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Can citrus farmers earn more from selling online?

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ABSTRACT

Online sales are essential for linking smallholder farmers to a wide range of markets. In essence, online sales not only influence the income received from selling a specific product but also generate spillover effects on total farm income and household income because they promote the sales of other agricultural products and generate regional off-farm work opportunities (e.g. product sorting, packaging, and delivery). Taking citrus as an example, this study explores the income effects of online sales with a focus on net returns from citrus production, net farm income, and household income. We used an endogenous treatment regression model to address the self-selection bias issues of online sales and estimated data collected from 926 citrus-producing households in Jiangxi Province, China. The results show that online citrus sales boost income growth in rural China. Specifically, online sales significantly increased net returns from citrus production, net farm income, and household income by 5,000 Yuan/capita, 8,580 Yuan/capita, and 17,830 Yuan/capita, respectively. The income-enhancing effects of online sales are greater for female household heads than they are for their male counterparts. Our findings emphasise the importance of promoting online sales to improve rural household welfare.

1. Introduction

Improving rural income has long been a priority for governments and establishing effective connections between smallholder farmers and a wide range of markets is crucial for accomplishing this task. However, in reality, farmers' access to markets is challenged by several factors, such as inadequate distribution channels (Liu et al., 2019; Markelova et al., 2009), high transaction costs (Liu et al., 2021; Ma et al., 2018), and information asymmetries between supply and demand (Ullah et al., 2020; Zheng et al., 2021). These barriers hinder farmers from capitalising on market opportunities. Consequently, numerous farmers struggle to identify appropriate markets and sell their agricultural products at reasonable prices. Particularly in remote areas, these marketing barriers render agricultural production unprofitable and exacerbate poverty and vulnerability amongst farmers. Therefore, effectively linking farmers to markets is important for boosting income growth and facilitating sustainable rural development.

Online sales have grown rapidly worldwide owing to the rapid development of e-commerce in recent decades and have proven to be an important way for farmers to access multiple markets (Li et al., 2021; Liu et al., 2021; O'Hara and Low, 2020; Peng et al., 2021; Vakulenko et al., 2022). Through online marketing platforms, buyers and sellers anywhere can instantly receive information on supply

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and demand, and they can access faster, more in-depth, and more frequent information interactions than in traditional sales markets (e.g. selling in rural spot markets) (O'Hara and Low, 2020), which effectively reduces information asymmetry. Thus, online sales by farmers contribute to lowering transaction costs, expanding sales, and improving sales prices and volumes (Baourakis et al., 2002; Li et al., 2021; Liu et al., 2021).

A growing body of literature demonstrates that online sales positively influence multiple aspects of farmers' lives (Ji et al., 2023; PENG et al., 2021; Qi et al., 2019; Wang et al., 2023; Yin and Choi, 2022). Online sales have been reported to increase agricultural returns (Liu et al., 2021), promote off-farm employment (Leong et al., 2016), and stimulate the entrepreneurial skills of rural people (Mei et al., 2020). Moreover, Couture et al. (2021) showed that online sales increase farmers' spending on durable goods such as electronic appliances. Shen et al. (2023) found that online sales significantly reduced farmers' consumption of staple foods such as grains and potatoes but increased their consumption of healthy foods (e.g., legumes, nuts, and dairy products). Furthermore, online sales reduce farmers' propensity to migrate, increase their capacity to be employed locally (Qi et al., 2019), and enhance their subjective well-being (Jin et al., 2020).

Some studies have investigated the association between online sales and household income; however, their findings remain mixed. For instance, Zheng et al. (2023) showed that online sales would boost potato farmers' annual net income per capita. Further, the study of Li et al. (2021) distinguishes income into sales income, property income, wage income, and transfer income and shows that e-commerce adoption boosts sales and property income but has a significant negative impact on wage income and no impact on transfer income. However, Couture et al. (2021) showed a different conclusion by analysing data on commodity prices collected from the household and village level in rural China, finding that e-commerce did not have a significant impact on local production and income. In addition, Peng et al. (2021) showed that the impact of online sales is regionally heterogeneous, with a positive and then negative impact in poorer areas, showing an inverted U-shape. These mixed findings highlight that more research work is needed to help clarify the association between online sales and farmers' incomes. By doing so, valuable insights can be gained for improving farmers' market access and rural development.

Our study investigates the impact of online sales on farmers' incomes using citrus production as an example. Specifically, online sales in this study refer to a case in which citrus farmers choose to sell their products through online platforms (e.g., Taobao, Jingdong, and Pinduoduo). This study contributes to the existing literature in three ways. First, our study considers multiple dimensions of farmers' income (i.e., net returns from citrus production, net farm income, and household income) as dependant variables when estimating the income effects of online sales. This differs from previous studies that focused only on one or two types of farm income (Komatsu and Suzuki, 2021; Zheng et al., 2023). Using multiple income indicators allows us to capture the spillover effects of online sales because online sales not only influence income from citrus production, but also affect the sales of other agricultural products and regional off-farm work opportunities (e.g., product sorting, packaging, and delivery). This highlights the fact that online sales of citrus would also affect total farm income and household income. Second, this study defines online sales in a general sense (considering multiple forms of online sales) rather than restricts it to a special case, such as 'Taobao Village' (Li and Qin, 2022). This can help estimate the real role of online sales in improving farmers' income and rural development. Third, we adopt an endogenous treatment regression (ETR) model to address the endogeneity issues associated with online sales. Compared with widely used methods such as the propensity score matching (PSM) model and the inverse-probability-weighted regression-adjustment (IPWRA) estimator, which can only address observed endogeneity issues (Li et al., 2023; Liu et al., 2019), the ETR model is efficient in addressing endogeneity issues generated by both observed and unobserved factors (Twumasi et al., 2021; Vatsa et al., 2022). Thus, the ETR model guarantees a rigorous estimation of the association between online sales and farmers' income.

This study analysed the data of citrus farmers collected from 926 citrus-producing households in Jiangxi Province, China. China is

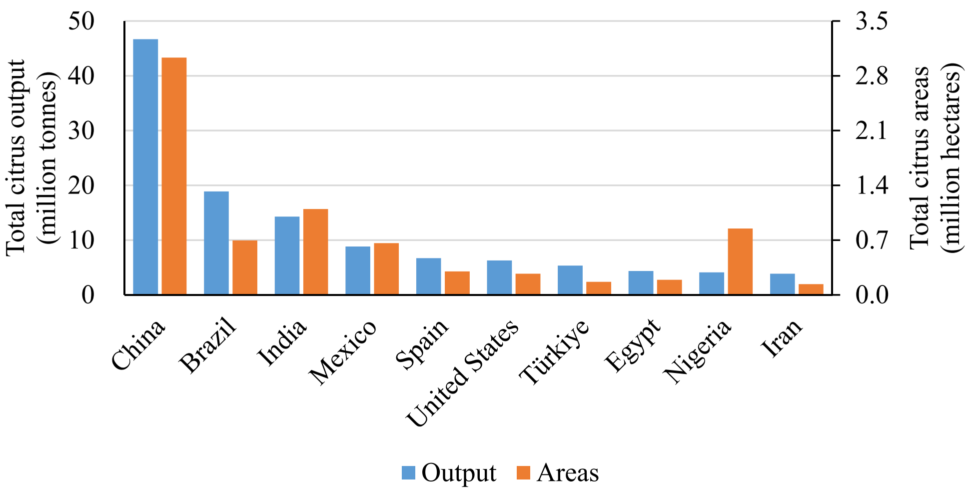

Fig. 1. Top 10 citrus-producing countries by total output and planting areas in 2021
Source: FAOSTAT.

the world's largest citrus producer, accounting for almost one-third of the global citrus production (FAOSTAT, 2022). Jiangxi is one of the main citrus planting areas in China, contributing to approximately 8 % of the citrus production in the nation. The average commercialisation rate of citrus in Jiangxi Province was approximately 56 % between 2012 and 2021, which is much lower than the average for the main planting areas (92 %) (NCAPCI, 2022). Thus, it is essential to further improve Jiangxi Province's citrus commercialisation rate to enhance rural incomes.

The remainder of this paper is organised as follows. Section 2 presents the background to this study. Section 3 introduces the analytical framework and estimation strategy. Section 4 presents data, variables, and descriptive statistics. This is followed by a discussion of the empirical results in Section 5. The final section concludes the paper and provides policy implications and limitations.

2. Background

2.1. Citrus production in China

Citruses are one of the most important cash crops in China. The total output and planting area of citrus are the highest worldwide (Fig. 1). In 2021, China's citrus output was 46.67 million tons, which was significantly higher than other major citrus-producing countries such as Brazil, India, and Mexico (FAOSTAT, 2022). The citrus planting areas were 3.03 million hectares in China by 2021 (Fig. 1), accounting for approximately 30 % of the world's citrus planting area (FAOSTAT, 2022). In comparison, India, the second-largest country in citrus planting areas, only grew 1.1 million hectares in 2021. Despite significant citrus production in China, its market value and commercialisation ratio are expected to improve further to enhance the performance of the citrus sector. For instance, the gross value of citrus production in China was US$4.21 billion in 2021, less than 55 % of that achieved by India (US$7.68 billion). Moreover, official estimates show that the price of Chinese citrus was only 90.21 USD per ton in 2021, ranking 70th in the world, which is dramatically lower than that of India (536.83 USD per ton) and Iran (259.75 USD per ton) (FAOSTAT, 2022). Although citrus commercialisation in China reached an average level of 89 % by 2021 (NCAPCI, 2022), it is relatively low in some regions. For instance, the citrus commercialisation rate in Jiangxi Province was only 75 %.

Jiangxi Province, the study area, is one of the eight citrus planting areas in the country. Other major citrus-planting areas in China include Fujian, Guangdong, Guangxi, Hubei, Hunan, Zhejiang, and Chongqing. Fig. 2 shows the citrus production and planting areas in Jiangxi Province between 2012 and 2021. It shows that although both the total citrus output and planting areas fluctuated from 2012 to 2017, they steadily increased in the last few years. In 2021, Jiangxi planted 336.2 thousand hectares of citrus and produced 4.45 million tons of citrus, contributing 11 and 8 % of the national total in planting areas and output, respectively (NBSC National Bureau of Statistics China, 2022).

2.2. Development of online sales markets

The rise of online sales can be traced back to the 1990s when the rapid development of the Internet provided a fundamental platform for conducting this practice. Global companies such as eBay, Amazon, and Alibaba emerged during this period with e-commerce as their primary business focus, providing specific application scenarios for online sales (Hänninen et al., 2019; Jung et al., 2015). From 2014 to 2021, global online retail sales experienced significant growth, increasing from USD 1.34 trillion to USD 5.21 trillion (Statista, 2022) — a 2.9-fold increase. China has made significant efforts to keep pace with this trend. In 2013, the Chinese State Council introduced the 'Broadband China' programme to expand Internet coverage in urban and rural areas by 2020. During this period, the value of China's online sales grew by 3.7 times, increasing from 2.79 trillion yuan in 2014 to 13.1 trillion Yuan in 2021. The value of online sales in China in 2021 accounted for approximately 40% of global online market sales (NBSC, 2022).

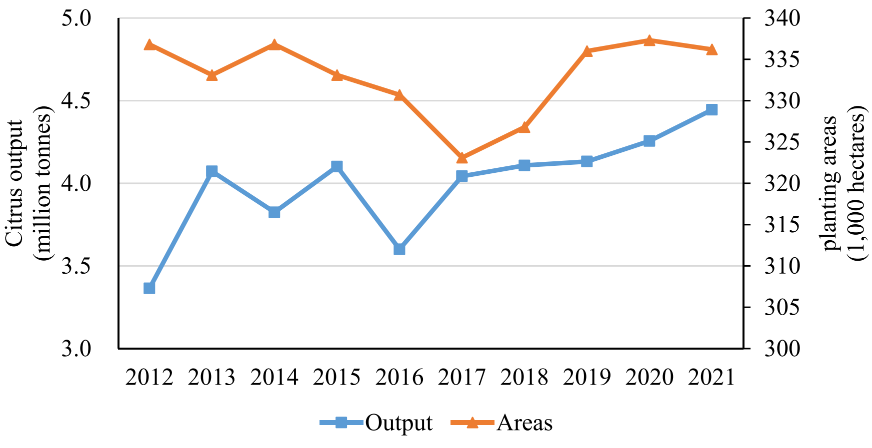

Fig. 2. Total citrus output and planting areas in Jiangxi province (2012–2021)
Source: China Rural Statistical Yearbooks (2013–2022).

The Chinese government has made significant efforts to support online sales in rural areas. Since 2014, the annual Central Document No. 1 has repeatedly emphasised the priority of e-commerce development, targeting the removal of market barriers to agricultural product commercialisation. Owing to these efforts, online retail sales in rural China experienced an 11.3% year-over-year increase from 2020 to 2021, reaching an astonishing 2.05 trillion yuan. This accounted for 15.66% of total national retail sales. Meanwhile, online retail sales of agricultural products amounted to 422.1 billion yuan in the same year, reflecting a 2.8% year-over-year growth during the same period (MC, 2022). Nevertheless, national online retail sales of agricultural products account for only 9.8% of total agricultural transactions, far from properly exploiting their potential to improve farmers' income and rural development. Accordingly, the Chinese government plans to increase this share to 15 % by 2025 (FAO, 2020). Therefore, optimising online sales of agricultural products is an important task for the Chinese government.

3. Analytical framework and estimation strategy

3.1. Analytical framework

Online sales open a new channel for smallholder farmers to access a wide range of agricultural product markets, empowering rural farmers to improve their income. Drawing on the literature on online sales (e.g., Couture et al., 2021; Liu et al., 2021; Mei et al., 2020) and rural income (e.g., Li et al., 2021; Peng et al., 2021; Tang et al., 2022), we depict the mechanisms linking online sales to rural income (i.e., income from selling citrus, farm income, and household income) and visualise them in Fig. 3.

First, online sales determine the net returns from citrus production by reducing the number of intermediaries and easing market information acquisition. Online sales are one of the two transaction modes (i.e., online sales and physical sales) of 'Business-to-Consumer' (B2C), which directly connects a business to consumers. Online sales reduce the intermediaries that exist in the traditional citrus supply chains, reducing transaction costs and profit losses (i.e., the profits taken away by intermediaries) (Serra and Davidson, 2021; Song et al., 2021). In addition, online sales allow agricultural product sellers to collect abundant market information, which helps reduce information asymmetry. For instance, by relying on big data techniques, online sales platforms (e.g., Taobao and Jingdong) can provide sellers with accurate portraits of consumers, enabling them to know what and when consumers may want to purchase. Finally, farmers can choose the right time to sell more products at higher prices. Through this channel, online sales can increase the net returns from citrus production. An increase in net returns from citrus production increases total farm income and household income.

Second, online citrus sales may have spillover effects on the income received from selling other agricultural products (e.g., tea, sweet potatoes, and passion fruits). In addition to citrus, farmers may choose to grow other agricultural products to reduce their income and production risks. The skills and knowledge learned from selling citrus online would motivate farmers to sell other agricultural products online. By doing so, online sales also increase the income that farmers receive from selling other agricultural products.

Third, online sales may also have spillover effects on off-farm income. Farmers and their household members have to learn additional skills, such as packaging, delivery, product promotion, and computer software applications, to better support the sales of their products (Li et al., 2021; Peng et al., 2021). Those skills can help farmers engage in other off-farm work activities during the non-selling season of citrus, increasing their off-farm income. Off-farm income further increases household income.

The analyses discussed above reveal that online sales not only influence the income received from selling citrus but also affect farm income and household income. We employ an appropriate econometric model to empirically analyse how and to what extent online sales influence the three income variables captured by net returns from citrus production, net farm income, and household income.

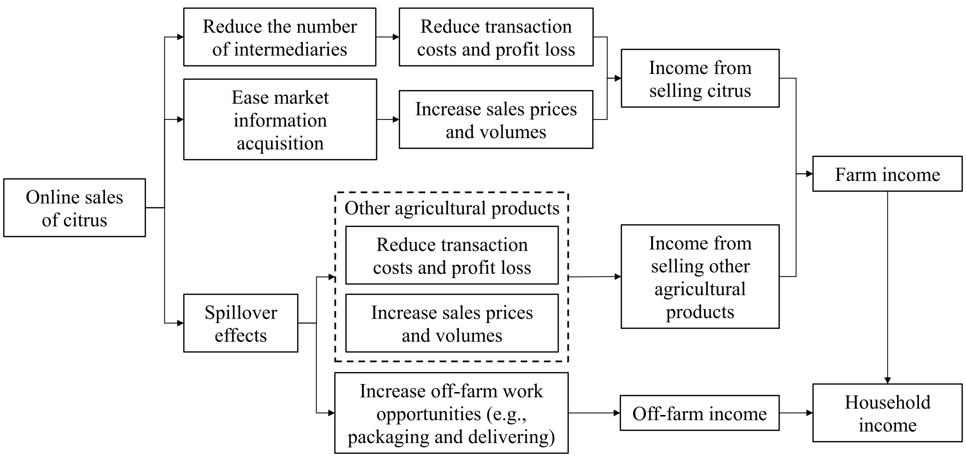

Fig. 3. Impact pathways of online sales on incomes.

3.2. Estimation strategy

Farmers are not randomly contracted for online sales but voluntarily conduct this practice depending on their endowments (Jin et al., 2020; Xinhua, 2023). Therefore, citrus farmers' participation in online sales tends to be influenced by observed (e.g., age, education, and financial condition) and unobserved (e.g., managerial skills and motivations) factors. Logically, our treatment variable, online sales, is recognised as endogenous and is associated with observed and unobserved endogeneity issues. If these endogeneity issues are ignored, biased estimates of the impact of online sales on farmers' income can be generated. Thus, the primary task is to address the endogeneity issues of online sales by assessing their impact on farmers' incomes.

Prior studies have suggested multiple econometric strategies, such as the PSM model (dos Santos et al., 2023; Ma et al., 2022), IPWRA estimator (Chigusiwa et al., 2023; Danso-Abbeam and Baiyegunhi, 2018), and ETR model (Li et al., 2023; Vatsa et al., 2022), to estimate the impact of an endogenous dummy (i.e. online sales participation) on a continuous outcome (e.g., net returns from citrus production). As mentioned earlier, the PSM and IPWRA approaches are efficient in addressing observed endogeneity, but neglect endogeneity stemming from unobserved factors (Li et al., 2023; Liu et al., 2019). By comparison, the ETR model helps estimate unbiased results by accounting for observed and unobserved endogeneity (Vatsa et al., 2022). Therefore, the ETR model was preferred in this study.

The ETR model is estimated in two stages. In the first stage, a probit model that includes a set of exogenous variables is estimated to describe farmers' decisions to participate in online sales. In the second stage, an ordinary least squares (OLS) regression model is used to estimate the effects of online sales and control variables on the income variables. Following Li et al. (2023), the two stages of the ETR model are as follows:

$$\text{Stage 1}: OS_i^* = \alpha_i X_i + \beta_i IV_i + \varepsilon_i, OS_i = \begin{cases} 1, & \text{if } OS_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$\text{Stage 2}: INC_i^J = \gamma_i OS_i + \delta_i X_i + \mu_i, J = 1,\ 2,\ 3 \tag{2}$$

where OS_i^* refers to the probability that a citrus farmer will choose to sell their products online. Although OS_i^* cannot be directly observed, it is observed by a dichotomous variable OS_i. Specifically, OS_i equals 1 if a citrus farmer chooses to sell his products online and 0 otherwise. INC_i^J is the measure of income variables, representing net returns from citrus production ($J = 1$), net farm income ($J = 2$), and household income ($J = 3$); X_i refers to a vector of control variables, which is allowed to have an overlap; IV_i indicates the selected instrumental variable (IV); α_i, β_i, γ_i, and δ_i are parameters to be estimated; ε_i and μ_i are the error terms.

The ETR model uses a maximum likelihood (ML) estimator to jointly estimate Eqs. (1) and (2) (Li et al., 2023). The ML estimator also calculates the correlation coefficient ($\rho_{\varepsilon\mu}$) of the error terms (i.e., ε_i and μ_i) in the two equations. A significant $\rho_{\varepsilon\mu}$ signals the existence of unobserved endogeneity of online sales, evidencing the reasonability of using the ETR model.

To guarantee the ETR model's efficiency in addressing endogeneity issues, at least one valid IV should be identified and included in Eq. (1) but not in Eq. (2). It has been well-documented that a valid IV should be correlated with the endogenous variable and uncorrelated with the dependant variable. Following this scenario, we considered two IVs: network fees and peer sales. The network fees variable refers to farmers' expenditures on phone and Internet bills, whereas the peer sales variable refers to the proportion of farmers participating in online sales, excluding respondents in the same village. Large Internet access bills indicate that farmers are deeply immersed in e-lifestyles. Thus, they are more likely to recognise the importance of the Internet in improving their economic performance and adopt online sales as a strategy for market participation. Meanwhile, peer effect theory suggests that individual behaviour largely depends on neighbours, friends, relatives, and even other villagers (Eilers et al., 2022; Sampson and Perry, 2019). Therefore, farmers living in villages with a higher proportion of online sales participants are more likely to conduct online citrus sales than their counterparts living in villages with lower levels of online sales. These two selected IVs are expected to be positively associated with online sales. However, they do not directly affect farmers' income variables but only through their impact on online sales participation. Theoretically, the selected IVs satisfy the scenarios they must satisfy. Mathematically, our IVs satisfied the corresponding tests. The estimates illustrated in Table 3 suggest that the Sargan and Basmann tests are insignificant, indicating that there is no over-identification problem. Thus, we can safely conclude that the selected IVs reliably address the endogeneity issues of online sales.

4. Data, variables, and descriptive statistics

4.1. Data

Data for this study were obtained from a survey of citrus farmers in Jiangxi Province, China. Data were collected between October and November 2022 and sponsored by the Huazhong Agricultural University, Wuhan, China. This information refers to the 2021 production year. Samples were collected in four stages using a multistage stratified random sampling technique. In the first stage, the survey randomly selected two of the 11 prefecture-level cities in Jiangxi Province, including Ganzhou and Fuzhou. Next, 7 townships were randomly selected from each sampled city. In the third stage, approximately four villages were chosen from each township based on the village-level citrus planting area. Finally, 10–30 citrus growers within each selected village, proportional to the village size, were randomly sampled and interviewed face-to-face, resulting in 1009 samples. During data cleaning, 83 samples with missing or abnormal values for the dependant variables were removed. Therefore, 926 samples were analysed in our study, of which 141 were online sellers.

The survey was conducted by enumerators who could speak both Mandarin and the local dialects in the sampled townships. Designing and utilizing a detailed and structured questionnaire, the survey gathered household- and farm-level information to comprehensively reflect the citrus growers' demographic characteristics (e.g., age, gender, and household size), economic performance (e.g., household income and employment), citrus production (e.g., planting area and output), and spatial distribution.

4.2. Measurements of key variables

4.2.1. Online sales variable

The online sales variable is used as a dummy variable. The variable takes the value of one if a citrus farmer in our sample chose to sell their products via online platforms (e.g., Taobao, Jingdong, and Pinduoduo) and zero otherwise.

4.2.2. Income variables

To understand the income effects of online sales, we considered three income variables as dependant variables: net returns from citrus production, net farm income, and household income. Net returns from citrus production were defined as the difference between the gross income from citrus production and the costs of citrus production inputs (fertilisers, pesticides, growth regulators, pest control facilities, irrigation, and hired labour). Net farm income refers to the difference between the gross income from all types of farming activities and the costs of total agricultural production. Household income is the aggregation of farm income, off-farm income, and other income (e.g., transfer income and property income). The three dependant variables were measured at 10,000 Yuan/capita/year to make them comparable across samples and estimations.

The income from citrus production directly determines the total farm and household income. In addition, online sales would generate spillover effects on total farm income and household income by influencing the sales of other agricultural products and off-farm employment at the regional level. Therefore, considering these three income variables (net returns from citrus production, net farm income, and household income) provides a comprehensive understanding of the income effect of online sales.

4.3. Selection of control variables

We also included a set of control variables in our empirical setting. Following previous studies (Khan et al., 2022; Li et al., 2021; Liu et al., 2021), we used variables, including age, gender, education, health status, village cadres, risk attitude, family size, and dependency ratio, to reflect the demographic characteristics of citrus growers. It is worth noting that old farmers tend to be reluctant to adopt improved practices (Qiu et al., 2021). Therefore, we expected a negative association between age and online sales participation.

Table 1
Variable definitions and summary statistics.

Variables	Definitions	Mean (S.D.)
Outcome variables		
Net returns from citrus production	The difference between gross income from citrus production and production costs (10,000 yuan/capita) [a]	0.31 (1.43)
Net farm income	The difference between gross income from all kinds of farming activities and total agricultural production costs (10,000 yuan/capita)	0.54 (1.73)
Household income	(10,000 yuan/capita)	3.43 (4.18)
Treatment variable		
Online sales	1 if household has sold citrus via online platforms (e.g., Taobao, Jingdong, and Pinduoduo), 0 otherwise	0.15 (0.36)
Control variables		
Age	Age of household head (HH) in years	53.23 (9.38)
Gender	1 if HH is male, 0 otherwise	0.77 (0.42)
Education	Education level of HH [b]	2.67 (1.03)
Health status	Self-reported health status: from 1 = very unhealthy to 5 = very healthy	4.20 (0.88)
Village cadre	1 if HH serves as a village cadre in a village, 0 otherwise	0.18 (0.38)
Risk attitude	1 if HH is a risk-lover, 0 otherwise	0.32 (0.47)
Family size	Number of people residing in a household in persons	5.11 (1.85)
Dependency ratio	Ratio of household members under the age of 15 and over the age of 60 to total household size	0.33 (0.21)
Property ownership	1 if household purchased another property in the county, 0 otherwise	0.22 (0.41)
Farming years	Number of years HH engaged in citrus farming (years)	19.56 (9.27)
Soil conditions	Self-reported soil conditions of farmland: from 1 = very poor to 5 = very good	3.50 (0.95)
Plot number	Number of cropland plots for citrus production	2.77 (2.64)
Distance	Distance from the village to the county (km)	18.16 (14.44)
Location	1 if HH resides in Ganzhou, 0 otherwise (i.e. Fuzhou)	0.47 (0.50)
Instrumental variables		
Network fees	Expenditure on phone and Internet bills (100 yuan/month)	2.76 (2.19)
Peer sales	Proportion of people selling online in the village to the village size (excluding the respondent)	0.15 (0.15)
Observations		926

Note: S.D. refers to the standard deviation;.
[a] Yuan is a Chinese currency (1 USD = 6.73 Yuan in 2022).
[b] 1 = illiterate; 2 = Primary school; 3 = Junior middle school; 4 = High school/technical school; 5 = College and above.

Dependents increase households' financial burdens and reduce their labour supply (Vatsa et al., 2022), hindering farmers from using improved practices and earning higher incomes. Accordingly, the dependency ratio variable may negatively impact online sales participation and household income. In addition, we used property ownership as a proxy for farmers' financial conditions. Good financial conditions allow farmers to afford the costs associated with practice adoption and selling agricultural products (Martínez-Domínguez and Mora-Rivera, 2020). Thus, property ownership is positively correlated with online sales and household income. Farming years, soil conditions, and plot numbers were used to describe citrus production conditions. Fertile land has been confirmed to be beneficial for increasing yield, allowing farmers to earn more income (Ngoma, 2018). Therefore, we included soil condition variables to reproduce this positive association. We also controlled the effects of farmers' geographical features by including variables representing the distance from the sampled village to the county and city dummies.

4.4. *Descriptive statistics*

Table 1 presents the definitions and descriptive statistics of selected variables. It shows that approximately 15% of the samples sell their citrus online, suggesting that the penetration rate of online sales remains at a low level in the study area. The mean values of the dependant variables suggest that citrus growers in our sample annually earned an average net return, net farm income, and household income of 3100 Yuan/capita, 5400 Yuan/capita, and 34,300 Yuan/capita, respectively. Table 1 also shows that our sample is dominated by relatively old, male, poorly educated, and healthy farmers. Approximately 18, 32 and 22 % of respondents reported serving as village cadres, holding risk-loving attitudes, and owning more than one property, respectively. Around 5.11 members are residing in the sampled households, 33 % of whom are dependants. On average, the respondents had planted citrus fruits for approximately 20 years. Meanwhile, they tend to cultivate three farmland plots with normal soil conditions. The average distance between the sampled village and the county is 18.16 km.

Table 2 details the mean differences in the selected variables between online sellers and non-online sellers. As can be seen, there exist significant mean differences in all the selected variables between the two cohorts. For instance, online sellers tend to have more net returns from citrus production, net farm income, and household income than non-online sellers. Relative to non-online sellers, online sellers tend to be younger, male, better-educated, healthier, and risk-loving. The significant differences in the variables for village cadre, family size, and dependency ratio suggest online sellers are more likely to take the role of village cadre and live in labour-scarce families compared with their non-online seller counterparts. The results in Table 2 also suggest that, compared with non-online sellers, online sellers tend to have a shorter citrus planting career and fewer farmland plots, while their soil condition appears to be better. Furthermore, compared with non-online sellers, online sellers are less likely to possess the location advantage as their villages are located remotely from the county.

Overall, the results in Table 2 indicate that online and non-online sellers systematically differ in terms of income and the observed control variables. However, these significant differences in income cannot be concluded as the real impact of online sales on farmers' incomes, as they neglect the effects of confounding factors. Therefore, a suitable econometric strategy, the ETR model, is used in our

Table 2
Mean difference in the selected variable between online sellers and non-online sellers.

Variables	Online sellers	Non-online sellers	Mean differences
Outcome variables			
Net returns from citrus production	0.75 (2.22)	0.23 (1.22)	0.52***
Net farm income	1.23 (2.80)	0.42 (1.42)	0.81***
Household income	5.19 (6.52)	3.11 (3.51)	2.08***
Control variables			
Age	51.15 (10.01)	53.60 (9.22)	−2.46***
Gender	0.87 (0.34)	0.76 (0.43)	0.11***
Education	3.21 (1.06)	2.57 (0.99)	0.64***
Health	4.40 (0.76)	4.16 (0.90)	0.25***
Village cadre	0.29 (0.46)	0.16 (0.37)	0.13***
Risk attitude	0.58 (0.50)	0.27 (0.45)	0.31***
Family size	5.36 (1.73)	5.06 (1.86)	0.30*
Dependency ratio	0.36 (0.22)	0.32 (0.2)	0.04**
Property ownership	0.28 (0.45)	0.21 (0.4)	0.07*
Farming years	18.31 (9.03)	19.78 (9.29)	−1.48*
Soil conditions	3.70 (1.00)	3.46 (0.93)	0.23***
Plots number	2.22 (2.16)	2.87 (2.71)	−0.65***
Distance	20.89 (14.64)	17.67 (14.36)	3.22**
Location	0.78 (0.42)	0.41 (0.49)	0.37***
Instrumental variables			
Network fees	3.68 (3.20)	2.60 (1.91)	1.08***
Peer sales	0.23 (0.16)	0.14 (0.14)	0.10***
Observations	141	785	

Note: Standard deviation is presented in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$;.

study.

5. Empirical results and discussion

Table 3 shows the first- and second-stage regression results of the ETR model for net returns from citrus production, net farm income, and household income. The first-stage regression results show the estimated effects of the factors that influence farmers' online selling behaviour (Columns 2, 4, and 6), and the second-stage regression results show the income effects of different factors (Columns 3, 5, and 7). As shown at the bottom of the table, the coefficients of $\rho_{\varepsilon\mu}$ for the models for net returns and net farm income are statistically significant, indicating the existence of selection bias due to unobserved factors. This demonstrates the efficiency of using the ETR model to query the impact of online sales on farmers' income.

5.1. Factors influencing online sales

As shown in Columns 2, 4, and 6 of Table 3, the estimation results of the first-stage regression are similar for all three models. For simplicity, we interpret only the results illustrated in Column 2. The results show a significantly positive relationship between educational level and online sales, indicating that people with higher educational levels are more likely to participate in online sales. Better education allows farmers to easily learn the skills and knowledge required for online sales and motivates them to practice. This finding is consistent with many existing studies on the relationship between education and e-commerce or e-business (Liu et al., 2021; Ma et al., 2020). Risk attitude is estimated to have a significant and positive impact on online sales, that is, risk lovers are more likely to participate in online sales. They are more willing to sell products via new channels such as online platforms, as these channels are associated with higher risks and returns than traditional sales methods (Liu et al., 2019; Schipmann and Qaim, 2011; Wainaina et al., 2012). There is also a significant location effect on the choice of online sales; people living in Ganzhou are more likely to participate in online sales than those living in Fuzhou. Compared with Fuzhou, Ganzhou is closer to major Chinese cities, such as Guangzhou and Shenzhen, providing a higher level of development of logistics facilities, consumer markets, and e-commerce (Zhang et al., 2022),

Table 3
Impact of online sales on net returns, net farm income, and household income: ETR model estimations.

	Model (1)		Model (2)		Model (3)	
Variables	Online sales	Net returns from citrus production	Online sales	Net farm income	Online sales	Household income
Online sales		0.500 (0.250)**		0.858 (0.302)***		1.783 (0.697)**
Age	−0.010 (0.007)	−0.014 (0.010)	−0.010 (0.007)	−0.028 (0.013)**	−0.009 (0.007)	−0.057 (0.025)**
Gender	−0.035 (0.162)	0.241 (0.158)	−0.029 (0.162)	0.449 (0.178)**	−0.038 (0.161)	0.299 (0.330)
Education	0.158 (0.064)**	−0.045 (0.077)	0.158 (0.064)**	−0.133 (0.093)	0.158 (0.064)**	0.164 (0.172)
Health	0.014 (0.071)	0.019 (0.049)	0.013 (0.072)	0.061 (0.061)	0.017 (0.071)	0.292 (0.138)**
Village cadre	0.039 (0.148)	0.214 (0.135)	0.040 (0.148)	0.304 (0.188)	0.035 (0.148)	0.376 (0.464)
Risk attitude	0.684 (0.117)***	0.149 (0.078)*	0.684 (0.117)***	0.097 (0.094)	0.676 (0.117)***	0.523 (0.246)**
Family size	−0.005 (0.034)	−0.035 (0.035)	−0.005 (0.034)	−0.079 (0.040)**	−0.006 (0.034)	−0.061 (0.084)
Dependency ratio	0.098 (0.336)	−0.403 (0.241)*	0.093 (0.336)	−0.333 (0.298)	0.097 (0.336)	−2.733 (0.662)***
Property ownership	0.097 (0.144)	0.065 (0.099)	0.105 (0.143)	0.197 (0.116)*	0.102 (0.143)	1.437 (0.351)***
Farming years	0.011 (0.007)	0.022 (0.006)***	0.011 (0.007)	0.019 (0.007)***	0.011 (0.007)	0.045 (0.017)***
Soil conditions	0.015 (0.063)	0.079 (0.042)*	0.019 (0.063)	0.125 (0.051)**	0.018 (0.063)	0.616 (0.135)***
Plots number	−0.002 (0.029)	−0.004 (0.012)	−0.003 (0.029)	−0.012 (0.016)	−0.003 (0.029)	0.019 (0.037)
Distance	0.003 (0.004)	0.001 (0.002)	0.003 (0.004)	0.000 (0.003)	0.003 (0.004)	−0.001 (0.006)
Location	0.744 (0.167)***	0.330 (0.113)***	0.736 (0.166)***	0.253 (0.141)*	0.726 (0.168)***	0.363 (0.336)
Network fees	0.067 (0.023)***		0.068 (0.023)***		0.068 (0.024)***	
Peer sales	0.749 (0.402)*		0.747 (0.401)*		0.790 (0.408)*	
Constant	−2.396 (0.633)***	0.185 (0.523)	−2.389 (0.632)***	1.108 (0.642)*	−2.419 (0.628)***	1.703 (1.383)
$\rho_{\varepsilon\mu}$	−0.088 (0.035)**		−0.101 (0.046)**		−0.076 (0.055)	
Wald test ($\rho_{\varepsilon\mu} = 0$)	Chi2 (1) = 6.27, Prob = 0.012		Chi2 (1) = 4.68, Prob = 0.031		Chi2 (1) = 1.88, Prob = 0.171	
Overidentification test of IVs						
Sargan test	Chi2 (1) = 0.418, Prob = 0.518		Chi2 (1) = 1.073, Prob = 0.300		Chi2 (1) = 0.052, Prob = 0.819	
Basmann	Chi2 (1) = 0.410, Prob = 0.521		Chi2 (1) = 1.055, Prob = 0.305		Chi2 (1) = 0.051, Prob = 0.821	
Observations	926	926	926	926	926	926

Note: Robust standard errors in parenthesis. The regional reference is Fuzhou.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

indicating a better chance of selling products online.

5.2. Impacts on rural incomes

5.2.1. Income impacts of online sales

As shown in Table 3 (Columns 3, 5, and 7), positive income effects of online sales exist across all three income types for farmers. This finding aligns with the results of existing studies on the income effects of e-commerce adoption (selling products online), where the adoption of the practice helps increase rural income (Li et al., 2021; Zheng et al., 2023). Specifically, the results in the third column show that online sales can increase net returns from citrus production by 5000 Yuan/capita (equivalent to approximately 691 USD/capita). As discussed in Section 3.1, selling online reduces transaction costs and information asymmetry. When selling citrus directly to consumers via online platforms, farmers can sell it promptly to ensure quality and higher sales prices. In reality, the price of citrus sold online is about 9 Yuan/kg, which is dramatically higher than that provided by middlemen (about 5 Yuan/kg). Therefore, if a farmer sold 1000 kg of citrus online, he could get an extra 4000 Yuan from citrus production, relative to those who did not sell online.

Online sales increased the net farm income by 8580 Yuan/capita (equivalent to approximately 1186 USD/capita), as shown in the fifth column. This can be explained by the fact that online platforms ease the way farmers obtain information about the production and marketing of their agricultural products, which helps increase farmers' net farm income. For instance, besides selling citrus, farmers can also sell other agricultural products such as tea, sweet potatoes, and passion fruits online, which takes full advantage of the synergistic effect of online sales. Regarding the effect of online sales on household income (Column 7), our results show that online sales increase household income by 17,830 Yuan per capita (equivalent to approximately 2464 USD/capita). In addition to generating a higher level of farm income, online sales can help both farmers and their household members access multiple market information and directly create off-farm employment opportunities (e.g., product sorting, packaging, and delivery) at the regional level, contributing to an increase in household income (Li et al., 2021).

5.2.2. Impacts of other factors on farm income

When examining the impact of the control variables on income, the factors acted differently across income types. Farmers with risk-loving attitudes tended to obtain higher net returns from citrus production. Risk lovers are more likely to try new marketing channels, production techniques, or improved inputs (e.g., fertilisers and pesticides), which enable them to take advantage of risky and rewarding opportunities (Gloede et al., 2015). Farming years also increase the net returns from citrus production, as people with more years of experience in farming can better cope with production situations and increase their income (Hossain et al., 2019). The dependency ratio is significantly and negatively related to the net returns from citrus production. This is because, as mentioned above, dependents increase the financial burden of households and reduce their labour supply (Vatsa et al., 2022), thus reducing farmers' income generation. In addition, the coefficient of location is significant and positive. This finding suggests that farmers in Ganzhou tended to have higher net returns than those in Fuzhou.

Age and family size have significant negative impacts on net farm income. Older farmers appear to be less productive (Ma et al., 2020), and receive lower net farm income. There is a negative correlation between family size and net farm income, which is consistent with the findings of Ma and Wang (2020) in China. A larger family size is not necessarily associated with a larger labour force, as a large family size usually means a higher proportion of the non-labour force—they are not capable of conducting agricultural production, and some (children and older adults) may need extra care from family members. Property ownership has a positive and significant impact on net farm income. This is understandable, as property owners are always in a good financial condition, allowing them to afford the costs of adopting improved practices and trading their outputs, thus bringing them more net farm income.

As for the impact on household income, health status and risk attitude are significantly and positively related to household income. Good health is an important driver of household income. Risk lovers tend to be more likely to be open to new opportunities, such as off-farm employment, and can therefore obtain higher incomes. In addition, high dependency ratios result in low per-capita incomes, and having property encourages farm households to earn more. Longer farming years and better soil conditions contribute to higher total household income.

5.3. Disaggregated analysis

Next, we discuss disaggregated analysis. Gender- and spatial-related disparities have been well-documented to be associated with heterogeneous endowments (Zhang et al., 2022) and market access (Mukarumbwa et al., 2018), which can significantly affect farmers' economic performance. Therefore, we differentiated the sample according to gender and the survey region. We observed three interesting findings from the gender analysis. First, online sales have a significant positive effect on net returns from citrus production for female household heads, whereas the same effect for male household heads is insignificant. This is consistent with our observations that most farmers who choose to sell online are women. Compared to men, women are more likely to communicate with consumers, know better how to move consumers through advertising, and possess richer marketing skills (Chen and Zheng, 2015); which allows female household heads to obtain higher net returns than men. This logic is also verified by the net farm income and household income results, in which all coefficients are significant. Second, as reflected by the estimated coefficients, the impacts of online sales on net returns from citrus production, net farm income, and household income are larger for female household heads than for male household heads. These findings confirm that online sales enable rural women to benefit from the market.

The results in Table 4 also suggest that online sales have heterogeneous effects on net returns from citrus production, net farm income, and household income depending on the survey locations. Regarding the net returns from citrus production, the coefficient of online sales for Ganzhou was higher than that for Fuzhou, which is consistent with the regression results for the entire sample. As Ganzhou has geographical advantages and convenient transportation conditions, it provides opportunities for farmers to gain higher incomes via online sales. The effect of online sales on net farm income was greater for farmers in Fuzhou than for those in Ganzhou. This is mainly because Fuzhou has a higher proportion of plains and better water infrastructure, elevating the yields and quality of its agricultural products. Therefore, farmers in Fuzhou were more likely to earn a higher net farm income. Interestingly, for household income, the increasing effect of online sales was higher for Fuzhou than for Ganzhou. This is mainly because of the difference in economic development between the two regions; Fuzhou is less developed than Ganzhou, with fewer off-farm working opportunities and relatively more information asymmetry. Therefore, farmers in Fuzhou may benefit more from online sales than those in Ganzhou.

6. Concluding remarks, implications, and limitations

6.1. Concluding remarks

Although online sales are rapidly growing in China, the proportion of agricultural products sold online is relatively low. Before encouraging farmers to sell agricultural products online, it is important to understand the potential benefits of online sales to farmers. Motivated by the importance of online sales to farmers' incomes, this study explores the income effects of online sales, with a focus on net returns from crop production, net farm income, and household income. We estimated the data collected from citrus producers in Jiangxi Province, China, and addressed the endogeneity issue of online sales using the ETR model.

The empirical analysis provides evidence of the positive effects of income on online sales. Specifically, online sales significantly increase net returns from citrus production, net farm income, and household income by 5000 Yuan/capita, 8580 Yuan/capita, and 17,830 Yuan/capita, respectively. In addition to directly increasing online sellers' income from citrus production, online sales generate spillover effects on net farm income by promoting the sales of other agricultural products and creating regional off-farm work opportunities (e.g., packaging and delivery), contributing to farm income and household income growth. Other factors were found to affect farmers' income to various degrees. Age, family size, and dependency ratio have negative effects on farmers' incomes, while risk attitude, property ownership, farming years, soil conditions, and location have positive impacts on income. Our disaggregated analyses show that online sales have a larger effect on females than on males for all three types of income; the effect of online sales differs across types of income—online sales affect net returns more for farmers in Ganzhou than in Fuzhou, but farmers in Fuzhou gain more from online sales regarding their net farm income and household income than those in Ganzhou.

6.2. Policy implications

The results of this study have several important policy implications. The positive income effects of online sales indicate the need to encourage farmers to conduct online sales to commercialise their agricultural products. Education is an important factor in the adoption of online sales, so policymakers may consider providing online sales-targeted training to farmers with a focus on the techniques and benefits associated with online sales. Note that, as for the design of training courses, policymakers need to consider regional differences, age, and education levels; with special consideration towards the poorly educated and older farmers in rural areas of less-developed countries, where farmers are relatively less educated and less productive. Providing targeted training can better facilitate the adoption of online sales and increase productivity in these countries. Meanwhile, training is also a good channel for farmers to learn from each other; information and experience can be shared and exchanged amongst farmers, and successful examples of online sales can further help build confidence for farmers to participate in online sales.

6.3. Limitations

This study has some limitations. First, our data were collected from only two municipalities (i.e. Ganzhou and Fuzhou) in one province (i.e., Jiangxi province) in China with a valid sample of 926 citrus farmers, of which only 15 % were sold online. Thus, more

Table 4
Disaggregated analysis by gender and survey regions: Second-stage estimations of the ETR model estimations.

	Net returns		Net farm income		Household income	
By gender	Male	Female	Male	Female	Male	Female
Online sales	0.463 (0.286)	0.965 (0.567)*	0.895 (0.363)**	1.103 (0.564)*	1.819 (0.809)**	4.595 (0.921)***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	715	211	715	211	715	211
By region	Ganzhou	Fuzhou	Ganzhou	Fuzhou	Ganzhou	Fuzhou
Online sales	0.604 (0.361)*	0.409 (0.217)*	1.172 (0.614)*	1.222 (0.521)**	2.015 (1.003)**	2.308 (1.150)**
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	435	491	435	491	435	491

Note: Robust standard errors in parenthesis.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

empirical analyses that focus on a larger sample size and a wide range of study areas are needed to help generalize our understanding of the income effects of online sales. Second, given the cross-sectional nature of the data, the dynamic effects (over time) of online sales could not be captured. Therefore, future studies should consider gathering panel data from broad regions to replicate and test the representativeness of the empirical analysis results of this study. Future studies should consider more factors (e.g., cognitive factors) to understand farmers' motivations to participate in online sales. Third, owing to the absence of required data, this study could not empirically test the spillover income effects of online sales on total farm income and household income. Future studies should explore the mechanisms through which online sales increase total farm and household incomes to improve our understanding of this field.

Declaration of Competing Interest

There is no conflict of interest.

Data availability

The data that support the findings of this study are available from Hepei Zhang upon request.

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