid to helping farmers use customer feedback, repeated interaction, and reputation management to strengthen consumer trust. In this way, smartphones can better function as “new farming tools” connecting agricultural production, marketing, and social networks.

Author Contributions: Conceptualization, J.L., L.C. and X.Z.; methodology, J.L. and L.C.; software, M.Z.; validation, L.C., G.C. and M.Z.; formal analysis, J.L. and L.C.; investigation, J.L. and L.C.; resources, X.Z.; data curation, J.L., L.C. and M.Z.; writing—original draft preparation, J.L. and L.C.; writing—review and editing, J.L. and L.C.; visualization, M.Z. and G.C.; supervision, X.Z.; project administration, X.Z.; funding acquisition, X.Z., J.L. and L.C. contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the General project of the National Social Science Foundation, grant number 22BGL176.

Institutional Review Board Statement: Ethical review and approval were waived for this study because it was based on an anonymous, non-interventional household survey of adult farmers. The study did not involve biomedical procedures, clinical intervention, human biological samples, or the collection of personally identifiable sensitive information, and posed no more than minimal risk to participants. All participants were informed of the purpose of the study and the use of the survey data before participation.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy concerns.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Summary of the main and robustness estimates.

Estimation Method	Outcome and Specification	Log Coefficient	Robust SE	Percentage Change (%)	Observations
OLS	Log of per capita net income	0.2866 ***	0.0386	33.19	724
PSM	Log of per capita net income; 1:1 nearest-neighbor matching	0.3342 ***	0.0678	39.68	378
IV-2SLS	Log of per capita net income; distance to the county seat as the instrument	0.6485 **	0.2905	91.27	724
Replacing the dependent variable	Log of total net income from peach production	0.2689 ***	0.0213	30.86	724
Winsorized regression	Dependent variable winsorized at the 5th and 95th percentiles	0.2632 ***	0.0372	30.11	724
Excluding assisting e-commerce farmers	Log of per capita net income	0.2785 ***	0.0385	32.12	721

Note. Percentage changes are calculated as $100 \times [\exp(\beta) - 1]$. Robust standard errors are reported. The PSM estimate represents the average treatment effect on the treated in the matched sample. The IV estimate identifies a local average treatment effect for households whose participation decisions are influenced by their distance from the county seat and is therefore not directly comparable with the population-average OLS and PSM estimates. *** and ** indicate significance at the 1% and 5% levels.

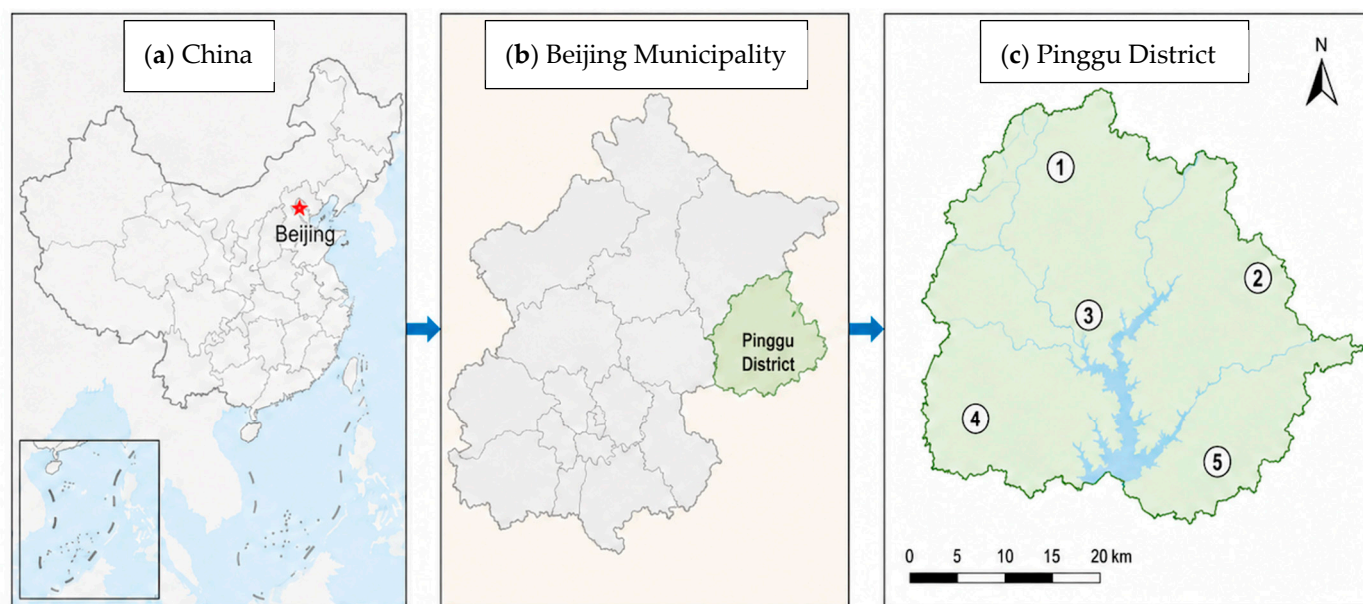


Figure A1. Location of the study area and surveyed villages in Pinggu District, Beijing, China. Note: Numbers 1–5 indicate five anonymized survey villages. To protect respondent confidentiality and reduce the risk of indirect identification, the specific village names are not reported. The locations are approximate and shown for illustrative purposes only. The map is not drawn to scale.

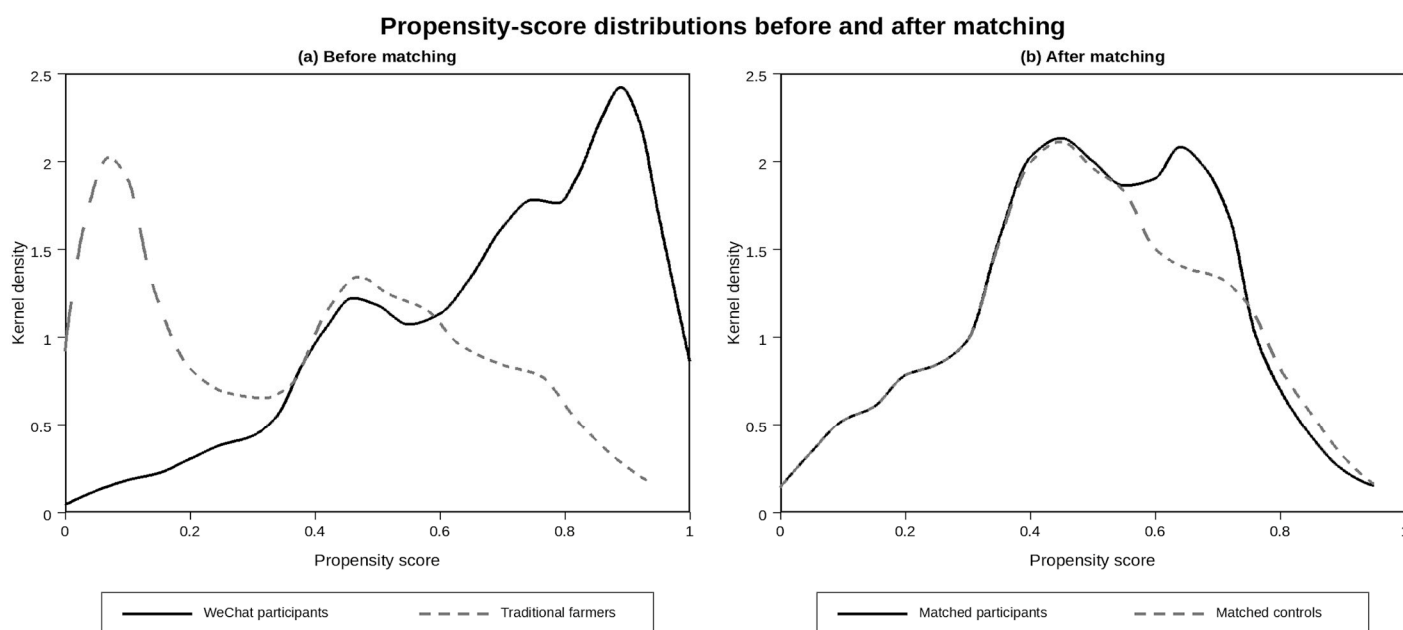


Figure A2. Propensity-score density distributions before and after matching. Note: Panel (a) presents the propensity-score distributions of the 401 participating households and 323 non-participating households before matching. Panel (b) presents the distributions of the 189 matched participating households and 189 matched control households after one-to-one nearest-neighbor matching without replacement, using a caliper of 0.05 and imposing the common-support restriction. Kernel densities are estimated using a bandwidth of 0.04.

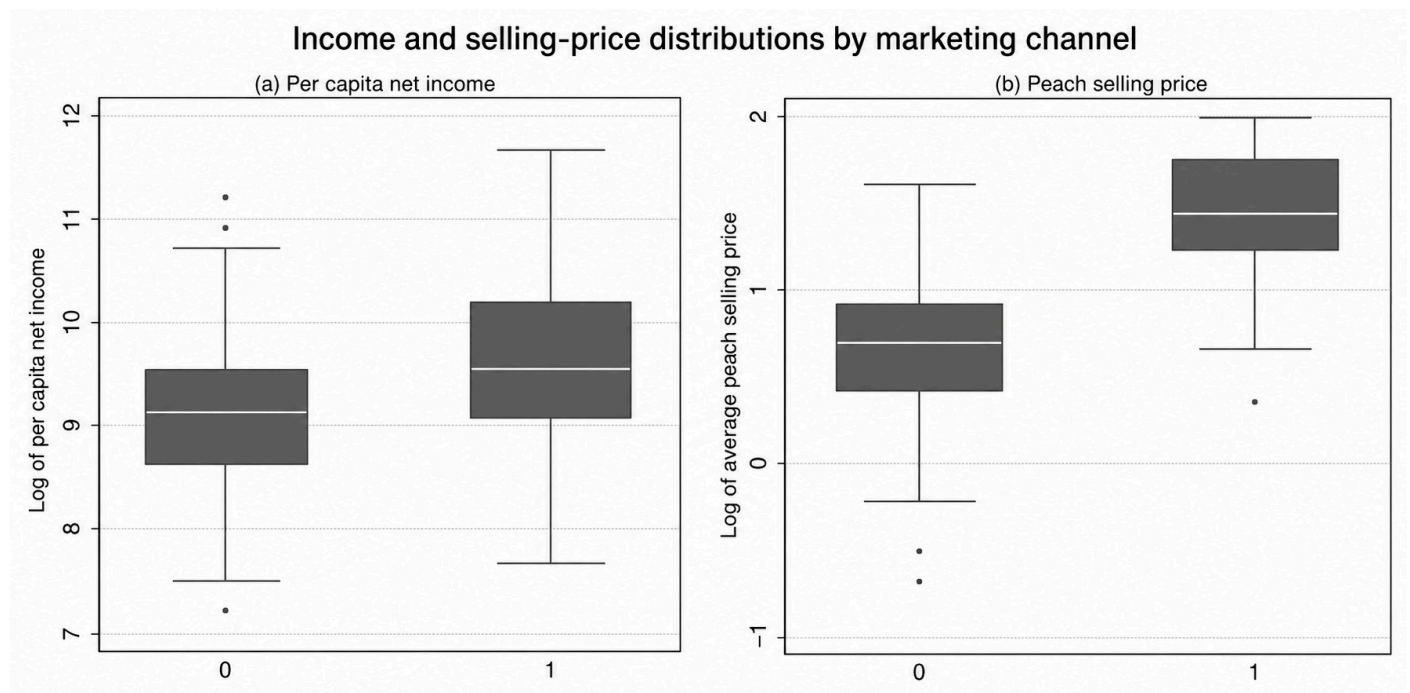


Figure A3. Distributions of per capita net income and peach selling prices by social-commerce participation. Note: The horizontal line within each box indicates the median, the box represents the interquartile range, and the whiskers extend to the adjacent values. Dots denote observations outside the whiskers. Both variables are expressed in logarithmic form.

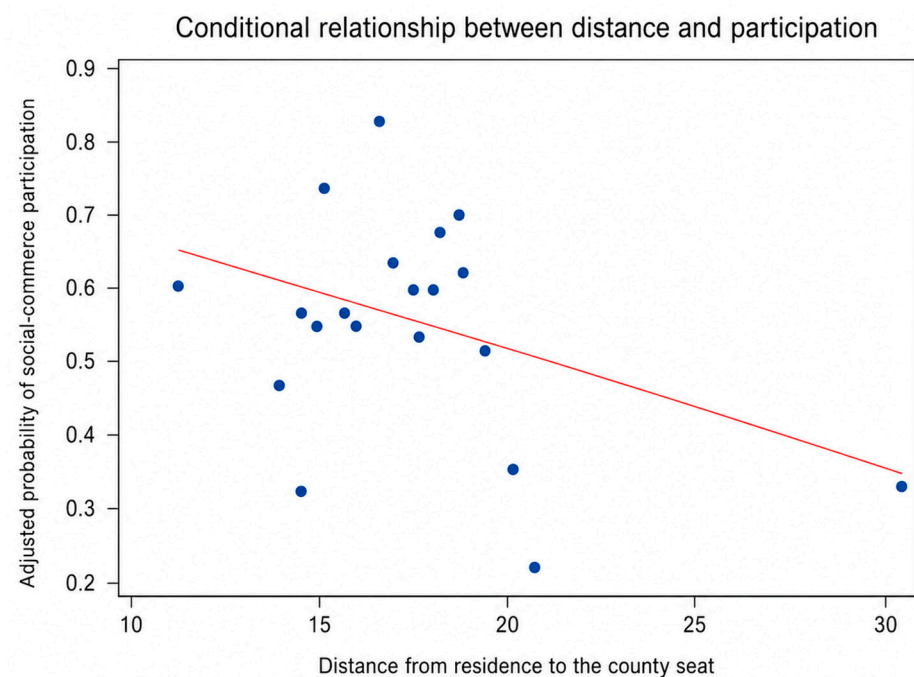


Figure A4. Conditional relationship between distance to the county seat and social-commerce participation. Note: The figure shows a negative conditional association between distance to the county seat and social-commerce participation after controlling for the covariates included in the first-stage regression.

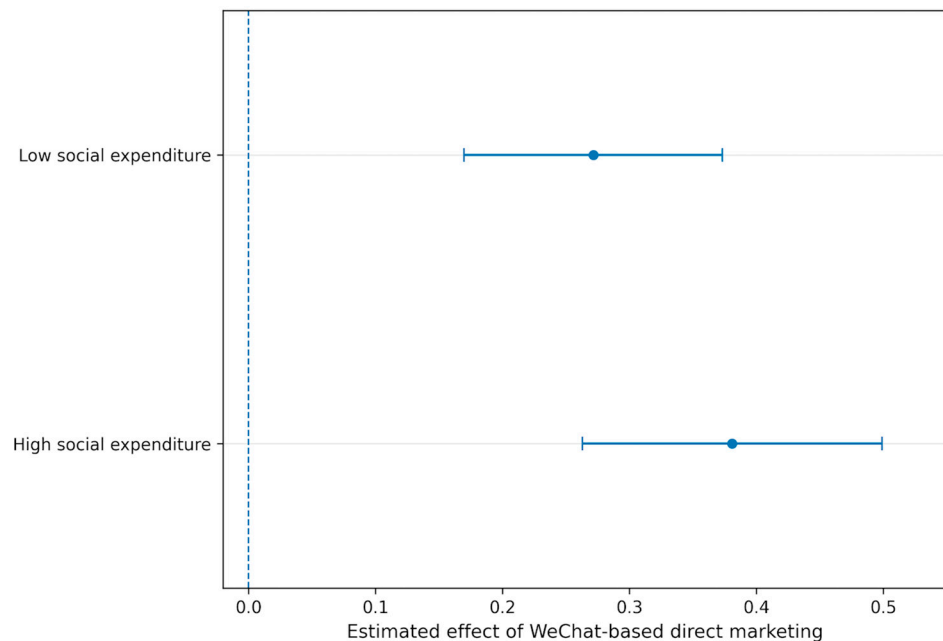


Figure A5. Coefficient estimates of the effect of WeChat-based direct marketing by household social expenditure. Note: Dots represent the estimated coefficients, horizontal lines represent 95% confidence intervals, and the dashed vertical line indicates a zero effect.

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