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Does Computer Usage Change Farmers' Production and Consumption? Evidence from China

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Abstract:

The purpose of this paper is to explore the impact of using computer to obtain information on the farm household's production and consumption, based on a field survey of farm households in northern China. The most important methods applied are instrumental variable (IV) method and propensity score matching (PSM). Estimators of IV, PSM and NNM(nearest neighborhood matching approaches are considered together to check the robustness of empirical results. This article carful impact evaluation results suggest that computer usages improves the size of arable land rented-in, but reduces family labor input intensity and the probability of selling agricultural outputs at farm-gate market. They also stimulated transportation, garment, housing and insurance expenditure per capita. First, we directly estimate computer usage impacts on a broader range of production and consumption indicators by including land-relative investments, variable investments, labor input and households' expenditure and provide rigorous impact evaluations on the impact of access to computer. Second, we use IV method PSM method to correct self-selection bias, going beyond the single equation approach in other studies. This enables us to identify the causal relationship between computer usage and farmer's production and consumption decisions.

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Keywords: Computer usage, information searching, farm households, China

1. Introduction

The importance of information for promoting markets functioning well and facilitating transition of traditional agriculture to modern agriculture has been realized in developing economy (Tadesse and Bahiigwa, 2015; Aker, 2011). Both policy makers and economists believe that access to timely information plays a pivotal role in improving market linkages and subsequently changing farmers' welfare (Goyal, 2010). This is supported by two of the most well known laws in economics: the First Fundamental Theorem of Welfare Economics and the "Law of One Price" (Jensen, 2007). Given the fact that information available to smallholders in most developing countries is often costly and incompletely, the potential value of information and communication technologies (ICTs) for providing reliable market information flows has highlighted (Aker and Mbiti, 2010).Therefore, a growing body of literature focuses on quantifying the role of modern ICTs (namely mobile phones and radios) in economic development and farmers' welfare gain in Africa(For instance, Tack and Aker, 2014; Zanello and Srinivasan, 2014; Aker and Mbiti, 2010;Aker and Fafchamps, 2014).Results suggest that information technologies, such as mobile phone, television and radio, have the ability to deliver relevant and timely information that facilitates making informed decisions to use resources in the most productive and profitable way (Ekbia and Evans, 2009; Ommani and Chizari, 2008)，but little work has been done on the role of another increasingly important modern ICTs——computers in agricultural development in emerging economies(Ali, 2012).

The spread of ICTs particularly personal computers (PC) in rural China has been both extensive and rapid in the past ten years (See Fig.1). As of 2014, there were 23.5 PC owners per 100 farmer households, which have grown eleven fold in that period. As part of the strategies to overcome low farm productivity and improve agricultural performance among smallholder farm households through improved information flow, ICT-based tools have been recently paid attention by policy makers and economists (Ogutu et al., 2014).

Insert Figure1 about here.

Despite the importance of this subject, only few studies have provided in-depth empirical evidence on the issue, the purpose of this study is to ascertain whether computer usage changes farmers' agricultural production and generates economic benefits to farmers. Specifically, the paper responds to the following research questions: (1) Do computer usages cause different production decisions? (2) Do computer usages change farmers' consumption? By addressing these questions, this paper uses nationally representative data from China to make two main contributions to the literature on the impact of computers on smallholders' production and welfare. First, we directly estimate computer usage impacts on a broader range of production and consumption indicators by including land-relative investments, variable investments, labor input and households' expenditure and provide rigorous impact evaluations on the impact of access to computer. Second, we use IV method PSM method to correct self-selection bias, going beyond the single equation approach in other studies. This enables us to identify the causal relationship between computer usage and farmer's production and consumption decisions.

The rest of the paper is organized as follows. In the next section, we review previous literatures regarding the effect of ICTs on agricultural markets and on the economy gains in developing countries. This section is followed by the theoretical foundation of the paper. The forth section is the empirical specification and the fifth section reports the data used to test the research questions sated above and how variables are identified. The sixth section presents the empirical results and discusses the main findings of this paper. The final part summarizes the paper and comes up with the relative policy implications.

2. Literature Review

2.1 How ICTs change farmers' production

Several studies have investigated impacts of ICTs based market information services (MIS) projects on farmers' production. As are specified by Ali and Abdulai (2010) and Becerril and Abdulai (2010), one way of illustrating that question is to assume that the decision to participation in the ICTs-based MIS project is dichotomous, where participation when the expected profit with participation is greater than without participation. Usually, farmers' decision to acquire information is positively affected by farmers' environmental awareness, access to credit and access to information (Ma et al., 2017). The farmer's net returns of profits can be expressed as a function of participation, variable inputs, output price, and household characteristics. Results based on this framework indicate that ICTs-based MIS intervention has a positive and significant impact on the use of seeds, fertilizers, land, and labor productivity (Ogutu et al., 2014). Similarly, Cole and Fernando (2012) show that in rural India, information provided via mobile phones to farmers increased their knowledge of available options for inputs such as seed and fertilizers as well as choices of different crops leading to changes in their investment decisions and eventually to planting more profitable crops. The study demonstrated that the low-cost (0.6 USD per month) information was able to change the behavior of the farmers. Aker and Ksoll (2016) found that farmers who receive access to a joint mobile phone and learn how to use it increase the number of types of crops grown, primarily by increasing their production of marginal cash crops. In addition, Deichmann, Goyal and Mishra(2016) also prove that digital technologies raise farmer's production efficiency by complementing other production factors and foster innovation by dramatically reducing transaction costs. However, Fafchamps and Minten(2012) didn't confirm this result when they treated farmers associate Reuters Market Light commercial information service with a number of decisions they have made and found no statistically significant average effect of treatment on the price received by farmers, crop value-added, crop losses resulting from rainstorms or the likelihood of changing crop varieties and cultivation practices.

2.2 How ICTs improve farmers' income and welfare

There are a growing number of empirical literatures focusing on the impacts of ICTs on farmers. Specifically, the spread and adoption of mobile phones in developing countries attract economists' attentions. The wide spread growth of mobile phone coverage over decade provides new opportunities to overcome these search and transaction costs and the potential to improve welfare (Aker and Ksoll, 2016).Specifically, theory suggests several primary channels in which mobile phones may impact smallholders' outcome. First, mobile phones technology could potentially reduce farmers' search costs, thereby allowing them to obtain price information in a greater number of markets and sell in the market with the highest price net of transports costs (Tack and Aker, 2014). Second, in the absence of selling in a different market, improved access to information could potentially improve farmers' bargaining position with traders (Zanello and Srinivasan, 2014). Third, mobile technology could potentially allow farmers to conclude a sale using a mobile phone, thereby reducing uncertainty associated with selling in a distant market (Aker and Mbiti, 2010). Forth, if information technology increases the prices that farmer receive, and agricultural production is price elastic, then this would increase the production of such commodities in the future (Aker and Fafchamps, 2014).

Under the perspective of arbitrage, previous studies suggest that if farmers can obtain information by ICTs on the selling price in the other markets and transportation costs are lower than the price difference between these markets, farmers in the market with the lower selling price will go to the other market to sell their product. As a result, arbitrage occurs between the markets will decrease, and Pareto efficiency will be achieved (Shimamoto et al., 2015). Along this line, Jensen (2010) examined the role of mobile phones in market arbitrage in local agricultural markets in Indian state. The main finding shows that the introduction of mobile phones spurred arbitrage across markets, price dispersion across markets diminished, and excess supply of sardines in individual local markets was eliminated. As a result, both the profits of producer and the consumers' surplus increased. Meanwhile, Aker (2010) investigated the impact of mobile phones in grain markets in Niger and found that price dispersion across markets declined.

Another important strand of research looks at the impact of information communication technology on marketplace choice, focusing mainly on mobile phones and radios (Zanello et al., 2014). Specifically, in many developing countries, farmers typically have a choice between selling their products to traders who travel between villages and markets and transporting their products to the nearest market themselves. Because of communities' remoteness and poor communications with marketplaces, farmers' uncertainty about market prices is usually high. Courtois and Suberview (2015) show the conditions for Market Information Services (MIS) to be profitable for farmers and examine efficiency issues associated with asymmetric information. The causal effect of a mobile-based MIS program on farmers' marketing performances in Ghana indicates that farmers who have benefited from the MIS program received significantly higher prices for maize and groundnuts: about 10% more for maize and 7% more for groundnuts than what they would have received had they not participated in the MIS program. Moreover, with a transaction costs framework, Zanello (2012) applied a novel dataset of 393 households in northern Ghana with detailed information on market transactions and ICTs usage. Results show that receiving market information via mobile phones has a positive and significant impact on market participation, with a greater impact for households with a surplus of food crops. In China, promotion of new media coverage can significantly enhance rural non-farm employment in China by 10-20 percent and ultimately increase earnings for rural residents (Zhou andLi, 2017).

In summary, the growth of ICT in developing countries offers a new technology and new opportunities for accessing information in poor countries. Specifically, the rapid growth of computer and mobile telephony have introduced new search technology that offer several advantages over other alternatives in terms of cost, geographic coverage. Compared with radio and newspaper, the one-way communications systems, access to modern information system to obtain information is more efficient. Table 1 provides an overview of these studies, based upon the types of ICT tools (mobile phones, TV, radio, and kiosks) and the outcome variable of interest (producer's welfare, price, type of crop planted, quantity produced and sold and general livelihoods).On the one hand, the results provide ambiguous evidence of the impact of ICT tools. On the other hand, it can be seen that little work has been done on the rigorous impact evaluation from computer usage on agricultural development in emerging economies. Especially in China, rapid growth of computers and Internet access, which have started an era in which everything has changed through information technologies, constitute an equalizing effect for rural farmers traditionally away from developments in information and technology. Specifically, Timely access to market information via communication networks may help farmers to make informed decisions about what crops to plant and where to sell their products and how to improve inputs efficiencies. ICT can also provide unprecedented access to rural finance, while the financial and information service network can offer micro-finance opportunities for local people and small enterprises (Abdur Rahman et al., 2005). As mentioned earlier, statistics and some empirical studies may provide a general pattern for mobile telegraphy. However, studies based on original data about developmental pattern of computer and Internet and their consequences are of special importance. Studies based on field data reveal the current status and possible problems.

Insert Table 1 about here.

3. Theoretical Foundation

The introduction of computer could potentially affect households' endowments as well as their production and trade entitlements, and hence influence their agricultural outcomes consumption in a number of ways (Aker and Ksoll, 2016). First, computer could potentially reduce farmer' s transaction costs, thereby allowing that group to obtain price information in a greater number of markets and buy production factors in the market with lower price. Specifically, if we could measure the costs of all transactions in an economy, we could arrange them from highest to lowest as in Figure2. New technology, especially the computer and Internet, facilitate information exchange and other forms of communication and thereby lowers the curve.

On the far left of Figure 2 there were some transactions whose cost was too high to take place. In the simplest case, two parties to a potential transaction simply didn't know each other or someone faced insurmountable barriers to participating in a market. The middle part of Figure 2 covers transactions that already took place, but that now have become cheaper, faster or more convenient thanks to new technologies. By automating or facilitating some processes, such as communicating with buyers or suppliers, it makes other factors more productive. Most importantly, easier coordination improves capital utilization as in the sharing or renting of tractors, and labor productivity, for example, through access to critical information via computer/Internet. Human capital augmenting technology has always been at the core of productivity improvements and therefore of increasing welfare, which also increases efficiency of the economy.

On the right of Figure 2, transaction costs fall to such a level that they are essentially negligible at the margin. Processes can be fully automated on at least one side of the transaction as in e-commerce applications or in matchmaking in the on-demand economy for agricultural extension services or agricultural initiatives. If the service is to provide a digital product, production costs are also essentially zero as in electronic news or information. Their cost structure of high initial investments to build an Internet platform but very low costs of individual transactions gives rise to scale economies both on the supply side. Especially, in order to raise on-farm productivity, the demand for timely and precise information on input use has increased. Better information delivered through extension services (like agricultural practices, new tools or improved seeds) increases access to suitable technologies and makes other forms of capital more productive, thereby making production more productive. Therefore, computer and the Internet have the potential to contribute to improve productivity in the rural sector (Deichmann, Goyal and Mishra, 2016).

Insert Figure2 about here.

Second, computer improves farmer's access to input and output suppliers. Information technology has enormous potential to link disconnected farmer households to large networks of agents with whom they can interact at low cost (Dillon et al., 2015). Similarly, improved communication between farmers and traders could reduce the uncertainty associated with travel delays and the demand of certain goods, thereby avoiding costly stock-outs and avoiding wasted trips.

A typical case is that the emergence of e-commerce in remote China has changed the production and consumption (Leong et al., 2016). Because ICT allows for visibility of involvement: ICT enables villagers to notice that someone is working from home, thus allowing villagers to learn about e-commerce. This gives rise to the growth of e-tailers, or villagers who sell products through e-commerce. They can learn about e-commerce by observing actions of the grassroots leaders or pioneers of e-commerce. This transparency, coupled with the significant improvement in the livelihood of those who are engaged in e-commerce.

Third, computer improves farmer's access to public information (Aker, Ghosh and Burrell, 2016). Reduced communication costs facilitated via information could increase farmers' access to public information provided via agricultural extension services, public healthy organization or other public service providers. For examples, to provide healthy information via website or remote video on average are cheaper than visit. In addition, ICTs could allow public information systems to provide more timely and context-specific information. This could, in turn, improve farmers' access to information at more crucial moments (Patel et al., 2000; Veeraraghavan et al., 2009).

The potential impacts of information technology on agricultural outcomes depend upon a variety of assumptions. In general, farmers are more likely to benefit when search costs are the primary reason for price dispersion or trade entitlement failures, rather than other market failures, such as credit constraints or uncompetitive markets. Second, even in the presence of these other market failures, the impact of information technology could depend upon the market structure for a given crop or crop's perishability.

4. Empirical Specification

We assume farmer's decisions of production and consumption are driven by utility maximization. Specifically, the utility of production and consumption decision is a function of expected returns, but constrained by endowments. Hence, each farmer will choose his or her optimal level of production and consumption. Following Mishra, Williams and Detre(2009), we hypothesize that the farmer's utility depends on a number of farm and household characteristics, which in turn influence the expected returns and costs. However, the actual utility of farmer is not known; Instead, we observe the outcome of the decision made by farmers. We test the affects from computer usage and farmer's household characteristics on these decisions by estimating linear or nonlinear models.

4.1 OLS Method

The traditional approach to consider when evaluating impact, in this case, of using computer and internet to obtain information on smallholder farm productivity would be to include a dummy variable equal to one in the outcome equation if a household searched information via computer and zero otherwise, and then applying OLS regression. The basic evaluation problem is a linear function comparing outcomes T without consideration of endogeneity of computer access:

$$Y = d_1 T + X b + n \tag{1}$$

where Y is a set of farmer household's production and consumption decision. T is a dummy variable equal to 1 for those who use computer and 0 who do not use. X is a set of farm, household and regional characteristics, d_1 and b are parameters to be estimated. Finally, n is an error term reflecting unobserved characteristics that also affect Y.

However, because the accesses to computer/Internet are not randomly assigned, information search decisions are likely to be influenced both by unobservable (e.g. study skills, motivation) and observable heterogeneity that may be correlated to the outcome of interest. Self-selection could be based on observed characteristics, unobserved factors, or both (Khandker, Koolwal and Samad, 2010). In other words, selection bias specifically occurs in the case of unobserved factors, the error term in the estimating equation will contain variables that are also correlated with the treatment dummy *computer*. In this case, the use of OLS is likely to generate biased estimates, including estimates of the impact effect (Becerril and Abdulai, 2010).

The empirical challenge in this impact assessment using observational studies is establishing a suitable counterfactual against which the impact can be measured because of self-selection problems. To accurately measure the impact of computerusage on production and welfare of farm households, the adoption of computer and internet should be randomly assigned so that the effect of observable and unobservable characteristics between the treatment and comparison groups is the same, and the effect is attributable entirely to the treatment.

A number of different methods can be used to control for selection bias, including propensity score matching (PSM), Double-difference (DD) methods, and instrumental variable (IV) methods. DD methods assume that unobserved selection is present and that it is time invariant—the treatment effect is determined by taking the difference in outcomes across treatment and control units before and after the program intervention. DD methods can be used in both experimental and non-experimental panel data. IV models can be used with cross-section or panel data and in the latter case allow for selection bias on unobserved characteristics to vary with time. In the IV approach, selection bias on unobserved characteristics is corrected by finding a variable (or instrument) that is correlated with computer usage but not correlated with unobserved characteristics affecting the outcome; this instrument is used to predict project participation. Based on the cross section data applied, we will use IV method and PSM method together to correct selection bias and check robustness.

4.2 IV Method

Given the endogeneity of T, it is very helpful to introduce Control Function approach to correct the selection bias. In other words, Control Function approach is another alternative approach, which adds more structure to explicitly account for the binary nature of the endogenous regressor by changing the first-stage model to be a latent variable model similar to the logit model. Specifically, let Y depend part on T a binary endogenous regressor. Then

$$Y = \delta_1 T + X\beta + \eta \tag{2}$$

$$T = X\gamma + \delta_2 z + v \tag{3}$$

$$T = \begin{cases} 1 \text{ if } T^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{4}$$

where the error(η, v) are assumed to be correlated bivariate normal with $Var(\eta) = \sigma^2$, $Var(v) = 1$,and $Cov(\eta v) = \rho\sigma^2$. Furthermore, the binary endogeneity regressor T can be received as a treatment indicator. If $T = 1$,we receive treatment, and if $T = 0$， we do not receive treatment. In addition, z is the instrumental variable.

4.3 PSM Method

Because the previous two methods vary by their underlying assumptions regarding how resolve selection bias in estimating treatment effect, we also introduce PSM method to check the robustness of treatment effect from computer usage on farmer's production and consumption. In the absence of an experiment, PSM methods compare treatment effects across participant and matched nonparticipant units, with the matching conducted on a range of observed characteristics. PSM methods therefore assume that selection bias is based only on observed characteristics; they cannot account for unobserved factors affecting participation. PSM method is likely to control for potential selection bias (Ogutu, Okello and Otieno, 2014). This method does not depend on the functional form and distribution assumptions and is intuitively appealing (Heckman, Ichimura, and Todd, 1998) since it compares the observed outcomes of the treatment and comparison groups. Specifically, the main advantage of PSM relies on the degree to which observed characteristics drive program participation. If selection bias from unobserved characteristics is likely to be negligible, then PSM may provide a good comparison with randomized estimates. To the degree participation variables are uncompleted, the PSM results can be suspect. This condition is, as mentioned earlier, not a directly testable criteria; it requires careful examination of the factors driving program participation (through surveys, for example). Another advantage of PSM is that it does not necessarily require a baseline or panel survey, although in the resulting cross-section, the observed covariates entering the logit model for the propensity score would have to satisfy the conditional independence assumption by reflecting observed characteristics X that are not affected by participation. A preprogram baseline is more helpful in this regard, because it covers observed X variables that are independent of treatment status (Heinrich, Maffioli and Vázquez, 2010). More details on PSM method are presented in appendix.

5. Data

5.1 Data Collection

The current study involved a field survey that was conducted by China Agriculture Research System (CARS) during the 2013/14. This survey was purposefully conducted in Coastal (Shandong Province), Centre (Henan Province), and Western (Shaanxi and Gansu Province) of China. A supplemental questionnaire administrated to specialized households with agricultural income contribution over half to total income. Especially, Apple production in the sample area remains the important source of income overall. The field survey involved in information searching, ICTs access, production and income levels by the respondent.

A multi-stage sampling procedure was used to select counties, sub-divisions and farm households. The first stage was the deliberate selection of 122 counties in 4 northern provinces, namely Shandong, Henan, Shaanxi, and Gansu (see Figure 3). To ensure all apple producers have the same probability of choosing in the sample, the Probability Proportional to Size sampling method was used. Overall, 12 counties were randomly selected in the seven provinces and 1079 samples were selected for interview. Via face-to-face questionnaire interview, detailed information on production and income are collected in 2014. Descriptive statistics are reported in Table 2.

Insert Figure3 about here.

Except newspaper, farm households' ownership of point-to-point ICT including TV and mobile phone are higher than 97%, which indicate that nearly every household has access to view television or use mobile phone (see Table.2). Obliviously, it's nearly impossible to gain information advantages given the uniform distribution of accesses. However, just a few of families have access to a computer. It should be noted that newspaper, mobile phone and TV provide a limited range of information and offer only one-way or point-to-point communication. In contrast to these ICT modes, Access to computer provides a point-to-face communication system. In addition, the digital divide between coastal, middle and western area are quite significant, because ownerships of computer/Internet are decreasing from east to west. This indicates that different access to computer/Internet technology could be pivotal reasons for farmers' distinct production and consumption decisions (Cechini and Scott, 2003).

Insert Table2 about here.

5.2 Variables Identification

Drawing from the empirical approach, the farm household decision is determined by the expected utility of production and consumption. Based on the data at hand and guided by previous literature, dependent variables may include production and consumption sets. Specifically, new apple orchard built after computer introduced in, land rented-in after computer introduced in, family labor man-days input per mu, pesticide investment per mu and sell at farm-gate market or not are included in production sets; garment, commodity, health, transportation, housing and insurance consumption per capita are included in consumption sets. Follwing by Hennessy, Läpple and Moran (2016), we also narrow the concept of computer usage as the Internet engagement through computers and measure it by asking farmers"Did you connect your computer to Internet?"

Meanwhile, explanatory variables that are likely to influence the utility are selected for the analysis. For example, apple orchard size, age and education of the farmer are generally included to explain farm household's decisions (e.g., Amponsa 1995; Pulter and ZIlberman 1988). In addition, the number persons living in the household usually also have been included (Mishra, Williams, and Detre 2009).

In relation to farmland, we choose apple orchard size to represent that because the sample sites of our research are highly specialization areas for fresh apple production. Moreover, as a high value fresh cash crop, apple production plays a pivotal role in household's income improvement. The impacts of apple orchard size on farm household's production, consumption and computer usage are predicted to be significant. In addition, we also consider the social dimension of production and consumption decision by including the age of farm household head, which reflects family life cycle of sample. We expect that the effect from household head on farm household's production, consumption and computer usage are ambiguous.

As we model the decision process as a household decision, education is expressed as whether the household head received the senior high education. It is hypothesized that higher education of household head has a positive impact on production and consumption decisions, as well as the decision to purchase a computer and engagement. In addition, we include a variable to indicate household population size, as we believe the more people live in household, the more probability to make productive production, consumption and own a computer. In addition, we also consider the impact from income on farm household's production, consumption and computer engagement. It is hypothesized that the higher total income per capita in last year, the higher production investment, expenditures and higher probability of owning a computer.

In addition, we include regional variables to account for differences in Internet availability, as well as apple production. The motivation for this variable is influenced by Mishra, Williams, and Detre (2009), who argue that regional variables also represent the effects of omitted variables that are correlated with location (e.g. climate, construction of Internet infrastructure, number of Internet providers). In addition, broadband access in Northern China varies by region and there is evidence that remote regions are deprived of broadband access (Hou and Huo 2017). Table 3 presents a description of all included depend variables and independent variables. Generally, Most of the household heads on average are over 50 years and have almost primary middle school education. Per capita total income on average was RMB 17.98 thousand Yuan, equivalent to US$2936.13, of which apple production was the main source (81%). On average, the average farm size of most growers is less than one hectare* (see Table.3).

Insert Table 3 about here.

Table 4 reports the mean differences on main characteristics of computer users and non users. It indicates that there are significant difference between computer users and non-users with respect to agricultural production and farm households' consumption. Specifically, computer users have more land relative investment and market participation, especially rented-in land size and lower probability to sell outputs at farm-gate market. Meanwhile, family consumptions per capita of computer users like garment, daily goods, transportation and housing are significantly higher than non-users. The t-value also suggests that there are significant differences in farmer characteristics used in empirical estimating. Computer users have higher average figures for education level, annual income per capita and apple orchard size than non-users,

Insert Table4 about here.

6. Empirical results

6.1 Empirical results without consideration of endogeneity

As our primary interest is in testing the effect of farmers' computer engagement, we firstly present the regression results without consideration of endogeneity of computer access. Table 5 and Table 6 respectively report estimation results of treatment effect from computer usage

*1 hectare equals 15 mu.

on farm households' production and consumption without consideration of endogeneity. Specifically, if farmers' endowments and geography heterogeneity are controlled, computer usage will affect most production and consumption decisions made by farmers. Specifically, Access to computer/Internet improves farmers' new apple orchard investment and size of land rented-in, reduces family labor man-days used per mu, and reduces the probability of selling at farm-gate market. Meanwhile, it also encourages household's garment, transportation and insurance expenses per capita, but reduces heal expenditure per capita.

Insert Table 5about here.

Insert Table 6about here.

6.2 Empirical results of instrumental variable approach

Based on the data at hand and guided by previous literature (e.g. Hou and Huo, 2017), we choose "is there any apple electronic commercial trade system(AECDS) provided locally? " as the instrumental variable, which satisfies the basic requirements of instrumental variable regression: $Cov(z,T) \neq 0$ and $Cov(z,Y)=0$, because AECDS built by local government will promote apple grower's access to computer/Internet to maximize their apple production profits. Meanwhile, AECDS provided by local government will not affect apple farmer's production and consumption behaviors directly. Furthermore, Table 7 and 8 reports the Effect from Computer Usage on Farmers Households' Production and consumption separately. It can be seen that computer usage has significantly effect on farm household's production and consumption decision. Specifically, it stimulates farmer to rent in more arable land and reduces family labor man-days input per mu, the probability of selling outputs at farm-gate market and pesticide investment per mu. Meanwhile, computer usage also promotes farm household's garment, transportation, housing as well as insurance expenditure per capita.

Insert Table 7 about here.

Insert Table 8 about here.

6.3 Empirical results of matching

Mean difference of farm households' production and consumption has shown significant differences between computer users and non-users. However, for effective analysis of whether there is causal relationship between computer usage and farm households' decisions, impact evaluation approaches are necessary. Specifically, using PSM, the procedure for estimating causal relationship can be divided into three straight forward steps: estimate the propensity score using a logit function; choose a matching algorithm that with use the estimated propensity score to match untreated units to treated units; and finally estimate the impact of the intervention with the matched sample and calculate standard errors.

One of the key issues in charactering the propensity score is the specification of the selection model especially the identification of the variables that determine the whether use a computer to obtain information. It is important to estimate model (3) directly to qualifythe variables that might also influence take-up of treatment. Table 9 presents the results of propensity score estimated by logit model. Generally, most of the variables in the model have the expected signs.

Insert Table 9 about here.

Before choosing algorithms to evaluate impact effect, it is important to check the assumptions that are made in the estimation and verify that the model specification is appropriate and the results do not suffer from bias. One way to check the common support between treatment and comparison groups is through visual inspection of the propensity score distributions for both treatment and comparison groups (See Figure 2). A visual analysis of the density distributions for the two groups reveal that all the treated and the untreated individuals were within the region of common support. That is, each individual had a positive probability of being either a computer user or a non-user. This implies that the Common Support Assumption, which requires each treated farm household to have a corresponding untreated household, as a match was satisfied.

Insert Figure.4 about here.

The impact evaluation results of computer use on farmers’ production and consumption estimated with nearest neighborhood matching (NNM) and propensity score matching (PSM)are presented in Table 10. The matching results indicate that computer usages have positive and significant impact on the size of arable land rented-in, garment consumption per capita, transportation expenditure per capita, housing expenditure per capita, and insurance expenditure per capita; They also have negative and significance on family labor man-days per mu, value of purchased pesticides per mu, and the probability of selling outputs at farm-gate market.

Insert Table 10 about here.

When interpreting the matching results, it is important to evaluate the robustness of the estimations by changing the matching algorithms or by altering the parameters of a given algorithm. Robustness checks help increase the reliability of the results by showing that the estimations do not depend crucially on the particular methodology chosen. One obvious approach is to use the different matching methods previously discussed to compare the results. The findings with different matching techniques are quite consistent.

6.4 Empirical results discussion

Now consider the IV approach and matching approach together. Suppose that if IV approach and matching approach provide the same significant estimators of the treatment effect of computer usage on production and consumption, then we can say the empirical results are robust and reliable. Careful inspections of Tables 7,8 and 10 reveal that there is significant causal effect relationship between computer usage and farm household's production and consumption. Overall, the results indicate that farmers' production and consumption decisions are influenced by computer engagement, while computer engagement appears to be driven mainly by farm characteristics. Moreover, our findings also suggest that the influencing directions and magnitudes are quite different.

In relation to the size of land rented-in, our models show that farm household owns a computer and connects it to Internet have larger rented-in land size. Both the coefficients of IV, NNM and PSM are positive and significant at 10% or 5%. The economic logic behind this is that the introduction of computer improves farmer's information access to public land policy as well as the searching cost of land transaction and reduces farmer's expectation of risk in the future in highly specialized apple production sites. Therefore, it encourages farmers to rent in more arable land for apple production for maximizing profits.

In addition, computer engagement via Internet reduces family labor man-days input per mu. In IV approach, computer usage has significant negative effect on family labor input. Accordingly, the ATT for family labor man-days per mu is -7.77 in PSM, -4.54 in NNM and are significantly different from zero at 1% level in two matching approaches. One possible explanation for this is that the household who owns a computer is more likely to replace family labor with machine investment or machine renting service.

Again, in line with previous literature (e.g.Zanello, Shankar and Srinivasan, 2011； Aker,2010), our results show a clear significant effect of computer usage on market participation. Specifically, Modern Information Communication Technology (MICT) reduces the probability of selling agricultural output at farm-gate market, and both coefficients in IV and Matching are significantly difference from zero at 5% or 1% level. This can be explained by two ways: on the one hand, computer engagement reduces farm household's search costs so that more price information is provided with low costs; On the other hand, ICT allowing villagers to learn about e-commerce, which gives rise to the growth of e-tailers, or villagers who sell products through e-commerce.

Finally, computer usage promotes most consumptions of farm household significantly. Specifically, it increases household's garment, transportation, housing and insurance consumption. Just like previous theoretical analysis said, the introduction of computer not only changes farmer's information access but also improves farmer's knowledge and overcomes the limitation of geography distance to markets.

7. Conclusions

Computer usage in rural China has grown sharply over the past decade and now covers more than 30 percent of the farm households. Empirical evidence shows that there is significant causal relationship between computer uses and farm households' production and consumption decisions, which also supports the policy of promoting Internet accesses in rural China made by central government.

Our first finding is that farm household owns a computer and connects it to Internet have larger rented-in land size. This is also evidence to suggest that construction of land transform information system based upon computer in rural China might encourage farmers to rent in more arable land for apple production for maximizing profits.

Our second finding is that computer engagement via Internet reduces family labor man-days input per mu. One possible explanation for this is that the household who owns a computer is more likely to replace family labor with machine investment or machine renting service. This result also proves that in the information ear, agricultural market structure will be changed (Martin, 2016).

Another interesting finding is that there is a clear significant effect of computer usage on market participation, which is also consistent with the previous research. This result indicates that computer usage may strengthening famer’s bargaining power and use the information on prices in specific marketplaces to travel further.

Finally, computer usage promotes most consumptions of farm household significantly. Specifically, it increases household’s garment, transportation, housing and insurance consumption. This may suggest that the important of improving computer access is crucial for stimulating rural consumption increase. Besides, the need for expansion of Internet network coverage in western areas like Gansu Province where mobile phone network is still poor is also of importance.

It should be noted that our limitation of our research is also obvious, cross section data are unavailable to support further robust check like DID method. If panel data were available measuring farmer characteristics, such as land holdings, quantity and quality of all the crops grown and harvested, transportation costs incurred, number of traders and daily prices, one could measure accurately the individual response to the intervention. Future work could then determine the general equilibrium effects of improved information on wages, poverty and investment incentives by farmers.

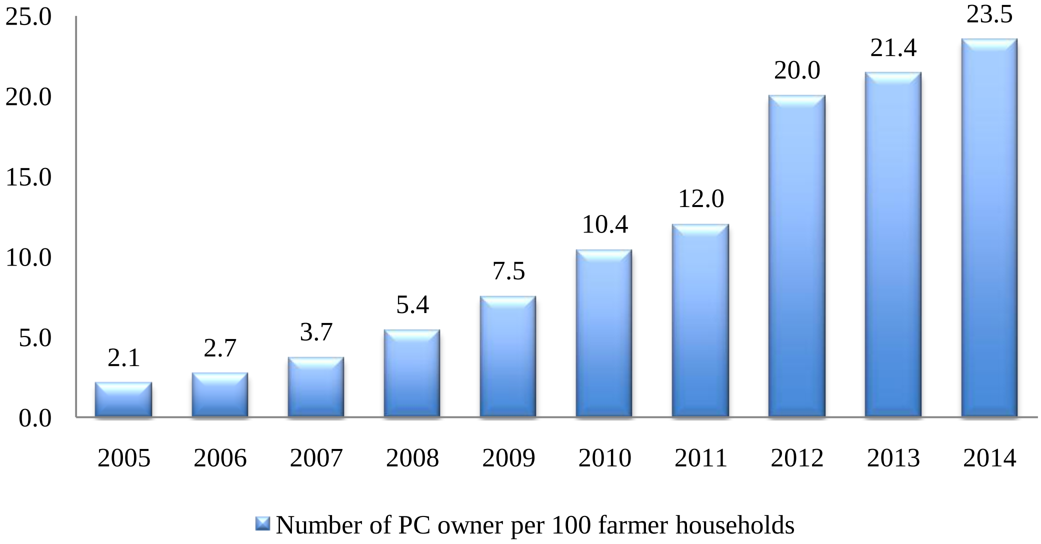
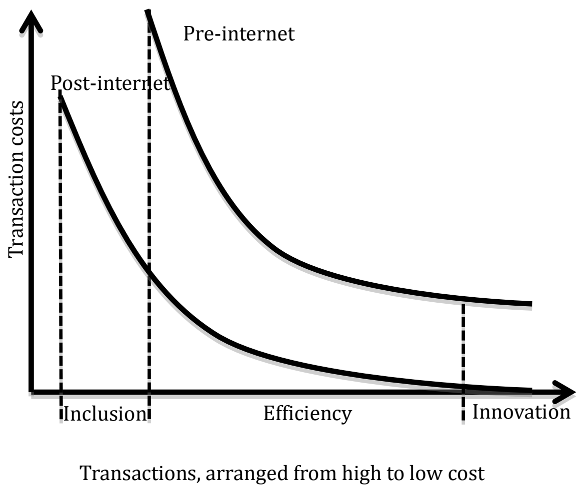


Figure 1. PC owners per 100 farmer households in rural China by Year[*]

[*]Notes: Data from China Rural Statistical Year Books (2006-2015)



Source: World Bank (2016).

Figure 2. The effects of falling of transaction costs

Figure 3. Geographic location of sample sites

Table 1 Review of Empirical Studies of ICT Tools Impact Evaluation

Type of tools	Study	Outcome variable	Results	Country
Mobile Phones	Tadesse and Bahiigwa(2015)	Marketing decision and price	Mixed	Ethiopia
Mobile Phones	Aker and Mbiti(2010)	General	Benefit producer welfare	Africa
Radios and Mobile Phones	Zanello and Srinivasan(2014)	Producer price	Positive effect	Ghana
Cell Phones	Aker (2010)	Market performance and traders welfare	Reduce price dispersion	Niger
Mobile Phones	Jension(2007)	Market performance and traders welfare	Reduce price dispersion and waste and increase fishermen's profits	India
Mobile Phones	Aker and Ksoll(2016)	Types of crops, quantity produced, quantity sold and price received	Mixed	Niger
Mobile Phones	Shimamoto, Yamada and Gummert(2015)	Producer price	Increase selling price of rice	Cambodia
TV	Cecchini and Scott(2003)	Poverty reduction	Positive effect	India
Kiosks	Goyal(2010)	Soy price and cultivated area	Positive effect	India

Table 2 Farmer Households' Access to Information Communication Technology in China

ICT Source	Shaanxi N=356	Gansu N=273	Shandong N=359	Henan N=91	Full Sample N=1079
TV	98.31%	97.43%	100%	100%	98.79%
Newspaper	7.30%	8.05%	6.96%	30.04%	8.71%
Mobile Phone	98.31%	98.17%	98.31%	100%	98.42%
Computer/Internet	34.83%	23.07%	42.06%	35.16%	34.29%

Table 3 Summary statistics of sample's characteristics

Variables	Shaanxi N=356	Gansu N=279	Shandong N=352	Henan N=91	Full Sample N=1079
Dependent Variables	Mean	Mean	Mean	Mean	Mean
Land rented in (mu)	1.46	2.40	0.38	1.60	1.35
New apple orchard built after computer introduced in (mu)	2.02	2.09	0.73	1.51	1.57
Family labor man-days per mu	17.57	33.11	48.24	37.81	33.41
Value of purchased pesticides per mu	262.50	300.85	800.16	399.75	462.67
Probability of selling agricultural outputs at farm-gate market	0.79	0.85	0.25	0.52	0.60
Garment consumption per capita (Y RMB)	592.23	517.86	530.77	503.24	545.50
Commodity consumption per capita (Y RMB)	1756.51	1309.50	1077.80	1003.13	1354.31
Health expenditure per capita (Y RMB)	1004.98	498.17	721.48	658.25	753.27
Transportation expenditure per capita (Y RMB)	183.65	162.97	961.57	321.04	448.27
Insurance expenditure per capita (Y RMB)	1676.19	505.30	1125.32	988.89	1139.37
Housing expenditure per capita (Y RMB)	2472.79	1912.42	1121.49	1375.00	1788.46
Farm characteristics					
Age of farm household head (Years)	48.96	50.42	50.06	54.26	50.13
Education of farm household head (1=illiteracy; 2=primary;3= primary middle school; 4=senior middle school ;5=college)	2.84	2.72	2.98	3.25	2.89
Household size	4.81	4.98	3.43	4.52	4.38
Annual income per capita in last year (Y RMB)	15574.23	16197.06	21781.81	15442.78	17788.59
Apple orchard size	10.05	5.84	4.22	5.31	6.64

Table 4 *Differences in means of computer users and non-users*

Variables	Users N=370	Non-users N=779	Mean difference	t values
Dependent Variables				
Land rented in (mu)	2.09	0.96	1.13**	2.02
New apple orchard built after computer introduced in (mu)	2.13	1.27	0.86***	2.37
Probability of selling at farm-gate market	0.4773	0.6577	-0.1804***	5.66
Family labor man-days per mu	28.78	35.82	-7.04***	-3.30
Value of purchased pesticides per mu	446.12	471.30	-25.18	-0.91
Garment consumption per capita	844.99	488.97	356.02***	6.68
Commodity consumption per capita(Yuan RMB)	650.07	490.61	159.46**	2.27
Health expenditure per capita(Yuan RMB)	1088.79	1493.65	-404.86*	-1.95
Transportation expenditure per capita(Yuan RMB)	1294.12	469.83	824.29***	7.17
Insurance expenditure per capita(Yuan RMB)	609.35	364.42	244.93	1.56
Housing expenditure per capita(Yuan RMB)	2119.00	1641.60	477.39	1.01
Farm characteristics				
Age of farm household head (Years)	47.58	51.47	-3.89***	-6.64
Education of farm household head	3.11	2.77	0.34***	6.42
Household size	4.46	4.32	0.14	1.32
Annual income per capita in last year(Yuan RMB)	20858.84	16227.34	4631.50***	3.21
Apple orchard size owned by farm household (mu)	7.07	6.45	0.62*	1.71

***Significant at 1% level.

**Significant at 5% level.

*Significant at 10% level.

Table 5 Treatment Effect from Computer Usage on Farmers Households' Production without Consideration of Endogenieuty

Variable	New apple orchard built after computer introduced in	Land rented-in after computer introduced in	Household labor man-days input per mu	Pesticide investment per mu	Market participation
Computer Usage	0.9760(0.013)**	1.1841(0.009)***	-4.4124(0.003)***	-61.1338(0.208)	-0.0955(0.001)***
Household head age	-0.0240(0.208)	-0.0302(0.171)	0.2146(0.003)***	1.0295(0.663)	-0.0010(0.493)
Households head education	0.6980(0.100)*	0.9805(0.047)**	-0.2613(0.870)	-23.8094(0.652)	0.0231(0.460)
Household population	-0.1040(0.408)	-0.2501(0.087)*	-0.3186(0.501)	-11.7734(0.451)	-0.0001(0.992)
Total income per capita in last year	-0.0140(0.319)	-0.0264(0.105)	-0.1683(0.002)***	-0.7752(0.656)	-0.0010(0.315)
Farm land size	0.0771(0.023)**	0.4962(0.000)***	-1.0907(0.000)***	-22.5597(0.000)***	0.0013(0.588)
Farm located in Gansu	0.6961(0.315)	0.7730(0.336)	2.4545(0.346)	-80.1186(0.351)	0.3112(0.000)***
Farm located in Shaanxi	0.1866(0.785)	-2.3731(0.003)***	-4.7809(0.064)*	-33.6991(0.691)	0.2670(0.000)***
Farm located in Shandong	-0.8635(0.205)	-0.9805(0.215)	17.4381(0.000)***	381.5869(0.000)***	-0.2645(0.000)***
Constant	2.5035*(0.070)	1.3975(0.383)	28.3017(0.000)***	660.1300(0.000)***	0.6025(0.000)***
F-test	3.55	23.31	54.25	19.74	51.79
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000
R-square	0.0291	0.1647	0.3145	0.1434	0.3046
Adjusted R-square	0.0209	0.1576	0.3087	0.1361	0.2987

Table 6 Treatment Effect from Computer Usage on Farmers Households' Annual Consumption per Capita without Consideration of Endogeneity

Variable	Garment	Commodity	Health	Transportation	Housing	Insurance
Computer Usage	273.4356(0.000)***	238.7806(0.156)	-900.8703(0.071)*	1302.1080(0.000)***	2352.8880(0.179)	362.1219(0.080)*
Household head age	-14.9032(0.000)***	-19.7965(0.016)**	-11.9696(0.622)	-40.6387(0.000)***	-456.0995(0.599)	-5.6977(0.571)
Households head education	-1.8744(0.975)	89.2851(0.626)	-684.3094(0.208)	425.5417(0.046)**	1277.7780(0.142)	223.8360(0.320)
Household population	-30.8360(0.083)*	115.1388(0.034)**	175.0721(0.275)	90.1238(0.153)	805.7148(0.361)	18.3992(0.782)
Total income per capita in last year	15.3617(0.000)***	15.4456(0.011)**	2.5732(0.886)	44.1520(0.000)***	30.1749(0.482)	10.1662(0.171)
Farm land size	-2.2520(0.636)	-18.9869(0.192)	28.0199(0.515)	40.2509(0.017)**	-36.7007(0.040)**	11.8133(0.507)
Farm located in Gansu	-24.8403(0.800)	182.7313(0.541)	616.5784(0.486)	242.2440(0.485)	-374.8834(0.019)**	-48.5075(0.895)
Farm located in Shaanxi	43.1491(0.655)	216.7178(0.463)	1460.4940(0.094)*	393.5374(0.251)	191.3185(0.723)	-220.7689(0.541)
Farm located in Shandong	-256.4449(0.008)***	-197.2744(0.502)	-236.9206(0.785)	-240.0695(0.482)	12.8843(0.594)	837.9660(0.020)**
Constant	1277.3460(0.000)***	1392.3620(0.019)**	2410.7270(0.170)	1644.7400(0.017)**	840.6271(0.091)*	401.3400(0.581)
F-test	20.14	3.03	2.84	21.74	1.81	4.13
Prob>F	0.0000	0.0014	0.0000	0.0000	0.0616	0.0000
R-square	0.1458	0.0251	0.0236	0.1560	0.0151	0.0340
Adjusted R-square	0.1386	0.0168	0.0153	0.1488	0.0068	0.0250

Table 7 IV Regression results of Effect from Computer Usage on Farmers Households' Production

Variable	New apple orchard built after computer introduced in	Land rented-in after computer introduced in	Family labor man-days input per mu	Market participation	Pesticide investment per mu
Computer Usage	1.2008(0.118)	1.4934(0.100)*	-17.3713(0.000)***	-0.0063(0.001)***	-196.5286(0.036)**
Household head age	-0.0217(0.281)	0.9463(0.058)*	0.0827(0.321)	0.0811(0.029)**	-0.3398(0.892)
Households head education	0.6732(0.117)	-0.2610(0.078)*	1.1707(0.492)	0.0184(0.096)*	-9.2609(0.862)
Household population	-0.1119(0.380)	-0.0276(0.095)*	0.1368(0.787)	0.0009(0.444)	-6.9805(0.660)
Total income per capita in last year	-0.0148(0.296)	0.4960(0.000)***	-0.1195(0.034)**	0.0017(0.557)	-0.2611(0.882)
Farm land size	0.0770(0.022)**	0.8237(0.309)	-1.0828(0.000)***	0.2252(0.000)***	-22.4610(0.000)***
Farm located in Gansu	0.7329(0.293)	-2.3521(0.003)***	0.3310(0.904)	0.2314(0.000)***	-102.2339(0.238)
Farm located in Shaanxi	0.2018(0.767)	-1.0067(0.203)	-5.6594(0.034)**	-0.2200(0.000)***	-43.2228(0.611)
Farm located in Shandong	-0.8825(0.195)	1.2062(0.470)	18.5355(0.000)***	-0.6207(0.000)***	393.0740(0.000)***
Constant	2.3644(0.099)*	1.4934(0.106)	36.3158(0.000)***	0.9273(0.000)***	743.2090(0.000)***
Wald Chi2(9)	28.39	207.45	468.92	388.91	80.78
Prob> Chi2	0.0008	0.0000	0.0000	0.0000	0.0000
Loglikelihood	-3965.02	-4125.22	-5386.05	-1157.64	-9115.66

Table 8 IV Regression results of Effect from Computer Usage on Farmers Households' Annual Consumption per Capita

Variable	Garment	Commodity	Health	Transportation	Housing	Insurance
Computer Usage	343.9485(0.009)***	79.4173(0.867)	-18.8894(0.499)	1389.0630(0.006)***	9904.5930(0.000)***	3448.7170(0.000)***
Household head age	-14.1882(0.000)***	-21.4017(0.022)**	-605.3673(0.283)	-39.7611(0.000)***	104.7822(0.000)***	25.2861(0.024)**
Households head education	-9.7268(0.874)	107.2687(0.571)	199.1361(0.234)	415.7174(0.057)*	-818.0551(0.185)	-124.0467(0.616)
Household population	-33.3272(0.067)*	120.7072(0.032)**	5.1401(0.782)	87.0705(0.179)	-695.1158(0.000)***	-89.0418(0.224)
Total income per capita in last year	15.0977(0.000)***	16.0432(0.010)***	28.4281(0.507)	43.8239(0.000)***	-70.6332(0.001)***	-1.3408(0.870)
Farm land size	-2.2940(0.629)	-18.8840(0.193)	504.2023(0.579)	40.1996(0.017)**	24.7786(0.613)	9.9807(0.609)
Farm located in Gansu	-13.1396(0.895)	156.5120(0.610)	1412.9340(0.106)	256.5553(0.469)	2309.7610(0.022)**	458.8555(0.254)
Farm located in Shaanxi	48.0972(0.619)	205.5999(0.486)	-178.4857(0.838)	399.6010(0.243)	1913.8240(0.054)*	-9.2804(0.981)
Farm locate d in Shandong	-262.2586(0.006)***	-183.8725(0.533)	-1584.4920(0.284)	-247.3384(0.469)	-1203.4040(0.224)	592.8768(0.133)
Constant	1233.7590(0.000)***	1490.4450(0.022)**	2832.0720(0.146)	1591.1930(0.033)**	-3249.9770(0.106)	-1496.3200(0.064)*
Wald Chi2(9)	164.82	25.46	23.58	160.17	230.66	146.54
Prob> Chi2	0.0000	0.0025	0.0050	0.0000	0.0000	0.0000
Log likelihood	-9262.11	-10420.51	-11577.80	-10589.78	-11588.94	-10591.42

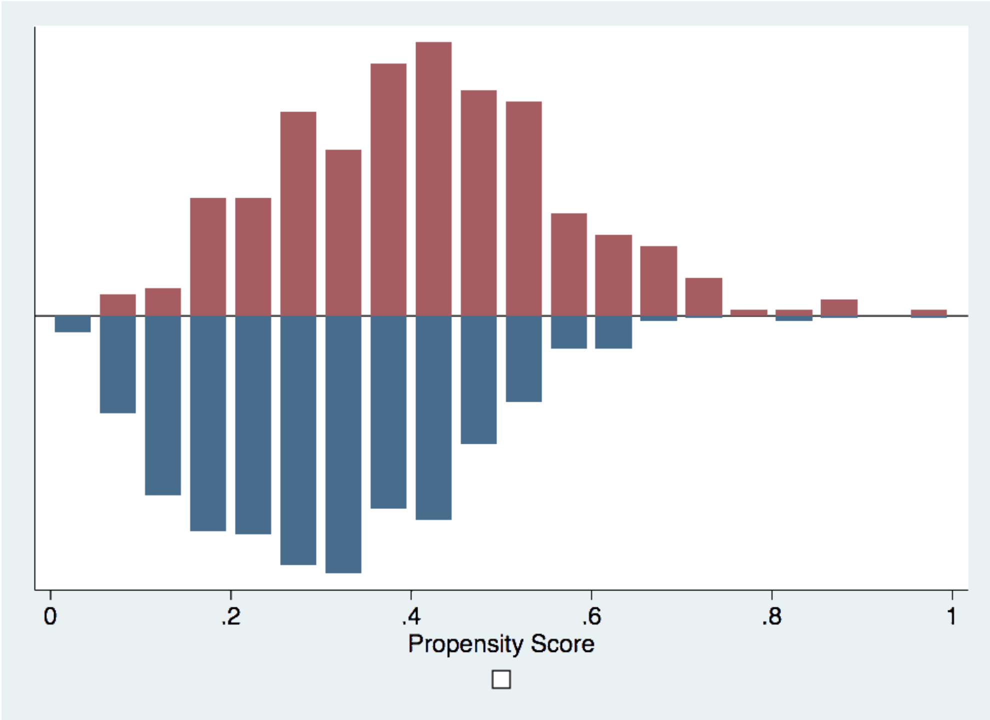
Table 9 Logit regression estimates of propensity score for computer use

Independent variables	Coeffiecient	p-value
Electronic commerce trade system provided	0.3066*	0.090
Age of farm household head(Years)	-0.0565***	0.000
Education of farm household head	0.5272***	0.002
Household size	0.1969***	0.000
Annual income per capita in last year(Y 1000)	0.0191***	0.001
Apple orchad size owned by farm household (mu)	0.0073	0.592
Shaanxi province (Yes=1;No=0)	-0.9984***	0.001
Gansu province (Yes=1;No=0)	-0.5727*	0.054
Shandong province (Yes=1;No=0)	0.3145	0.253
LR Chi(9)	129.82	
Log likelihood	-598.44	
Pseudo R-square	0.0979	

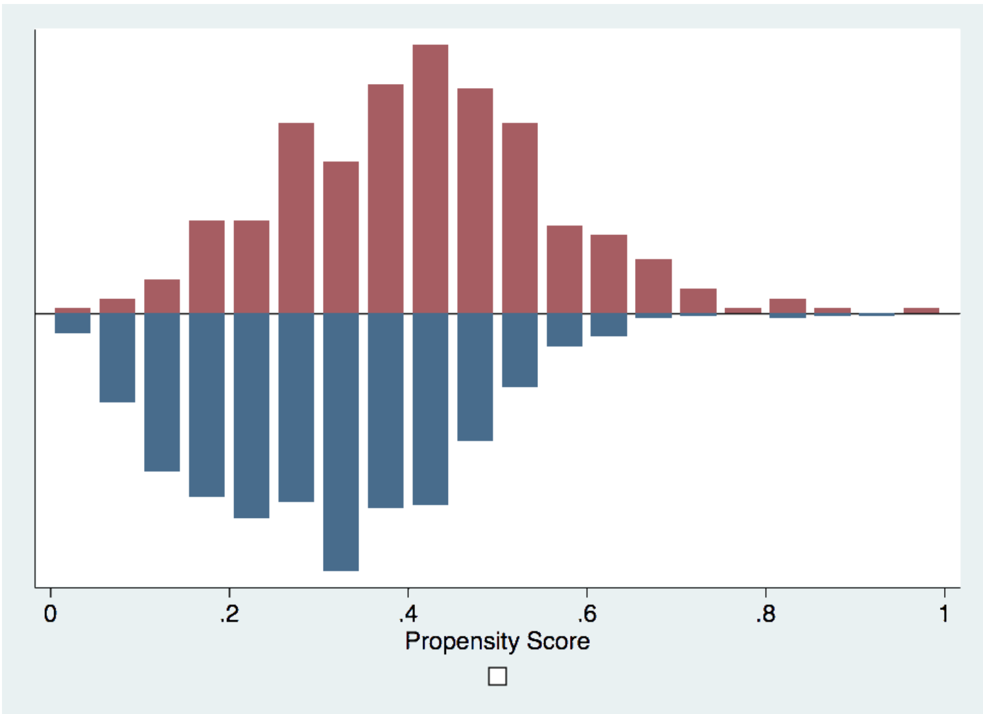
***Significant at 1% level.

**Significant at 5% level.

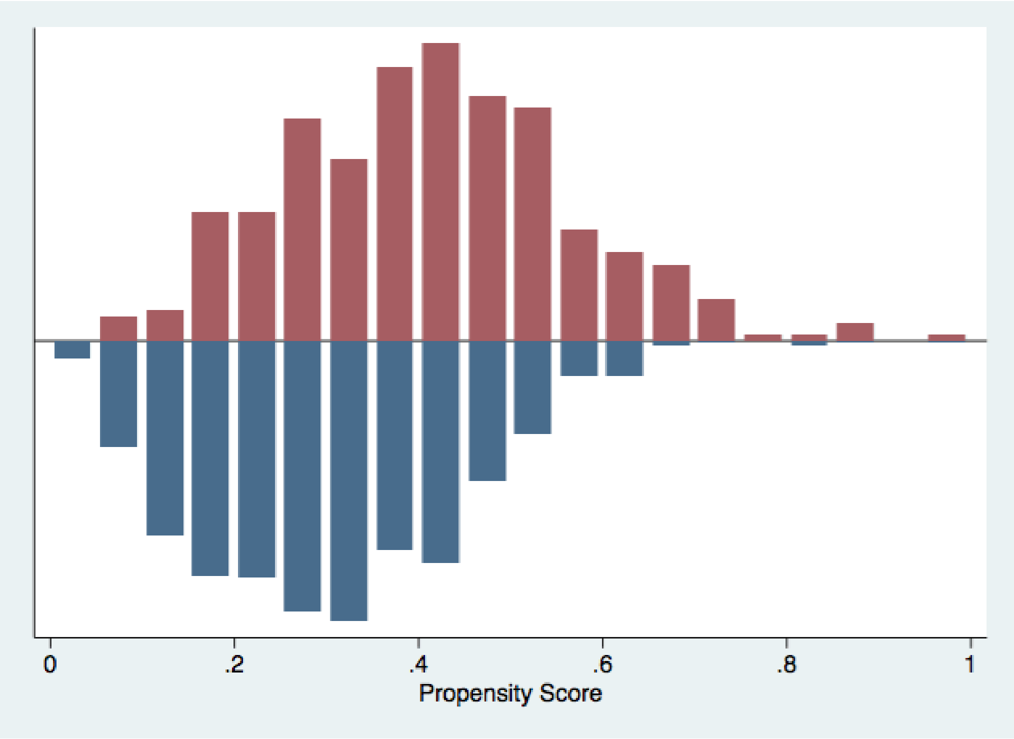
*Significant at 10% level.



(a).NNM



(b) KM



(c) RM

Figure 4. Histograms of propensity for treatment and comparison groups

Table 10 Impact of computer use on farm households' production and consumption

	PSM		NNM	
Production	ATT	P-stat	ATT	P-stat
Land rented in	1.6404**	0.011	1.4196**	0.024
Fresh apple trees planted	0.8969	0.105	1.0676**	0.048
Family labor man-days per mu	-7.7766***	0.003	-4.5440***	0.003
Value of purchased pesticides per mu	-49.7100	0.343	-81.6200*	0.056
Sell agricultural outputs at farm-gate market	-0.1208***	0.005	-0.0815**	0.040
Consumption				
Garment consumption per capita	315.8657***	0.000	304.5700***	0.000
Everyday goods consumption per capita	183.5200	0.423	447.5400**	0.013
Health care expenditure per capita	-789.7210	0.242	-837.7309	0.150
Transportation expenditure per capita	1190.9150***	0.000	1700.1580***	0.000
Housing expenditure per capita	1150.9760***	0.000	1238.3840***	0.007
Insurance expenditure per capita	624.8440**	0.027	447.5447*	0.088

Note: nearest neighborhood matching uses 1 nearest neighbor

***Significant at 1% level.

**Significant at 5% level.

*Significant at 10% level.

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Appendix:

Given the PSM methods provides unbiased estimation of treatment effects and can be used to draw causal inference with non-experimental data by constructing a counter factual of the outcome of the participants conditional on non-participation(Heckman and Navarro-Lozano，2004), the impact evaluation problem can be presented in a conceptual framework as follows. Let Y_1 and Y_0 represent the outcomes of household i that uses computer to search information and one that does not use, respectively. Then the average treatment effect on the treated in a counter factual framework can be specified as (Woodridge, 2010):

$$ATT = E(Y_1 | T = 1) - E(Y_0 | T = 0) \tag{1}$$

Since the treated and non-treated groups may not be the same prior to the intervention, so the expected difference between those groups may not be due entirely to program intervention. This implies it is likely to be biased using $E(Y_0 | T = 0)$ to estimate. Therefore, the central focus of impact inference lies in estimating $E(Y_0 | T = 1)$ rather than $E(Y_0 | T = 0)$. This can be also written as follows:

$$\begin{aligned} ATT &= E(Y_1 | T = 1) - E(Y_0 | T = 0) + E(Y_0 | T = 1) - E(Y_0 | T = 1) \\ &= ATE + E(Y_0 | T = 0) - E(Y_0 | T = 0) \\ &= ATE + z \end{aligned} \tag{2}$$

where ATE is the average treatment effect indicating the average gain in outcomes of participants relative to one does not use computer. z is the effect lead by selection bias is the extent of selection bias that crops up in using T as an estimate of the ATE. The basic objective of PSM is to get rid of selection bias by capturing the effects of various observed covariates (X) in a single propensity score or index. Then, outcomes of using and no using households with similar propensity scores are compared to obtain the impact effect. Households for which no match is found are dropped because no basis exists for comparison. PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment T conditional on observed characteristics X, or the propensity score:

$$p(X) = \Pr(T = 1 | X) \tag{3}$$

Rosenbaum and Rubin (1983) proved that, under certain assumptions, matching on P(X) is as good as matching on X. There are two necessary assumptions for identification of the program effect named conditional independence assumption (CIA) and common support assumption (CSA). Specifically, CIA implies that given a set of observable covariates X that are not affected by treatment, potential outcomes Y are independent of treatment assignment T. Then Equation (4) can be written as follows:

$$p(X) = \Pr(T = 1 | X) = E(T | X) \tag{4}$$

Usually, the propensity score can be obtained from preliminary logit estimation. On the other hand, the second assumption CSA ensures that treatment observations have comparison observations in the propensity score distribution. Based on these two assumptions, he ATT can be specified as follows:

$$\begin{aligned} ATT &= E\{Y_1 - Y_0 | T = 1\}, \\ ATE &= E[E\{Y_1 - Y_0 | T = 1, p(X)\}], \\ ATNT &= E[E\{Y_1 | T = 1, p(X)\} - E\{Y_0 | T = 0, p(X)\} | T = 1]. \end{aligned} \tag{5}$$

Several matching methods have been developed to match adopters with non-users of similar propensity scores. Asymptotically, all matching methods should yield the same results (Asfaw et al., 2012). However, in practice, there are trade-offs in terms of bias and efficiency with each method (Caliendo and Kopeinig, 2008). Here, we use Propensity Score matching (PSM) and nearest neighbor matching (NNM) . The basic approach is numerically to search for neighbors' of non-adopters that have a propensity score that is very close to the propensity score of the computer users. The two matching method are used to check the robustness of estimated results.