The Effects of Distance Education on Agricultural Performance and Household Income: Evidence from Suburban Beijing

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Abstract: This paper evaluates the impacts of a rural distance education program (RDEP) on total household income, agricultural land productivity, agricultural labor use efficiency, and off-farm employment using household survey data of 783 randomly selected farmer households in 54 villages of 3 districts in suburban Beijing in 2014. To deal with the selection biases associated with the fact that RDEP was implemented in a non-random fashion, we adopted Propensity Score Matching method (PSM) to assess the program effects. While the program effects based on the entire sample are generally limited, there are immense heterogeneous effects across districts and households. RDEP is found to have significant effects on several outcome indicators related to agricultural production (agricultural land productivity, agricultural labor use efficiency, input use intensity, and labor allocation) in Tongzhou, an agriculturally more important district with a more intensive RDEP usage. But in Pinggu a district with much less land, the only effect of the RDEP is the significant and large increase in off-farm labor employment. We also find that the RDEP has bigger and statistically more significant productivity effects for households with less education and more assets. The large heterogeneous effects of RDEP highlight that a more effective distance education program should be customized to the local endowments and learning needs.

1. Introduction

With the rapid development of information and communication technology (ICT) and enormous progress in informatization infrastructure, the existing agricultural extension system started to offer services by ICT means, or new ICT-based extension services have been set up to alter and challenge the use of traditional systems (Anastasios, et al. ,2010; Li et al., 2014; Sun Chu et al., 2014). Recognizing the potential advantages of ICT-based extension service system over the traditional extension service system, governments of many developing countries have already committed huge amount of resources to establish comprehensive ICT-based extension systems. For example, Chinese government has already invested hundreds of millions of yuan on informatization infrastructure and ICT-based educational programs in rural China to help rural farmers gain knowledge, skills and information to improve their livelihood (Sun Chu et al., 2014).

The emergence of the ICT and ICT-based services has also attracted attentions from scholars to study the effectiveness of these services. While studies based on macro data generally find that ICT-based services have positive effects on overall GDP growth (Waverman, Meschi, and Fuss 2005) and agricultural productivity (Monchi and Chun 2006), the results based on micro-level data are more mixed. On the one hand, several studies show evidence that

ICTs (mainly mobiles) reduce the informational asymmetry problem, improve market efficiency (Jensen, 2007; Muto et al., 2009; Jenny Aker, 2010; Ogutu et al. 2013), and increase adoption of improved inputs and agricultural productivity (Kiiza et al., 2012). On the other hand, these same studies also show that the effects of ICTs vary greatly across farmers, communities, crops, and the specific outcomes measured. For instance, Megumi Muto et al. (2009) found that mobile phone usage increased the sales of banana farmers but not maize farmers in remote communities in Uganda. In Kenya, while participation in the ICT-based MIS project is found to have positive and significant impact on the usage of improved seeds, fertilizers, land and labor productivity, but negative and significant effect on the usage of hired and family labor (Ogutu et al. 2013).

Like any impact evaluation of a non-experimental program, to identify the impact of an agriculture extension service has long known to be empirically challenging (Anderson and Feder, 2004)[1]. Furthermore, there is even a bigger challenge to identify the impacts of ICT-based agricultural extension services (Aker, 2011; Nakasone, 2014). First, ICT includes many different types of technologies and terminals, so the impact of ICT varies widely according to the form and content of conveying information by different technologies (Anderson et al., 2004), thus, it requires to have more appropriate counterfactual group for the treatment group. Second, ICT system affects many aspects in addition to agriculture, such as wealthy effect and information exchange efficiency improvement, which means more difficulties of disentangling the effects of ICT system and ICT-based service. Third, there are difficulties to separate the adoption decision of ICT-based service and the knowledge conveyed by it because of the threshold effect of more ICT operating skill (Gruber et al., 2011; Jenny C. Aker, 2011).

In this paper, we conduct an empirical analysis of the impacts of the RDEP on farmers' technology adoption, agricultural productivity, off-farm employment, and income using household survey data of 783 randomly selected farmer households in 54 villages of 3 districts

[1] In a related literature, the effectiveness of Farm Field School programs (FFS) is also found to be largely inconclusive based on a large number of international studies. The results vary considerably across the content, evaluation method and specific outcome measured (Erin M. Godtland et al. ,2004,; K. Davis et al., 2011; Esbern Friis-Hansen et al. , 2012). Inability to account for the selectivity issues is again one of the main reasons for the inconclusive results.

in suburban Beijing in 2014. Among them, 324 are beneficiary households from 27 RDEP villages (9 villages in each of the 3 districts) and 459 households from villages that have similar agroecological and socioeconomical characteristics as the RDEP villages but have not yet received the project (again 9 villages in each district). To deal with the selection bias associated with the non-random program placement and/or non-compliance, we employed the Propensity Score Matching method (PSM) to estimate the treatment impacts of the RDEP. For robustness check, we also estimate the effects of RDEP using difference-in-difference (DID) on matched sample for income and assets, the only variables for which recalled data were collected before RDEP was introduced. We find that while the overall effects of RDEP using the whole sample is quite limited, there are marked heterogeneous effects across districts and household characteristics. While RDEP significantly increased the agricultural land productivity, agricultural labor use efficiency and input use intensity in both Tongzhou and Huairou districts but had no such effects in the Pinguo district. On the other hand, RDEP significantly increased the time spent on off-farm employment (by 5 months) in Pinggu but not in the other two districts. While the productivity effects of RDEP is positive and statistically significant for households with less education or more assets, but insignificant for those with higher education or less assets.

The rest of the paper is organized as follows. Section 2 provides additional background of the RDEP project and data collection. Section 3 presents the econometric methods. Section 4 discusses the main estimated results. Section 5 concludes.

2. Project and data description

The Chinese rural informatization campaign has been a nation-wide effort. Since 2003, every province has successively constructed an ICT platform to deliver various training courses to the grass roots level villagers. Although numerous descriptive studies have demonstrated the positive effects of the ICT-based farmer educational programs on farmer household's agricultural productivity and household income, rigorous quantitative evidence on the effects of these programs based on credible control-treatment evaluations is scant.

The Beijing rural distance education project (BRDEP) was initiated in 2008. It consists of a municipal platform (to develop training materials and courseware) and many remote stations located in villages to educate and train the grass roots villagers. The platform was constructed and operated by the Beijing Academy of Agricultural and Forestry Sciences (BAAFS), while the remote stations were set by district governments and located in village public places (meeting rooms, training classes, offices, etc). College graduate students, village officials or the village committee members serve as part-time administrators of these local stations. The three fundamental tasks of BRDEP are: (1) to introduce new agricultural technologies and market information; (2) to train employment skills and information, and (3) to disseminate rural policies and to improve health knowledge of villagers. The courseware and the curriculum in the teaching platform are developed to facilitate the implementation of these three tasks. The station administrators operate the terminal computers for farmers to learn or search for information at the request of farmers. In addition, at least two collective training events are arranged to help train villagers. As the data recording system, the time, content and other learning behaviors are recorded in the platform, information on trainees' participation and leaning intensification is also recorded by the administers of the local remote stations.

2.1 The Knowledge and Service Offered by BRDEP

The municipal level platform is connected to all the village level distance education stations, so farmers can receive various information about new technologies and services from their own stations. The information about specific technologies and services of the platform is listed in table 1.

Users of the BRDEP are expected to benefit from the program from the following four main training modules of the education program. First, BRDEP educates farmers about new agricultural technologies with modern curriculum, at a low cost and a flexible time and a convenient location. Second, BRDEP offers villagers real-time market information including the daily wholesale and retail prices of agricultural commodities in four major agricultural commodity markets in Beijing. Third, BRDEP offers training courses on small business operation and employment skills and provides successful examples. Finally, BRDEP offers villagers health education. In our study districts, BRDEP introduced all the four modules but the specific content and intensity of each module may slightly vary from district to district and from village to village. The top 10 popular courses offered in the 2013 BRDEP are listed in table 2.

2.2 Sample and Data Collecting

A total of 783 households were drawn from 3 peri-urban districts based on a three-stage stratified random sampling technique, as reported in table 3. In the first stage, 3 districts in 10 rural districts were selected, based on the different divisions of regional planning, economic conditions and program intensity (time used) in each station. In the second stage, we first randomly sampled 9 program (treatment) villages in each district, and then selected 9 villages that have similar agroecological and socioeconomical characteristics as the treated villages but have no distance learning station yet by the time of the survey. These 9 villages serve as control villages. Finally, 12 households in each treatment village and 17 households in each control village were randomly sampled. The fact that we selected more households in the control villages than in the treatment villages was to increase the probability of having households in the treated group to be matched by households in the treatment group.

Data were collected at both the village and household level using purposively designed village and household questionnaires. At the village level, data were collected on village basic characteristics, economic conditions, total land endowment and non-land assets. For treatment villages, detailed information on the content and implementation of BRDEP was also collected. At the household level, data on demographic characteristics, land and non-land asset holdings, agriculture production, off-farm employment, business income, non-labor income and farmers' evaluation of the BRDEP were collected. The survey was conducted in August-October 2014 by Beijing Academy of Agricultural and Forest Sciences. All completed questionnaires were checked and validated for accuracy by respondents before data processing and tabulation started.

3. Methods

In order to estimate the effects of an intervention (or a treatment) on participants (or the treatment group), it is required to draw counterfactual outcomes that would have been observed for the treated (those who received the intervention) in the absence of the treatment (Rubin, 1974; Rosenbaum & Rubin, 1983). For any impact evaluation exercise, the key challenge is to develop a valid counterfactual – a group which is as similar as possible (in observable and unobservable dimensions) to those receiving the intervention. If the treatment and control groups were assigned randomly, a simple comparison of outcomes between treatment and control groups allows for the establishment of definitive causality – attributing the observed differences in outcomes to the intervention. However, if the assignment of treatment and control villages and/or households is not random, a simple comparison of outcomes (e.g., crop productivity, household income, farm and off-farm labor use, etc.) between participants and nonparticipants would yield biased estimates of the project impacts. And in such cases, an alternative impact evaluation method that can control or account for the selection bias is needed.

In this paper, we employ the PSM method to estimate the impacts of the BRDEP in three peri-urban districts in Beijing on crop productivity, input use intensity, labor allocation between on-farm and off-farm employments and household income. PSM, developed by Rosenbaum and Rubin (1983), was mainly proposed to find in a large group of nonparticipants that are similar to the participants in all relevant pretreatment characteristics (X). Under PSM, the average treatment effect is equal to the expected difference in the observed outcomes between participants and matched nonparticipants. The underlying identifying assumption is known as unconfoundedness, selection on observables or conditional independence.

$$\mathrm{E}\,[Y_1 - Y_2 \mid P(X)] = \mathrm{E}\,[Y_1 \mid D=1, P(X)] - \mathrm{E}\,[Y_2 \mid \mathrm{D}=0, P(X)]. \qquad (1)$$

The key question is how to match participants to nonparticipants, because conditioning on all relevant covariates is limited in the case of a high dimensional vector X. Rosenbaum and Rubin (1983) suggest the use of probability propensity score (PPS), modeling the probability of treatment given covariates (observable characteristics) X.

$$P(\mathrm{X}) = P\,(\mathrm{D} = 1 \mid \mathrm{X}) \qquad (2)$$

Where D is a dummy variable indicating treatment status. They proved that if outcomes Y_1 (Y_0) are independent of treatment status conditional on X or Y_1, Y_0: D | X, then they are also independent of treatment conditional on the propensity score P(X).

$$\mathrm{Y}_1, \mathrm{Y}_0 : \mathrm{D} \mid P(\mathrm{X}) \qquad (3)$$

So that a multi-dimensional matching exercise is then reduced to a single dimensional matching problem: matching on the propensity score. A discrete regression function such as logit or probit model can be applied to estimate the propensity scores. After propensity scores are obtained from the estimation of (2), the average treatment effects on the treated (ATT) can be computed as in (1).

However, the assumption for equation (1) to be valid after a period of treatment is whether the households selected into beneficiaries or not based on unobserved characteristics, so further improvement in impact evaluation can be made by combining propensity score matching and DiD.

To find individuals in the control group to have the exact same propensity scores as those in the treatment group is impractical, several matching techniques have been proposed to match treatment individuals with control individuals in terms of similarity of propensity scores. The four most commonly used matching algorithms are nearest neighbor (NN), Caliper and radius, stratification & interval and kernel & local linear with each having its own pros and cons. Which matching algorithms should be chosen depends on the sample size and structure (Dehejia & Wahba, 1999, 2002; Smith and Todd, 2005; Marco Caliendo, 2008). As the sample size increases to a sufficient level, all PSM estimators should yield the same results. In small samples, it is a trade-off between bias and variance arises. Considering our sample size and the common support region, we used NN matching algorithms to estimate the ATE of the BRDEP, as the method introduced in reference (Shahidur R et al., 2010). For robustness check, we also apply direct NN matching instead of estimating the PS first.

To take advantage of the panel information for two key outcome variables (income and total asset), we also estimated a PS weighted DID regression method proposed by Hirano and Imbens (2002) to control for the potential selection on unobservables. Specifically, DID PS-weighted estimator is obtained by regressing the change in outcome on the treatment as follows:

$$\Delta Y_{it} = \alpha' + \beta' D_i + \gamma' X + \varepsilon_{it} \qquad (5)$$

Where we assign weight $\omega(t, x) = (t/\hat{P}(X)) + (1-t)/(1-\hat{P}(X))$ to each observation, t is an indicator for treatment status (=1 if treated, 0 otherwise), $\hat{P}(X)$ is propensity score of the treatments and $0 < \hat{P}(X) < 1$.

4. Results and discussion

4.1 Descriptive Analysis of treated and untreated households

Table 4 reports descriptive statistics for the participant and nonparticipant households. The descriptive analysis suggests noticeable differences between the RDEP participants and nonparticipants in their observed demographic characteristics. There are a total of 11 variables that are significantly different between participant and nonparticipant households. Among them, 4 are village level variables and 7 are household level variables. Compared to a typical nonparticipant household, a typical participant household in 2010 was bigger in household size (3.45 vs. 3.05), had a younger and more educated head, and owned more assets. At the village level, the collective dividend per capita in 2010 of a typical control village was significantly higher than that of a typical treatment village. At the same time, the differences in these characteristics are not consistent across districts. For example, while a participant household had higher value of total assets than an average nonparticipant household in Tongzhou, the opposite was true in the case of Huairou. The three districts also appear to be quite different in demographic and socio-economic conditions. For example, the household size in Pinggu is bigger than Huairou and Tongzhou by almost one member and 1.5 members, respectively. A typical household in Huairou owned 1.5 times (or 2 times) more arable land than a typical household in Tongzhou (or Pinggu). In terms of geographical location, Tongzhou is closer to Beijing and enjoyed much higher gross collective income than the other two districts. All these noticeable differences across districts points toward the need to assess the impact of the project separately for each district.

4.2 Estimation of the probability propensity score

Descriptive analysis on household characteristics gives an overview of the households surveyed. The large number of household and village variables that are statistically different between the treatment and control groups suggest the importance to include these covariates in the probit model. A number of factors that are documented to influence farmers' extension participation and technology adoption decisions. Esther Duflo et al. (2011) used several demographics and household asset variables in their model to estimate the adoption of fertilizer by Kenya farmers. Ellen Verhofstadt et al (2014) included demographic characteristics, asset ownership, market access and social capital, in their matching regression to match the participants and nonparticipants of smallholder cooperatives in Rwanda. Similar discussions can be found in Erin M. Godtland et al (2004), Dominique et al (2007), Shaohua Chen et al (2008) and Ma. Lucila. Lapar et al. (2011). In this paper, the choice of covariates is guided by previous literature and the availability of data. Four sets of characteristics are used as covariates in the probit models: household demography, asset ownership, village background and access to market.

Table 5 reports the probit model results on the probability for households to participate in the BRDEP program. The results show that a household's decision to participate in the BRDEP is significantly influenced by a large number of factors. Specifically, the likelihood for a household to participate in the BRDEP is higher among those with bigger household size, with head receiving more education, of higher income per capita but less fixed asset in 2010, who live closer to the county center but a little farther away from the Beijing municipal center, and in a lower collective income but higher dividend village (2010). All the factors mentioned above are all statistically significant. Based on these results, it can be argued that the BRDEP is not targeted for the relatively backward farmers (poorer, less educated), which is in line with the work of Lefort (2010) and Asres et al. (2013) on agricultural extension programs in Africa.

As demonstrated by Dehejia & Wahba (1999) and Marco Caliendo (2008), it is an important step to check the overlap in estimated propensity scores between treatment and comparison groups (known as the region of common support), because a violation of the common support condition is a major source of evaluation bias. To check the quality of matching, the distributions of propensity scores for the BRDEP participants and nonparticipants is displayed in figure 1 and the balance results for the key covariates before and after matching are reported in table 6. Figure 1 shows that the matching is well done as supported by a broad range of common support. Since no untreated observations can be matched with treated observations for the propensity score above 0.8, so we dropped the observations with PS>0.8 (six observations) to increase the matching quality.

The matching also considerably improves the balance in covariates between the treated and untreated group. As reported in table 6, out of the 25 covariates, the number of covariates that are stistically different between the control and treatment groups were reduced from the original 7 (before matching) to only 3 after matching, including HH size 2010, HH head education and village population. The magnitude of difference is also small for all the three variables. So overall, the matching performed well as supported in terms of common support and reducing the pre-matching differences of variables between the treatment and control groups.

4.3 Impact of BRDEP

The impact of farmer training and information service performs in many aspects, including agricultural intensification, agriculture productivity, off-farm employment and income. This paper estimates the impacts in terms of the following performance indicators: (1) HH gross income[2]; (2) HH annual agricultural income[3]; (3) agricultural labor use efficiency (agricultural income per agricultural worker per month)[4]; (4) agricultural land productivity (crop income per mu)[5]; (5) input use intensity (fertilizer, pesticide, seed use per unit of land); (6) total labor months working on agriculture; (7) off-farm labor efficiency (off-farm income per non-agricultural worker per month); (8) total labor months working off-farm. The first one measures overall income effects; (2)-(6) measure the agriculture productivity and intensification effects; (7)-(8) measures off-farm labor productivity effects, and (6), (8) also captures HH labor allocation effects.

The discussion below on impacts of BRDEP is divided into four subsections. The first subsection discusses the overall impacts of BRDEP using the whole sample. The second and third subsections presents the results on the heterogeneous program effects, first by districts, and then by the level of education and the level of initial assets in 2010. The final subsection

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[2] Annual HH gross income is calculated as the sum of income of agriculture, off-farm employment, business operation and transferred income (including rent, dividend, subsidy).

[3] HH annual agricultural income is calculated as the value of crop and livestock production (including nonmarketed produce valued at market prices) minus variable production costs (including purchased inputs, hired labor, land rent, etc.).

[4] Agricultural labor use efficiency is calculated as the annual agricultural income divided by the totally labor month working on agriculture.

[5] Agricultural land productivity is calculated as annual crops income divided by land area (mu), where annual crop income is calculated as the value of crop and production (including nonmarketed produce valued at market prices) minus variable production costs (including purchased inputs, hired labor, land rent, etc.)

reports DID-PSM results for income and total value of assets, also by districts

4.3.1 Overall impact of BRDEP

The estimated overall impacts of the BRDEP are presented in table 7. In addition to reporting the main PSM results (column3-4 for PSM-NN and columns 5-6 for NNmatch), we also present the simple mean difference between the treatment and control groups for comparison purpose (columns 1-2). As expected, the simple mean difference between participants and nonparticipants would yield biased estimates. In general, compared to PSM results, the simple mean comparison would underestimate the impact on agriculture productivity but overestimate the effects on input use intensity and off-farm employment. Both PSM methods consistently showed that BRDEP has a significant and positive impact on agriculture land productivity (crop income per mu). Participation in the BRDEP would increase crop productivity by￥435 yuan per mu ($ 1064.38/acre). It is argued that the effects are robust if the results from both PSM-NN and NNmatch methods are highly consistent (Khandker, 2010). Though the effects on agriculture labor use efficiency and input use intensity are positive and statistically significant based on NN method, the effects are not robust as they are no longer significant based on NNmatch method. Similarly, the person months spent on off-farm work is positive and significant based on NNmatch, but not significant based on PSM-NN. At the same time, table 7 shows BRDEP has no significant effects on all other indicators though the gross income and agriculture income have the expected positive sign. The findings are common in the literature on impact evaluation of agricultural extension projects, because farmers need information on a variety of topics at a variety of stages before adopting a new technology, and the gross income is connected to more affecting factors (Jenny C. 2011).

4.3.2 Heterogeneous effects of BRDEP across districts

The descriptive findings that the three districts have distinct differences in agro-ecological and socio-economic characteristics and the level of BRDEP involvement suggest the importance to evaluate the effects of BRDEP separately for each district. The results from individual districts are reported in table 8. Our results show that the effects of BRDEP vary considerably across districts. For example, the effects of BRDEP on agriculture land productivity and agricultural labor productivity are positive and significant in both Tongzhou and Huairou based on both matching methods but both are not significant in Pinggu. RDEP significantly increased agricultural labor use efficiency and agricultural land productivity by ￥814.5 ($131.2/month) and ￥663.66 ($1603.73/acre) in Tongzhou and ￥1457.24 （$234.76/month） and ￥474.57/mu（$1146.69/acre） in Huairou, respectively. RDEP also significantly increased input use intensity in Tongzhou by￥139.19 ($336.35/acre) and significantly reduced labor use on agriculture (between -2.7 and - 3.4 person months), suggesting the possibility of having adopted more labor saving technologies. It is interesting to note that the increased number of months working off-farm is almost the same as the reduced months working on agriculture (thought statistically insignificant), suggesting the shift from agricultural activities to non-farm activities. In Pinggu, the only outcome variable that is significantly affected by the program is the person months spent on off-farm employment. And the effect is substantial as the participant households spent 5 more person months working off-farm than nonparticipant households.

The differences in the effects of BDREP across the three districts could be explained by the differences in the intensity of BDREP and agriculture resource endowments. Table 2 shows that the average number of hours spent on BDREP by an average user in a year is much higher in Tongzhou than in Pinggu and Huairou. The more intensive use of the BDREP is rewarded with more significant effects in more outcome indcators. On the other hand, Huairou is a mountainous district with a much more land than Pinggu and Tongzhou, which is consistent with the findings that BDREP has significant effects on agricultural land productivity and agricultural labor use efficiency. Finally, Pinggu has the smallest land endowment (between 1/3 and 1/2 of land area per household of Huairou) and largest household size. Given the relatively unimportance of agricultural production in Pinggu compared to the other two districts, it is not surprising that that BDREP has no significant effect on agricultural productivity in Pinggu. Instead, the main benefits of BDREP in Pinggu is the significant increase in months working on off-farm employment.

4.3.3 Heterogeneous effects across household characteristics

To explore the potential heterogeneous effects of BRDEP across household characteristics, we divided all the households by the head’s level of education (>=9 years or <9 years) as well as by the level of household total asset value (>216550 which is the median value of assets, or <216550). The results for different levels of education and for different levels of assets are reported on Table 9 and Table 10, respectively.

Table 9 shows that BRDEP benefits the households with lower level of education more than those with higher level of education in terms of agricultural labor use efficiency and input use intensity. The difference in agricultural labor use efficiency and input use intensity between participant households and nonparticipant households of lower level education is ￥1176/month ($189.45/month) and ￥252.39/mu ($609.87/acre), respectively. None of the effects is significant for households with higher level of education. From pobit model, we know that the level of education is positively related with the probability to participate in the BRDEP program. So it is important to take measures to increase household with less education to take on the BRDEP program. This finding is similar with the research by K. Davis et al (2011) on FFS in East Africa.

In terms of heterogeneous effects across the level of assets, our results show that BRDEP mainly benefits the households with more assets. Participating in BRDEP would significantly increase agricultural labor use efficiency by ￥1008.9/month ($162.53/month), agricultural land productivity by ￥935.48/mu ($2260.47/acre) and input use intensity by￥260.94/mu ($630.53/acre) for households with the higher level of assets. Though the effects on these outcomes are also positive for the lower level of assets, they are largely insignificant. These results may suggest that farmers with less assets would have less capacity to adopt or invest in new technologies promoted by the BRDEP. If the aim of the project is to narrow the agriculture productivity between poor and rich farmers, technology extension packaged with improved seeds or other inputs could be in consideration in the future.

4.3.4 Impact of BRDEP on income per capita and assets using DID-PSM approach, 2010-2013

During the survey, we also collected recalled data for two key outcome variables, income per capita and total value of fixed assets in 2010. This additional information allows us to estimate the effects of BRDEP on per capital income and total value of fixed assets using DID as well as the combination of DID and PSM (DID-PSM) approach. The advantage of DID/DID-PSM is its ability to control for time invariant unobservable that cannot be controlled by the PSM. The results based on DID-PSM are reported in Table 11. With the trimmed samples, BRDEP increased the income per capita by 14.8% at the level of significance just above 10% (p=0.12). The effects varies across districts. While the effects is large (37%) and significant at 10% in Tongzhou, the effects is not significant in Huairou. The effects on total asset value is insignificant no matter whether the evaluation is based on the full trimmed sample or subsamples from individual districts.

5. Conclusion and policy implication

This paper conducts an empirical assessment of the impacts of a rural distance education project on the performance of farmer households in peri-uban areas in Beijing. Using propensity score matching to deal with the selection bias, the authors evaluated the short-term impacts of the BRDEP on farmers' agricultural productivity, technology adoption, off-farm employment, labor resource allocation and overall welfare.

Our analysis highlights the importance to localize the extension or farmer educational programs. Analyzing an educational program as a whole could mask the marked differences in program effects across districts. Even with data from three relatively nearby districts from peri-urban areas in suburban Beijing, our analysis already revealed marked heterogeneous program effects across districts. Tongzhou and Huairou are agriculturally more important districts than Pinggu because of the relatively more abundant land endowment and other agroecological conditions, the program has much more significant effects on agricultural land productivity, agricultural labor use efficiency, input use intensity, or labor allocation in Tongzhou and Huairou than in Pinggu. On the other hand, Pinggu has very little land (1/3-1/2 of Huairou) and therefore agricultural production is likely to be an insignificant part of their livelihood. As a result, BRDEP does not have any significant effects on agricultural land productivity or other outcomes that are related to agricultural production. But the effects on off-farm labor use is significant and of large magnitude. The effect of the program also tend to vary with the use intensity of the training program. Tongzhou users spent more time on the program than other two districts, and the BRDEP has more significant effects on more outcomes.

Our analysis also find heterogeneous effects across household head's education and household's asset value. The finding that BRDEP has bigger effects on households with less education together with the fact that households with less education is less likely to participate in BRDEP suggests the needs to provide incentives for less educated households to participate in the BRDEP to benefit. On the other hand, the fact that effects are more significant for households with more assets suggest that educational program teamed with the support of inputs may be more effective if equity is an important consideration.

There are also a couple of caveats of our study. We focus on a relatively short-term effects. As adoption of new technologies or services is likely to take time to be effective. On the other hand, there is also studies showing that the effects of training program may decay over time. We would like to explore the long-term vs. short-term effects in our future research. While PSM is the most popular method to evaluate training and extension programs. The fact that PSM is unable to control for selection on unobservables is always a little bit of concern. In the future, we would like to pursue RCT-based evaluation of similar programs in other part of the country. Many parts of China are not yet affected by RDEP or any similar programs yet.

Table 1. BRDEP Platform Subsystems and Service Mechanisms

Types	Subsystem	Technologies and Mechanisms	Service Content
Information Resource Backup	E-learning Classroom online	Video on Demand, Smart Phone APP	agricultural technology, employment skill, Medical and health, small business operation, Rural policy, etc. (more than 30 thousands courseware)
	Information Service	Web station, Smart phone APP	products marketing price information, agriculture inputs knowledge
Consulting Service	Two-way Video Online Diagnosis	Video Conference	agriculture technologies consulting
	Intelligent Voice Question Answering System	Voice	agriculture technologies consulting, agricultural knowledge information searching, products marketing price information
	Consulting Online	BBS, SMS	agriculture technologies consulting , system operation question
Interactive Communication	Network Community	Social Networks Service	Emotional support and identification

Table 2. Hot Topic of Course on BRDEP IN 3 Districts

Top Ranking of Courses	Tongzhou	Pinggu	Huairou
1	Foreign Catering and Service Process	Application of Ornamental Sunflower Landscape planting	Sightseeing Orchard Construction
2	Cultivation South Species Fruits in North	Urban and Rural Residents' Pension Insurance System	Foreign Catering and Service Process
3	The Soil Free Cultivation Technology in the Back Wall of the Greenhouse	How to implement the formula fertilization technology by Soil testing	Application of Ornamental Sunflower Landscape planting
4	Small Celery Cultivation Technology	Sightseeing Orchard Construction	The Soil Free Cultivation Technology in the Back Wall of the Greenhouse
5	Scientific fitness and nutrition recipe to maintain female personal health	Using Technologies of Natural Energy in Rural Area	How to Save Gas
6	Health Station	Policy Interpretation of rural women employment and entrepreneurship in new situation	Cultivation techniques of chestnut for high yield
7	Balcony agriculture	the Selection and Using of Corn Herbicide	Agricultural water-saving technology
8	Automotive decorative skills training	Agriculture Energy Saving and Emission Reduction	Physical exercise and rehabilitation of pain of common joints in middle aged and old patients
9	Urban and rural residents' pension insurance system	Business strategy of leisure farm	Egg carving art
10	Cultivation techniques of high yield and efficiency of white radish in Greenhouse	Pig-Biogas-Fish Ecological Breeding Technology	Villagers' autonomous lecture

Table 3. Distribution of Sample Villages/Households

District characteristics (subtotal counties)	Sample district (total villages)	Average using time (hour/year*station)	Number of treated villages	Number of treated households	Number of untreated villages	Number of untreated household (control HHs)
plain, development zone (3)	Tongzhou (436)	100.41	9 (332)	108	9 (104)	153
semi-mountainous , ecological conservation zone (3)	Pinggu 272	34.88	9 (187)	108	9 (85)	153
mountainous ,ecological conservation zone (4)	Huairou 280	67.37	9 (192)	108	9 (88)	153

Table 4. Household and Village Characteristics

	Total sample(n=783)		Tongzhou sample(n=261)		Pinggu sample(n=261)		Huairou sample(n=261)	
	treat (n=324)	control (n=459)	treat (n=108)	control (n=153)	treat (n=108)	control (n=153)	treat (n=108)	control (n=153)
DEMOGRAPHIC CHARACTERISTICS								
HH size in 2010 (#)	3.40***	3.04	2.70	2.76	4.38***	3.44	3.11	2.92
	(1.40)	(1.21)	(0.92)	(1.07)	(1.39)	(1.44)	(1.08)	(0.86)
HH head age(years)	54.18**	55.86	55.69	56.58	56.23**	59.07	50.63	51.93
	(10.91)	(10.77)	(10.34)	(10.27)	(12.31)	(10.60)	(9.02)	(10.28)
HH head gender (dummy)	0.86	0.88	0.89	0.92	0.81	0.85	0.88	0.88
	(0.35)	(0.33)	(0.32)	(0.28)	(0.40)	(0.36)	(0.33)	(0.33)
HH head education(years)	10.12***	9.52	9.87**	9.04	10.13 (3.01)	9.48	10.36	10.04 (3.41)
	(2.87)	(3.13)	(2.55)	(2.86)		(3.05)	(3.02)	
HH member maximum	12.81**	12.30	11.51	11.45	13.96***	12.37	12.95	13.07
education (years)	(3.12)	(3.45)	(3.26)	(3.27)	(2.59)	(3.59)	(2.99)	(3.31)
HH size of children (age =<14)	0.23	0.18	0.19	0.13	0.24	0.19	0.24	0.22
in 2010	(0.44)	(0.41)	(0.40)	(0.34)	(0.43)	(0.46)	(0.49)	(0.41)
HH size of labor(14<age<60)	2.67***	2.33	2.01	2.16	3.40	2.39	2.59	2.45
in 2010	(1.23)	(1.28)	(1.10)	(1.26)	(1.30)	(1.56)	(0.83)	(0.95)
HH size of elder than 60 in	0.51	0.52	0.50	0.46	0.74	0.85	0.28	0.25
2010	(0.79)	(0.81)	(0.79)	(0.78)	(0.87)	(0.92)	(0.64)	(0.58)
HOUSEHOLD ASSETS								
Land HH owned in 2010 (Mu)	4.45	5.06	3.80	4.85	2.93	2.63	6.64	7.69
	(9.22)	(10.89)	(3.56)	(7.13)	(7.24)	(4.98)	(13.56)	(16.40)

Land rented from other HH (Mu)	0.14 (1.26)	0.29 (2.85)	0.20 (1.57)	0.00 (0.00)	0.17 (1.46)	0.81 (4.89)	0.04 (0.38)	0.06 (0.48)
Land rented to other HH (Mu)	0.97* (2.63)	1.50 (4.65)	2.17** (3.26)	3.77 (7.25)	0.42 (2.68)	0.34 (1.90)	0.31 (0.91)	0.39 (1.06)
Gross value of fixed assets in 2010 (￥yuan)	238304.8* (492294.4)	182505.4 (349617.8)	447558.8*** (764738.1)	200910.4 (444872.9)	1*		264976.0** (201574.3)	342311.5 (328025.7)
VILLAGE CHARACTERISTICS								
Resident population of village(#)	1337.3*** (2214.85)	1038.11 (757.88)	841.44 (490.86)	862.89 (750.50)	2407.22 *** (3508.69)	1267.78 (612.40)	763.22 ** (721.27)	983.67 (839.92)
Distance from county center (Km)	18.52*** (15.29)	22.50 (20.74)	22.72*** (6.09)	30.22 (19.30)	5.50 *** (1.49)	10.67 (6.19)	18.67 (20.87)	18.72 (22.39)
Distance from Beijing Center (Km)	59.92 (25.94)	57.69 (28.76)	48.14 (13.52)	48.89 (30.08)	75.00* (18.05)	70.00 (8.25)	66.67 (32.03)	62.39 (29.32)
Collective assets (￥10 thousand yuan)	712.64 (753.30)	638.99 (669.74)	768.92 (643.38)	778.14 (939.81)	995.92 (976.23)	774.41 (558.83)	373.08 (381.39)	394.40 (255.17)
Collective assets in 2010 (￥10 thousand yuan)	538.54 (632.01)	541.43 (676.56)	529.60 (440.73)	615.89 (822.30)	1038.37** (1122.52)	646.38 (549.12)	361.16 (441.76)	431.99 (524.75)
Gross collective income in 2010 (￥10 thousand yuan)	410.18*** (1370.02)	140.22 (174.53)	819.51*** (1969.37)	223.39 (228.30)	92.33 (99.18)	104.33 (111.17)	68.88 (60.07)	69.02 (51.58)
Collective dividend per capita in 2010 (￥yuan)	355.09*** (761.59)	628.57 (1512.13)	111.11*** (315.73)	766.67 (1660.06)	276.67 *** (396.82)	0.00 (0.00)	625.2 (1036.16)	700 (1562.89)

Notes: Mean values are shown, standard deviations are shown in parentheses.

treat are compared with control using *t*-test,*,**,and *** denote 10%, 5% and 1% significance level.

1*, HH Asset data is missed in Pinggu

Source: calculation based on data from own village and household survey (2014)

Table 5. Estimated Coefficients for PSM

VARIABLES	Coefficients
HH size in 2010 (#)	0.213***
	(-0.043)
Distance from DE station in village	-0.0001
	(0.0001)
HH head gender	-0.143
	(0.1433)
HH head age (log)	-0.348
	(0.2935)
HH head education level (dummy)	0.342***
	(0.1142)
Marriage status of head	0.200
	(0.2317)
Proportion of child (14 less) and aged (60 more) of HH in 2010	-0.114
	(0.1718)
Education level of head's father (dummy)	0.210
	(0.1388)
Maximums education level of HH member (dummy)	-0.166
	(0.1106)
Party membership	0.041
	(0.1181)
Village committee cadre membership	-0.017
	(0.1383)
Land owned by HH in 2010 (mu)	0.009
	(0.0114)
Square of land owned by HH in 2010	-0.000093
	(0.000150)
Proportion of cultivable land	0.001*
	(0.000652)
Gross value of asset in 2010	-0.157*
	(0.0841)
Square of gross value of asset in 2010	0.00981*
	(0.00493)
HH income per capita in 2010 (log)	0.341***
	(0.127)
Square of the log of HH income per capita in 2010	-0.024**
	(0.0106)
logcas2010	-0.0346
	(0.0360)
Village collective dividend in 2010 (log)	0.062***
	(0.0232)
Distance from county center (km)	-0.0281***
	(0.00569)

Distance from Beijing center (km)	0.0173***
	(0.0036)
village collective income in 2010 (￥10 thousand)	-0.0215
	(0.0291)
County ID	-0.409***
	(-0.091)
Constant	-0.021
	(0.0406)
Observations	783
ll_0	-530.2
Ll	-485.6
chi2	89.03
r2_p	0.0840

Notes: standard deviations are shown in parentheses.*,**,and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 6. Balance of Covariates

	Total sample (N=783)		PSM (trimed) (N=751)	
	Treat (N=324)	Control (N=459)	Treat (N=318)	Control (N=433)
DEMOGRAPHIC CHARACTERISTICS				
HH size 2010 (#)	3.398*** (1.346)	3.037 (1.182)	3.393*** (1.341)	3.090 (1.180)
HH head age(years)(log)	3.971** (0.211)	4.003 (0.202)	3.975 (0.210)	3.997 (0.201)
Proportion of children(less than 14) and old (more than 60) in HH	0.21*** (0.28)	0.25 (0.36)	0.207 (0.285)	0.242 (0.349)
HH head education(dummy: educated years>9 is 1, educated yeas<=9 is 0)	0.438*** (0.497)	0.328 (0.466)	0.440*** (0.497)	0.330 (0.471)
HH member maximum education (dummy: educated years>=12(high school)is 1, educated years <12 is 0)	0.407** (0.492)	0.386 (0.487)	0.409 (0.492)	0.395 (0.489)
VILLAGE CHARACTERISTICS				
Distance from the county center (Km)	16.833** (13.995)	19.648 (19.150)	16.808 (14.039)	18.236 (17.091)
Resident population in village (log)	6.571 * (1.005)	6.683 (0.733)	6.565 ** (0.997)	6.707 (0.730)

Notes: 25 covariates are used in probit model, only different significantly listed. Mean values are shown, standard deviations are shown in parentheses.

*,**,and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 7. Estimated RDEP Impacts

	TTEST Dif(T-C)	PSM-NN (t=318, c=188) ATT	NNMATCH (n=751) Coef
Gross income of HH in 2013 (￥yuan)	15630.19* (9256.52)	10774.873 (11251.043)	9763.446 (14523.73)
HH income from agriculture(￥yuan)	12603.27 (4272.92)	13666.889 (10296.019)	9300.953 (14380.98)
Agricultural labor use efficiency (￥yuan per person month)	234.54 (343.56)	928.272* (512.848)	539.372 (782.983)
Agricultural land productivity (￥yuan/mu)	230.94 (178.02)	435.733* (239.643)	437.160* (234.715)
Input per mu(￥yuan)	193.38*** (62.02)	194.360* (111.605)	139.099 (129.028)
HH nonagricultural income per off-farm working month (￥yuan)	- 237.7063 (479.158)	-37.286 (531.877)	-635.087 (742.756)
Totally person month working on agriculture (person*month)	0.98 (0.71)	-0.686 (1.092)	0.621 (1.058)
Totally person month working on non-agriculture (person*month)	4.72*** (0.98)	1.884 (1.403)	2.503** (1.233)

Notes: estimated values are shown, standard deviations are shown in parentheses. *, **, and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 8. Impacts of RDEP Across Districts

	Tongzhou		Pinggu		Huairou	
	PSM-NN (t=100,c=57)	NNMATCH (n=222)	PSM-NN (t=100,c=56)	NNMATCH (n=210)	PSM-NN (t=108,c=104)	NNMATCH (n=238)
Gross income of HH in 2013 (￥yuan)	1845.01 (8539.08)	6867.175 (7127.535)	33301.017 (33299.380)	4326.718 48687.86)	-7873.21 (6803.02)	2910.43 (5807.41)
HH income from agriculture(￥yuan)	4275.97 (4100.50)	6981.85 (4639.411)	32978.587 (32022.833)	-3094.542 (49281.19)	1944.65* (1130.01)	1442.68 (1780.82)
Agricultural labor use efficiency (￥yuan per person month)	814.50** (411.62)	889.540* (460.122)	30.555** (1446.292)	-2693.348 (2656.951)	1457.244** (577.387)	1663.087** (667.606)
Agricultural land productivity (￥yuan/mu)	663.66* (362.72)	700.476* (407.436)	-365.738 (560.022)	283.144 (469.819)	474.57** (174.93)	418.90* (217.00)
Input per mu(￥yuan)	139.194 (87.875)	183.916** (69.259)	323.130 (233.826)	326.636 (257.602)	117.80** (47.98)	73.46 (71.64)
HH nonagricultural income per person month (￥yuan)	-459.659 (742.390)	-151.613 (639.584)	-2245.642 (2278.481)	-1350.448 (1719.632)	-555.810 (1097.198)	877.588 (571.566)
Total person month working on agriculture (person*month)	-3.410** (1.704)	-2.790** (1.424)	-0.955 (2.449)	2.49 (2.417)	2.32** (1.00)	1.62 (1.31)
Total person month working on non-agriculture (person*month)	3.500 (2.763)	2.590 (1.984)	4.930* (2.540)	5.02* (2.583)	0.60 (1.61)	0.38* (1.73)

Notes: estimated values are shown, standard deviations are shown in parentheses. *, **, and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 9. Impacts of RDEP Across Education Level

	Low education		High education	
	PSM-NN (t=40,c=24) ATT	NNMATCH (135) Coef	PSM-NN (t=136, c=77) ATT	NNMATCH (294) coef
Gross income of HH in 2013 (￥yuan)	566.982 (9893.997)	2535.794 (7724.022)	5976.716 (14566.66)	-7066.322 (22418.27)
HH income from agriculture(￥yuan)	169.645 (0.061)	1949.676 (2521.584)	11387.307 (12067.96)	-619.340 (21148.58)
Agricultural labor use efficiency (￥yuan per person month)	1176.590 (849.889)	1464.216 (928.601)	1058.592 (997.335)	-23.811 (1710.536)
Agricultural land productivity (￥yuan per mu)	1008,351** (449.138)	397.377 (509.793)	165.198 (390.668)	246.408 (409.187)
Input per mu(￥yuan)	252.390** (100.529)	206.884** (97.928)	157.020 (85.948)	130.549 (122.105)
HH nonagricultural income per person month (￥yuan)	-3917.898 (2431.909)	-747.621 (1352.277)	-1185.468 (1379.586)	-400.280 (1144.261)
Total person month working on agriculture (person*month)	-4.875 (4.535)	3.521 (2.731)	-0.471 (1.400)	-0.619 (1.506)
Total person month working on non-agriculture (person*month)	4.325 (4.058)	4.979* (2.644)	0.596 (1.961)	-1.343 (1.482)

Notes: estimated values are shown, standard deviations are shown in parentheses. *, **, and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 10. Impacts of RDEP Across Asset Level

	Low Assets		High Assets	
	PSM-NN (t=75,c=38)	NNMATCH	PSM-NN (t=102, c=60)	NNMATCH (237)
	ATT	Coef	ATT	Coef
Gross income of HH in 2013	-2258.206	-4510.336	928.849	7729.977
(￥yuan)	(10188.184)	(5810.759)	(8802.272)	(5817.138)
HH income from	-3016.347	-1660.344	5726.281	6593.928
agriculture(￥yuan)	(7068.384)	(3112.354)	(3544.206)	(4379.704)
Agricultural labor use efficiency	1452.435**	1336.709	1008.901*	1345.939***
(￥yuan/person month)	(721.853)	(875.144)	(564.750)	(515.653)
Agricultural land productivity	424.454	84.616	935.484***	842.861**
(￥yuan/mu)	(499.435)	(335.667)	(318.115)	(383.102)
Input per mu (￥yuan)	156.038**	88.862	260.940***	236.214***
	(67.589)	(55.306)	(69.781)	(72.001)
HH nonagricultural income per	560.162	-1050.171	1.986	240.274
person month (￥yuan)	(926.645)	(1301.8)	(871.378)	(567.737)
Total person month working on	-4.573**	-1.08	1.176	1.627
agriculture (person*month)	(2.330)	(1.371)	(1.367)	(1.338)
Total person month working on	3.427	2.8	1.412	0.166
non-agriculture (person*month)	(2.967)	(1.873)	(2.309)	(1.740)

Notes: estimated values are shown; standard deviations are shown in parentheses. *, **, and *** denote 10%, 5% and 1% significance level.

Source: calculation based on data from own village and household survey (2014)

Table 11. Impacts on income per capita and assets, 2010-2013

Outcomes	Trimmed Sample (Tongzhou+Huairou)	Tongzhou	Huairou
DIFF Income per capita (log)	0.1483	0.3781 *	0.0639
	(0.0949)	(0.2009)	(0.1402)
DIFF Values of Fixed Assets (log)	-0.1106	0.1352	-0.2813
	(0.1708)	(0.2206)	(0.3119)

Notes: Mean values are shown, standard deviations are shown in parentheses. *,**,and *** denote 10%, 5% and 1% significance level.

Income and asset data in 2010 were not collected in Pinggu, so trimmed sample are 502 observations.

Source: calculation based on data from own village and household survey (2014)

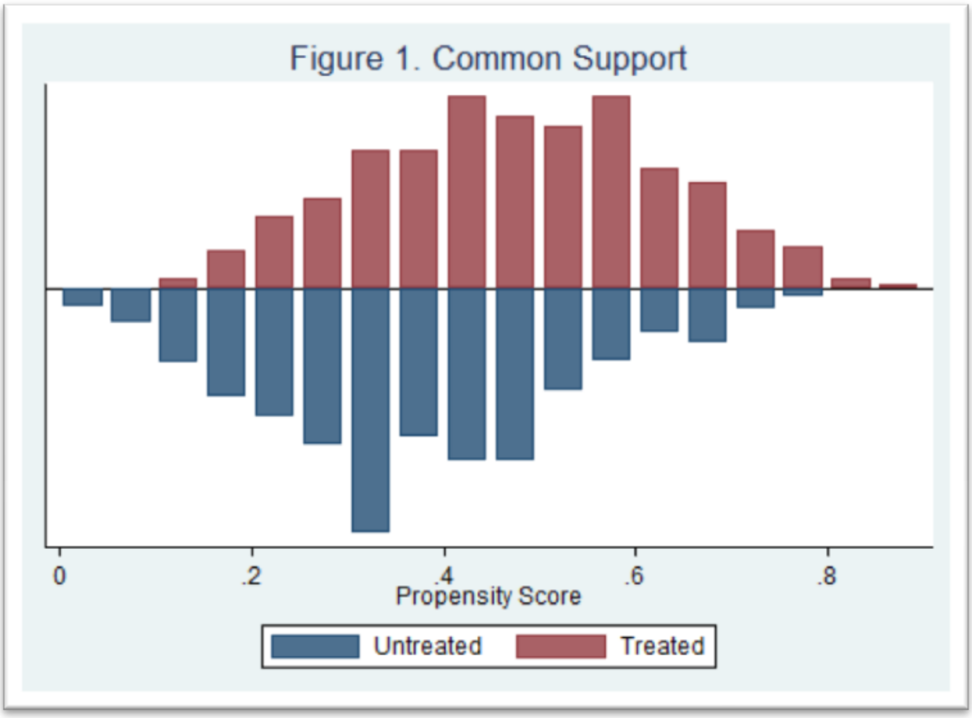

Figure 1. Common Support

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