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# Do Farmers Gain Internet Dividends from E-commerce Adoption? Evidence from China

Hongdong GUO
Professor and Chair, Department of Agricultural Economics and Management
Zhejiang University
Email address: guohongdong@zju.edu.cn

Xiaokang LI
PhD candidate, Department of Agricultural Economics and Management
Zhejiang University
Email address: lindared602@163.com

Yiwu ZENG
PhD candidate, Department of Agricultural Economics and Management,
Zhejiang University.
Email address: 11420050@zju.edu.cn

Songqing JIN
Professor, Department of Agricultural Economics and Management
Zhejiang University
Associate Professor, Department of Agricultural, Food and Resource Economics
Michigan State University
Email address: sjin@zju.edu.cn

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**Abstract:** The revolution of information technology and communications has drastically changed the way people conduct business. With the rapid emergence of Taobao villages and other e-trading platforms in its rural areas, China is leading the developing world in rural e-commerce. Despite the potential of e-commerce to improve agriculture profits and farmer's income, whether and to what extent farmers really benefit from it remains a question. Using household survey data from farmers selling products through e-trading platform and those selling products through traditional market channel, we aim to rigorously assess the effects of e-commerce adoption on farmer's income and identify the key mechanisms through which the impact comes about. Propensity score matching (PSM) methods were adopted to deal with the fact that farmers' participation in selling products through e-commerce is not random. The PSM results show that the adoption of e-commerce has a positive effect on farmers' income, especially in the villages with more e-commerce adoption. And the increase in the profit margin and the growth of sales are the two main channels through which e-commerce impacts farmers' income.

**Key words:** e-commerce, farmers' income, market channels, rural China

## 1. Introduction

The extensive application of information communication technology, represented by the Internet, has a comprehensive and profound influence on human society. However, there is an endless debate about its influence. One argument is that the development of the Internet is likely to further enlarge the gap between the developed and the undeveloped regions, the urban and the rural areas, and the rich and the poor. The two main reasons why small farmers in developing countries are difficult to share the digital dividends are the lack of the access to the information technology infrastructure and the lack of ability to use the information technologies. Despite the extensive application of the information technology such as cellphone and the Internet, many scholars, insist that the development of the Internet only benefits the wealthy with better education and higher level of income, leading to a growing gap between low-income and high-income groups (Britz & Blignaut 2001, DiMaggio & Hargittai 2001, Bonfadelli 2002, and Clark & Gorski 2002).

By contrast, proponents argue that producers, especially those smallholders in traditional industries in rural areas, are able to share the digital dividends. Indeed, a number of empirical studies have shown positive effects of mobile phones and the Internet on the sales and the prices of agricultural products, as well as farmers' welfare (e.g. Jensen, 2007; Burga & Barreto, 2014; Shimamoto *et al*., 2015). Yet, others found that information communication technology has no significant impact on farmers (e.g. Monloy, 2008; Futch & McIntosh, 2009; Fafchamps and Minten, 2012).

The existing empirical research has demonstrated that the economic effects of the application of cellphones and the Internet on farmers in developing countries are complicated. While the mixed results may be related to many contributing factors, different samples from different regions with different categories of products could be an important factor. In addition, while most of the existing studies tend to focus on the perspectives of the accessibility, coverage, quantity, time and cost of using cellphone and the Internet, the boarder impact of using these technologies are much less studied. Despite some anecdotal evidence and the recent hype in the media and newspapers about the importance of rural e-commerce in rural development, rigorous evidence on the economic impact of e-commerce on rural community and farmers in developing countries have been extremely rare, partly due to the fact that the development of rural e-commerce in developing countries is a relatively new thing, and partly due to the stringent data requirement.

The combination of the mixed results on impact of ICT and the paucity of rigorous evidence on importance of rural e-commerce on rural community and farmers is the main motivation of this study. To contribute to the limited but important literature on impact of rural e-commerce, we aim to assess the causal relationship between rural e-commerce and farmers' income using survey data from 1009 farmers (including 327 farmers adopting e-commerce and 682 farmers not adopting e-commerce) from 22 Taobao villages in Shuyang County, Jiangsu Province. The propensity score matching (PSM) method is used to address the possibility that farmers are likely to self-select to participate in e-commerce, and a sensitivity analysis method is used to check the robustness of PSM results to the influence of unobservable factors. The results of the empirical analysis show that the adoption of e-commerce led to a large and significant increase in farmers' income and, and the improvement of profit margin and total sales constitute the two main mechanisms through which rural e-commerce impacts farmers' income.

The remainder of this article is organized as follows. Section 2 provides the background of the study. Section 3 justifies the use of PSM and presents the PSM method. Section 4 describes the data and presents the descriptive analysis. Section 5 presents the PSM results, followed by a conclusion in section 6.

## 2. Background

*Emergence of e-commerce in rural China*

Over the past decade, both the Internet coverage and the number of the Internet users have been growing exponentially in China. According to the survey of the CNNIC (China Internet Network Information Center), the Internet penetration rate in China increased from 8.5% in 2005 to 54.3% in June 2017, and the number of the Internet users grew from 110 million to 751 million in the same period.[1] By June 2017, the Internet users in rural area account for 26.7% of the total Internet users, reached 201 million. With the rapid expansion of the Internet access and development of logistics infrastructure, China is now leading the developing world in e-commerce. According to China's Ministry of Commerce, the average annual growth rate of national e-commerce transactions was 34% between 2012 and 2016, with a total sale through e-commerce of 26.1 trillion yuan in 2016. Meanwhile, the growth rate of online retail sale was 26.2% in 2016 with a total online retail sale of 5.16 trillion yuan, number one in the world.[2]

The development of e-commerce in rural areas has been very impressive in recent years. The internet penetration rate in rural China increased to 34% by June 2017, though still 35.4% lower than the urban area. In 2016, the rural online retail sales was 894.5 billion yuan, accounting for 17.4% of the total retail sales, and the growth rate was higher than urban area. In terms of agricultural products, the online retail sales reached 158.9 billion yuan in 2016. By 2015, Alibaba Rural Taobao Plan[3] has built 9278 village service stations in 202 counties of 22

[1] Data source: China Internet Network Information Center released the 40th *China Statistical Report on Internet Development* in August 4, 2017. http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/hlwtjbg/201708/t20170803_69444.htm

[2] Detailed information: China's Ministry of Commerce released *E-commerce in China 2016* in May 29, 2017. *http://dzsws.mofcom.gov.cn/article/dzsw/tjjc/201706/20170602591881.shtml*

[3] Alibaba Group issued *Rural Taobao Plan* on October, 2014. The plan presented that Alibaba group will invest 10 billion yuan to build 1000 county operation centers and 10 thousand village service stations in three to five years, in order to construct rural e-commerce service system. The plan on the one hand gets access to the information flow and logistic channels for selling goods in rural areas, on the other hand, explores the sale channels of agricultural products, and ultimately forms a service ecosystem of e-commerce for the rural areas.

provinces to provide local residents a variety of e-services such as purchasing commodities from Taobao portal, selling agricultural products online, and paying mobile phone, electricity and water bills by the web (AliResearch, 2015). The number of Taobao villages increased from 20 in 2013 to 2118 in 2017.[4] These Taobao villages are widely distributed in 24 provinces, and the total sales of these villages amounted to over 120 billion yuan in 2017 (AliResearch, 2017). In some areas, Taobao villages and Taobao towns have played an important role in promoting the local economic development.[5]

*Evidence on impact of rural e-commerce*

The rapid development of e-commerce in rural China and the emergence of Taobao villages have also attracted much attention of scholars (Guo et al., 2014; Leong et al., 2016; Zeng et al., 2017). Research on this and related topics emerged rapidly in the past few years. Many studies have examined the determinants and mechanisms of the formation of Taobao Villages, and the evolution process of these villages (Zeng & Guo, 2016; Cui et al., 2014). Others looked at the role of entrepreneurship, supply network and social innovation in the development of e-commerce using Taobao villages as cases (Zou & Liang, 2015; Wan, 2015; Cui et al., 2017). There are also a few studies analyzing the spatial distribution of Taobao villages (Zhu et al., 2016; Xu et al., 2017) to reflect the fact that Taobao villages are widely distributed in 24 provinces in China.

However, rigorous evidence on the economic effect of the Taobao villages or rural e-commerce in general have been extremely scarce except for some anecdotal evidence based on qualitative and descriptive analysis of very small sample. For example, Guo et al. (2014) used Potter's diamond model and studied the case of Junpu village. They found that the Taobao

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[4] The concept of Taobao village was proposed by AliResearch (founded in April, 2007, belongs to Alibaba Group), refers to a phenomenon that a large number of e-businessmen gather in a village using Taobao as the main trading platform, based on the Taobao e-commerce system, thereby forming an Internet business cluster with agglomeration effects. There are three standards for the identification of Taobao village: first, the business premises are in rural areas and the measurement takes administrative village as a unit; second, the annual e-commerce transaction of the village reaches 10 million yuan; third, the number of the active online shops is over 100 or the proportion of the active online shops is more than 10% of the total number of local households in the village. According to these three standards, AliResearch attaches the annual Taobao village list to the *China Taobao Village Research Report*, released at the end of each year. The villages having met the standards will be awarded the honor plaque of *China Taobao Village*.

[5] On the basis of the concept of Taobao village, AliResearch further proposed the concept of Taobao town, in which there are no less than three Taobao villages.

village has an external effect on the local industry due to agglomeration of participants of e-commerce. In fact, rigorous evidence on economic effects of e-commerce on rural farmers are also rare in the international literature. A descriptive study of U.S. farmers using MarketMaker to sale online found that e-commerce benefits the majority of the farmers with the increase in their income ranging from 10% to 25% (Cho and Tobias 2010). Another descriptive study also found that e-commerce helps farmers increase orders of the products, develop new customers and promote the sales (Zapata et al., 2016). To help understand the potential of rural e-commerce in economic development, rigorous study on the impact and mechanisms of impact of rural e-commerce on farmers are warranted. The rapid development of rural e-commerce in China provides a unique and timely opportunity for this type of research.

Leong et al. (2016) argued that the Taobao village essentially represents a community-driven rural economic development model facilitated by the information communication technology. Unlike Taobao village and rural e-commerce, the literature about the influence of the application of cellphone and internet is large. However, the results on the impact of ICT on rural farmers are mixed partly due to the variation in regions and categories of the agricultural products (Tadesse & Bahiigawa, 2015; Shimamoto et al., 2015; Aker & Ksoll, 2016; Chang & Just, 2009; Khanal & Mishra, 2016). It is also widely known that many studies of ICT impacts might have suffered from methodological issues (Aker 2011; Labonne and Chase 2009) related to the fact that ICT applications is not random. Unlike the short message service, digital subscriptions, website browsing, email, e-commerce not only has the function of information gathering and communication promotion, but also can change the marketing mode (Zeng et al. 2017). It is hypothesized that selling products through e-trading platforms have a number of advantages such as lower transaction costs (due to reduction or elimination of intermediate traders), more transparent market information, broader demand base, etc. and the benefits may vary with the online business platforms, logistics and other supporting conditions (Zeng et al., 2017). For all the above-mentioned reasons, the effects of e-commerce is likely to be even more complicated than an application of ICT, and the study of the impact of e-commerce adoption also tends to suffer from similar methodological issues. These issues are carefully addressed in our study.

## 3. The Evaluation Problem and Matching Methods

*The Problem of Naive Approach*

To measure the impact of e-commerce adoption on a farmer's income, one may use the following simple model:

$$Y_i = \alpha + \delta D_i + \beta X_i + \varepsilon_i \tag{1}$$

where *i* refers to a farm household, and *Y* is the farmers' income of the household, *D* is a dummy variable for the status of e-commerce adoption ($= 1$ if i is an adopter, =0 othersie), $X_i$ is a vector of other explanatory variables, $\alpha$ is the constant term and $\varepsilon_i$ is the random disturbance term. If farmers are randomly assigned to the two groups, then the parameter $\delta$ can accurately reflect the income effect of e-commerce adoption. However, the adoption of e-commerce is the result of the farmers' choice, so there are observable and unobservable factors influencing their decisions. And if these factors are also correlated with the outcome variable *Y*, then the estimated $\delta$ will be biased and inconsistent.

*Propensity Score Matching Method (PSM)*

PSM is a main method dealing with biases associated with selection on observables and has been widely used in the impact evaluation literature. Ideally, one would want to match adopters to non-adopters according to all the observed characteristics (X), however, matching over a large number of variables is unmanageable in practice, known as the curse of dimensionality. It has been proven that matching based on propensity scores is equivalent to matching over a large number of characteristics between an adopter and non-adopter(s) (Rosenbaum and Rubin 1983). The general steps of PSM are as follows. First, a simple probit or logit model is estimated to model the probability of a household to participate in e-commerce. The estimated propensity scores are obtained based on the regression results. Second, each adopter is matched with one or more non-adopters according to the estimated propensity scores (PS) and the specific matching methods adopted. Third, the difference in the outcome variable between each adopter and the matched non-adopter(s) is the estimated net effect of the e-commerce adoption for a given adopter. And finally, the average of the difference in outcome over the entire e-commerce adoption group is the average treatment effect on treated (ATT). Theoretically, a variety of matching methods can be used to achieve the matching objective, and the results are asymptotically equivalent. However, it has shown in practice that the matching results of different methods are not always the same because of the different tradeoffs between deviations and efficiency (Caliendo & Kopeinig, 2008). In order to obtain robust matching results, various matching methods are used, and the mean values of ATT obtained by all the matching methods are calculated.

In addition, we will decompose farmers' income change into four sources of income variables –profit margin, the growth of sales, working hours, and operating expense. We adopt two separate approaches in conducting the decomposition analysis. The first approach closely follows Xu et al. (2013), and Chen & Zhai (2015) and ATT for profit rate, the growth of sale, working hours, and operating expenditure are directly estimated using the PSM method. The second approach is a regression adjustment method proposed by Rubin (1997). Specially, the following decomposition equation of the income effect of farmers' e-commerce adoption is specified and estimated:

$$\Delta Y_i = \lambda + \theta \Delta Z_i + \mu_i \tag{2}$$

Where $i$ indicates farmers, and $\Delta Y_i$ is the difference of income variable between the e-commerce adopters and their matched non-adopters, $\Delta Z_i$ is the difference in income associated with different income sources between the adopters and non-adopters.

## 4. Data and Descriptive Analysis

*Data Source*

The data used in this article is from a household survey of floriculture farmers from 22 Taobao villages in Shuyang County, Jiangsu Province. The survey was carried out by the research group of Rural E-commerce Research Center of China Academy for Rural Development (CARD), Zhejiang University, in May 2016. Shuyang County is known for its floriculture and nursery stock industry. The planting area of flowers and trees in Shuyang has grown from 3 thousand mu[6] in the early 1990s to 481 thousand mu in 2015, and the total sale from 1 million yuan to 8.5 billion yuan during the same period. Shuyang has become the county with the largest planting area of flowers and trees in Jiangsu Province, and the floriculture and nursery stock is a dominant industry in Shuyang. After nearly ten years of exploration, Shuyang has successfully integrated e-commerce in floriculture and nursery stock industry. According to the statistics of AliResearch in 2014 and 2015, the total sales of agricultural products in Shuyang via the Ali retail trade platform continuously ranked number three among all the counties in China.[7] In 2015, Shuyang has 22 Taobao villages and 3 Taobao towns, and almost all the households in most of the Taobao villages have engaged in the planting of flowers and trees, and the proportion of the households with an online shop is at about 35%. To analyze the impact of e-commerce adoption, we collected data from 327 households who adopted e-commerce (adopters) and 682 households who had no experience with e-commerce (non-adopters). On average, a random sample of 15-20 adopters and 30-50 non-adopters from each Taobao village were surveyed. The fact that more non-adopters than adopters in the sample would help the high quality of matching.

*Descriptive Analysis*

Before presenting the descriptive analysis, it is important to define some of the key variables used in the analysis. The farm income, the key variable of the study, is measured by either the total net revenue or net revenue per capita. The net revenue refers to the net revenue earned from the production in floriculture and nursery stock industry, and the net revenue per capita is simply calculated by dividing the total net revenue of the household by the number of the family members engaged in this industry. The key variables included as the key right hand side variables in the income decomposition analysis are profit margins, the growth of sale, working hours, and total operating expenses. Working hours refer to the total working hours of all the

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[6] Mu is commonly used in the calculation of farmland in China. One hectare equals to fifteen mu.
[7] Data source: AliResearch's official website, *Ali Agricultural Product E-commerce White Book 2014*, and *Ali Agricultural Product E-commerce White Book 2015*.

family members who were engaged in floriculture and nursery stock industry, and total operating expenses is the sum of all the operating expenses of the household in floriculture and nursery stock industry. For the farmers adopting e-commerce, the total operating expenses are the sum of six items: planting investment, employment cost, logistic expense, packaging cost, operating expense related to the online trading, and broadband network cost. For the farmers who did not adopt e-commerce, the operating expense include four items: planting investment, employment cost, logistic expense, and packaging cost.

**Table 1. Variable Description and Descriptive Analysis**

| Variable Type | Variables | Variable Description | All Samples | |
|---|---|---|---|---|
| | | | Mean | S.D. |
| Outcome variables | Gross net income (10000 yuan) | Net income of floriculture and nursery industry | 8.76 | 13.132 |
| | Net income per capita (10000 yuan) | Net income per capita of the family members in floriculture and nursery industry | 4.39 | 6.375 |
| Matching variables | Sex | Male =1; Female =0 | 0.90 | 0.304 |
| | Age | Age of the head of the household | 39.88 | 11.680 |
| | Education level | Junior high school and below =1; High school or technical secondary school =2; junior college or bachelor degree =3; above bachelor degree =4 | 1.33 | 0.584 |
| | Health level | Very well =1；general =2；not well =3 | 1.24 | 0.516 |
| | Work experience | Previous work experience | 8.86 | 8.071 |
| | Entrepreneurial experience | The times of the previous entrepreneurial experiences | 1.62 | 2.280 |
| | Family cultivated area (mu) | Land allocated from the village collective | 4.16 | 3.006 |
| | Political resources | Whether there is a relative or friend who is a government officer: yes=1; no=0 | 0.18 | 0.385 |
| Income source variables | Profit margin (%) | The profit margin of floriculture and nursery industry | 33.50 | 22.146 |
| | Growth of sales (%) | The growth of sales of floriculture and nursery industry | 24.30 | 24.019 |
| | Working hours (hour) | The total working hours of the family members in floriculture and nursery industry | 20.41 | 9.931 |
| | Operation expense (10000 yuan) | The total operation expense of floriculture and nursery industry | 11.32 | 22.232 |

*Note: the sample size is 1009.*

The detailed definitions of variables and the basic descriptive analysis results of all the variables are shown in Table 2. The average total net revenue of the household is 87,600 yuan, and the mean of the net revenue per capita is 43,900 yuan. The household heads are mostly male and of good health with an average age at about 40, the education level concentrated between senior high school and junior high school and below. On average, an average household head has about 9 years of working experience and 1.6 times of entrepreneurial experience. Eighteen percent of household heads reported to have a relative or friend serving as a government officer. The average profit margin and the growth rate of the sales are about 33% and 24%, respectively, and the average working hours is 20.41 hours, while the average operating expense is 113,200 yuan.

**Table 2. Descriptive Analysis of Variable Differences between Two Groups of Farmers**

| Variable Type | Variables | E-commerce adoption | | Non-adoption | | Mean difference |
|---|---|---|---|---|---|---|
| | | Mean | S.D. | Mean | S.D. | (T test) |
| Outcome variables | Gross net income (10000 yuan) | 12.27 | 20.236 | 7.07 | 7.104 | $5.19^{***}$ |
| | Net income per capita (10000 yuan) | 6.00 | 9.193 | 3.62 | 4.226 | $2.38^{***}$ |
| Matching variables | Sex | 0.86 | 0.351 | 0.92 | 0.277 | $-0.06^{***}$ |
| | Age | 29.97 | 6.082 | 44.63 | 10.698 | $-14.66^{***}$ |
| | Education level | 1.47 | 0.663 | 1.27 | 0.531 | $0.20^{***}$ |
| | Health level | 1.06 | 0.269 | 1.32 | 0.580 | $-0.26^{***}$ |
| | Work experience | 4.16 | 3.951 | 11.11 | 8.559 | $-6.967^{***}$ |
| | Entrepreneurial experience | 1.58 | 3.473 | 1.65 | 1.386 | -0.07 |
| | Family cultivated area (mu) | 3.99 | 2.276 | 4.25 | 3.297 | -0.26 |
| | Political resources | 0.21 | 0.406 | 0.17 | 0.373 | 0.04 |
| Income source variables | Profit margin (%) | 42.12 | 22.652 | 29.36 | 20.675 | $12.77^{***}$ |
| | Growth of sales (%) | 33.83 | 28.383 | 19.74 | 20.093 | $14.09^{***}$ |
| | Working hours (hour) | 21.11 | 9.215 | 20.07 | 10.246 | 1.04 |
| | Operation expense (10000 yuan) | 11.45 | 14.404 | 11.25 | 25.145 | 0.20 |

*Note: the sample size of the e-commerce adoption group and non-adoption group is 327 and 682, respectively; *** Significant at 1% level.*

Table 3 divides the sample into adopters and non-adopters of e-commerce. Comparison of the key outcome variables and the key characteristics yield a number of additional insights. First, an average adopter earned 122,700 yuan net revenue and 60,000 yuan net revenue per capita, significantly higher than what the non-adopters did (51,900 yuan total net revenue and

23,800 yuan net revenue per capita, respectively). Second, the two groups of farmers also differ considerably in sex, age, education level, health level, and the working experience. For example, the head of an e-commerce adopter is more likely to be female, younger, with higher level of education and better health condition, but less working experience. Third, the e-commerce adopters also enjoy a significantly higher profit margin and the growth rate of sales than non-adopters with the differences being 12.8 percentage points and 14.1 percentage points, respectively. Although the working hours and the total operating expense of the e-commerce adoption group is also higher than the non-adoption group, the difference is not statistically significant.

The descriptive findings presented above have a couple of important implications. First, the fact that the two groups differ significantly in a number of key household characteristics further highlights the need of matching adopters to non-adopters in order for them to be comparable. Second, while the significant higher net revenue and net revenue per capita is an indicative for the possible positive effect of e-commerce on household income, a rigorous casual analysis is warranted to draw a more decisive conclusion, which is the focus of the following section.

## 5. Results

*The Estimation of Farmers' E-commerce Adoption Decision Equation*

In order to match the e-commerce adopters with the non-adopters, we first need to estimate a logit model as follow:

$$ln(\frac{p_i}{1-p_i}) = \alpha_0 + \alpha_i X_i + \pi_i \qquad (3),$$

where $i = 1, 2, \ldots, n$ refers to different individual households, and $p_i = P(T_i = 1|X_i)$ indicates the conditional probability that the farmer $i$ chooses to adopt e-commerce. $X$ is the vector of explanatory variables, and $\pi$ is the random disturbance item.

Table 4 reports the logit model estimation results. The results show that the magnitude, sign and the significance level of the coefficients of almost all the explanatory variables are highly consistent across different model specifications and the results in large part are also in line with the descriptive evidence. The logit results indicate that the variables significantly influence farmers' e-commerce adoption include gender, age, health condition, work experience, the square of the work experience, entrepreneurial experience and whether the household has a relative or friend serving as a government officer. While the main purpose of the logit model regression is to estimate the propensity scores to be used to match adopters with non-adopters, the logit results also yield a number of interesting insights. A female head has a higher probability to adopt e-commerce, suggesting that the e-commerce tends to promote women entrepreneurship. The older the head is, the less a household is willing to adopt e-commerce, and better health condition of a head is likely to encourage a household to adopt e-commerce. The combination of the positive and significant coefficient on the square term and negative and significant coefficient on the linear term of the work experience variable implies that the relationship between a farmer's work experience and e-commerce adoption is U-shaped. More specifically, the additional work experience encourages e-commerce adoption only after the work experience reaches to a certain level (27 years based on the estimation results). Given that the average work experience in our sample is way smaller than the threshold level, the additional work experience for majority of the heads in our sample serves as substitutes rather than complements for e-commerce adoption. The results also show that entrepreneurial experience has positive effect on e-commerce adoption. However, the education level and land area have no significant influence on farmers' e-commerce adoption decision.

**Table 3. The Estimation Result of the Decision Equation of Farmer's E-commerce Adoption Based on Logit Model**

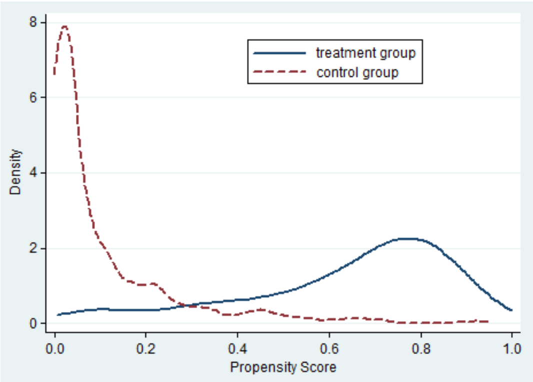
| Variables | Model I | | Model II | | Model III | | Model IV | |
|---|---|---|---|---|---|---|---|---|
| | Co. | S.E. | Co. | S.E. | Co. | S.E. | Co. | S.E. |
| Sex | -0.600** | 0.293 | -0.600** | 0.293 | -0.519* | 0.293 | -0.519* | 0.293 |
| Age | -0.149*** | 0.013 | -0.150*** | 0.013 | -0.146*** | 0.013 | -0.147*** | 0.013 |
| Education level | 0.060 | 0.146 | | | 0.057 | 0.146 | | |
| Health level | -0.853*** | 0.292 | -0.849*** | 0.291 | -0.901*** | 0.292 | -0.899*** | 0.291 |
| Work experience | -0.216*** | 0.033 | -0.217*** | 0.033 | -0.213*** | 0.033 | -0.214*** | 0.033 |
| The square of work experience | 0.004*** | 0.001 | 0.004*** | 0.001 | 0.004*** | 0.001 | 0.004*** | 0.001 |
| Entrepreneurial experience | 0.179*** | 0.065 | 0.183*** | 0.065 | 0.197*** | 0.067 | 0.197*** | 0.067 |
| Family cultivated area | 0.006 | 0.037 | | | 0.002 | 0.037 | | |
| Political resources | 0.428* | 0.243 | 0.431* | 0.242 | 0.511** | 0.247 | 0.516** | 0.246 |
| Constant | 6.810*** | 0.685 | 6.939*** | 0.624 | 5.899*** | 0.685 | 5.899*** | 0.624 |
| Town level fixed effect | No | | No | | Yes | | Yes | |
| Pseudo-$R^2$ | 0.4101 | | 0.4100 | | 0.4178 | | 0.4177 | |
| LR Statistic | 521.36*** | | 529.16*** | | 531.13*** | | 530.98*** | |

| | | | | |
|---|---|---|---|---|
| Sample size | 1009 | 1009 | 1009 | 1009 |

*Notes: *, **, *** Significant at 10%, 5%, and 1% levels, respectively.*

*Common Support and Balancing Test*

The reliability of PSM results are highly dependent on the matching quality. How well the estimated propensity scores are overlapped between the treatment (adopters) and control (non-adopters) groups and how well the difference in key characteristics between the two groups improve after matching are two important criteria to measure the quality of matching. Below we will check the two criteria one at a time.



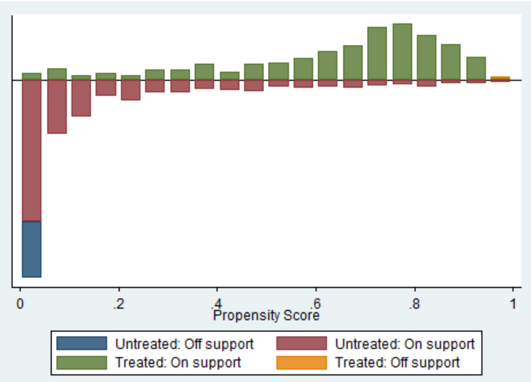




**Figure 4. Empirical Density of Propensity Score**　**Figure 5. The Common Support of Propensity Score**

Common support is the overlap interval between the propensity score of the individuals in the treatment group (adopters) and the control group (non-adopters). A large range of common support is generally associated with a better matching quality. It is clear from Figure 4 that there is a considerable range of overlap between the propensity score of the adoption group and the non-adoption group. More specifically, the common support area is [0.0061, 0.9445], which is associated with a loss of very few observations owing to matching. However, the loss of the exact number observations varies with the matching methods. It is common in the matching exercise that multiple matching methods are employed. In our analysis, we chose four matching methods which include the nearest neighbor matching (1-5 matching), the nearest neighbor matching (1-10 matching), kernel matching (window width = 0.06) and kernel matching (window width = 0.10). Regardless of which matching method is employed, the common support condition is highly satisfied (Figure 5).

The results of the balance test are given in Table 4 and Table 5. From Table 4, we note that matching has drastically improve the balance of variables between the two groups. For example, while 6 out of 9 variables are statistically different at 1% before matching, none of the variables are statistically different after matching (with the p-values associated with the t-test of mean differences of variables between the two groups ranging from 0.19 to 0.99). Table 5 shows that matching leads to a vast reduction in the Pseudo-R2 values (from 0.406 to 0.010—0.012 regardless of matching methods), and correspondingly, the value of LR statistics dropped from 516.29 (before matching) to 8.95—10.64 (after matching). The joint test of all the explanatory variables being equal between the two groups were highly significant at 1% level before matching, it can't be rejected at 10% level after matching. The test results suggest that the propensity score estimation and the sample matching are successful, and the e-commerce adopters are comparable to the matched non-adopters.

**Table 4. The Bias of the Mean of the Explanatory Variables Before and After Matching**

| Variables | Unmatched & matched | Mean | | Bias ( % ) | Reduced Bias ( % ) | T test | |
|---|---|---|---|---|---|---|---|
| | | Treated | Control | | | Statistic | P value |
| Sex | Unmatched | 0.86 | 0.92 | -19.0 | 97.8 | -2.95 | 0.003 |
| | Matched | 0.86 | 0.86 | -0.4 | | -0.05 | 0.961 |
| Age | Unmatched | 29.97 | 44.63 | -168.5 | 95.5 | -23.06 | 0.000 |
| | Matched | 29.95 | 29.28 | 7.7 | | 1.32 | 0.186 |
| Education level | Unmatched | 1.47 | 1.27 | 33.2 | 98.9 | 5.14 | 0.000 |
| | Matched | 1.47 | 1.47 | -0.4 | | -0.04 | 0.968 |
| Health level | Unmatched | 1.06 | 1.32 | -57.4 | 89.6 | -7.71 | 0.000 |
| | Matched | 1.07 | 1.09 | -6.0 | | -1.23 | 0.220 |
| Work experience | Unmatched | 4.16 | 11.11 | -104.4 | 97.5 | -14.00 | 0.000 |
| | Matched | 4.16 | 4.33 | -2.6 | | -0.56 | 0.573 |
| The square of work experience | Unmatched | 32.84 | 196.65 | -72.2 | 99.9 | -9.38 | 0.000 |
| | Matched | 32.94 | 32.84 | 0.0 | | 0.02 | 0.987 |
| Entrepreneurial experience | Unmatched | 1.58 | 1.65 | -2.6 | -149.5 | -0.45 | 0.653 |
| | Matched | 1.38 | 1.20 | 6.5 | | 1.23 | 0.217 |
| Family cultivated area | Unmatched | 3.99 | 4.25 | -9.2 | 25.9 | -1.29 | 0.197 |
| | Matched | 3.99 | 4.19 | -6.8 | | -1.03 | 0.305 |
| Political resources | Unmatched | 0.21 | 0.17 | 10.5 | 48.7 | 1.58 | 0.115 |
| | Matched | 0.21 | 0.19 | 5.4 | | 0.67 | 0.502 |

*Notes: this article gives the balance test result of the nearest neighbor matching (1-5 matching), and the results of other matching methods are very similar with it, thus are no longer listed.*

**Table 5. Sample Matching Methods and the Results of Balance Tests**

| Matching Methods | Pseudo-$R^2$ | LR Statistics (P value) | Bias of Mean | Bias of Median |
|---|---|---|---|---|
| Unmatched | 0.406 | 516.29 (0.000) | 53.0 | 33.2 |
| Nearest neighbor matching (1-5 matching) | 0.011 | 9.63 (0.382) | 4.0 | 5.4 |
| Nearest neighbor matching (1-10 matching) | 0.012 | 10.64 (0.301) | 4.8 | 4.5 |
| Kernel matching (window width = 0.06) | 0.010 | 8.95 (0.442) | 4.5 | 4.7 |
| Kernel matching (window width = 0.10) | 0.010 | 9.34 (0.407) | 4.7 | 4.6 |

*The Estimation of the Income Effect of Farmers' E-commerce Adoption*

Table 6 reports the PSM estimates on the effect of e-commerce adoption on farmers' income. The PSM results show significant and large income effects of e-commerce adoption. The results are also highly consistent across different matching methods. In terms of the magnitude of effects, participation in e-commerce would increase a household's total net revenue or net revenue per capita by between 58,770 yuan and 59,210 Yuan, and between 24,780 yuan and 35,050 yuan, respectively.

**Table 6. The Income Effect of Farmers' E-commerce Adoption**

| Matching Methods | Total Net Revenue (10000 yuan) | | | Net Revenue per Capita (10000 yuan) | | |
|---|---|---|---|---|---|---|
| | Treated | Control | ATT | Treated | Control | ATT |
| Nearest neighbor matching (1-5 matching) | 12.282 | 6.502 | 5.780*** | 5.981 | 3.527 | 2.454*** |
| Nearest neighbor matching (1-10 matching) | 12.282 | 6.391 | 5.891*** | 5.981 | 3.490 | 2.491*** |
| Kernel matching (window width = 0.06) | 12.282 | 6.364 | 5.918*** | 5.981 | 3.497 | 2.484*** |
| Kernel matching (window width = 0.10) | 12.282 | 6.361 | 5.921*** | 5.981 | 3.504 | 2.477*** |
| Mean | 12.282 | 6.405 | 5.877 | 5.981 | 3.505 | 2.476 |

*Note: *** Significant at 1% level; The significance test result of ATT value was obtained by Bootstrap, and the number of repeated sampling was 300 times.*

*The Sources of the Increased Income*

Table 7 reports the PSM-based (top panel) and regression-based (bottom row) results on the effect of e-commerce adoption on different sources of income change, namely the profit margin, the growth of sale, working hours and operating expense. As in the case of Table 6, the PSM results in Table 7 are robust across different matching methods and consistent with the descriptive findings presented earlier. We find that the significant and large income gains from the adoption of e-commerce is related to the significant and large increase in the profit margins and the growth of sales of farmers' products. For example, the adoption of e-commerce caused the profit margins and the growth of sales to increase by approximately 10% and 16%, respectively. While e-commerce adoption also led to an increase in working hours and a reduction of operation expenses, however, these results are not statistically significant. Finally, the regression-based decomposition results (bottom row, table 7) are largely consistent with the PSM-based results. Specifically, the regression results show that the adoption of e-commerce caused the profit margins and the growth of sales to increase by 12% and 21.8%, respectively.

**Table 7. The Impact of E-commerce Adoption on Farmers' Income Sources (Decomposition analysis)**

| | Profit Margin ATT | Sales Growth ATT | Working Hours ATT | Operation Expense ATT |
|---|---|---|---|---|
| *PSM-based decomposition* | | | | |
| Nearest neighbor matching (1-5 matching) | 9.898*** | 15.983*** | 0.898 | -0.919 |
| Nearest neighbor matching (1-10 matching) | 10.398*** | 16.312*** | 1.116 | -2.254 |
| Kernel matching (window width = 0.06) | 10.562*** | 15.947*** | 1.071 | -2.517 |
| Kernel matching (window width = 0.10) | 10.583*** | 15.784*** | 1.125 | -2.829 |
| Mean | 10.360 | 16.006 | 0.830 | -2.006 |
| *Regression-based decomposition* (Based on equation 3) | 12.30*** | 21.82*** | -2.32 | 9.53* |

*Note: *** Significant at 1% level; The significance test result of ATT value was obtained by Bootstrap, and the number of repeated sampling was 300 times.*

According to the empirical results above, the effect of e-commerce adoption of farmers' income is mainly achieved via raising the profit margins and increasing the sales. In other words, the improvement in profit margins and the sales growth constitute the main sources of the income effect of the e-commerce adoption.

*Sensitivity Analysis (Rosenbaum Bounds Analysis)*

Table 8 reports the sensitivity analysis results for the ATT of e-commerce on total net revenue. $\Gamma$ is an index to indicate the relative importance of unobserved factors relative to observed factors in affecting farmers decision to adopt e-commerce. When there are no unobservable bias (Γ=1), the PSM result is significant at 1% level. A bigger Γ means a bigger unobservable bias. We follow the literature to increase Γ from 1 to 2. According to Becker and Caliendo (2007), upper bound (sig+) is the relevant bound to check for the estimated positive effect. Since the estimated income effect is positive, we need to focus on sig+. As can be seen, the level of significance increases as Γ gets larger. When Γ adds to 1.8, the upper bound of the significant level is 0.08, the estimated income effect is still significant at 10%. Until Γ =1.9, the estimated income effect is insignificant with p=0.15. The bounds analysis results show that the estimated income based on PSM method is not sensitive to the unobservable factors, which to a certain extent allays our concerns that the estimated significant income effect could be caused by unobserved factors.

**Table 8. Sensitivity Analysis of the Impact of E-commerce Adoption on Farmers' Total Net Income**

| Gamma | sig+ | sig- | t-hat+ | t-hat- | CI+ | CI- |
|---|---|---|---|---|---|---|
| 1.0 | 3.2e-09 | 3.2e-09 | 2.05 | 2.05 | 1.31667 | 2.8 |
| 1.1 | 2.0e-07 | 2.7e-11 | 1.75 | 2.3 | 1.06667 | 3.1 |
| 1.2 | 5.3e-06 | 2.0e-13 | 1.5 | 2.6 | 0.85 | 3.41667 |
| 1.3 | 0.000072 | 1.2e-15 | 1.3 | 2.8 | 0.6 | 3.7 |
| 1.4 | 0.000581 | 0 | 1.1 | 3.05 | 0.42 | 4 |
| 1.5 | 0.003097 | 0 | 0.916666 | 3.3 | 0.25 | 4.25 |
| 1.6 | 0.011835 | 0 | 0.75 | 3.55 | 0.1 | 4.51 |
| 1.7 | 0.034492 | 0 | 0.6 | 3.75 | -0.05 | 4.75 |
| 1.8 | 0.080529 | 0 | 0.45 | 3.96667 | -0.2 | 5 |
| 1.9 | 0.156697 | 0 | 0.3 | 4.15 | -0.3 | 5.25 |
| 2.0 | 0.262518 | 0 | 0.2 | 4.31667 | -0.433333 | 5.5 |

*Note: 1. Gamma indicates the ratio of logarithmic occurrence to different arrangements due to unobserved factors, and sig+ and sig- refer to the upper and lower bound of the significant level. And t-hat+ and t-hat- represent the upper and lower bound of the Hodges-Lehmann point estimation, while CI+ and CI- refer to the upper and lower bound of confidence interval (0.95). 2. The sample size of the sensitivity analysis is 325. 3. The sensitivity analysis results of ATT on net income per capita, profit margin and the increase of sales are similar with the results above.*

## Conclusion

This paper provides empirical evidence that e-commerce can help raise rural farmers' income mainly through reduction of transaction costs and expanding of sales. Based on the survey data of 900 farmers specialized in flower and tree plantation in 22 Taobao villages in Shuyang

County, we have shown that it is possible that farmers benefits from selling agricultural products through e-commerce platforms. The results in this paper are also consistent with the findings by Jensen (2007), Aker (2008), Dobson et al. (2010), Burga & Barreto (2014) that small households in the rural areas of developing countries can share the digital dividend.

One may argue that the results based on a relatively more homogenous group of farmers from one county may not be easily generalized to other farmers in other regions. While this is a concern that we will discuss later, the justification for sampling farmers specialized in similar agricultural industry from one county is mainly to ensure the internal validity of the study. As mentioned in an early section, the diversity of agricultural products and regions makes identification of ICT or e-commerce effect difficult. In other words, it is not easy to identify whether the change in outcome is due to the adoption of ICT (or e-commerce) or due to the difference in products and regions. Focusing on a group of farmers producing the same product(s) from similar areas but using different marketing channels enables us to identify the market channel effect on household income by holding other effects constant. Our sampling strategy is driven by the general principal of impact evaluation which is that ensuring internal validity is generally more important than achieving external validity. However, in our future research, we would like to conduct a more comprehensive study to include much large sample with farmers from multi regions and multi industries to address the external validity concern.

We would also like to point out that there is a possibility that the true impact of e-commerce in our study area may be underestimated because we fail to account for the possible spillover effect of e-commerce on farmers who did not adopt e-commerce in the same village (Zeng et al, 2015). For example, it is possible that some farmers who did not participate in e-commerce trading might have sold part or all of their products to farmers who adopted e-commerce, thus indirectly share dividend of the e-commerce. Another source of spillover effects could be that the popularity of e-commerce activities in a particular village or town raises the awareness and reputation of that village or town, which makes buyers more willing to purchase products from that village or town either online or off-line. However, even with the possible underestimation, we still identify a large and significant income effect of e-commerce. Nonetheless, it would be extremely interesting and important to identify both the direct effect and the indirect spillover effects in future research.

Another potential concern is that the adoption of e-commerce could potentially result in the shift of family members' labor allocation between agricultural and non-agricultural activities. For example, it is possible that farmers adopting e-commerce allocate more labor to agriculture at the cost of migration and/or local off-farm labor. So the identified increase in farmers income from selling flowers and baby trees may be overestimated because the increase in income may achieved at the cost of wage earnings. While we are unable to directly test for the wage earnings due to the mistake of not collecting information on wage income, our concern is partially allayed by the PSM results that the adoption of e-commerce has not significantly changed the number of family members working in the floriculture and nursery stock industry. In the future research, we plan to collect income from all activities so we could address this important concern.

Finally, other limitations of our study include cross-sectional data at a single point time, and the potential issue associated with the PSM method. Cross-sectional data not only limits the possibility to study longer term effect, but also limit the possibility of using DID methods which could potentially address the unobservable issues. The main limitation of PSM method is that it does not allow to address the bias associated with selection on unobservables. While the bound analysis increases our confidence about the PSM results, we would like to have panel data that allow us to explore different evaluation methods to better address the unobservables.

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