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Do farmers get a greater return from selling their agricultural products through e-commerce?

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Abstract

E-commerce allows farmers to cut out intermediaries and sell agricultural products to consumers directly. This raises the question of whether farmers get a greater return when they use e-commerce to sell their products than when they use conventional marketing channels (i.e., intermediaries). To answer this question, we collected rural household data on sales of agricultural products from Zhejiang and Shandong provinces, in which we selected pairs of villages where e-commerce was advanced and villages where e-commerce was less advanced and households in each village that used or did not use e-commerce. We employed a fixed effects model to investigate the impacts of e-commerce on the selling prices and marketing costs of agricultural products. The model results revealed that compared with the conventional marketing channel through intermediaries, the marketing costs through the e-commerce channel significantly increased, but the selling price increases much more, which results in increases in gross returns for farmers. The increases in selling prices and marketing costs using e-commerce varied among agricultural products and between different qualities of the same product. It has important policy implications for improving farmers' incomes and agricultural marketing channels in developing countries.

KEYWORDS
agricultural product, e-commerce, farmer, marketing cost, price

JEL CLASSIFICATION
O13, O33, P22, P25

1 | INTRODUCTION

Digital technologies can promote economic development and generate digital dividends by reducing information costs (Du, Wang, & Hatzenbuehler, 2022; World Bank, 2016). According to some researchers and policymakers, developing rural economies through adopting digital technologies is a practical solution to address the disparity between the city and the countryside (Aker, Ghosh, & Burrell, 2016; Malecki, 2003; Salemink, Strijker, & Bosworth, 2017). For instance, in 1984, the International Telecommunication Union proposed to eliminate poverty through developing a telecommunications infrastructure (World Bank, 2016). Rural e-commerce is one of the major applications of digital technologies in developing rural economies. It allows producers in towns and villages to participate in the national and even global economy (Aker et al., 2016; Deichmann, Goyal, & Mishra, 2016; World Bank, 2016). According to a report by the World Bank (2016), using e-commerce to sell agricultural products from rural areas improves price transparency, cuts out intermediaries, and makes markets more efficient. A number of studies have reported that internet use significantly increases household incomes, expenditures, technical efficiencies, educational expenditures, and urban innovations (Li & Li, 2022; Ma, Nie, Zhang, & Renwick, 2020; Tabetando & Matsumoto, 2020; Zheng, Ma, Wang, & Li, 2021).

E-commerce activities are expanding from major cities to smaller cities and villages in some developing economies, such as India, Indonesia, and China (Kshetri, 2018; Li & Qin, 2022). It was reported that consumers from small towns accounted for 60% of the revenue of the Indian e-retailer website Jabong.com (Kshetri, 2018). In addition, more than one-third of the consumers of a popular online shopping website in Indonesia, BliBli, which has 2.5 million customers, were from rural areas (Kshetri, 2018). Rural e-commerce began to emerge in China in the 2000s. At this time, a number of e-commerce companies turned their attention to rural markets due to saturation of urban markets. In 2010, various e-commerce platforms were developed by e-commerce companies, such as Taobao, Jingdong, Suning, Pinduoduo, Yunji, Youzan, and Ganjie, to support farmers selling agricultural products to urban areas (China International Electronic Commerce Center [CIECC], 2018). At the same time, national and local governments in China embraced the revitalization of the rural economy by the development of rural e-commerce (Ministry of commerce of China [MCC], 2018). In early 2010, the national government put forward the strategy of “poverty alleviation through developing rural e-commerce” to promote the development of rural e-commerce in poor areas. In 2014, a national project entitled “the Pilot Counties of Introducing E-commerce to Rural Areas” was established, focusing on providing funding to poverty-stricken areas to develop e-commerce (MCC, 2018). The number of funded counties increased from 56 in 2014 to 1,231 in 2019, including 831 national-level poverty-stricken counties (The State Council Leading Group Office of Poverty Alleviation and Development [TSCLGOPAD], 2020).

However, according to the data from Chinese rural households, selling agricultural products through e-commerce has not been prevalent among farmers yet, especially in some remote areas (Liu, Zhang, Gao, & Huang, 2020). Although e-commerce allows farmers to cut out intermediaries and sell agricultural products to consumers directly, farmers have additional costs for operating e-commerce that were formerly undertaken by intermediaries. The costly marketing cost of conducting e-commerce has been a barrier for farmers. The existed literatures lack rigorous empirical research to examine the costs and gross returns of conducting e-commerce for farmers, which is crucial to improve the development of rural e-commerce. Many empirical studies have focused on the impact of digital technologies, such as cell phones and the internet, on farm gate prices, sales of agricultural products, and pesticide and fertilizer expenditures (e.g., Deichmann et al., 2016; Ma & Zheng, 2022; Mitra, Mookherjee, Torero, & Visaria, 2018). Among studies that have focused on rural e-commerce, most are based on quantitative discussions that depict the developing status, development patterns, and existing problems in the process of developing rural e-commerce (e.g., Zhang, 2015; Zapata, Isengildina-Massa, Carpio, & Lamie, 2016). Some researchers have focused on the spatial distribution of the development of rural e-commerce in China (e.g., Liu et al., 2020; Shan & Luo, 2017; Zhu, Song, Li, & Yu, 2016). In addition, many governments, NGOs, and researchers have asserted that e-commerce has positive impacts in terms of farmers' incomes, poverty reduction, and rural transformation (e.g., Wang, Miao, Phelps, & Zhang, 2021; Yang, 2020; Zeng, Guo, & Jin, 2018). In contrast, Couture, Faber, Gu, and Liu (2021), based on a randomized control trial with survey and administrative microdata, found no income gains to rural producers and workers associated with the implementation of the first nationwide e-commerce expansion program in rural China. As such, this study focuses on examining the influence of e-commerce on selling prices, marketing costs, and gross returns of agricultural product sales by farmers.

Individual farmers in developing countries sell the majority of their agricultural products to local intermediaries or bulk buyers, because they have few channels through which they can sell their products to supermarkets or distant consumers by themselves. Thus, farmers lack direct access to the market and have low bargaining power with intermediaries. Using e-commerce to sell agricultural products provides farmers with opportunities to participate in the market without intermediaries. The research findings of this study will provide empirical data for countries or areas considering rural e-commerce as a method to facilitate their rural economies. We introduce the data source in Section 2. The econometric method is presented in Section 3. Section 4 presents the results of the empirical model. The research findings are discussed in Section 5, followed by our conclusions.

2 | MATERIALS

2.1 | Data collection

Considering that the use of e-commerce to sell agricultural products is not widespread in China at present, we conducted household surveys in Shandong and Zhejiang provinces where rural e-commerce is more advanced than other areas of China (Liu et al., 2020). Feicheng and Qixia in Shandong Province and Linan in Zhejiang Province were selected as sample counties, in which local rural households maintain their lives by producing peaches, apples, and pecans, respectively. Sample villages were selected in pairs. We selected villages where farmers commonly use e-commerce platforms to sell their agricultural products, hereafter referred to as "advanced e-commerce villages," and villages where farmers do not commonly use these platforms, hereafter referred to as "less advanced e-commerce villages." Importantly, the farmers in the paired villages produce the same type of cash crop and have similar environmental and economic conditions. In total, we selected four paired villages in Qixia County, where apple production predominates; four paired villages in Feicheng County, where peach production predominates; and six paired villages in Linan County, where pecan production predominates.

In this study, households with experience of selling agricultural products online, through either e-commerce (e.g., Tmall) or social media platforms (e.g., WeChat), were defined as e-commerce households. We planned on selecting 15 sample households from each advanced e-commerce village, including 10 sample households that used e-commerce and 5 sample households that did not use e-commerce. In addition, it was planned to select 10 sample households from each less advanced e-commerce village, including 3 sample households that used e-commerce and 7 sample households that did not use e-commerce. However, in practice, it was difficult to maintain the ratio to select sample households as we planned because there were fewer than 10 e-commerce households in some of the selected advanced e-commerce villages. Likewise, fewer than three households used e-commerce in some of the selected less advanced e-commerce villages. Hence, the ratio of selecting sample households was adjusted when there were insufficient numbers of e-commerce or non-e-commerce households.

Ultimately, 175 households located in 7 townships and 14 villages were selected to take part in questionnaires and face-to-face interviews. The distribution of the sample households in different types of villages is shown in Table 1. As shown in the table, 95 of 175 households used e-commerce to sell their products. Among these households, 73 e-commerce households were located in seven advanced e-commerce villages, and the remaining 22 e-commerce households were located in seven less advanced e-commerce villages. The remaining 80 sample households had no experience of conducting e-commerce: 32 households in seven advanced e-commerce villages and 48 households in seven less advanced e-commerce villages.

In addition, the price offered for cash crops (apples, peaches, and pecans) varies according to product quality, with the crops classified according to classes or grades (first, second, or third). For instance, the first grade of apple is the apple with the best quality, the second grade has the second-best quality, the third grade has the third-best quality, and remaining low-quality and small apples belong to the fourth grade. The grading of peaches is similar to that of

TABLE 1 Numbers of sample households in the paired villages by products in Shandong and Zhejiang

Province/product	E-commerce households		Non-e-commerce households	
	E-commerce villages	Less advanced e-commerce villages	E-commerce villages	Less advanced e-commerce villages
Shandong				
Peach	22	7	8	13
Apple	19	8	11	12
Zhejiang				
Pecan	32	7	13	23
Total	73	22	32	48

apples. In terms of pecans, the first grade of pecan is highly processed, the second grade is roughly processed, and the third is not processed. Ungraded and low-grade products are not sold on online platforms and are therefore not included in this study. Thus, only first- and second-grade apples and peaches were included in this study, which accounted for 80% and 70% of the total yields of apple and peach, respectively. In addition, only highly processed and roughly processed grades of pecans were included.

The questionnaire included questions on selling prices and marketing costs of selling agricultural products across 3 years (2015–2017). In terms of its content, the questionnaire focused mainly on the demographic characteristics of households and the sales of agricultural products. In the empirical analysis, we focused on the product level, instead of household level; that is, one observation is a product that has been graded into a specific grade by each household and is distinguishable by whether it is sold via e-commerce by farmers themselves in each year. For example, if a household sold their first-grade apple through both e-commerce and intermediaries, then their first-grade apples were regarded as two observations to be analyzed, including the first-grade e-commerce apple and the first-grade non-ecommerce apple from this household. As such, we obtained 789 observations in total for the empirical analysis: 329 apple observations, 303 peach observations, and 157 pecan observations.

2.2 | Data description

Table 2 presents the differences in selling prices, marketing costs, and specific costs for products sold through e-commerce (e-commerce products) and those not sold through e-commerce (non-e-commerce products) based on the results of a *t*-test on the survey data. The selling price of apples sold through e-commerce was 0.82 RMB/kg higher than that of apples not sold through e-commerce. The marketing cost of apples sold through e-commerce was 0.52 RMB/kg higher than that of apples not sold through e-commerce. The packing cost and delivery cost of apples sold through e-commerce were 0.14 RMB/kg and 0.38 RMB/kg higher than that not sold through e-commerce, respectively. The delivery costs of apples sold through e-commerce were higher than those apples distributed via conventional marketing channels due to the geographic spread of online consumers and the relatively small size (kg) of each delivery. Thus, farmers undertake additional costs relating to deliveries when selling online (Kosec & Wantchekon, 2018). On the contrary, delivery costs when selling through conventional channels were much lower than when selling online because farmers conveyed their products to local collection spots on tricycles or intermediaries purchased their products directly and transported them to the marketplace. Thus, farmers engaging in e-commerce incurred new costs related to product delivery. Similarly, the selling prices and marketing costs of peaches and pecans sold through e-commerce were significantly higher than those not sold through e-commerce. The increase in the marketing cost was attributed mainly to increases in packing and delivery costs.

As shown in Table 3, the average selling prices and marketing costs for e-commerce products were significantly higher than those for non-e-commerce products each year, and this also happened for both each product and each grade. According to the descriptive analysis presented in Tables 2 and 3, it is plausible that using e-commerce to sell agricultural products can increase selling prices and marketing costs, and that the impacts vary for different products and grades over time. However, these findings need to be proved or disproved rigorously in a subsequent empirical analysis.

TABLE 2 The differences in selling price and marketing cost of each product sold through e-commerce and non-e-ecommerce (RMB/kg)

	E-commerce ($n = 253$)	Non-e-commerce ($n = 536$)	Diff. in mean
Apple	$n = 94$	$n = 235$	
Selling price	1.92	1.10	0.82***
Marketing cost	0.66	0.13	0.53***
Storing cost	0.05	0.05	0.00
Processing cost	0.00	0.00	0.00
Packing cost	0.22	0.07	0.15***
Delivery cost	0.39	0.01	0.38***
Peach	$n = 83$	$n = 220$	
Selling price	2.27	1.24	1.03***
Marketing cost	0.77	0.13	0.64***
Storing cost	0.02	0.01	0.01
Processing cost	0.00	0.00	0.00
Packing cost	0.28	0.10	0.18***
Delivery cost	0.48	0.02	0.46***
Pecan	$n = 76$	$n = 81$	
Selling price	19.75	15.91	3.84***
Marketing cost	2.04	1.24	0.80***
Storing cost	0.03	0.02	0.01
Processing cost	1.11	1.00	0.11
Packing cost	0.42	0.20	0.22***
Delivery cost	0.48	0.02	0.46***

Source: Authors' calculations.
***$p < .01$.

3 | METHODS

3.1 | Fixed effects model

We employed a fixed effects model for empirical analysis of the impacts of e-commerce on the selling prices and marketing costs of the agricultural products. Fixed effects models are widely used in economic research, primarily to study the impacts of changes within entities over time. The model is performed in deviations from individual means, in which all time-invariant (fixed) explanatory variables are removed (Verbeek, 2012). As such, it provides a method that takes observable explanatory variables as well as unobservable time-invariant variables into account, but the estimation does not depend on the value of time-invariant (fixed) variables, such as geographical positions of sample households, in the case of this study (Verbeek, 2012). In this regard, a fixed effects model was appropriate for this study because the research target is to estimate the impacts of using e-commerce within households over time based on panel data. Moreover, all unobservable time-invariant variables were controlled for although we did not have

TABLE 3 The differences in selling price and marketing cost between e-commerce and non-e-ecommerce over different products and grades (RMB/kg)

	2015		2016		2017	
	E-commerce	Non-e-commerce	E-commerce	Non-e-commerce	E-commerce	Non-e-commerce
Apple						
Selling price	1.97	1.15	1.91	1.06	1.89	1.08
Grade 1	2.15	1.35	2.08	1.24	2.06	1.25
Grade 2	1.61	0.91	1.56	0.85	1.53	0.89
Marketing cost	0.63	0.14	0.67	0.14	0.67	0.13
Grade 1	0.63	0.14	0.67	0.14	0.67	0.14
Grade 2	0.63	0.14	0.66	0.13	0.66	0.13
Peach						
Selling price	2.36	1.25	2.28	1.24	2.22	1.22
Grade 1	2.73	1.52	2.53	1.47	2.45	1.45
Grade 2	1.77	0.98	1.72	1.01	1.72	1.01
Marketing cost	0.81	0.13	0.77	0.13	0.74	0.13
Grade 1	0.85	0.13	0.79	0.14	0.76	0.13
Grade 2	0.74	0.13	0.73	0.13	0.70	0.13
Pecan						
Selling price	19.63	16.03	19.88	15.75	19.73	15.93
Grade 1	25.05	20.99	25.76	21.80	26.43	21.44
Grade 2	15.19	12.39	14.91	12.34	14.51	12.26
Marketing cost	2.05	1.22	2.06	1.28	2.03	1.24
Grade 1	2.36	1.62	2.41	1.86	2.36	1.81
Grade 2	1.79	0.92	1.76	0.95	1.78	0.85

Source: Authors' calculations.

data to present them in the model. In the case of this study, we performed the household fixed effects model as presented in Equation 1, which indicates the average effects of using e-commerce on households. Considering that the heterogeneous characteristics among individual households are also meaningful to investigate the effects of adopting e-commerce, we conducted the village fixed effects model that included the household characteristics, as presented in Equation 2. Similarly, we performed the county fixed effects model that included the characteristics of individual households and villages, as presented in Equation 3. The model specification was derived from a general two-way fixed effects model:

$$Y_{it} = a_1 E_{it} + h_n + \text{year}_t + \mu_{it,} \tag{1}$$

$$Y_{it} = \beta_1 E_{it} + \beta_2 X_n + v_m + \text{year}_t + \eta_{it}, \tag{2}$$

where i and t are the ith observation (product) and year t, respectively; t equals 2015, 2016, and 2017; and n and m represent the household n and village m, respectively. Y_{it} is a vector of the dependent variables, including the selling price and marketing cost of observation i in year t. Therefore, Equation 1 represents two models: the price model with household-level fixed effects and marketing cost model with household-level fixed effects. Similarly, Equation 2 represents two models: price model with village-level fixed effects and marketing cost model with village-level fixed effects.

The variable E_{it} indicates whether the product i in year t was sold by e-commerce. h_n in Equation 1 represents the heterogeneity among households, which does not change over time and is controlled by the dummy variable of each household in the model. To take account of the impacts of individual characteristics of rural households on selling prices and marketing costs, for example, the age and education level of the head of the household or cropland area, X_n is included as a vector of household-level variables in Equation 2. v_m presents the heterogeneity among villages, which does not change over time and is controlled by the dummy variable of each village in the model. The $year_t$ denotes year-specific effects to control for factors that change over time. μ_{it} and η_{it} are random error terms.

In addition, the impacts of the e-commerce policy of the government on selling prices and marketing costs were investigated. Equation 2 was further reformulated as follows:

$$Y_{it} = \gamma_1 E_{it} + \gamma_2 X_n + \gamma_3 P_{jt} + \gamma_4 (E_{it} * P_{jt}) + c_j + \text{year}_t + \delta_{it}, \quad (3)$$

where P_{jt} represents the accumulated number of policy documents about e-commerce published on the government website by county j up to year t, which presents the supports by local governments on developing local e-commerce. E-commerce policies can focus on various issues (e.g., local logistics or internet infrastructure), which can influence selling prices and marketing costs of agricultural products sold via e-commerce and conventional channels, although the impacts of the policies on both differ. The cross terms of E_{it} and P_{jt} were included to take account of the impacts of e-commerce policy on products sold via online platforms. c_j represents the time-invariant characteristics of county j, which is controlled by the dummy variable of each county in the model. δ_{it} is a random error term.

3.2 | Variables

A descriptive analysis of all the variables is displayed in Table 4. The variable Y_{1it} represents the average price of selling agricultural product i. The variable Y_{2it} indicates the sum of the costs for storing, processing, packing, and delivering each kilogram of product i, which reflects the direct costs incurred in the process of selling agricultural products through both e-commerce and non-e-commerce channels. These two variables are the dependent variables in our models, and the data on them have been deflated with the consumer price index of rural China, which is based on the consumer price of 1978. E_{it} is a dummy variable. If product i is sold through e-commerce, E_{it} equals 1, otherwise 0. To assess the impacts of e-commerce on different quality of agricultural products, the variables of $EGrade1_{it}$, $NEGrade1_{it}$, and $EGrade2_{it}$ are included as dummy variables. $EGrade1_{it}$ equals 1 if product i is the first-grade and sold by e-commerce, otherwise 0. Similarly, $NEGrade1_{it}$ equals 1 if product i is the first-grade and not sold by e-commerce, otherwise 0. $EGrade2_{it}$ equals 1 if product i is the second-grade and sold by e-commerce, otherwise 0. The characteristics of the household n include the age, gender, and education level of the head of the household,

TABLE 4 Variable definitions and statistical description

Variables	Variable definitions	Apple ($n = 329$) Mean	Apple S.D.	Peach ($n = 303$) Mean	Peach S.D.	Pecan ($n = 157$) Mean	Pecan S.D.
Y_{1it}	Selling price	1.33	0.55	1.52	0.65	17.77	5.62
Y_{2it}	Marketing cost	0.28	0.26	0.30	0.31	1.63	0.83
E_{it}	=1 if product is sold through e-commerce, otherwise 0	0.29	n.a.	0.27	n.a.	0.48	n.a.
$EGrade1_{it}$	=1 if product is the first-grade and sold by e-commerce, otherwise 0	0.19	0.39	0.18	0.39	0.22	0.41
$NEGrade1_{it}$	=1 if product is the first-grade and not sold by e-commerce, otherwise 0	0.39	0.49	0.36	0.48	0.20	0.40
$EGrade2_{it}$	=1 if product is the second-grade and sold by e-commerce, otherwise 0	0.09	0.29	0.09	0.29	0.27	0.44
X_{1n}	Age of household head	44.82	9.30	43.59	10.85	41.72	12.63
X_{2n}	=1 if household head is male, otherwise 0	0.80	n.a.	0.70	n.a.	0.67	n.a.
X_{3n}	Education level of household head	10.04	2.46	9.24	2.29	11.17	3.46
X_{4n}	Experience in conducting e-commerce of household head	1.11	1.57	1.37	2.35	2.84	3.13
X_{5n}	Cropland area	0.75	0.74	0.56	0.37	0.21	0.19
X_{6n}	Distance from household to local village committee	0.65	0.80	0.56	0.52	1.01	1.67
X_{7n}	Distance from household to local town center	4.12	3.07	5.72	2.83	7.04	5.41
P_{jt}	The accumulated number of policy documents about e-commerce published on the government website	5.81	3.31	11.52	6.14	17.96	8.26

Source: Authors' calculations.

as well as experience in conducting e-commerce, cropland area, distance from household to local village committee, and distance from household to local town center, which are presented by the variables of $X_{1n} - X_{7n}$, respectively. P_{jt} indicates the accumulated number of policy documents about e-commerce published on the government website of each county.

4 | ESTIMATION RESULTS

Tables 5, 6, and 7 present the impacts of using e-commerce on the selling prices and marketing costs of apples, peaches, and pecans, respectively. Models 1–6 present the overall effects of using e-commerce on the selling prices and marketing costs, and models 7–12 present the heterogeneous effects on selling prices and marketing costs of different grades of the same product. Models 1, 4, 7, and 10 are based on Equation 1, which controls all the time-invariant factors at the household level. Models 2, 5, 8, and 11 are based on Equation 2, which controls all the time-invariant factors at the village level and includes the variables encompassing the main characteristics of rural households. Models 3, 6, 9, and 12 are based on Equation 3, which controls all the time-invariant factors at the county level and includes the main characteristics of rural households and the variable e-commerce policy.

As shown in Table 5, the results of model 1 revealed that the selling price of apples sold through e-commerce increased by 0.784 RMB/kg compared with that of apples not sold through e-commerce when the household variable was fixed, and the price of apples increased by 71.3% due to the use of e-commerce. The results of model 2 showed that the selling price of apples sold through e-commerce increased by 0.824 RMB/kg compared with that of apples not sold through e-commerce when the village variable was fixed. In this model, the price of apples increased by 74.9% due to the use of e-commerce. The results of model 3 revealed that the selling price of apples sold through e-commerce increased by 0.846 RMB/kg when the county variable was fixed. In this case, the price of apples increased by 76.9% due to the use of e-commerce. The model results indicated that cropland area influenced the selling price of apples significantly and positively. Moreover, e-commerce policy had a significant, negative effect on the selling price of apples, and there are no significant differences in the impact of e-commerce policy on the selling price between e-commerce products and non-e-commerce products.

Similarly, the results of model 4 showed that the marketing cost of apples sold through e-commerce increased by 0.523 RMB/kg as compared with that of apples not sold through e-commerce when the household variable was fixed. The price of apples increased by 402.3% due to the use of e-commerce. The results of model 5 showed that the marketing cost of apples sold through e-commerce increased by 0.535 RMB/kg compared with that of apples not sold through e-commerce when the village variable was fixed. In other words, the marketing cost of apples increased by 382.1% due to the use of e-commerce to sell agricultural products. The results of model 6 showed that the marketing cost of apples sold through e-commerce increased by 0.541 RMB/kg when the county variable was fixed. This finding indicated that the marketing cost of apples increased by 386.4% due to the use of e-commerce. Interestingly, e-commerce policy decreased the marketing cost of apples significantly, and the decrease is more obvious for e-commerce products.

Most importantly, the gross return, which equals the selling price − the marketing cost, on apples sold through e-commerce increased by 0.261 RMB/kg (i.e., 0.784 RMB/kg − 0.523 RMB/kg) compared with that of apples not sold through e-commerce when the household variable was fixed. When the village variable was fixed, the gross return on apples sold through e-commerce increased by 0.289 RMB/kg (i.e., 0.824 RMB/kg − 0.535 RMB/kg) compared with that of apples not sold through e-commerce. The gross return increased by 0.305 RMB/kg (i.e., 0.846 RMB/kg − 0.541 RMB/kg) when the county variable was fixed.

Different grades of apples provided additional insights into the effects of using e-commerce. The results of model 7 showed that the selling price of first-grade apples sold through e-commerce increased by 0.758 RMB/kg (i.e., 1.190 RMB/kg − 0.432 RMB/kg) compared with that of first-grade apples not sold through e-commerce when the household variable was fixed. In addition, the selling price of second-grade apples sold through e-commerce rose by 0.545 RMB/kg compared with that of second-grade apples not sold through e-commerce. The results of model 8 showed that when the village variable was fixed, the selling price of first-grade

TABLE 5 Impacts of e-commerce on selling price and marketing cost of apple: fixed effects model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	0.784***	0.824***	0.846***	0.523***	0.535***	0.541***						
	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.04)						
$EGrade1_{it}$							1.190***	1.225***	1.251***	0.533***	0.545***	0.551***
							(0.09)	(0.09)	(0.11)	(0.04)	(0.04)	(0.04)
$NEGrade1_{it}$							0.432***	0.415***	0.415***	0.004	0.008	0.008
							(0.05)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
$EGrade2_{it}$							0.545***	0.624***	0.650***	0.506***	0.525***	0.531***
							(0.08)	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)
X_{1n}		0.007	0.007		0.001	0.001		0.007	0.007		0.001	0.001
		(0.01)	(0.01)		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
X_{2n}		0.059	0.060		0.008	0.008		0.119*	0.119*		0.011	0.011
		(0.07)	(0.07)		(0.03)	(0.03)		(0.07)	(0.07)		(0.03)	(0.03)
X_{3n}		0.034	0.034		0.000	0.000		0.039	0.038		0.001	0.000
		(0.03)	(0.03)		(0.01)	(0.01)		(0.03)	(0.03)		(0.01)	(0.01)
X_{4n}		−0.020	−0.017		0.002	0.003		−0.010	−0.007		0.002	0.003
		(0.02)	(0.02)		(0.00)	(0.00)		(0.02)	(0.02)		(0.00)	(0.00)
X_{5n}		0.073**	0.072**		−0.005	−0.005		0.081**	0.081**		−0.004	−0.005
		(0.03)	(0.03)		(0.01)	(0.01)		(0.04)	(0.04)		(0.01)	(0.01)
X_{6n}		0.039	0.039		0.009	0.009		0.039	0.039		0.009	0.009
		(0.05)	(0.05)		(0.02)	(0.02)		(0.05)	(0.05)		(0.02)	(0.02)
X_{7n}			0.043			0.003			0.007			0.002
			(0.06)			(0.02)			(0.06)			(0.02)

(Continues)

TABLE 5 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
P_{jt}			−0.007*			−0.002**			−0.009**			−0.002**
			(0.00)			(0.00)			(0.00)			(0.00)
E_{it}* P_{jt}			−0.004			−0.001			−0.005			−0.001
			(0.01)			(0.00)			(0.01)			(0.00)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 329.
***$p < .01$; **$p < .05$; *$p < .10$.

apples sold through e-commerce increased by 0.810 RMB/kg (i.e., 1.225 RMB/kg − 0.415 RMB/kg) compared with that of the same grade of apples not sold through e-commerce. Furthermore, the selling price of second-grade apples sold through e-commerce increased by 0.624 RMB/kg. The results of model 9 showed that the selling price of first-grade apples sold through e-commerce increased by 0.836 RMB/kg (i.e., 1.251 RMB/kg − 0.415 RMB/kg) compared with that of first-grade apples not sold through e-commerce when the county variable was fixed. In addition, the selling price of second-grade apples sold through e-commerce increased by 0.650 RMB/kg compared with that of second-grade apples not sold through e-commerce. The results showed that gender and cropland area had a significant and positive influence on the selling price. The impact of e-commerce policy on the selling price was significant and negative, and there were no significant differences in the impact of e-commerce policy on selling price between e-commerce products and non-e-commerce products.

Similarly, the results of model 10 showed that when the household variable was fixed, the marketing cost of first-grade apples sold through e-commerce increased by 0.533 RMB/kg compared with that of first-grade apples not sold through e-commerce. The marketing cost of second-grade apples sold through e-commerce rose by 0.506 RMB/kg compared with that of second-grade apples not sold through e-commerce. The results of model 11 showed that the marketing cost of first-grade apples sold through e-commerce increased by 0.545 RMB/kg when the village variable was fixed, and the marketing cost of second-grade apples sold through e-commerce increased by 0.525 RMB/kg. The results of model 12 showed that the selling price of first-grade apples sold through e-commerce increased by 0.551 RMB/kg, compared with that of first-grade apples not sold through e-commerce when the county variable was fixed. The marketing cost of second-grade apples sold through e-commerce rose by 0.531 RMB/kg compared with that of the same grade of apples not sold through e-commerce. Moreover, the results revealed that e-commerce policy had a significant and negative effect on the marketing cost of apples.

The gross return on first-grade apples sold through e-commerce increased by 0.225 RMB/kg (i.e., 0.758 RMB/kg − 0.533 RMB/kg) compared with that of first-grade apples not sold through e-commerce when the household variable was fixed and increased by 0.265 RMB/kg (i.e., 0.810 RMB/kg − 0.545 RMB/kg) when the village variable was fixed. The gross return on first-grade apples sold through e-commerce rose by 0.285 RMB/kg (i.e., 0.836 RMB/kg − 0.551 RMB/kg) when the county variable was fixed. When the household variable was fixed, the gross return on second-grade apples sold through e-commerce increased by 0.039 RMB/kg (i.e., 0.545 RMB/kg − 0.506 RMB/kg) and increased by 0.099 RMB/kg (i.e., 0.624 RMB/kg − 0.525 RMB/kg) when the village variable was fixed compared with that of second-grade apples not sold through e-commerce. The gross return on second-grade apples sold through e-commerce rose by 0.119 RMB/kg (i.e., 0.650 RMB/kg − 0.531 RMB/kg) compared with that of the same grade of apples not sold through e-commerce.

Our findings showed that the selling price and marketing cost of apples significantly and positively increased in accordance with the use of e-commerce. E-commerce also had a positive impact on the gross return on apples, showing that farmers got a greater return through using e-commerce to sell apples than through intermediaries. The effect of e-commerce differed according to apple grade. Specifically, increases in selling price, marketing cost, and gross return associated with the use of e-commerce were higher for first-grade than second-grade apples. Details on changes in selling price, marketing cost, and gross return associated with the adoption of e-commerce by farmers are presented in Table 8. Moreover, gender and cropland area had a significant influence on the selling price of apples. E-commerce policy affected the marketing cost of apples significantly and negatively.

TABLE 6 Impacts of e-commerce on selling price and marketing cost of peach: fixed effects model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	0.932***	0.920***	0.951***	0.590***	0.603***	0.621***						
	(0.12)	(0.09)	(0.10)	(0.05)	(0.04)	(0.04)						
$EGrade1_{it}$							1.380***	1.376***	1.422***	0.612***	0.626***	0.646***
							(0.14)	(0.12)	(0.13)	(0.05)	(0.05)	(0.05)
$NEGrade1_{it}$							0.491***	0.504***	0.506***	−0.004	0.008	0.009*
							(0.04)	(0.04)	(0.04)	(0.01)	(0.00)	(0.01)
$EGrade2_{it}$							0.599***	0.592***	0.634***	0.512***	0.557***	0.575***
							(0.11)	(0.08)	(0.09)	(0.05)	(0.04)	(0.04)
X_{1n}		−0.004	−0.004		−0.001	−0.001		−0.007	−0.007		−0.001	−0.001
		(0.01)	(0.01)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
X_{2n}		−0.061	−0.062		−0.027	−0.028		−0.057	−0.058		−0.026	−0.027
		(0.11)	(0.11)		(0.04)	(0.04)		(0.10)	(0.10)		(0.04)	(0.04)
X_{3n}		−0.009	−0.009		0.004	0.004		−0.015	−0.015		0.003	0.003
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
X_{4n}		0.039***	0.045***		−0.004	0.001		0.051***	0.056***		−0.004	0.001
		(0.01)	(0.01)		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
X_{5n}		0.075	0.074		0.066**	0.065**		0.122*	0.121*		0.071**	0.070**
		(0.07)	(0.07)		(0.03)	(0.03)		(0.06)	(0.06)		(0.03)	(0.03)
X_{6n}		−0.055	−0.053		0.033	0.034		−0.078	−0.076		0.030	0.031
		(0.06)	(0.06)		(0.03)	(0.03)		(0.06)	(0.06)		(0.03)	(0.03)
X_{7n}			0.014			0.012			0.015			0.011
			(0.07)			(0.02)			(0.06)			(0.02)

TABLE 6 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
P_{jt}			−0.003**			0.000			−0.003**			0.000
			(0.00)			(0.00)			(0.00)			(0.00)
$E_{it}*P_{jt}$			−0.003			−0.002***			−0.004			−0.002***
			(0.00)			(0.00)			(0.00)			(0.00)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 303.
***$p < .01$; **$p < .05$; *$p < .10$.

TABLE 7 Impacts of e-commerce on selling price and marketing cost of pecan: fixed effects model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	4.713***	4.076***	3.665***	0.907***	0.706***	0.767***						
	(0.73)	(0.75)	(0.84)	(0.23)	(0.17)	(0.17)						
$EGrade1_{it}$							14.526***	13.580***	13.030***	1.202***	1.207***	1.244***
							(0.60)	(0.57)	(0.74)	(0.23)	(0.18)	(0.19)
$NEGrade1_{it}$							9.546***	9.121***	9.179***	0.494**	0.711***	0.707***
							(0.57)	(0.50)	(0.51)	(0.21)	(0.20)	(0.20)
$EGrade2_{it}$							3.149***	2.318***	1.676**	1.019***	0.775***	0.823***
							(0.91)	(0.63)	(0.81)	(0.29)	(0.20)	(0.21)
X_{1n}		0.031	0.002		0.012	0.011		0.025	0.017		0.011	0.011
		(0.08)	(0.07)		(0.01)	(0.01)		(0.02)	(0.02)		(0.01)	(0.01)
X_{2n}		−2.250*	−2.326**		0.070	0.048		−0.865	−0.964*		0.111	0.090
		(1.18)	(1.08)		(0.32)	(0.31)		(0.55)	(0.56)		(0.32)	(0.32)
X_{3n}		−0.175	−0.339*		0.031	0.022		0.141*	0.097		0.044	0.041
		(0.26)	(0.20)		(0.03)	(0.03)		(0.08)	(0.07)		(0.03)	(0.03)
X_{4n}		0.295	0.207		0.091**	0.099***		−0.016	−0.035		0.074**	0.079**
		(0.20)	(0.21)		(0.04)	(0.04)		(0.09)	(0.10)		(0.03)	(0.03)
X_{5n}		2.230	3.226		−0.229	−0.202		−0.159	0.108		−0.340	−0.328
		(2.56)	(2.84)		(0.56)	(0.54)		(1.05)	(1.07)		(0.48)	(0.47)
X_{6n}		−1.608	−0.313		0.002	0.065		−0.428	−0.047		0.065	0.076**
		(1.10)	(0.37)		(0.17)	(0.05)		(0.38)	(0.15)		(0.13)	(0.04)
X_{7n}			−0.221***			−0.008			−0.068			0.001
			(0.07)			(0.01)			(0.05)			(0.01)

TABLE 7 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
P_{jt}			−0.016			−0.004			−0.006			−0.003
			(0.02)			(0.00)			(0.01)			(0.00)
$E_{it}* P_{jt}$			0.024			−0.004			0.033			−0.003
			(0.02)			(0.00)			(0.02)			(0.00)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 157.
$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .10$.

TABLE 8 Changes in selling price, marketing cost, and gross return due to the adoption of e-commerce by farmers

					Household fixed		Village fixed		County fixed	
Products		**Household fixed**	**Village fixed**	**County fixed**	**First grade**	**Second grade**	**First grade**	**Second grade**	**First grade**	**Second grade**
Apple	Selling price (RMB/kg)	0.784	0.824	0.846	0.758	0.545	0.810	0.624	0.836	0.650
	Marketing cost (RMB/kg)	0.523	0.535	0.541	0.533	0.506	0.545	0.525	0.551	0.531
	Gross return (RMB/kg)	0.261	0.289	0.305	0.225	0.039	0.265	0.099	0.285	0.119
Peach	Selling price (RMB/kg)	0.932	0.920	0.951	0.889	0.599	0.872	0.592	0.916	0.634
	Marketing cost (RMB/kg)	0.590	0.603	0.621	0.612	0.512	0.626	0.557	0.637	0.575
	Gross return (RMB/kg)	0.342	0.317	0.330	0.277	0.087	0.246	0.035	0.279	0.059
Pecan	Selling price (RMB/kg)	4.713	4.076	3.665	4.980	3.149	4.459	2.318	3.851	1.676
	Marketing cost (RMB/kg)	0.907	0.706	0.767	0.708	1.019	0.496	0.775	0.537	0.823
	Gross return (RMB/kg)	3.806	3.370	2.898	4.272	2.130	3.963	1.543	3.314	0.853

Tables 6 and 7 present that the use of e-commerce increased selling price and marketing cost of peaches and pecans significantly, which is consistent with the results presented in Table 5. It indicates that the impacts of e-commerce on selling price and marketing cost are robust. In addition, the results presented in Tables 5, 6, and 7 based on Equation 1, which includes all the time-invariant factors at the household level, are consistent with those based on Equations 2 and 3, which include all the time-invariant factors at the village level and county level, respectively. It indicates that the model results are robust. We employed ordinary least square (OLS) to check the robustness of the model results. The model results based on the pooled data on each of the agricultural products are presented in Tables A1, A2, and A3 of the appendix, which are consistent with the results in Tables 5, 6, and 7, respectively. They further verify that our results based on the fixed effects model are robust.

5 | DISCUSSION AND CONCLUSIONS

In developing countries, due to high transport costs and the lack of reliable market information, individual farmers who sell agricultural products are often exploited by intermediaries (Goyal, 2010). With the adoption of e-commerce, farmers can cut out intermediaries and sell agricultural products to consumers directly. As such, the selling prices for farmers through e-commerce is higher than the farm gate prices offered by intermediaries, because the supply chain between farmers and consumers that excludes intermediaries is shortened. To be more specific, the profits that were obtained by intermediaries go to farmers although consumers pay the same prices for online products compared with the offline ones. Meanwhile, the costs for famers to sell their agricultural products to individual consumers are also higher than that to intermediaries because farmers have additional costs for operating e-commerce that were formerly undertaken by intermediaries, such as the costs for storing, processing, packing, and delivering. Especially the online consumers are geographically spread, and each transaction amount is relatively small, which results in high transportation costs for farmers to sell their products. This study based on specific data and empirical analysis proved that compared with the conventional marketing channel of selling agricultural products through intermediaries, farmers get a greater return by selling their products through e-commerce. Although the use of e-commerce resulted in extra marketing costs for the farmers, the increase in the product prices was significantly more than the additional cost, which led to increases in gross return.

In addition, we found that the impacts of using e-commerce were multifold. First, the increases in selling price, marketing cost, and gross return varied among agricultural products. The increases in selling price, marketing cost, and gross return for pecans were higher than those for apples and peaches, and the increases in these variables for peaches were higher than for apples. Among pecans, peaches, and apples, pecans have the highest value, and apples have the lowest value. It indicates that selling higher-value products through e-commerce results in greater returns for farmers than selling the lower-value products. Second, the increases in selling price, marketing cost, and gross return varied across the different grades of the same product. In general, the increases in selling price, marketing cost, and gross return of first-grade apples and peaches due to the use of e-commerce were higher than for second-grade apples and peaches. Although the increase in the marketing cost of roughly processed pecans was higher than that of highly processed pecans, the increases in selling price and gross return of the highly processed pecans were still higher than for roughly processed pecans.

This finding indicates that selling better quality products through e-commerce results in greater returns for farmers than selling the lower quality products.

The results of this study have several implications for agricultural development and policy. First, the use of e-commerce allows farmers to market their products directly to consumers, which can help to create jobs and increase gross returns of selling agricultural products. The results of this study also provide supporting evidence for recent initiatives embraced by international development communities, China, and many other developing countries to alleviate rural poverty and raise farmers' income through promoting rural e-commerce in less developed regions. Second, considering that farmers can get a greater return from using e-commerce to sell higher-value and better-quality agricultural products, rural e-commerce expansion can be expected to improve the structure of agricultural production at the farm level, thereby improving the variety of agricultural products and the quality of each product. At industry and national levels, the development of rural e-commerce has important implications for agricultural structural transformation, moving from low-value agriculture to high-value agriculture. Third, when consumers transact with farmers directly, consumers can know the origin of the product and can ask for a refund if they are not satisfied with the quality or safety of the product. This can resolve the difficulty of food traceability under the small-farm dominated system in China and many developing countries and address the problem of food safety in developing countries. Fourth, the development of rural e-commerce has important implications for the transformation of conventional agricultural markets and various stakeholders associated with these markets and online businesses.

The present study was conducted in regions of China where e-commerce use is relatively advanced. To generalize the findings, studies in other regions of China and in other countries are needed. In addition, it would be interesting to investigate the impacts of e-commerce on the volume of sales of agricultural products based on data collected during a longer period. In this study, with only 3 years of data, we are not able to provide rigorous evidence on the likely effects of rural e-commerce on the quantity of products sold by farmers. Furthermore, we did not consider the spillover effect among farmers in this study, which could be considered in future research.

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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.

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REFERENCES

Aker, J. C., Ghosh, I., & Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, *47*(S1), 35–48.

China International Electronic Commerce Center (CIECC). (2018). *The report on the development of rural e-commerce of China (2017–2018)*. Retrieved from https://www.sohu.com/a/259675536_99947052. Access: 8th of May, 2019.

Couture, V., Faber, B., Gu, Y., & Liu, L. (2021). Connecting the countryside via E-commerce: Evidence from China. *American Economic Review: Insights, 3*(1), 35–50.

Deichmann, U., Goyal, A., & Mishra, D. (2016). Will digital technologies transform agriculture in developing countries? *Agricultural Economics (United Kingdom)*, *47*, 21–33. https://doi.org/10.1111/agec.12300

Du, X., Wang, X., & Hatzenbuehler, P. (2022). Digital technology in agriculture: A review of issues, applications, and methodologies. *China Agricultural Economic Review* (ahead-of-print).

Goyal, A. (2010). Information, direct access to farmers, and rural market performance in Central India. *American Economic Journal: Applied Economics*, *2*(3), 22–45.

Kshetri, N. (2018). Rural e-commerce in developing countries. *IT Professional*, *20*(2), 91–95.

Kosec, K., & Wantchekon, L. (2018). Can information improve rural governance and service delivery? *World Development*, *115*, 104376. https://doi.org/10.1016/j.worlddev.2018.07.017

Liu, M., Zhang, Q., Gao, S., & Huang, J. (2020). The spatial aggregation of rural e-commerce in China: An empirical investigation into Taobao villages. *Journal of Rural Studies*, *80*, 403–417.

Li, J., & Li, B. (2022). Digital inclusive finance and urban innovation: Evidence from China. *Review of Development Economics*, *26*(2), 1010–1034.

Li, G., & Qin, J. (2022). Income effect of rural E-commerce: Empirical evidence from Taobao villages in China. *Journal of Rural Studies*, *96*, 129–140.

Ma, W., Nie, P., Zhang, P., & Renwick, A. (2020). Impact of internet use on economic well-being of rural households: Evidence from China. *Review of Development Economics*, *24*(2), 503–523.

Ma, W., & Zheng, H. (2022). Heterogeneous impacts of information technology adoption on pesticide and fertiliser expenditures: Evidence from wheat farmers in China. *Australian Journal of Agricultural and Resource Economics*, *66*(1), 72–92.

Malecki, E. J. (2003). Digital development in rural areas: Potentials and pitfalls. *Journal of Rural Studies*, *19*(2), 201–214. https://doi.org/10.1016/S0743-0167(02)00068-2

Ministry of Commerce of China (MCC). (2018). The implementation of the project of "introducing e-commerce to rural areas" in 2018. Retrieved from http://scjss.mofcom.gov.cn/article/bnjg/201809/20180902790214.shtml. Access: 8th of May, 2019.

Mitra, S., Mookherjee, D., Torero, M., & Visaria, S. (2018). Asymmetric information and middleman margins: An experiment with Indian potato farmers. *Review of Economics and Statistics*, *100*(1), 1–13.

Salemink, K., Strijker, D., & Bosworth, G. (2017). Rural development in the digital age: A systematic literature review on unequal ICT availability, adoption, and use in rural areas. *Journal of Rural Studies*, *54*, 360–371.

Shan, J. S., & Luo, Z. D. (2017). Agglomeration and fission: Spatial distribution characteristics and evolution trends of Taobao villages and towns. *Shanghai Urban Planning Review*, *2*, 98–104.

Tabetando, R., & Matsumoto, T. (2020). Mobile money, risk sharing, and educational investment: Panel evidence from rural Uganda. *Review of Development Economics*, *24*(1), 84–105.

The State Council Leading Group Office of Poverty Alleviation and Development (TSCLGOPAD). (2020). The list for the Pilot Counties of Introducing E-commerce to Rural Areas in 2019. Retrieved from http://www.cpad.gov.cn/art/2019/8/27/art_624_102341.html. Access: 8th of June, 2020.

Verbeek, M. (2012). *Models based on panel data a guide to modern econometrics* (4th ed.). Hoboken: John Wiley & Sons Ltd.

Wang, C. C., Miao, J. T., Phelps, N. A., & Zhang, J. (2021). E-commerce and the transformation of the rural: The Taobao village phenomenon in Zhejiang Province, China. *Journal of Rural Studies*, *81*, 159–169.

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

Yang, Y. M. (2020). A study on the poverty reduction through developing rural e-commerce. *Rural Economy*, *6*, 133–135.

Zapata, S. D., Isengildina-Massa, O., Carpio, C. E., & Lamie, R. D. (2016). Does E-commerce help Farmers' Markets? Measuring the impact of MarketMaker. *Journal of Food Distribution Research*, *47*, 1–18.

Zeng, Y. W., Guo, H. D., & Jin, S. Q. (2018). Does E-commerce increase Farmers' income? Evidence from Shuyang County, Jiangsu Province, China. *Chinese Rural Economy*, *02*, 49–64.

Zhang, X. C. (2015). Present situation, problems and countermeasures of E-commerce in rural areas. *Agricultural Economics and Management*, *3*, 71–80.

Zheng, H., Ma, W., Wang, F., & Li, G. (2021). Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy*, *102*, 102044.

Zhu, B., Song, Y., Li, G., & Yu, T. (2016). Spatial aggregation pattern and influencing factors of "Taobao Village" in China. *Economic Geography*, *36*, 92–98.

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APPENDIX A

TABLE A1 Impacts of e-commerce on selling price and marketing cost of apple: ordinary least square model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	0.777***	0.809***	0.812***	0.507***	0.528***	0.492***						
	(0.06)	(0.07)	(0.08)	(0.04)	(0.04)	(0.04)						
$EGrade1_{it}$							1.189***	1.205***	1.215***	0.514***	0.535***	0.499***
							(0.09)	(0.09)	(0.12)	(0.04)	(0.04)	(0.04)
$NEGrade1_{it}$							0.426***	0.403***	0.403***	0.002	0.005	0.005
							(0.05)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
$EGrade2_{it}$							0.529***	0.598***	0.608***	0.496***	0.521***	0.485***
							(0.09)	(0.08)	(0.07)	(0.05)	(0.05)	(0.05)
X_{1n}		0.010	0.010		0.001	0.001		0.010	0.010		0.001	0.001
		(0.01)	(0.01)		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
X_{2n}		0.055	0.055		0.007	0.007		0.103	0.103		0.008	0.008
		(0.06)	(0.06)		(0.03)	(0.03)		(0.06)	(0.06)		(0.03)	(0.03)
X_{3n}		0.033	0.033		0.003	0.003		0.038	0.038		0.003	0.003
		(0.03)	(0.03)		(0.01)	(0.01)		(0.03)	(0.03)		(0.01)	(0.01)
X_{4n}		0.004	0.004		−0.016*	−0.016*		0.017	0.017		−0.016*	−0.016*
		(0.03)	(0.03)		(0.01)	(0.01)		(0.03)	(0.03)		(0.01)	(0.01)
X_{5n}		0.093**	0.093**		0.003	0.004		0.111**	0.110**		0.003	0.004
		(0.04)	(0.04)		(0.02)	(0.02)		(0.05)	(0.05)		(0.02)	(0.02)
X_{6n}		0.048	0.048		0.008	0.008		0.036	0.036		0.008	0.007
		(0.04)	(0.04)		(0.02)	(0.02)		(0.04)	(0.04)		(0.02)	(0.02)

(Continues)

TABLE A1 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
X_{7n}			−0.128**			−0.037			−0.112**			−0.037
			(0.05)			(0.03)			(0.05)			(0.03)
P_{jt}			−0.012**			0.000			−0.014**			0.000
			(0.01)			(0.00)			(0.01)			(0.00)
E_{it}* P_{jt}			−0.001			0.006*			−0.002			0.006*
			(0.01)			(0.00)			(0.01)			(0.00)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 329.
***$p < .01$; **$p < .05$; *$p < .10$.

TABLE A2 Impacts of e-commerce on selling price and marketing cost of peach: ordinary least square model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	1.003***	0.908***	0.940***	0.592***	0.618***	0.677***						
	(0.13)	(0.10)	(0.15)	(0.05)	(0.04)	(0.04)						
$EGrade1_{it}$							1.419***	1.382***	1.450***	0.616***	0.641***	0.705***
							(0.15)	(0.13)	(0.15)	(0.05)	(0.05)	(0.05)
$NEGrade1_{it}$							0.467***	0.493***	0.493***	−0.004	0.005	0.006
							(0.04)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)
$EGrade2_{it}$							0.621***	0.533***	0.599***	0.500***	0.567***	0.628***
							(0.13)	(0.09)	(0.12)	(0.05)	(0.04)	(0.04)
X_{1n}		−0.004	−0.004		−0.001	−0.001		−0.006	−0.006		−0.001	−0.001
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
X_{2n}		−0.068	−0.068		−0.014	−0.014		−0.048	−0.049		−0.012	−0.012
		(0.11)	(0.11)		(0.03)	(0.03)		(0.09)	(0.09)		(0.03)	(0.03)
X_{3n}		−0.012	−0.012		0.001	0.001		−0.017	−0.016		0.000	0.001
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
X_{4n}		0.058***	0.058***		−0.007*	−0.008*		0.068***	0.068***		−0.007	−0.007*
		(0.02)	(0.02)		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)
X_{5n}		0.072	0.073		0.061*	0.062**		0.124*	0.125*		0.066**	0.067**
		(0.07)	(0.07)		(0.03)	(0.03)		(0.07)	(0.07)		(0.03)	(0.03)
X_{6n}		−0.031	−0.030		0.025	0.025		−0.056	−0.055		0.021	0.021
		(0.07)	(0.07)		(0.03)	(0.03)		(0.06)	(0.06)		(0.03)	(0.03)
X_{7n}			0.003			0.011			0.004			0.011
			(0.06)			(0.01)			(0.06)			(0.01)

(Continues)

TABLE A2 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
P_{jt}			−0.005**			0.001*			−0.004**			0.001*
			(0.00)			(0.00)			(0.00)			(0.00)
E_{it}* P_{jt}			−0.002			−0.005**			−0.005			−0.005**
			(0.01)			(0.00)			(0.01)			(0.00)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 303.
***$p < .01$; **$p < .05$; *$p < .10$.

TABLE A3 Impacts of e-commerce on selling price and marketing cost of pecan: ordinary least square model

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
E_{it}	4.679***	3.744***	3.615***	0.917***	0.667***	0.729**						
	(0.71)	(0.81)	(1.03)	(0.23)	(0.19)	(0.27)						
$EGrade1_{it}$							14.430***	13.295***	12.975***	1.215***	1.185***	1.249***
							(0.68)	(0.63)	(0.90)	(0.26)	(0.20)	(0.25)
$NEGrade1_{it}$							9.436***	8.872***	8.912***	0.498*	0.724***	0.729***
							(0.52)	(0.52)	(0.53)	(0.25)	(0.23)	(0.24)
$EGrade2_{it}$							3.325***	2.305***	1.968*	1.073***	0.773***	0.837***
							(1.10)	(0.77)	(1.04)	(0.31)	(0.22)	(0.28)
X_{1n}		0.074	0.056		0.015	0.013		0.027	0.020		0.011	0.010
		(0.08)	(0.07)		(0.01)	(0.01)		(0.02)	(0.02)		(0.01)	(0.01)
X_{2n}		−3.140**	−3.373**		−0.076	−0.097		−0.876	−1.003*		0.017	0.005
		(1.29)	(1.25)		(0.33)	(0.34)		(0.54)	(0.56)		(0.35)	(0.35)
X_{3n}		−0.062	−0.210		0.030	0.018		0.162*	0.110		0.036	0.030
		(0.24)	(0.19)		(0.04)	(0.03)		(0.09)	(0.07)		(0.03)	(0.03)
X_{4n}		0.604***	0.634***		0.124***	0.127***		−0.013	−0.001		0.091***	0.092***
		(0.17)	(0.18)		(0.03)	(0.04)		(0.09)	(0.09)		(0.03)	(0.03)
X_{5n}		1.506	1.889		−0.235	−0.200		−0.291	−0.153		−0.331	−0.312
		(2.24)	(2.42)		(0.64)	(0.63)		(1.03)	(1.09)		(0.55)	(0.54)
X_{6n}		−1.097	0.011		0.010	0.093*		−0.402	−0.035		0.057	0.094**
		(1.14)	(0.28)		(0.20)	(0.05)		(0.41)	(0.14)		(0.16)	(0.04)
X_{7n}			−0.255***			−0.004			−0.060			0.008
			(0.07)			(0.01)			(0.05)			(0.02)

(Continues)

TABLE A3 (Continued)

	Selling price			Marketing cost			Selling price			Marketing cost		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
P_{jt}			−0.025			−0.005			−0.001			−0.004
			(0.04)			(0.00)			(0.01)			(0.00)
$E_{it}{*}\,P_{jt}$			0.003			−0.004			0.018			−0.003
			(0.04)			(0.01)			(0.02)			(0.01)
Household dummy	Yes			Yes			Yes			Yes		
Village dummy		Yes			Yes			Yes			Yes	
County dummy			Yes			Yes			Yes			Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses and clustered at household level. Obs. = 157.
***$p < .01$; **$p < .05$; *$p < .10$.