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REGULAR ARTICLE OPEN ACCESS

How Does the Adoption of e-Commerce Impact the Selling Prices of Agricultural Products? Empirical Evidence From Apple Farmers in China

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Keywords: apple production | e-commerce | marketing flexibility | rural China | selling price

ABSTRACT

The sale of products through e-commerce is emerging in rural China, and it cuts out intermediaries and allows farmers direct access to the market. To understand how adopting e-commerce impacts the selling prices of agricultural products and who benefits more from adopting e-commerce, we interviewed 480 apple farmers from the three representative provinces in China. The Propensity Score Matching approach combined with sensitivity analysis is employed to address the potential self-selection bias in estimating the impacts of adopting e-commerce. We find that adopting of e-commerce drives significant increases in the selling prices of apple products, including the average price, the maximum price and the minimum price. The heterogeneity analysis suggests that the adoption of e-commerce has significant heterogeneous effects on selling prices across various ages and education of household heads, land area, distance to the local town centre and social capital. The analysis of potential pathways reveals that increases in selling prices are attributed to farmers achieving more marketing flexibility through more adaptable sale times and extended sale periods due to adopting e-commerce. The research findings provide rigorous evidence on optimal future policy design regarding the development of rural e-commerce for poverty alleviation in China and other developing countries.

JEL Classification: O33, P22, P25, R58

1 | Introduction

Digital technologies can promote economic development and generate digital dividends by reducing information costs (World Bank 2016). The International Telecommunication Union proposed the elimination of poverty by developing telecommunications infrastructure in 1984 (World Bank 2016). Rural

e-commerce is one typical application of digital technologies to develop rural economies and allow producers in towns and villages to participate in the national and even global economy (Aker, Ghosh, and Burrell 2016; Deichmann, Goyal, and Mishra 2016; World Bank 2016). In this regard, it has been stated that adopting e-commerce in rural areas improves price transparency, cuts out intermediaries and makes markets more

Abbreviations: ATE, average treatment effect; ATT, average treatment effect for the treated; CPI, consumer price index; ICTs, information and communication technologies; IV, instrumental variable; KNM, K-nearest neighbour matching; NMC, nearest-neighbour matching within callipers; OLS, ordinary least squares estimation; PSM, propensity score matching; TE, treatment effect.

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efficient (World Bank 2016). Nevertheless, rigorous evidence-based studies on the specific effects of rural e-commerce on the selling prices of agricultural products for farmers are scant. Thus, this paper aims to empirically and rigorously examine the causal effects of adopting e-commerce on selling prices of agricultural products for farmers based on rural household survey data.

Rural e-commerce has been booming in China since the 2010s, although it did not appear until the late 2000s. The value of online retail sales of agricultural products was 159 billion RMB¹ in 2016, which increased to 397.5 billion RMB in 2019 (Ministry of Commerce of China 2020). Fruits, teas and nuts have been the top three agricultural products in online retail sales, and aquatic products, vegetables, and dairy products have ranked highest in the magnitude of the increase in their sales (China International Electronic Commerce Center (CIECC) 2018). Rural online stores reached nearly 12 million in 2019 (Ministry of Commerce of China 2020). Most of these stores are found on e-commerce platforms like Taobao, Jingdong, Pinduoduo, Yunji, Youzan and Ganjie. The number of Taobao villages, aggregations of e-commerce vendors in rural villages that pass a certain threshold regarding their numbers of online sales and stores, increased from 16 in 2012 to 4310 in 2019 (Aliresearch 2020). In the meantime, the Chinese national government put forward a 'poverty alleviation strategy through developing rural e-commerce' to bolster the development of rural e-commerce in poor rural areas in the early 2010s. In particular, the national project 'the Pilot Counties of Introducing E-Commerce to Rural Areas', which focuses on funding poverty-stricken areas to conduct e-commerce, was started in 2014 (Ministry of Commerce of China 2018). Every county involved in this project, which included 756 counties by 2017, was given 20 million RMB by the national government to develop local e-commerce based on the particular products produced by residents (Ministry of Commerce of China 2018). The local governments have also paid increasing attention to developing local rural e-commerce. By 2018, 77.7% of Chinese counties had established specialised offices for addressing e-commerce affairs (CIECC 2019).

Although some scholars have been interested in the impacts of developing e-commerce in the agricultural field from various perspectives, most of them engage in qualitative discussion and empirical analysis is limited. For instance, based on theoretical discussion, Buhr (2000) pointed out, that the development of e-commerce would cause dramatic changes in the organisational structure of the agri-food supply chain. Mueller (2001) intuitively demonstrated how the functions of the intermediaries between producers and consumers are being eliminated through a digital network. De Silva and Ratnadiwakara (2008), based on a case study from Sri Lanka, suggested that using information and communication technologies (ICTs) reduces transaction costs in agriculture by enabling timely and affordable communication. It has been deduced that the improvement of market transparency due to the use of digital technologies would result in more significant arbitrage opportunities for farmers, a reduction in spatial price dispersion, lower wastage and an increase in both consumer and producer welfare (Jensen 2010; Deichmann, Goyal, and Mishra 2016; World Bank 2016). In addition, an increasing amount of literature (mainly from Chinese scholars) is analysing the impacts of rural e-commerce based on the cases of

Taobao villages. For instance, Zhang et al. (2018) analysed the process and mechanism of rural economic restructuring driven by the development of e-commerce based on the case of Xiaying Village. Yu and Cui (2019) presented the impacts of the development of rural e-commerce on women's empowerment based on the cases of several successful Taobao villages. Cui et al. (2017) revealed that the development of e-commerce enables social innovation in rural China. Tang and Zhu (2020) observed that the diffusion of e-commerce in Taobao villages, combined with the informality found in rural China, results in some adverse effects on leading local enterprises.

In terms of examining the specific effects of adopting e-commerce on the selling prices of agricultural products, based on our knowledge, this is one of the first studies to use a rigorously empirical method and unique data taken from a large number of rural households that have or have not adopted e-commerce to sell their agricultural products. Existing studies touched on this research question while exclusively focusing on other ICTs, such as mobile phone and internet use; information provision is one of the most critical mechanisms when arguing their effect on the farm-gate price (e.g., Aker 2011; Aker and Fafchamps 2015). For instance, it was found that the market price of soybeans increased after internet kiosks were introduced (Goyal 2008). It is further supported by Courtois and Subervie (2015). They found that farmers received significantly higher selling prices for their maize and groundnuts if they participated in the mobile-based Market Information Services programme. Nevertheless, some other studies found that providing price information via mobile phones to farmers did not drive better selling prices for their products (Camacho and Conover 2011; Fafchamps and Minten 2012). Mitra et al. (2018) also found that the average farm-gate prices were unaffected when potato price information was provided to farmers via phone calls. In terms of these inconsistent research results, it has been revealed that the lack of direct access to markets depresses other options for farmers, limits their bargaining power with intermediaries and thus prevents informational interventions from benefitting farmers (Jaleta and Gardebroek 2007; Nakasone 2013; Aker, Ghosh, and Burrell 2016; Hildebrandt et al. 2020). It is particularly true in developing countries where farmers' access to markets is scarcer, and mediators depress the selling price of farmers' products and appropriate significant margins (Mitra et al. 2018; Bergquist and Dinerstein 2020). Emerging e-commerce provides farmers with a new outside option, which allows them to bypass middlemen and enter a market to sell their products directly (Zhang et al. 2018; Yu and Cui 2019). In this paper, whether this new selling channel increases farmers' prices significantly and how this happens will be studied by comparing it with the traditional selling channel through middlemen.

This paper estimates the effects of adopting e-commerce for farmers with unique data on farmers' agricultural products sold (or not) through e-commerce. To address the potential self-selection bias in e-commerce participation, the propensity score matching (PSM) method is applied to the surveyed data from 480 apple farmers, which constitute 2027 valid observations at the product level. Our main findings include the following: (1) the adoption of e-commerce increases the average selling price, maximum selling price and minimum selling price for apple farmers; (2) the selling prices for rural households that have

older and less-educated household heads and that have smaller areas of land for growing apples increase more significantly, and households that are located closer to local town centres and that have better social capital benefit more from the adoption of e-commerce; and (3) the increases in selling prices are attributed to the fact that farmers achieve more marketing flexibility through more adaptable sale times and more extended sale periods due to the adoption of e-commerce. This paper provides rigorous evidence on optimal future policy design regarding the development of rural e-commerce for poverty alleviation in China and other developing countries.

Our paper is organised as follows: Section 2 introduces the traditional selling channel for Chinese apple farmers and the corresponding changes due to the appearance of rural e-commerce. Section 3 presents the empirical methods, and the data collection and descriptive analysis are also described. Section 4 demonstrates the overall effects of adopting e-commerce for farmers. Sensitivity analysis and robustness checks are carried out to test the PSM results. After that, the heterogeneous analysis is presented, and the potential pathways are analysed. The research findings and the corresponding policy implications are discussed in Section 5.

2 | Background on Apple Selling by Chinese Farmers

We used apple selling as a typical case to investigate how the adoption of e-commerce impacts the selling prices of agricultural products, considering that compared with other agricultural products, the apple industry has a more developed supply chain and a wider planting area, becoming a key economic pillar in many rural areas (Wang and Huo 2014; Ma and Abdulai 2016; Liu et al. 2021). China is the largest apple-producing country in the world, followed by India and Russia. Since the late 20th century, apple cultivation has rapidly developed in China, forming major apple-producing regions in provinces such as Shandong, Shaanxi, Hebei and Gansu. According to data published by FAO (2020), the total area covered by apple orchards in China was about 2 million hectares in 2018, which accounts for 42% of the total area occupied by apple orchards in the world. Although China's apple yield per hectare ranked 31st, its total yield ranked highest and was about 40 million tons in 2018, accounting for 46% of the world's total yield, followed by those of the United States and Poland (FAO 2020). However, its exports are always relatively low compared with other countries. Only about 1.4 million tons of apples entered the international market in 2017, which accounted for 3% of China's total yield (FAO 2020). Consequently, most of the apples produced by Chinese farmers are for domestic sale.

Chinese apple farmers traditionally sell their products to middlemen, the local agencies of bulk buyers, or the bulk buyers themselves. A limited number of bulk buyers come from distant cities to conduct aggregate purchases yearly during the apple harvesting season. Selling all or a majority of their apples to middlemen is the only choice for most farmers because they lack access to the national market. Middlemen have monopsony power in this case. They take advantage of farmers' information asymmetry and unaffordable market transaction costs by

offering low product prices. Apple farmers, particularly those living in remote areas, are forced to accept a low price to avoid the risk of not selling. Thereby, farmers are simply price-takers in the transaction. Ma and Abdulai (2016) also found that Chinese apple farmers who engage in marketing are severely constrained by information asymmetry and high transaction costs. In recent years, the rapid diffusion of e-commerce in rural China has provided apple farmers with opportunities to cut out the middlemen direct access to the national and even the global market. This new selling mode is restructuring the relations among apple farmers, middlemen and the market.

In practise, some farmers sell their products directly to middlemen when they harvest their apples. Others send their products to the local farmers' market via their agricultural tricycles and sell them to middlemen who have purchasing stores in local town centres. The choice of selling method mainly depends on the local transport infrastructure. Generally, harvesting season usually starts in the middle of September and ends in early November in our surveyed area. This period, however, varies slightly across regions and years. It is usual for most individual apple farmers to sell all their products within 2 or 3 weeks during the harvesting season. Only a few farmers store their apples in cold storage and sell them later due to the incurred cost of storing and the unpredictability of prices in the future. With the diffusion of e-commerce in rural areas, some farmers have started to reserve some of their products to sell online, but they still sold the majority of their products to middlemen at the time of our survey. However, it is fascinating to find that the development of rural e-commerce is driving an increasing number of farmers to no longer sell their products exclusively to middlemen. Moreover, since apples are less perishable compared with most other agricultural products, the online sale period can last several months and extend beyond the harvesting season. As such, the development of rural e-commerce in the apple sector has become a typical example for illustrating the impacts of e-commerce adoption by farmers, particularly for non-perishable agricultural products.

3 | Method

To estimate the treatment effect on the selling prices of agricultural products after adopting e-commerce, we place product i in the treatment group if it is sold through e-commerce; otherwise, it belongs to the control group. Y_i^e presents the selling price of the product i sold through e-commerce. Y_i^{ne} presents the selling price of the same product i have not sold through e-commerce. According to Rosenbaum and Rubin (1983), the treatment effect on selling prices of adopting e-commerce is shown below:

$$TE = Y_i^e - Y_i^{ne} \quad (1)$$

where TE represents the treatment effect. We are interested in its expectation, which is denoted as the average treatment effect (ATE), as shown below:

$$\begin{aligned} ATE &= E(Y_i^e | D_i = 1) - E(Y_i^{ne} | D_i = 0) \\ &= E(Y_i^e | D_i = 1) - E(Y_i^{ne} | D_i = 1) + E(Y_i^{ne} | D_i = 1) - E(Y_i^{ne} | D_i = 0) \end{aligned} \quad (2)$$

D_i is the treatment variable that identifies whether or not the product i is sold through e-commerce. The term $[E(Y_i^e | D_i = 1) - E(Y_i^{ne} | D_i = 1)]$ is the average treatment effect for the treated (ATT). The other term, $[E(Y_i^{ne} | D_i = 1) - E(Y_i^{ne} | D_i = 0)]$, explains the pre-existing difference between selling or not selling products through e-commerce, also known as self-selection bias. The problem of self-selection bias occurs when there are significant differences in the characteristics between the treatment and control groups (Rosenbaum and Rubin 1983).

In our case, the self-selection bias is non-zero because the e-commerce adopters and non-adopters are not assigned randomly. For example, a household may be more likely to sell products through e-commerce if it has some unique characteristics, like having a household head with previous experience in conducting e-commerce. Since Y_i^e and Y_i^{ne} are not observed simultaneously, we have the problem of missing data about estimating Equations (1) and (2). However, various empirical methods have been developed to combat these problems, including the PSM approach.

This paper employs PSM to estimate the e-commerce effects on selling prices for apple farmers, as PSM is a standard non-parametric method and has been widely used as an evaluation method for treatment effects (e.g., Ali et al. 2018; Ji et al. 2019). In our case, it pairs together the products that are sold by e-commerce (e-commerce products) and those that are not sold by e-commerce (non-e-commerce products) that are similar in terms of their observable characteristics (Abebaw and Haile 2013). To match the e-commerce products to the non-e-commerce products, propensity scores are estimated by using logit or probit regression (Hujer, Caliendo, and Thomsen 2004). There are several algorithms to conduct the matching based on the propensity scores, including **K-nearest neighbour matching** (KNM), **nearest-neighbour matching** within callipers (NMC), kernel matching and radius matching (Ji et al. 2019). To check the robustness of our estimation results, the estimates from these four matching methods are reported and compared in this paper.

However, PSM has a drawback because it only considers the effects of the observable factors. It assumes that no unobservable factors impact the adoption of e-commerce and its outcomes. As such, classic ordinary least squares estimation (OLS) is employed to conduct a robustness check on the PSM results. Moreover, when considering the potential endogenous problem, the instrumental variable (IV) treatment effects model is employed for the robustness check. To be more specific concerning the potential endogenous problem, the adoption of e-commerce and selling prices have simultaneous causality towards each other. This may omit unobservable factors that impact the choice to adopt e-commerce and selling prices. The model specification is as follows:

$$\log(Y_i) = \beta_1 D_i + \beta_2 X_i + \text{year}_t + \text{village}_v + \eta_i \quad (3)$$

where Y_i is a vector of the outcome variables, including the average price of, the maximum price of, and the minimum price of selling observation i , taking the logarithm as the dependent variable. D_i indicates whether observation i is sold through

e-commerce. X_i is the vector of the observable variables, including the characteristics of products and households, which impact the selling prices of observation i . The year t and village v in which the households are located are controlled. η_i is the error term. Specific definitions of all the variables and their descriptive statistics are listed in Table 1.

4 | Sample and Variables

4.1 | Sample and Data Collection

We used a stratified random sampling method for data collection. In autumn 2019, we conducted a household survey in Shandong, Henan and Shaanxi provinces. According to the Chinese National Bureau of Statistics, these three provinces had a combined apple orchard area of 984,670 ha in 2018, representing 51% of the total apple orchard area in China. Specifically, Shaanxi province had 597,570 ha (the largest among all provinces), Shandong had 258,040 ha (second largest) and Henan had 129,060 ha (sixth largest).

In each province, we selected two prominent apple-producing counties. Since e-commerce adoption is still relatively limited in rural China, we focused on counties where online sales by farmers had increased in recent years. From each county, we chose two towns with significant e-commerce activity. All villages in each town were ranked by average per capita income and divided into two groups: one with higher incomes and one with lower incomes. We then randomly selected one village from each group. In each village, 20 households were randomly selected, all of which produce and sell apples. The locations of the sampled counties are shown in Figure 1.

In total, we surveyed 480 households from 3 provinces, 6 counties, 12 towns and 24 villages. The households were interviewed face-to-face using a structured questionnaire. To compare apple sales outcomes before and after adopting e-commerce, the survey included retrospective questions about selling prices for the years 2015, 2016, 2017 and 2018. The questionnaire also covered topics such as e-commerce usage, household characteristics and details of apple sales.

Most apple farmers in our sample sell apples at varying prices based on type and quality. In all cases, the farmers primarily or exclusively grow Fuji apples. According to China's national standard, Fuji apples are classified into four quality grades: first-class, second-class, and third-class, with smaller or lower quality apples categorised as fourth-class, which are typically sold to local juice factories at lower prices. In our survey, we asked each household to provide detailed information on the quality classes of their apples. Our data show that 68% of Fuji apples were classified as first-class in 2018.

Ultimately, our data encompass 480 households over the years 2015 to 2018. Among these households, 195 have utilized e-commerce to sell their apples. Given that each household has multiple apple classes and that apples can be sold both through e-commerce and traditional channels, we collected 6082 product-level observations. Each observation represents a product that

TABLE 1 | Definition of variables and descriptive statistics.

Variable	Variable definition	Units	Obs.	Mean	SD	Min	Max
price _{<i>i</i>}	The average selling price of observation <i>i</i>	RMB/kg	2027	0.29	0.13	0.06	1.38
maxprice _{<i>i</i>}	The maximum selling price of observation <i>i</i>	RMB/kg	2027	0.32	0.19	0.08	4.46
minprice _{<i>i</i>}	The minimum selling price of observation <i>i</i>	RMB/kg	2027	0.28	0.12	0.04	0.92
season _{<i>i</i>}	=1 if observation <i>i</i> is not only sold during the harvesting season (September, October and November), =0 otherwise	n.a.	2027	0.32		0	1
period _{<i>i</i>}	The number of months during which observation <i>i</i> is sold every year	Months	2027	2.41	1.88	1	12
<i>D_i</i>	=1 if observation <i>i</i> is sold by e-commerce, =0 otherwise	n.a.	2027	0.20		0	1
IV _{<i>n</i>}	Instrumental variable. The number of acquaintances who are known by household <i>n</i> to use e-commerce to sell goods	Heads	2027	13.65	40.36	0	400
age _{<i>n</i>}	The age of the household head of household <i>n</i>	Years	2027	52.05	9.01	23	80
edu _{<i>n</i>}	The number of years of education completed by the household head of household <i>n</i>	Years	2027	8.94	2.99	0	16
sphone _{<i>n</i>}	The number of years that the household head of household <i>n</i> has used a smart phone	Years	2027	5.41	3.52	0	12
hhsiz _{<i>n</i>}	The number of members in the household <i>n</i>	Heads	2027	4.20	1.37	1	9
off_farm _{<i>n</i>}	The number of family members in household <i>n</i> who have or have had off-farm employment	Heads	2027	1.35	1.16	0	5
experi _{<i>n</i>}	=1 if a family member(s) of household <i>n</i> has (have) previous experience in conducting e-commerce, =0 otherwise	n.a.	2027	0.09		0	1
land _{<i>n</i>}	The area of land that household <i>n</i> has for growing apples	Hectares	2027	0.59	0.48	0.00	3.33
distance _{<i>n</i>}	The distance from household <i>n</i> to the local town centre	km	2027	7.45	6.27	0.1	35
delivery _{<i>n</i>}	=1 if packages are directly delivered to household <i>n</i> , =0 otherwise	n.a.	2027	0.33		0	1
contact _{<i>n</i>}	The social capital of household <i>n</i> , which is proxied by how many guests would attend a child's wedding	Heads	2027	232.33	198.31	12	1200

Note: 7.1 RMB=1 USD (2020 data). The town government seat is used to locate the town centre.

Source: survey data.

has been classified into a specific grade by each household and indicates whether it was sold via e-commerce.

Since our research focuses on the impact of e-commerce on apple sales and the data show that 87% of the apples sold through e-commerce were first-class Fuji apples, we concentrated on first-class Fuji apples for the subsequent PSM analysis. Including other apple classes would have resulted in most of them being automatically excluded during the PSM, as only a small proportion of these other classes are sold through e-commerce. Consequently, 2027 observations were used for our empirical analysis.

4.2 | Variable Description and Statistical Analysis

We used three indicators to measure the farmers' selling prices of apples, including the average selling price (price_{*i*}), maximum selling price (maxprice_{*i*}) and minimum selling price (minprice_{*i*}). The prices were deflated by the consumer price index (CPI) of China, which is based on consumer prices of 1978. Two other indicators present changes in farmers' apple sales due to the adoption of e-commerce. They are the season for selling apples (season_{*i*}) and the period for selling apples (period_{*i*}), and these were used to analyse the potential pathway of changes in terms of the selling prices of apples

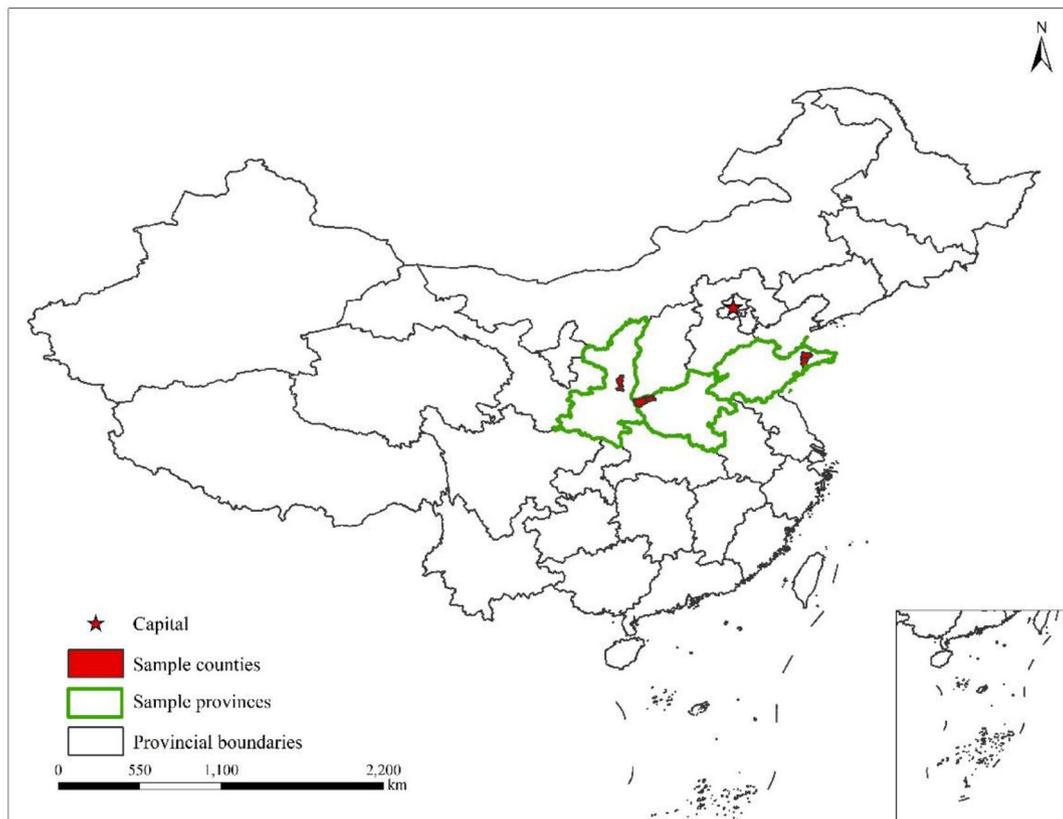


FIGURE 1 | The location of the surveyed counties. [Colour figure can be viewed at wileyonlinelibrary.com]

due adopting e-commerce. The instrumental variable (IV_n) is also listed since it was used for the robustness check in the IV treatment effects model.

As presented in Table 1, besides the concerned variable of using e-commerce (D_i), the other variables that potentially impact the selling prices of observation i are considered, especially the characteristics of household heads and rural households (Negi et al. 2018). It is noted that the observations only refer to first-class Fuji apples. Therefore, the selling prices are assumed not to be impacted by the product quality and type of apple. According to the existing literature, the related characteristics of household heads that impact selling prices include their age (age_n), education level (edu_n) and use of smartphones ($sphone_n$) (e.g., Aker and Ksoll 2016; Fałkowski, Malak-Rawlikowska, and Milczarek-Andrzejewska 2017). The characteristics related to rural households refer to the household size ($hhsizen$), off-farm employment (off_farm_n), working experience ($experin$), available land resources ($land_n$), geographic location ($distance_n$), delivery conditions ($delivery_n$) and social capital ($contact_n$) (e.g., Aker and Ksoll 2016; Fałkowski, Malak-Rawlikowska, and Milczarek-Andrzejewska 2017). The specific definition of these variables and their descriptive statistics are listed in Table 1.

Table 2 compares the observations that are sold through e-commerce with those that are not. The difference in the means in the last column shows that the average price, maximum price and minimum price of apples sold through e-commerce are significantly higher than those not sold through e-commerce. Whether this result indicates that using

e-commerce improves the selling prices of apples will be further examined through the following empirical analysis. It also indicates that the selling period does not only include the harvesting season and that the selling period is significantly longer if apples are sold through e-commerce. In addition, all the other indicators that reflect the characteristics of household heads and rural households are significantly different regarding e-commerce products and non-e-commerce products. For instance, the results show that household heads with e-commerce products are younger, more educated and have a longer history of using smartphones. They also show that households are more likely to adopt e-commerce to sell products if they have a larger household size, have more family members that have or have had off-farm employment, have experience in conducting e-commerce, have more land for growing apples, are located further away from the local town centre, have better delivery conditions and have better social capital. These significant differences indicate potential factors that may impact the adoption of e-commerce. They also reflect the existence of self-selection bias in our cases. As such, it is appropriate to use the PSM approach.

5 | Results

5.1 | Logit Model Results

The propensity score for matching the e-commerce products and non-e-commerce products was estimated by logit regression. The dependent variable describes whether observation i is sold via e-commerce. The independent variables include the

TABLE 2 | The differences between e-commerce products and non-e-commerce products for all variables.

Variable	With e-commerce (n = 414)				Without e-commerce (n = 1613)				Diff. in mean
	Mean	SD	Min	Max	Mean	SD	Min	Max	
price _i	0.49	0.13	0.24	1.38	0.24	0.07	0.06	0.66	0.24***
maxprice _i	0.54	0.27	0.24	4.46	0.26	0.11	0.08	2.69	0.28***
minprice _i	0.45	0.11	0.14	0.92	0.23	0.06	0.04	0.66	0.21***
season _i	0.59		0	1	0.25		0	1	0.34***
period _i	3.42	2.08	1	12	2.15	1.73	1	12	1.28***
IV _n	26.71	52.35	0	400	10.30	35.92	0	400	16.41***
age _n	51.01	8.90	23	80	52.32	9.01	23	80	-1.30***
edu _n	9.84	2.97	0	16	8.71	2.96	0	16	1.13***
sphone _n	6.49	3.33	0	12	5.13	3.51	0	12	1.36***
hhsz _n	4.29	1.38	1	8	4.17	1.37	1	9	0.11*
off_farm _n	1.57	1.17	0	5	1.29	1.15	0	5	0.28***
experi _n	0.16		0	1	0.08		0	1	0.09***
land _n	0.72	0.55	0.07	3.33	0.56	0.45	0.00	3.33	0.17***
distance _n	9.01	7.02	0.10	35	7.05	6.00	0.10	35	1.96***
delivery _n	0.40		0	1	0.31		0	1	0.09***
contact _n	266.04	188.95	30	1000	223.67	199.78	12	1200	42.37***

*p < 0.10.

***p < 0.01.

Source: Survey data.

characteristics of household heads and rural households that potentially impact the adoption of e-commerce by or the selling prices of apple farmers. The village and year variables were controlled for as well.

Besides the propensity score, the logit regression results shown in Table 3 are also informative. They prove that using e-commerce to sell apples is significantly determined by the household head's education level and his/her history of using a smartphone, the off-farm employment of the family members of a rural household and their experience in conducting e-commerce, the land area that a household has available to grow apples, geographic location, delivery conditions and social capital. The marginal effects indicate the magnitude of the impact of these significant variables. For instance, if the education level of a household head and the number of years a household head has used a smartphone increase by a year, the likelihood of the household's products being sold by e-commerce increases by 1.2% and 0.7%, respectively. Having an additional family member who engages in an off-farm job and has experience conducting e-commerce increases the likelihood of the household's products being sold through e-commerce by 2% and 9.6%, respectively. Similarly, if a rural household has an additional hectare of land for growing apples, has couriers that provide a door-to-door service and improves its social capital by one unit, the likelihood of the

household's products being sold by e-commerce increases by 4.3%, 3.1%, and 0.02%, respectively.

The non-linear relationship between the adoption of e-commerce and the geographic location of rural households has been proven. This result indicates that the possibility of adopting e-commerce rise an increase in the distance between rural households and the local town centre. However, that possibility decreases if the distance is more than 14 km. The possible reason could be that farmers who live closer to the township would have more off-farm employment opportunities, which would lower their motivation to conduct e-commerce by themselves. In addition, if farmers live far away from the township, they would have much less convenient logistics for conducting e-commerce, which is also presented in the case of Taobao villages, as studied by Liu et al. (2020). They demonstrated that the number of e-commercial villages increases with the distances between village committees and their townships before a distance of fewer than 2.4 km. However, the number of e-commercial villages decreases with the increase in the distances between village committees and their townships after the distance exceeds 2.4 km.

The e-commerce products and non-e-commerce products were matched based on their propensity scores. Subsequently, the treatment effects were estimated based on the matched

TABLE 3 | The determinants of using e-commerce: logit regression model.

	Regression results		Marginal effects	
	Coef.	z values	Coef.	z values
age _n	0.0003	0.04	0.00004	0.04
edu _n	0.086***	3.65	0.012***	3.69
sphone _n	0.049**	2.22	0.007**	2.23
hhszize _n	-0.040	-0.72	-0.005	-0.72
off_farm _n	0.152**	2.46	0.020**	2.47
experi _n	0.714***	3.55	0.096***	3.59
land _n	0.323**	2.25	0.043**	2.26
distance _n	0.083**	1.96	0.011**	1.96
distance _n ²	-0.003**	-1.99	-0.0004**	-2.00
delivery _n	0.231*	1.65	0.031*	1.65
contact _n	0.002***	3.65	0.0002***	3.68
Village FE	YES			
Year FE	YES			
Log likelihood	-852.20			
LR χ^2	347.85			
Prob > χ^2	0.000			
Pseudo R ²	0.1695			
Obs.	2027			

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Source: Authors' calculations.

observations. Before we present the results of the treatment effects, the matching quality is checked and demonstrated in the following section.

5.2 | Testing the Matching Quality

Testing the matching quality involves testing the common support between the treatment and control groups and testing the balance of the explanatory variables before and after the matching.

Figure 2, created based on the radius matching, shows that most of the observations are on support. The results based on other matching algorithms are similar. More specifically, 149 observations from the control group and no observations from the treatment group off support. In other words, only 149 of the 2027 observations, which are not in the common support region, were excluded from the analysis. Hence, the remaining 1878 observations were used to estimate the treatment effects, and dropping 149 observations did not cause biased results.

Table 4 presents the balance test before and after matching. The bias reduction for all the variables is positive, indicating that the matching reduced all the standardised bias between the

treatment and control groups. Moreover, based on the results of t -tests, there are significant differences in the variables between the treatment and control groups before matching, but the differences become insignificant after matching. The results indicate that the matching under all four matching algorithms significantly reduced the systematic bias between the treatment and control groups.

Figure 3 presents the probability distribution of the propensity scores before and after matching. The two graphs show that the distribution curves of the treatment and control groups become much more similar after matching than before matching. This result indicates that the treatment and control groups are generally well-matched. In brief, all the above test results imply that our matching quality is high.

5.3 | PSM Results

5.3.1 | Overall Effects

Table 5 presents the overall effects on selling prices of adopting e-commerce, which are estimated by PSM using four different matching algorithms.

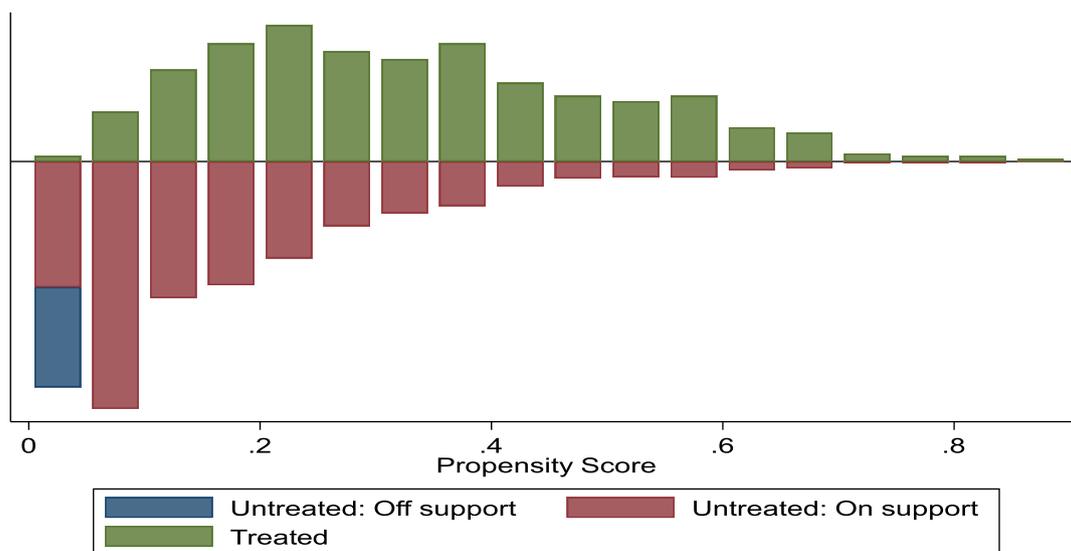


FIGURE 2 | Distribution of the propensity scores and the common support. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 | The balance test before and after matching.

Variable	Unmatched/ matched	% reduction [bias]				t-test (t values)			
		KNM	NMC	Radius	Kernel	KNM	NMC	Radius	Kernel
age _n	U					-2.63	-2.63	-2.63	-2.63
	M	72.3	71.9	90.5	90.6	-0.58	-0.59	-0.20	-0.20
edu _n	U					6.95	6.95	6.95	6.95
	M	97.0	98.7	95.5	92.6	0.17	0.08	0.25	0.41
sphone _n	U					7.09	7.09	7.09	7.09
	M	90.1	90.9	96.8	95.0	0.58	0.53	0.19	0.29
hhsize _n	U					1.49	1.49	1.49	1.49
	M	52.3	52.0	94.5	89.6	0.57	0.58	0.07	0.13
off_farm _n	U					4.42	4.42	4.42	4.42
	M	96.4	97.3	96.0	99.7	0.12	0.09	-0.14	0.01
experi _n	U					5.47	5.47	5.47	5.47
	M	90.3	87.5	91.6	89.8	0.33	0.43	0.29	0.35
land _n	U					6.48	6.48	6.48	6.48
	M	83.8	84.8	94.9	88.9	0.71	0.67	0.22	0.48
distance _n	U					5.70	5.70	5.70	5.70
	M	95.3	93.7	97.7	90.9	-0.19	-0.25	0.09	0.37
distance _n ²	U					4.93	4.93	4.93	4.93
	M	95.3	93.1	98.4	89.6	-0.15	-0.22	0.05	0.33
delivery _n	U					3.52	3.52	3.52	3.52
	M	98.0	94.5	95.8	94.0	0.05	0.15	0.11	0.16
contact _n	U					3.89	3.89	3.89	3.89
	M	92.3	92.1	92.5	92.3	0.25	0.25	0.24	0.24

Note: The village and year variables are also included. The matching algorithms include K-nearest neighbour matching (KNM), nearest-neighbour matching within callipers (NMC), kernel matching and radius matching.

Source: Authors' calculations.

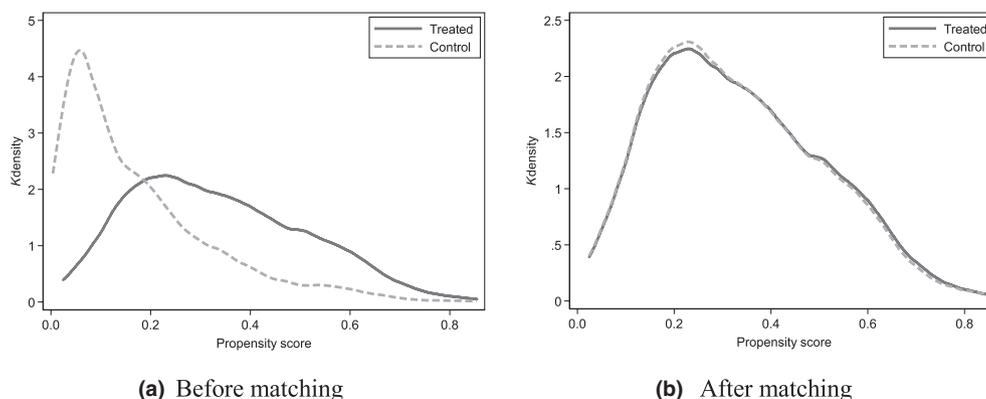


FIGURE 3 | The probability distribution of the propensity scores before and after matching.

TABLE 5 | The overall effects of adopting e-commerce on selling prices for apple farmers.

Matching algorithm	Number of treated	Number of control	ATT	t values	Change (%)
Average price					
KNM	414	1464	0.220***	30.58	88.7
NMC	414	1464	0.219***	30.40	88.1
Radius	414	1464	0.220***	31.10	88.6
Kernel	414	1464	0.220***	31.28	88.8
Maximum price					
KNM	414	1464	0.246***	17.35	93.1
NMC	414	1464	0.245***	17.24	92.5
Radius	414	1464	0.247***	17.89	93.5
Kernel	414	1464	0.248***	18.00	93.9
Minimum price					
KNM	414	1464	0.197***	31.56	83.6
NMC	414	1464	0.196***	31.37	83.1
Radius	414	1464	0.197***	32.26	83.7
Kernel	414	1464	0.197***	32.44	83.8

*** $p < 0.01$.

Source: Authors' calculations.

All the ATTs shown in Table 5 are statistically significant at the 1% level of significance, which indicates that the differences in the average price, maximum price and minimum price of apples that are sold through e-commerce compared with those that have similar propensity scores but are not sold through e-commerce are significant. The magnitude of the ATT with different matching algorithms is consistent for each outcome, which indicates that the estimated results are robust. Most importantly, the change rate is measured by the ratio of the ATT to the mean of the outcome of the matched observations from the control group. It reveals that the average price, maximum price and minimum price of apples sold through e-commerce increased by 88%, 93% and 83%, respectively, compared with those of apples with similar characteristics but not sold through e-commerce. Many studies have found that the development of rural e-commerce has improved farmers' incomes (e.g., Li and

Qin 2022; Liu et al. 2023). However, there is a lack of empirical research on the specific impacts of rural e-commerce on the selling prices of agricultural products, particularly regarding how improving market access for the rural poor through e-commerce affects these prices. Although some studies have examined the effects of mobile phone use on market access and farm gate prices (e.g., Camacho and Conover 2011; Fafchamps and Minten 2012), this specific aspect has not been thoroughly explored.

Moreover, whether adopting e-commerce has a spillover effect on the offline selling prices that middlemen provide is considered. The PSM results shown in Table 6 present how not all the ATTs are statistically significant at the 10% level of significance, which indicates that adopting e-commerce does not cause significant changes in the selling prices through middlemen for farmers who

TABLE 6 | The effects of adopting e-commerce on the offline selling prices for farmers in exchange transactions with middlemen.

Selling prices	Number of treated	Number of control	ATT	t values	Change (%)
Average price	513	831	0.004	0.73	1.8
Maximum price	513	831	0.014	1.54	5.6
Minimum price	513	831	0.004	0.75	1.9

Note: The matching algorithm is radius matching.
 Source: Authors' calculations.

TABLE 7 | Rosenbaum bounds sensitivity analysis for selling prices.

Gamma	Average price		Maximum price		Minimum price	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
1.0	0.000	0.000	0.000	0.000	0.000	0.000
1.1	0.000	0.000	0.000	0.000	0.000	0.000
1.2	0.000	0.000	0.000	0.000	0.000	0.000
1.3	0.000	0.000	0.000	0.000	0.000	0.000
1.4	0.000	0.000	0.000	0.000	0.000	0.000
1.5	0.000	0.000	0.000	0.000	0.000	0.000
1.6	0.000	0.000	0.000	0.000	0.000	0.000
1.7	0.000	0.000	0.000	0.000	0.000	0.000
1.8	0.000	0.000	0.000	0.000	0.000	0.000
1.9	0.000	0.000	0.000	0.000	0.000	0.000
2.0	0.000	0.000	0.000	0.000	0.000	0.000

Note: The matching algorithm is radius matching, and the results based on other matching algorithms are highly consistent with those of the radius matching algorithm. Gamma presents the log odds of differential assignment due to unobserved factors. Sig+ stands for the upper bound significance level. Sig- stands for the lower bound significance level.
 Source: Authors' calculations.

adopted e-commerce or for those who did not. In this regard, it proves that adopting e-commerce has yet to have such spillover effects on offline selling prices. It also reflects that information provision has no significant effects on the selling prices for farmers in their exchange transactions with middlemen in our case, considering that the farmers who adopted e-commerce can obtain sufficient price information compared with the others.

5.3.2 | Sensitivity Analysis

The PSM approach assumes that adopting e-commerce to sell apples depends on observable factors, not unobservable ones. Considering that the PSM approach cannot fully account for selection bias or unobservable characteristics, we followed Rosenbaum (2002) and performed a sensitivity analysis to examine the vulnerability of the estimated impact to unobservables. Rosenbaum (2002) introduced the bound analysis to test whether there exist unobserved factors that impact the selection into treatment based on the observed data. It has been used widely for empirical studies related to PSM analysis (Ji et al. 2019). The PSM results would be more reliable if they were less sensitive to increases in the impacts of unobserved factors relative to the observed ones (Ji et al. 2019).

Table 7 presents the results of the Rosenbaum bounds sensitivity analysis for the selling prices of apples. Gamma indicates the impacts of the unobserved variables on the adoption of e-commerce. The PSM results are always statistically significant at the 1% significance level when Gamma approaches 2.0, indicating that the treatment effects estimated by PSM are not sensitive to the unobserved variables. It proves that, in our case, the PSM results are reliable and that the excluded unobserved factors do not cause a significant bias.

5.4 | Robustness Check

To check the robustness of the PSM results, we employed regular OLS regression and the IV treatment effects model to estimate the impacts of adopting e-commerce on selling prices and control for both observed and unobserved indicators. The IV treatment effects model is used to solve the potential endogenous problem. One selection and outcome equation assumes that the impacts on the outcome variables are represented as a parallel shift. Before the IV treatment effects model was employed, we used a falsification test to analyse the validity of the instrumental variable (IV_n) (e.g., Di Falco, Veronesi, and Yesuf 2011; Shiferaw et al. 2014). In our case, the instrumental variable (IV_n) is the

number of acquaintances known by each sample household to have used e-commerce to sell goods in 2019. On the one hand, it has been proved that acquaintances using e-commerce can motivate farmers to adopt e-commerce due to the peer effect (Liu et al. 2020), and Table 8 presents that the number of acquaintances using e-commerce (IV_n) has a significant and positive effect on the probability of e-commerce adoption. It proves that the IV satisfies the relevance condition. Table 8 also reveals that

the number of acquaintances using e-commerce (IV_n) has no significant impact on the outcome variables of $price_i$, $\max price_i$ and $\min price_i$ for the sub-samples in which e-commerce is not adopted. In this regard, we established the admissibility of the instrumental variable (IV_n) through a falsification test, which proves that the IV satisfies the exclusion restriction. Therefore, the IV is valid because it affects the adoption decision but does not affect the outcome of non-adopters. Moreover, the F -statistic

TABLE 8 | The results of the falsification test on the instrumental variable.

	D_i (1)	$\log(price_i)$ (2)	$\log(\max price_i)$ (3)	$\log(\min price_i)$ (4)
IV_n	0.007*** (4.94)	-0.00001 (-0.04)	-0.00001 (-0.06)	-0.00003 (-0.21)
age_n	0.006 (0.74)	-0.001* (-1.78)	-0.0002 (-0.23)	-0.002*** (-3.08)
edu_n	0.081*** (3.43)	0.005*** (2.98)	0.003 (1.63)	0.007*** (3.25)
$sphone_n$	0.060*** (2.71)	0.004** (2.06)	0.004** (1.99)	0.004* (1.77)
$hhsizen$	-0.013 (-0.22)	0.012*** (2.91)	0.011** (2.36)	0.016*** (3.26)
off_farm_n	0.157** (2.53)	-0.018*** (-3.62)	-0.018*** (-3.26)	-0.022*** (-3.84)
$experi_n$	0.768*** (3.78)	0.019 (0.96)	0.052** (2.37)	-0.009 (-0.40)
$land_n$	0.266* (1.82)	0.013 (0.99)	0.009 (0.59)	0.015 (1.02)
$distance_n$	0.111** (2.54)	0.013*** (3.53)	0.013*** (2.97)	0.014*** (3.21)
$distance_n^2$	-0.004*** (-2.69)	-0.0004*** (-3.30)	-0.0004*** (-2.60)	-0.0005*** (-3.07)
$delivery_n$	0.100 (0.70)	0.047*** (4.03)	0.069*** (5.34)	0.023* (1.74)
$contact_n$	0.002*** (3.44)	0.0001* (1.88)	0.0001** (2.17)	0.00004* (1.67)
Village FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R^2		0.467	0.442	0.386
F	10.65	38.18	34.63	27.72
Obs.	2027	1613	1613	1613

Note: t -statistics based on robust standard errors are shown in parentheses. The F -statistic in column (1) is based on the OLS estimation.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.010$.

Source: Authors' calculations.

presented in column (1) of Table 8 is 10.65, and a value larger than 10, as a rule of thumb, indicates that a weak instrument problem does not exist. The AR test was conducted and also suggests that there is no weak instrument problem for the instrumental variable (IV_n).

Table 9 presents the regression results estimated by OLS with robust standard errors and the IV treatment effects model results estimated by maximum likelihood. The coefficients of adopting e-commerce (D_t) have no differences in the significance with the results estimated by PSM, and their magnitude is approximate as well. For instance, the results of OLS and the IV treatment effects model show that the selling prices increase by around 60% due to the adoption of e-commerce. The PSM results in Table 5 reveal that adopting e-commerce drives about 90% of the selling price increases. As such, the PSM results are consistent with the results estimated by OLS and the IV treatment effects model, proving that the PSM results are generally robust. Nevertheless, Table 9 also shows that the rho for all three models is insignificant in the IV treatment effects model estimation, suggesting that the results from the IV treatment effects model are similar to those from the PSM and OLS. Given that OLS regression does not consider the endogenous problem that can result in biased parameter estimation, the PSM results are thus preferable in our case.

5.5 | Heterogeneous Analysis

Table 10 presents the considerable heterogeneous effects of adopting e-commerce on the average price, maximum and minimum price across different scenarios. All the PSM results in Table 10 are estimated separately for different sub-samples. Tables A1–A3 present the mean of each group of sub-samples and the t -test results concerning the selling prices of e-commerce and non-e-commerce products across different scenarios. The PSM results are based on radius matching, but the results are consistent across the four matching algorithms.

First, all the samples were divided into two groups according to the age of the household head: a young group and an old group. The cut-off was the median age of all the household heads. The significantly positive results of the ATTs shown in Table 10 indicate that the effects on selling prices of adopting e-commerce vary with a change in the age of household heads. The change rate, calculated based on the ATT values, reveals that, for the young group, the average selling price of apples increases by 81% if the products are sold through e-commerce, compared with an increase of 96% for the old group. Similarly, the maximum price increases by 91% and 95% and the minimum price by 73% and 96% for the young and old groups, respectively. These results indicate that the selling prices of households with an older household head increase more obviously because of the adoption of e-commerce, which is in line with the findings by Huang et al. (2022). This finding is practical for the ageing rural labour force from a policy perspective when considering the strategy of ‘poverty alleviation through developing rural e-commerce’ issued by the Chinese national government.

Second, all the samples were divided into two groups according to the education level of the household head: a low group and

a high group. The cut-off was the median education level of all the household heads. The results of the ATTs are significantly positive at the 1% level of significance, which indicates that the effects of adopting e-commerce on selling prices vary with changes in the education level of household heads. The results show that, for the low group, the average selling price of apples increases by 93% if the products are sold through e-commerce, compared with an increase of 77% for the high group. Similarly, the maximum price increases by 92% for the low group and 88% for the high group; the minimum price by 90% for the low group and 71% for the high group. These findings indicate that the selling prices of households with less-educated heads increase more significantly due to adopting e-commerce.

Third, all the samples were divided into two groups according to the size of the land area allocated for growing apples in each sample household: a small group and a large group. The cut-off was the median size of the land area available for growing apples in all the rural households. The ATT results are significantly positive at the 1% level of significance, which indicates that the effects of adopting e-commerce on selling prices vary with changes in the land area of rural households. The results reveal that, for the small group, the average selling price of apples increases by 93% if the products are sold through e-commerce, compared to an increase of 83% for the large group. Similarly, the maximum price increases by 93% for the small group and 92% for the large group, and the minimum price by 87% for the small group and 79% for the large group. These findings indicate that the selling prices for households with smaller land areas for growing apples increase more significantly due to the adoption of e-commerce, which is also practical from a policy perspective.

Fourth, all the samples were divided into two groups according to the distances between rural households and the local town centre: a close group and a far group. The cut-off was the median distance. The ATT results are significantly positive at the 1% level of significance, which indicates that the effects of adopting e-commerce on selling prices vary with the geographic location of rural households. They reveal that, for the close group, the average selling price of apples increases by 89% if the products are sold through e-commerce, compared with an increase of 85% for the far group. Similarly, the maximum price increases by 96% and 87% and the minimum price by 86% and 80% for the close and far groups, respectively. These results indicate that rural households that are located closer to the local town centre benefit more from the adoption of e-commerce.

Fifth, all the samples were divided into two groups according to the social capital that a rural household has: a bad group and a good group. The number of guests attending a child of the sample household’s wedding was used as the proxy variable for social capital. The cut-off was the median number of guests. The results of the ATTs are significantly positive at the 1% level of significance, which indicates that the effects of adopting e-commerce on selling prices vary with the social capital of rural households. They reveal that, for the bad group, the average selling price of apples increases by 77% if the products are sold through e-commerce, compared with an increase of 94% for the good group. Similarly, the maximum price increases by 79% for the bad group and 99% for the good group. The minimum price by 72% for the bad group and 90% for the good group. These

TABLE 9 | The impacts of using e-commerce on selling prices: OLS and IV treatment effects models estimation.

	OLS model estimation			IV treatment effects model estimation		
	log(price _i)	log(maxprice _i)	log(minprice _i)	log(price _i)	log(maxprice _i)	log(minprice _i)
<i>D_i</i>	0.621*** (39.49)	0.634*** (34.34)	0.605*** (37.51)	0.631*** (17.81)	0.649*** (16.04)	0.576*** (11.45)
age _n	-0.0002 (-0.23)	0.001 (0.68)	-0.001 (-1.43)	-0.0001 (-0.22)	0.001 (0.73)	-0.001 (-1.50)
edu _n	0.006*** (2.66)	0.005** (2.04)	0.007*** (2.92)	0.006*** (3.05)	0.005** (2.32)	0.007*** (3.39)
sphone _n	0.006*** (3.25)	0.006*** (2.93)	0.006*** (2.72)	0.006*** (3.45)	0.006*** (2.94)	0.006*** (2.95)
hhsiz _n	0.006 (1.44)	0.003 (0.64)	0.011** (2.32)	0.006 (1.50)	0.003 (0.69)	0.011** (2.34)
off_farm _n	-0.011** (-2.06)	-0.008 (-1.48)	-0.014** (-2.38)	-0.011** (-2.15)	-0.008 (-1.49)	-0.014** (-2.51)
experi _n	0.026 (1.36)	0.064** (2.57)	-0.006 (-0.26)	0.026 (1.45)	0.064*** (3.15)	-0.006 (-0.32)
land _n	0.001 (0.09)	0.017 (0.91)	-0.007 (-0.51)	0.001 (0.09)	0.017 (1.18)	-0.007 (-0.48)
distance _n	0.013*** (3.13)	0.014*** (3.24)	0.010** (2.09)	0.013*** (3.54)	0.014*** (3.36)	0.010** (2.50)
distance _n ²	-0.0004*** (-3.20)	-0.0005*** (-3.22)	-0.0003** (-2.12)	-0.0004*** (-3.53)	-0.0005*** (-3.38)	-0.0003** (-2.31)
delivery _n	0.035*** (2.92)	0.054*** (4.04)	0.015 (1.14)	0.035*** (3.05)	0.053*** (4.17)	0.016 (1.25)
contact _n	0.0001*** (2.92)	0.0001*** (3.58)	0.0001** (2.48)	0.0001*** (2.64)	0.0001*** (3.25)	0.0001** (2.19)
Village FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R ²	0.677	0.642	0.611			
rho				-0.226 (-0.29)	-0.037 (-0.41)	0.071 (0.60)
Obs.	2027	2027	2027	2027	2027	2027

Note: *t*-statistics based on robust standard errors are shown in parentheses.

***p* < 0.05.

****p* < 0.01.

Source: Authors' calculations.

results indicate that rural households with social capital benefit more from adopting e-commerce.

Sixth, all the samples were divided into three groups according to the province in which the sample household is located: Shandong, Henan and Shaanxi. The results of the ATTs are significantly positive at the 1% level of significance, which

indicates that the effects of adopting e-commerce on selling prices vary with the provinces. They show that, for the Shandong group, the average selling price of apples increases by 82% if the products are sold through e-commerce, compared with increases of 66% and 118% for the Henan group and the Shaanxi group, respectively. Similarly, the maximum price increases by 81% for the Shandong group, 78% for the

TABLE 10 | The heterogeneous effects of adopting e-commerce on selling prices for apple farmers.

	Number of treated	Number of control	ATT on average price		ATT on maximum price		ATT on minimum price	
			ATT	Change (%)	ATT	Change (%)	ATT	Change (%)
Age								
Young	222	622	0.208***	81.1	0.249***	91.3	0.179***	73.1
Old	192	677	0.234***	96.0	0.250***	95.4	0.219***	96.1
Education								
Low	233	936	0.228***	93.0	0.244***	92.0	0.208***	89.7
High	178	331	0.204***	76.5	0.246***	87.9	0.180***	71.2
Land area								
Small	175	720	0.227***	92.7	0.244***	93.0	0.201***	87.2
Large	239	656	0.210***	82.8	0.249***	92.1	0.191***	79.0
Distance								
Close	185	810	0.212***	89.3	0.240***	96.2	0.194***	85.8
Far	226	591	0.223***	84.6	0.248***	86.7	0.198***	79.8
Social capital								
Bad	148	611	0.204***	76.9	0.227***	79.2	0.179***	72.0
Good	265	609	0.227***	94.1	0.254***	98.9	0.206***	89.6
Province								
Shandong	103	394	0.224***	81.5	0.243***	80.9	0.192***	74.9
Henan	145	391	0.169***	66.3	0.206***	77.6	0.157***	64.6
Shaanxi	163	449	0.267***	117.8	0.291***	121.4	0.241***	111.5

Note: The matching algorithm is radius matching.

*** $p < 0.01$.

Source: Authors' calculations.

Henan group and 121% for the Shaanxi group. The minimum price increases by 75% for the Shandong group, 65% for the Henan group and 112% for the Shaanxi group. These results indicate that the rural households in Shaanxi province benefit the most from adopting e-commerce compared with those in the other two provinces. Regional disparities in the development of rural e-commerce have also been highlighted in other studies (e.g., Liu et al. 2020; Huang et al. 2022).

5.6 | Potential Pathway Analysis

The PSM results in Table 11 show that adopting e-commerce to sell apple increases selling prices significantly. This section aims to analyse how it happens, that is, to investigate the potential pathway of increases in selling prices due to the adoption of e-commerce. Before the appearance of e-commerce, farmers had very few other options for selling their products that were not through middlemen because of the unaffordable transaction costs related to accessing the market by themselves. The diffusion of e-commerce among farmers improves market prices' transparency for them and provides farmers with more marketing flexibility to sell their products

(Shalender and Singh 2015). This improvement in marketing flexibility is reflected in the changes in terms of the sale times and sale periods for farmers. To be more specific, selling all or most their products during the harvesting season is one of many choices for farmers. They can sell their products beyond the harvesting season when middlemen do not conduct aggregate purchases. In this case, the sale time is defined with a dummy variable regarding whether farmers sell products beyond the harvesting season. The sale period is indicated by a continuous variable of the period covering when apples are sold by farmers each year. The specific effects of adopting e-commerce on sale times and sale periods for farmers are estimated next.

The results in Table 11 demonstrate that the adoption of e-commerce increases the likelihood that products are not only sold during the harvesting season by about 64% (the average result based on the four matching algorithms above). Similarly, the likelihood of an increase in the period for selling them increases by about 32% due to the adoption of e-commerce (the average result based on the four matching algorithms above). Traditionally, most apples are immediately sold to middlemen during the harvesting season. Farmers hardly have any

TABLE 11 | The effects of adopting e-commerce on sale times and sale periods.

Matching algorithm	Number of treated	Number of control	ATT	t values	Change (%)
Sale time					
KNM	414	1464	0.159***	5.15	59.0
NMC	414	1464	0.155***	5.03	57.7
Radius	414	1464	0.182***	6.19	67.7
Kernel	414	1464	0.189***	6.47	70.2
Sale period					
KNM	414	1464	0.694***	5.46	31.5
NMC	414	1464	0.668***	5.26	30.3
Radius	414	1464	0.718***	5.87	32.6
Kernel	414	1464	0.749***	6.18	34.0

*** $p < 0.01$.

Source: Authors' calculations.

flexibility in the sale times and sale periods because middlemen usually conduct aggregate purchases during harvesting. In this regard, farmers are price-takers and rarely possess marketing flexibility.

Nevertheless, e-commerce provides farmers with a much bigger and open market with more buyers. Therefore, farmers have much more choice in terms of whom to sell their products to and when, and they tend to exert dynamic pricing according to market information, which allows them to become price-makers to some extent. Moreover, farmers who adopt e-commerce can avoid the homogeneous competition of selling apples during the harvesting season and have a more extended period during which they can sell their products, all of which can help them avoid price competition with other apple farmers. In brief, farmers achieve more marketing flexibility through more adaptable sale times and extended sale periods when e-commerce is adopted, which further drives increases in selling prices. Although there are some studies exploring the mechanism on how e-commerce impacts farmers' income, there are limited evidence focusing on the perspective of agricultural products. For instance, Li and Qin (2022) presented that the positive impacts of developing rural e-commerce on farmers' income are attributed to changes in local industry structure and the proportion of export to GDP.

6 | Discussion and Conclusion

Improving market access for the rural poor is central to current thinking concerning poverty reduction and alleviation (World Development Reports 2001, 2006; Emran and Hou 2013; Negi et al. 2018). The Chinese national government has issued and carried out a strategy of 'poverty alleviation through developing rural e-commerce' across the whole country in recent years, which aims to provide the rural poor with direct access to the agricultural market and further support their economic advancement. However, there need to be more empirical evidence on whether the adoption of e-commerce impacts the selling prices

of agricultural products for farmers, who benefit more from it and how it occurs at the household level. This paper contributes to the literature by answering these questions based on empirical analysis and unique data on agricultural products (apples) sold through e-commerce (or not) by farmers.

The PSM results prove the causal impacts of adopting e-commerce on selling prices of apples for farmers. More specifically, they reveal that compared with apples that have similar characteristics but are not sold through e-commerce, the average price, the maximum price and the minimum price of apples that are sold through e-commerce increase by 88%, 93%, and 83%, respectively. These results confirm that promoting the adoption of e-commerce by farmers could be an effective way to increase the selling prices of agricultural products for farmers, which would contribute to the alleviation of poverty in rural areas. It is in line with the widely embraced opinion that using digital technologies to sell agricultural products is a solution for farmers looking to participate in the national and even global economy and thereby obtain digital dividends (Deichmann, Goyal, and Mishra 2016; World Bank 2016). The analysis of the potential pathway of the increases in selling prices due to the adoption of e-commerce reveals that farmers achieve more marketing flexibility through having more flexible sale times and longer sale periods in their exchange transactions, which is one innovation of this study because it focuses on the selling procedure of agricultural products considering that the existed literature mainly focused on the mechanism analysis at household, village or regional level (e.g., Liu et al. 2020; Li and Qin 2022).

According to the results of the heterogeneity analysis, the impacts of adopting e-commerce on the selling prices of agricultural products vary with several characteristics of rural households. Specifically, the average, the maximum and minimum prices increase more significantly if the products are sold through e-commerce by rural households with older and less-educated household heads and smaller areas of land for growing apples. In other words, the selling prices for this disadvantaged

group increase more significantly due to the adoption of e-commerce. This outcome may be explained by Nakasone (2013), who states that information asymmetry is particularly acute in agricultural markets and primarily affects vulnerable people in developing countries. In fact, the adoption of e-commerce improves the price transparency of this disadvantaged group more so than the others, because younger, more-educated and larger-land-owning households are usually less subject to information asymmetry regarding the market. In this sense, a preferred policy for promoting the adoption of e-commerce in rural areas is to target disadvantaged households, which follow the target of poverty alleviation.

The adoption of e-commerce has heterogeneous effects on selling prices that depend on rural households' geographic location and social capital. The results of the heterogeneous analysis prove that rural households closer to their local town centre and have better social capital benefit more from adopting e-commerce. It is understandable as these rural households have a more suitable condition for conducting e-commerce and thus achieve higher selling prices. The policy implication based on these findings is first to motivate households that are close to town centres and have good social networks to adopt e-commerce since the adoption of e-commerce has not been widely accepted by farmers yet and has been expanding slowly and with difficulty in some remote areas. It has been proven that neighbourhood effects exist in the development of rural e-commerce in China (Liu et al. 2020). As such, some farmers' selling price increases resulting from adopting e-commerce can stimulate other rural households to follow suit.

In addition, the effects of adopting e-commerce are heterogeneous across provinces. Rural households in Shaanxi Province benefit the most compared with those in Shandong and Henan provinces and those in Henan Province benefit the least. This order is consistent with the ranking of the area covered by apple orchards in each province. A region like Shaanxi, which has a larger production scale and higher apple yields, faces fiercer homogeneous competition and price competition during harvesting. Therefore, selling prices increase more obviously when intermediaries are cut out, and farmers participate in the broader market by adopting e-commerce. This finding should be taken into account when considering future policy design. Expanding rural e-commerce must be given priority to areas where farmers produce the same agricultural products. It could be an effective way to diminish local homogeneous competition and the corresponding price competition.

This paper makes the following contributions to the literature and economic development practises: (1) it innovatively utilises product-level data on agricultural products to provide a detailed estimation of the impact of e-commerce adoption on agricultural product prices, including average, maximum and minimum prices. The paper also explores how e-commerce adoption affects these prices, such as providing more flexible sales times and longer sales periods. While existing literature indicates that e-commerce adoption has positive impacts on agricultural product prices, there is a lack of empirical evidence and in-depth analysis on the specific impacts on price structures and how these impacts occur. This paper addresses this research gap. (2) The study finds that e-commerce adoption significantly increases prices for vulnerable groups, providing theoretical support for poverty alleviation through e-commerce development in

low-income countries and offering insights into addressing the challenges of agricultural product sales in the context of rural ageing. (3) The research results indicate that the impact of e-commerce adoption on sales prices varies among farmers, suggesting that e-commerce development is not a one-size-fits-all solution but requires tailored approaches. This provides empirical evidence for how developing countries or regions can promote the development of e-commerce in rural areas.

Ultimately, we would like to point out that this paper only focuses on how the adoption of e-commerce affects selling prices, bearing in mind that the impacts of adopting e-commerce on transaction costs and net benefits has been examined in our other papers (Liu et al. 2021, 2023). Moreover, this study has several research limitations that should be considered by future research. First, adopting e-commerce may have different impacts on different agricultural products. Although it is typical to take the apple sector as an example for the purpose of studying the impacts of rural e-commerce, the research findings would be more fruitful and practical if other agricultural products were included. Second, a future study on how the adoption of e-commerce influences farmers' positions in the agricultural supply chain would tell a richer story and make a more significant contribution to the practical and theoretical development of agricultural economics (Grant and Startz 2019). Last, the study provides empirical evidence of the benefits of adopting e-commerce for farmers. However, the barriers to and negative impacts of developing rural e-commerce must also be investigated.

Author Contributions

Study design: Min Liu and Yanjun Ren. Data analysis: Min Liu. Writing original draft: Min Liu. Manuscript review and editing: Min Liu, Tianjun Liu, Yanjun Ren and Leslie Wu. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

¹ 7 RMB = 1 USD (2020 data).

References

Abebaw, D., and M. G. Haile. 2013. "The Impact of Cooperatives on Agricultural Technology Adoption: Empirical Evidence From Ethiopia." *Food Policy* 38: 82–91.

- Aker, J. C. 2011. "Dial "A" for Agriculture: A Review of Information and Communication Technologies for Agricultural Extension in Developing Countries." *Agricultural Economics* 42, no. 6: 631–647.
- Aker, J. C., and M. Fafchamps. 2015. "Mobile Phone Coverage and Producer Markets: Evidence From West Africa." *World Bank Economic Review* 29, no. 2: 262–292.
- Aker, J. C., I. Ghosh, and J. Burrell. 2016. "The Promise (and Pitfalls) of ICT for Agriculture Initiatives." *Agricultural Economics* 47, no. S1: 35–48.
- Aker, J. C., and C. Ksoll. 2016. "Can Mobile Phones Improve Agricultural Outcomes? Evidence From a Randomized Experiment in Niger." *Food Policy* 60: 44–51. <https://doi.org/10.1016/j.foodpol.2015.03.006>.
- Ali, A., I. Hussain, D. B. Rahut, and O. Erenstein. 2018. "Laser-Land Leveling Adoption and Its Impact on Water Use, Crop Yields and Household Income: Empirical Evidence From the Rice-Wheat System of Pakistan Punjab." *Food Policy* 77 (February): 19–32. <https://doi.org/10.1016/j.foodpol.2018.03.018>.
- Aliresearch. 2020. "The Research Report on Taobao Villages of China in 2019."
- Bergquist, L. F., and M. Dinerstein. 2020. "Competition and Entry in Agricultural Markets: Experimental Evidence From Kenya." *American Economic Review* 110, no. 12: 3705–3747. <https://doi.org/10.1257/aer.20171397>.
- Buhr, B. L. 2000. "Information Technology and Changing Supply Chain Behaviour: Discussion." *American Journal of Agricultural Economics* 82, no. 5: 1130–1132.
- Camacho, A., and E. Conover. 2011. *The Impact of Receiving SMS Price and Weather Information in Colombia's Agricultural Sector. Working Paper 220*. Washington, DC: Inter-American Development Bank.
- China International Electronic Commerce Center (CIECC). 2018. "The Report on the Development of Rural e-Commerce of China (2017–2018)." https://www.sohu.com/a/259675536_99947052.
- China International Electronic Commerce Center (CIECC). 2019. "The Report on the Development of Rural e-Commerce of China at the County-Level (2017–2018)." <http://www.199it.com/archives/966155.html>.
- Courtois, P., and J. Subervie. 2015. "Farmer Bargaining Power and Market Information Services." *American Journal of Agricultural Economics* 97, no. 3: 953–977.
- Cui, M., S. L. Pan, S. Newell, and L. Cui. 2017. "Strategy, Resource Orchestration and e-Commerce Enabled Social Innovation in Rural China." *Journal of Strategic Information Systems* 26, no. 1: 3–21.
- De Silva, H., and D. Ratnadiwakara. 2008. *Using ICT to Reduce Transaction Costs in Agriculture Through Better Communication: A Case-Study From Sri Lanka*. Colombo, Sri Lanka: LIRNEasia.
- Deichmann, U., A. Goyal, and D. Mishra. 2016. "Will Digital Technologies Transform Agriculture in Developing Countries?" *Agricultural Economics* 47: 21–33. <https://doi.org/10.1111/agec.12300>.
- Di Falco, S., M. Veronesi, and M. Yesuf. 2011. "Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective From Ethiopia." *American Journal of Agricultural Economics* 93, no. 3: 825–842. <https://doi.org/10.1093/ajae/aar006>.
- Emran, M. S., and Z. Hou. 2013. "Access to Markets and Rural Poverty: Evidence From Household Consumption in China." *Review of Economics and Statistics* 95, no. 2: 682–697.
- Fafchamps, M., and B. Minten. 2012. "Impact of SMS-Based Agricultural Information on Indian Farmers." *World Bank Economic Review* 26, no. 3: 383–414.
- Fałkowski, J., A. Malak-Rawlikowska, and D. Milczarek-Andrzejewska. 2017. "Farmers' Self-Reported Bargaining Power and Price Heterogeneity." *British Food Journal* 119, no. 8: 1672–1686.
- FAO. 2020. "Crops and Livestock Products." <http://www.fao.org/faostat/en/#data/QC>.
- Goyal, A. 2008. "Information Technology and Rural Market Performance in Central India." Doctoral diss. <https://drum.lib.umd.edu/bitstream/handle/1903/8126/umi-umd-5296.pdf?sequence=1&isAllowed=y>.
- Grant, M., and M. Startz. 2019. "Cutting Out the Middleman: The Structure of Chains of Intermediation." (Preliminary Draft). https://economics.yale.edu/sites/default/files/grantstartz_middlemen_latest_ada-ns.pdf.
- Hildebrandt, N., Y. Nyarko, G. Romagnoli, and E. Soldani. 2020. "Price Information, Inter-Village Networks, and Bargaining Spillovers: Experimental Evidence from Ghana." (Preliminary Draft). http://sites.bu.edu/neudc/files/2014/10/paper_345.pdf.
- Huang, J., L. Su, Q. Huang, and X. Liu. 2022. "Facilitating Inclusive ICT Application and e-Commerce Development in Rural China." *Agricultural Economics* 53, no. 6: 938–952.
- Hujer, R., M. Caliendo, and S. L. Thomsen. 2004. "New Evidence on the Effects of Job Creation Schemes in Germany—A Matching Approach With Threefold Heterogeneity." *Research in Economics* 58, no. 4: 257–302.
- Jaleta, M., and C. Gardebroek. 2007. "Farm-Gate Tomato Price Negotiations Under Asymmetric Information." *Agricultural Economics* 36, no. 2: 245–251.
- Jensen, R. T. 2010. "Information, Efficiency, and Welfare in Agricultural Markets." *Agricultural Economics* 41: 203–216.
- Ji, C., S. Jin, H. Wang, and C. Ye. 2019. "Estimating Effects of Cooperative Membership on farmers' Safe Production Behaviors: Evidence From Pig Sector in China." *Food Policy* 83 (July): 231–245. <https://doi.org/10.1016/j.foodpol.2019.01.007>.
- Li, G., and J. Qin. 2022. "Income Effect of Rural E-Commerce: Empirical Evidence From Taobao Villages in China." *Journal of Rural Studies* 96: 129–140.
- Liu, M., S. Min, W. Ma, and T. Liu. 2021. "The Adoption and Impact of E-Commerce in Rural China: Application of an Endogenous Switching Regression Model." *Journal of Rural Studies* 83: 106–116.
- Liu, M., P. Shi, J. Wang, H. Wang, and J. Huang. 2023. "Do Farmers Get a Greater Return From Selling Their Agricultural Products Through e-Commerce?" *Review of Development Economics* 27, no. 3: 1481–1508.
- Liu, M., Q. Zhang, S. Gao, and J. Huang. 2020. "The Spatial Aggregation of Rural e-Commerce in China: An Empirical Investigation Into Taobao Villages." *Journal of Rural Studies* 80: 403–417. <https://doi.org/10.1016/j.jrurstud.2020.10.016>.
- Ma, W., and A. Abdulai. 2016. "Does Cooperative Membership Improve Household Welfare? Evidence From Apple Farmers in China." *Food Policy* 58: 94–102. <https://doi.org/10.1016/j.foodpol.2015.12.002>.
- Ministry of Commerce of China. 2018. "The Implementation of the Project of "Introducing e-Commerce to Rural Areas" in 2018." <http://scjss.mofcom.gov.cn/article/bnjg/201809/20180902790214.shtml>.
- Ministry of Commerce of China. 2020. "E-Commerce in China 2019." <http://images.mofcom.gov.cn/wzs2/202007/20200703162035768.pdf>.
- Mitra, S., D. Mookherjee, M. Torero, and S. Visaria. 2018. "Asymmetric Information and Middleman Margins: An Experiment With Indian Potato Farmers." *Review of Economics and Statistics* 100, no. 1: 1–13.
- Mueller, R. A. 2001. "E-Commerce and Entrepreneurship in Agricultural Markets." *American Journal of Agricultural Economics* 83, no. 5: 1243–1249.
- Nakasone, E. 2013. "The Role of Price Information in Agricultural Markets: Experimental Evidence from Rural Peru." *Agricultural &*

Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, 1–54.

Negi, D. S., P. S. BIRTHAL, D. Roy, and M. T. Khan. 2018. "Farmers' Choice of Market Channels and Producer Prices in India: Role of Transportation and Communication Networks." *Food Policy* 81 (October): 106–121. <https://doi.org/10.1016/j.foodpol.2018.10.008>.

Rosenbaum, P. R. 2002. "Observational Studies." In *Observational Studies: Springer Series in Statistics*. New York, NY: Springer.

Rosenbaum, P. R., and D. B. Rubin. 1983. "The Central Role of Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70, no. 1: 41–55.

Shalender, K., and N. Singh. 2015. "Marketing Flexibility: Significance and Implications for Automobile Industry." *Global Journal of Flexible Systems Management* 16, no. 3: 251–262.

Shiferaw, B., M. Kassie, M. Jaleta, and C. Yirga. 2014. "Adoption of Improved Wheat Varieties and Impacts on Household Food Security in Ethiopia." *Food Policy* 44: 272–284. <https://doi.org/10.1016/j.foodpol.2013.09.012>.

Tang, W., and J. Zhu. 2020. "Informality and Rural Industry: Rethinking the Impacts of E-Commerce on Rural Development in China." *Journal of Rural Studies* 75: 20–29.

Wang, L. J., and X. X. Huo. 2014. "Transaction Costs Comparison Between Cooperatives and Conventional Apple Producers: A Case Study of Northwestern China." *Annals of Public and Cooperative Economics* 85, no. 2: 233–255.

World Bank. 2016. *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank. <https://doi.org/10.1596/978-1-4648-0671-1>.

World Development Report. 2001. *Attacking Poverty*. New York: Oxford University Press.

World Development Report. 2006. *Equity and Development*. New York: Oxford University Press.

Yu, H., and L. Cui. 2019. "China's E-Commerce: Empowering Rural Women?" *China Quarterly* 238: 418–437.

Zhang, Y., H. Long, L. Ma, S. Tu, Y. Li, and D. Ge. 2018. "Analysis of Rural Economic Restructuring Driven by e-Commerce Based on the Space of Flows: The Case of Xiaying Village in Central China." *Journal of Rural Studies* 93: 196–209. <https://doi.org/10.1016/j.jrurstud.2018.12.001>.

Appendix A

TABLE A1 | The differences in the average price between e-commercial products and non-e-commercial products across different groups.

	Groups	Mean	E-commercial products	Non-e-commercial products	Diff. in mean
Age					
	Young (average at 45 years old)	0.30	0.48	0.25	0.23***
	Old (average at 59 years old)	0.29	0.49	0.24	0.25***
Education					
	Low (average at 8 years)	0.28	0.48	0.24	0.24***
	High (average at 12 years)	0.33	0.49	0.26	0.23***
Land scale					
	Small (average at 0.29 ha)	0.28	0.49	0.24	0.25***
	Large (average at 0.94 ha)	0.31	0.49	0.25	0.24***
Distance					
	Close (average at 3.14 km)	0.28	0.47	0.23	0.24***
	Far (average at 12.35 km)	0.32	0.50	0.26	0.24***
Social capital					
	Bad (average at 94 heads)	0.29	0.48	0.25	0.23***
	Good (average at 371 heads)	0.30	0.49	0.24	0.25***
Province					
	Shandong	0.30	0.52	0.26	0.26***
	Henan	0.29	0.45	0.24	0.21***
	Shaanxi	0.29	0.50	0.23	0.27***

*** $p < 0.01$.

Source: Authors' calculations.

TABLE A2 | The differences in maximum price between e-commercial products and non-e-commercial products over different groups.

	Groups	Mean	E-commercial products	Non-e-commercial products	Diff. in mean
Age					
	Young (average at 45 years old)	0.30	0.55	0.26	0.29***
	Old (average at 59 years old)	0.29	0.52	0.26	0.26***
Education					
	Low (average at 8 years)	0.28	0.53	0.26	0.27***
	High (average at 12 years)	0.33	0.54	0.27	0.27***
Land scale					
	Small (average at 0.294 ha)	0.28	0.52	0.26	0.26***
	Large (average at 0.939 ha)	0.31	0.55	0.27	0.28***
Distance					
	Close (average at 0.151 km)	0.30	0.52	0.25	0.27***
	Far (average at 0.844 km)	0.29	0.55	0.28	0.27***
Social capital					
	Bad (average at 94 heads)	0.29	0.53	0.27	0.26***
	Good (average at 371 heads)	0.30	0.54	0.25	0.29***
Province					
	Shandong	0.30	0.56	0.29	0.27***
	Henan	0.29	0.51	0.25	0.26***
	Shaanxi	0.29	0.55	0.24	0.31***

*** $p < 0.01$.

Source: Authors' calculations.

TABLE A3 | The differences in minimum price between e-commercial products and non-e-commercial products over different groups.

	Groups	Mean	E-commercial products	Non-e-commercial products	Diff. in mean
Age					
	Young (average at 45 years old)	0.30	0.44	0.24	0.20***
	Old (average at 59 years old)	0.29	0.45	0.23	0.23***
Education					
	Low (average at 8 years)	0.28	0.45	0.23	0.22***
	High (average at 12 years)	0.33	0.45	0.24	0.20***
Land scale					
	Small (average at 0.294 ha)	0.28	0.44	0.23	0.21***
	Large (average at 0.939 ha)	0.31	0.45	0.24	0.21***
Distance					
	Close (average at 0.151 km)	0.30	0.44	0.22	0.22***
	Far (average at 0.844 km)	0.29	0.45	0.24	0.21***
Social capital					
	Bad (average at 94 heads)	0.29	0.44	0.24	0.20***
	Good (average at 371 heads)	0.30	0.45	0.23	0.22***
Province					
	Shandong	0.30	0.46	0.25	0.21***
	Henan	0.29	0.43	0.23	0.20***
	Shaanxi	0.29	0.46	0.22	0.24***

*** $p < 0.01$.

Source: Authors' calculations.