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Productivity effects and farmland management: econometric evidence from farmland renting market in China

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Abstract

Using cross-sectional farm-level data from 1363 farming households in four regions of China, we provide empirical evidence concerning the effects of farmland renting on productivity and technical efficiency (TE), measure the impact of farmland renting on farm productivity while disentangling technology gaps (the distance between production frontiers) from managerial gaps (differences in technical efficiency). To do so, we combine a recently developed stochastic production frontier framework with impact evaluation techniques to control for biases stemming from observable variables. First, we find an adequate control group using propensity score matching to mitigate the effect of biases from observable variables. Then, we estimate SPF models for full sample and matched sample. Finally, we estimate meta-frontiers to assess productivity differences between renters and non-renters. The analysis shows that the renting of farmland has a significant and positive impact on productivity, efficiency and total value of agricultural production. This study contributes to the literature on impact evaluation by showing how an activity of renting farmland to improve farmland use efficiency can also enhance the income of farm households through increases in productivity.

Key Words

Farmland rental market; technical efficiency; propensity score matching; stochastic production frontier; meta-frontier

1. Introduction

China is facing the problem of how to consolidate small farmland plots into sufficiently large size ones, given fragmented and small-scale agricultural production due to the egalitarian distributed farmland since the late 1970s. In the search for ways to address the efficient use of farmland as well as to reduce poverty among farmers who work on various size of farmland, farmland rental markets for farmland use rights transferring has drawn increasing attention as an important instrument to improve efficiency with regard to resource allocation efficiency and agricultural productivity in China by both researchers and policy-makers. However, farmland in China is legally owned by the village collective, was initially not allowed for renting, because policy makers believed that farmland renting would lead to a concentration of farmland in the hands of a few households, leaving most households landless. Under the household responsibility system (HRS), farmland use rights have been equally assigned by the village collective to individual farm households for a period of up to 15 years, depending on family size, labor force, or a combination of both. Instead of farmland renting, frequent administrative re-allocations of farmland by the village collective have been used to correct for demographic changes. In 1997, an extension of land use right for 30 years was allowed, a rural farmland rental market has emerged in rural China in an attempt to ensure secure farmland use rights of farm so that they could benefit from better access to production management and from long-term farmland investment. In 2016, Chinese government has permitted another 30 years' land use rights after the first 30 years is expired in 2028.

Theoretically, well-functioning farmland rental market can achieve the goals of efficiency in two mechanisms. One Mechanism, farmland rental markets tend to equalize productive factor ratios across households with different farmland and non-farmland endowments by allowing productive resources (i.e. labor, agricultural assets) rich but landless or land-poor households to rent in farmland, and thus enhance allocative efficiency (Rahman, 2010; Huang *et al.*, 2012; Jin and Jayne, 2013). And the other mechanism, farmland rental markets contribute to agricultural productivity by facilitating transfers of farmland from less efficient producers to more efficient ones (Feng, 2008; Deininger *et al.*, 2008a).

Despite the potential of farmland rental markets to enhance efficiency, the conclusions on whether farmland rental markets will achieve the optimum outcomes remain elusive in practice, whether participation in farmland rental markets improves efficiency is an empirical issue. For example, in China, where credit and labor markets are imperfect, farmland rental markets often reach efficiency goal less than expectation. The more efficient but poor smallholders may not only have a greater disadvantage in accessing both farmland and capital inputs, but also lack insurance to avoid crop risks due to market variations and natural disasters in undeveloped credit markets (Tian *et al.*, 2012). Neither allocative efficiency nor increasing agricultural productivity effect of farmland distribution could achieve in farmland transactions because farmland rental markets could even transfer farmland from poor and farmland-constrained households to relatively rich and farmland-abundant ones (Jin and Jayne, 2013) in above case. And farmland rental markets may also fail to reach the goal of increasing agricultural productivity.

Available research on determinants of participating farmland rental market and farmland efficiency can be divided into three groups. One group examines the factors of farmland rental market participation in order to identify ways to encourage farmland transfers among farmers. Characteristics of household, household head and regions are the determinants tested in these studies (Deininger *et al.*, 2008; Jin and Deininger, 2009; Rahman, 2010; Huang *et al.*, 2012; Jin and Jayne, 2013). The second group examines farmland renting managerial performance, commonly proxied by technical efficiency

(TE). And the third group focuses on both farmland rental market participation determinants and farmland efficiency (Deininger & Jin, 2005).

Although the impact evaluation of participation in farmland rental market have been studied by some researchers, the effects of land rental markets on TE have received much less attention. There are still two remaining gaps that we are going to address in this paper: (1) We use a more recent dataset to explore the impacts (if any) that a better-developed farmland rental market has on household technical efficiency instead of the data from the early development period; and (2) An even more striking gap is the dearth of IE work that focuses on TE and that utilizes counterfactual methods to correct for selection bias (González-Flores et al., 2014). Our study contributes to closing this gap in the literature by using data from treatment and control groups along with stochastic production frontier (SPF) methods that correct for selection bias. This framework, based on De los Santos-Montero & Bravo-Ureta (2017) and Awal&Awudu (2018), allows us to obtain unbiased managerial TE and technological change (TC) effects attributable to farmland renting. The insights obtained from this study can provide an important input into the design of appropriate policies to improve the functioning of land rental markets and increase rural household TE.

The remainder of the paper is organized as follows. In the next section, we outline the study area and data source. In section 3, we describe our analytical framework and the estimation strategy. Results are presented in section 4, and the paper ends with some concluding remarks.

2. Study area and data source

To capture the agricultural production activities and the households' characteristics of Rural China, a household survey was conducted by Nanjing Agricultural University in Jiangsu province and Jiangxi province in 2015, Liaoning Province and Chongqing municipality in 2016. These four regions are located in different parts of China. Rice is the dominant crop, corn and wheat are also planted. The information collected in the survey includes crop production inputs and outputs, and farm and farmers' characteristics. Out of households that were interviewed, households (1486) provided 1363 (244 in Jiangsu, 356 in Jiangxi, 407 in Liaoning and 356 in Chongqing) sufficient information on crop production and characteristics that can be used for our analysis.

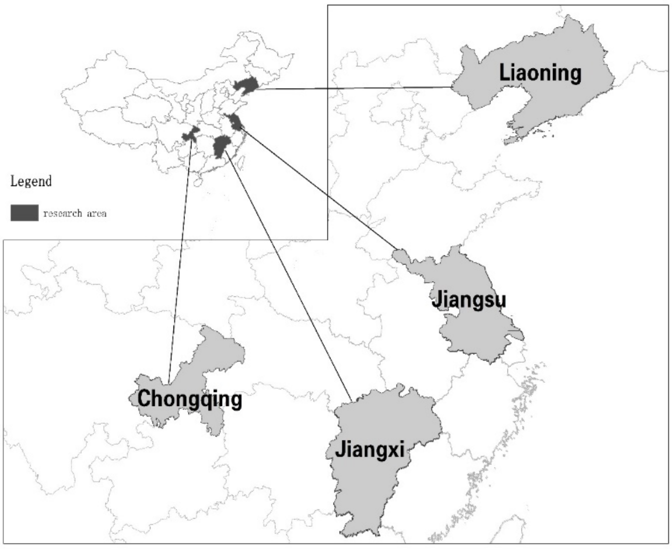


Figure1. Research Area

3. Econometric Analytical Framework

The main motivation of this study is to disentangle the effects of managerial ability on the productivity of farmers. To assess productivity differentials between treatment and control groups, we employ a multi-stage procedure in order to control for biases from observable variables and address some of the shortcomings in previous studies. First, propensity score matching (PSM) is used to select a sample of farmland renters (BENF) and non-renters (CONF) of with comparable time-invariant characteristics, so as to control for biases from observables since in our case panel data is not available. Next, standard stochastic production frontiers (SPFs) are estimated to measure productivity. And then, we estimate meta-frontier models to compare TE for BENF and CONF by providing a common technology of reference.

3.1. Propensity score matching (PSM)

To mitigate biases coming from observables, in the first step we use PSM to create a suitable counterfactual dataset. The use of PSM makes it possible to match BENF with CONF on observed time-invariant characteristics so that both groups are as similar as possible except for farmland renting.

To implement PSM, a binary choice model is used to generate a 'propensity score' (PS) for each farmer in the sample. These scores represent the probability of renting farmland, considering both BENF and CONF, based on a set of covariates (Becker and Ichino, 2002; Cameron and Trivedi, 2005; Imbens and Wooldridge, 2008). We assume that farmers rent the farmland in order to maximize the expected profits from production, and that the decision by farmers to rent the farmland can be explained by demographic, social and bio-physical characteristics. In general, the sample selection model can be expressed as:

$$rent_i = \alpha_0 + \sum_{j=1}^{no.v} \alpha_{ij} Z_{ij} + w_i$$

where *rent* is a dichotomous variable equal to 1 for renters, Z is a vector of exogenous variables explaining the decision of farmers to rent the farmland, are the unknown parameters, and is the disturbance term.

The PSs predicted after estimation of equation 1 are then used to match BENF with CONF for those farmers falling within a ‘common support’ area whereby observations from BENF with a PS smaller than the minimum or larger than the maximum for the CONF group are removed from the sample (Caliendo and Kopeinig, 2008). To ensure that the samples within the common support area have the same distribution of observable characteristics, regardless of whether the farmer has rented farmland or not, it is necessary to test for the ‘balancing property’ (Becker and Ichino, 2002). Once appropriately matched samples are identified, and assuming that there are no biases from unobservable variables, the impact of an intervention (farmland renting in our study) is often measured as the average treatment effect on the treated or ATT (Khandker et al., 2010). The ATT is the average impact of the treatment on those individuals who rented and, again assuming no selection bias, can be calculated as (Winters et al., 2010):

$$ATT = E\ (Y_1 \mid D = 1) - E\ (Y_0 \mid D = 0)$$

where Y_1 and Y_0 are the average total value of agricultural production for BENF and CONF, respectively, and D is a dummy variable equal to 1 (BENF) and 0 (CONF).

While different matching criteria are available, we use the 1-to-1 nearest neighbor matching (NNM) criterion without replacement, because this method is easy to interpret and reflects a clear match for individuals based on the assumption of common support (Caliendo and Kopeinig, 2008).

3.2. Stochastic production frontiers (SPF)

The second step involves the estimation of SPF methods. The limitation of most studies that have used SPFs to compare the TE of BENF versus CONF is the failure to account for selectivity biases arising from observable variables in a manner that is compatible with the nonlinear nature of the SPF approach. First, the estimation is done using the pooled (P) unmatched (U) sample of BENF and CONF groups. Next, we estimate two separate models using unmatched data, one for BENF and a second for CONF. Then, we perform a likelihood ratio test (LR) for the equality of the last two models. If there is no difference, then the model using the pooled dataset is supported. Subsequently, the process is repeated using the matched samples to estimate a pooled model. Then, two separate standard SPFs are estimated using the matched subsamples, one for BENF and another for CONF. Thus, the models in this step incorporate corrections for biases from observable variables (Bravo-Ureta, et al., 2012).

We use a Cobb-Douglas (CD) SPF model to estimate efficiency. The CD model can be formally expressed as follows:

$$\ln(Y_i) = \beta_0 + \sum_{j=1}^{no.v} \beta_j \ln X_{ij} + D + v_i - u_i$$

where Y_i represents output of the i[th] farm; X_{ij} is the quantity of the j[th] input; D denotes dummy variables; β_0 and β_j are unknown parameters; and v and u are the elements of the composed error term. The dependent variable in the estimated SPF model is total output (yuan). The explanatory variables comprise three conventional inputs. The conventional inputs include total area planted with crops (in mu), total labor used in farm activities (in worker-days), and purchased inputs presents the production costs, excluding labor (yuan). Table 1 presents the definition of variables (i.e., household characteristics, human, social and physical capital, village characteristics, and household incomes) used in the matching of farmers and villages, as well as the estimation of the SPF models.

Table1. Definition of variables used in the PSM and SPF models

Variables	Definition
Probit model	
Age	Age of the household head (years)
Education	Schooling of the household head(years)
Village official	=1 if the head of household is/was village official
Household size	Number of family members
Dependency no.	Number of dependents in household
Non-farm no.	Number of family members who do nonfarm work
Distance	Distance of each administrative village to the county seat (km)
Jiangsu	=1 if the household resides in Jiangsu,=0 otherwise
Jiangxi	=1 if the household resides in Jiangxi,=0 otherwise
Liaoning	=1 if the household resides in Liaoning,=0 otherwise
Chongqing	=1 if the household resides in Chongqing,=0 otherwise

SPF model	
TVAP	Total value of agricultural production (yuan)
LAND	Total land devoted to agricultural production (mu)
LABOR	Total value of family and hired labor (worker-days)
PINP	Purchased inputs present the production costs, excluding labor (yuan)
RENT	=1 if the household rent farmland from other farmers

3.3. Meta-frontier

A limitation of the methodological framework described above is that a direct comparison of TE between BENF and CONF is not possible because these scores are relative to each group's own frontier (González-Flores et al., 2014). To address this issue we estimate meta-frontiers for the preferred model as discussed below. Following the approach outlined by O'Donnell et al. (2008), we estimate a meta-frontier that envelops the deterministic component of the BENF and CONF group frontiers. This enables the estimation of the gaps between the meta-frontier and the individual group frontiers, termed the meta-technology ratio (MTR). O'Donnell et al. (2008) define the meta-frontier enveloping the deterministic component of the individual group frontiers (j) as:

$$y_i^* = f(x_i, \beta^*) = e^{x_i\beta^*}$$

where y_i^* is the meta-frontier output, β^* denotes the vector of parameters such that $x_i\beta^* \geq x_i\beta_j$ and β_j are parameters obtained from the BENF and CONF group frontiers. For given levels of inputs, the meta-technology ratio is calculated as the ratio of the highest attainable group output to the highest possible meta-frontier total value of agricultural production and is therefore an index lying between 0 and 1, defined as:

$$MTR = \frac{e^{x_i\beta_j}}{e^{x_i\beta^*}}$$

TE with respect to the meta-frontier is then calculated as:

$$TEM = TE_j \times MTR_j$$

To reiterate, our goal is to identify the impact of farmland renting on two components of productivity: (1) technological change, captured as a shift in the frontier due to farmland renting; and (2) managerial performance, measured by TE scores. The estimation process is summarized as follows. First, all available data are used to estimate a probit model to calculate PSs, which are the basis for matching BENF and CONF and thus correct for biases from observed characteristics. Second, a pooled SPF model is estimated where the binary variable farmland renting (0 for CONF, 1 for BENF) is included as a regressor to account for technological change attributable to farmland renting. Third, separate SPF models are estimated using the matched subsamples, one for BENF and the second for CONF. Various hypotheses are evaluated using log-likelihood ratio tests. All models are estimated using Stata , R and OX softwares.

4. Empirical Results

4.1. Descriptive analysis

Table 2 presents the descriptive statistics for the variables included in our models before and after matching. The farmland renting rate in our sample is 26.49%. On average, the mean of three inputs are all statistically different from the CONF at 1% significance level. The data shows that BENF displays a higher TVAP (29106.03 yuan), a higher farmland size (27.05 mu), more labor input (88.93 days) and much more cost input (9305.29 yuan) compared to the CONF. It is found that there are remarkable differences in the composition of the asset portfolio between BENF and CONF, with the former having relatively younger household while the latter older and larger household size while the latter smaller. Once matching is done, the mean value of age and household size do not exhibit any statistical difference between RENT and CONF. In sum, the balance condition indicates that matching generated a suitable counterfactual group for our analysis.

Table2. Descriptive statistics of variables used in the matching and production models

Variable	Pooled		BENF		CONF		
	Mean	S.D.	Mean	S.D.	Mean	S.D.	t-test
Unmatched sample							
TVAP	15577.56	23607.49	29106.03	35295.92	11744.85	17076.58	**0.000**
LAND	14.13	25.28	27.05	43.02	10.40	12.82	**0.000**
LABOR	43.88	115.94	88.93	207.09	26.28	39.55	**0.000**
COST	4970.59	7035.24	9305.29	10842.88	3688.22	4331.87	**0.000**
Age	57.28	10.22	55.63	9.72	55.85	9.95	**0.000**
Education	6.86	2.58	6.69	2.51	6.74	2.53	0.130
Village official	0.24	0.43	0.21	0.41	0.23	0.42	0.191
Household size	4.01	1.68	4.17	1.69	4.21	1.74	**0.034**
Dependency no.	1.05	0.99	1.05	1.02	1.02	0.98	0.951
Nonfarm no.	1.16	1.07	1.12	1.08	1.21	1.11	0.493
Distance	5.65	4.19	5.52	3.95	5.62	4.01	0.487
Jiangsu	0.18	0.38	0.10	0.30	0.09	0.29	**0.000**
Jiangxi	0.26	0.44	0.28	0.45	0.28	0.45	0.349
Liaoning	0.30	0.46	0.33	0.47	0.35	0.48	0.102
Chongqing	0.26	0.44	0.29	0.45	0.28	0.45	0.224
Observations	1363		361		1002		
Matched sample							
TVAP	20425.44	29036.13	29106.03	35295.92	12069.12	18533.74	**0.000**
LAND	18.72	32.80	27.05	43.02	10.19	12.13	**0.000**
LABOR	57.60	152.24	88.93	207.09	27.38	41.39	**0.00**

COST	6496.76	8716.13	9305.29	10842.88	3736.73	4511.19	**0.000**
Age	55.74	9.83	55.63	9.72	55.59	9.98	0.759
Education	6.71	2.52	6.69	2.51	6.70	2.63	0.791
Village official	0.22	0.41	0.21	0.41	0.22	0.41	0.654
Household size	4.19	1.72	4.17	1.70	4.20	1.67	0.762
Dependency no.	1.03	1.00	1.05	1.02	1.03	0.97	0.629
Nonfarm no.	1.17	1.09	1.12	1.08	1.21	1.11	0.308
Distance	5.57	3.97	5.52	3.95	5.62	4.34	0.718
Jiangsu	0.10	0.30	0.10	0.30	0.11	0.31	0.708
Jiangxi	0.28	0.45	0.28	0.45	0.30	0.46	0.934
Liaoning	0.34	0.47	0.33	0.47	0.31	0.46	0.695
Chongqing	0.28	0.45	0.29	0.45	0.28	0.45	0.804
Observations	722		361		361		

4.2. Determinants of farmland renting

Prior to the discussion of this part's findings, we mention that, our data were collected in different year for different regions, as we already have dummy variables for regions so we did not add one more dummy for year.

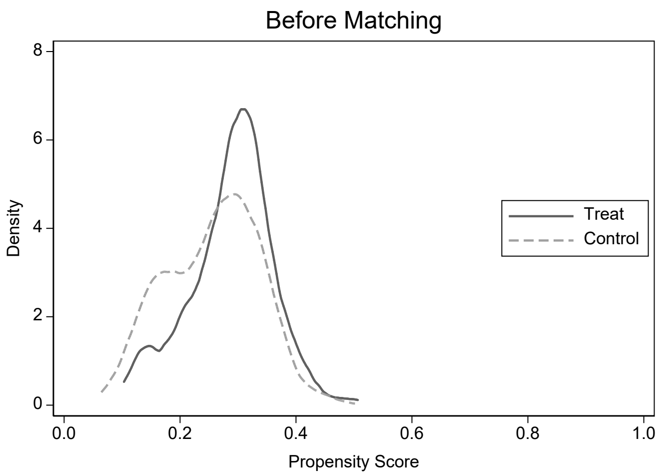
The estimated results from the bivariate probit model for households' participation in farmland rental markets are reported in Table 3. A statistically significant Chi-Square of 43.35, rejects the null hypothesis that all coefficients in participation of farmland rental markets equation are equal to zero. It also clearly shows that household head age, education, dependency numbers and nonfarm numbers do affect farm households' participation in farmland renting in a negative direction, while household size affects in a positive direction. With respect to household head age and education, younger household heads are more likely to rent in farmland from others, whereas the higher level education of household heads decreases the likelihood of renting in farmland. The significant and negative coefficients of dependency number and nonfarm number are consistent with our expectation, households with less dependency and non-farm members are more likely to rent in farmland. With more dependents in a household, they need to be taken care of by other working members and the work time on farmland is reduced, as a result they are less likely to rent in farmland.

Table3. Estimate of the Probit selection equation for land rental market participation

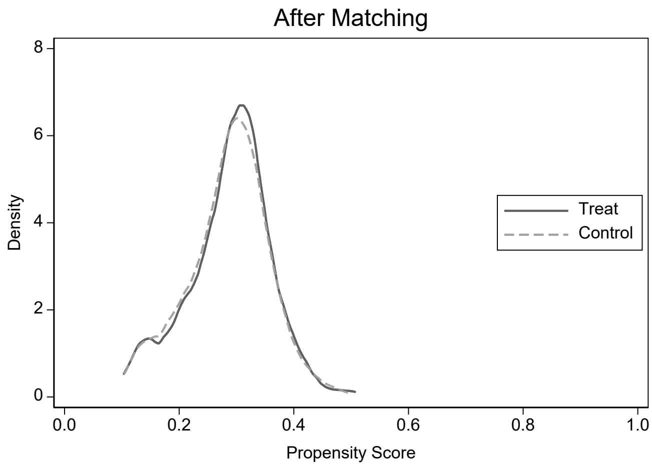
Variables	Coefficient	Standard error
AGE	-0.013***	0.004
Education	-0.033**	0.016
Village official	0.006	0.093
Household size	0.111**	0.037
Dependency no.	-0.111**	0.055
Non-farm no.	-0.078*	0.043
Distance	-0.006	0.010
Jiangxi	0.358***	0.128
Liaoning	0.403***	0.123
Chongqing	0.446***	0.126
Constant	-0.239	0.340
Log likelihood	-764.603	
Chi-squared	46.63	
N	1363	

Three geographic location dummies (i.e., Jiangxi province, Liaoning province, and Chongqing) also provide some evidence of regional effect (market information, market wage and other factors), Households in Jiangxi, Liaoning, Chongqing were more likely to rent additional farmland than households in Jiangsu. The possible reason could be the renting market is pretty developed while in the above three still are growing up.

The NNM criterion produced 361 pairs of observations for BENF and CONF. In the former group, 0 observation was discarded for BENF and 641 from CONF due to a lack of common support as showed in Figure 2 (a) and (b).



(a)



(b)

Figure 2.Kernel distribution of propensity scores for BENF (Treat) and CONF (Control)

Source: Authors' elaboration.

4.3. Production technology estimates

We next show results of separate and pooled SPF models for the unmatched samples for BENF and CONF for each of the two production systems. Preliminary comparisons lead to the acceptance of the CD functional form over the Translog (TL), and thus we use the former throughout. To compare the separate versus the pooled models, we use a likelihood ratio test based on Greene (2007), which can be expressed as:

$$LR = 2(\ln L_P - (\ln L_B + \ln L_C))$$

where lnLp, $\ln L_B$, and lnLc represent the loglikelihood function values obtained from the pooled (unrestricted model), and BENF and CONF subsamples (restricted), respectively. The LR tests confirm that BENF and CONF display different technologies.

Table 5 shows that Land and Cost (purchased inputs) are positively related to TVAP, as expected. The estimated parameters are (partial) production elasticities, which measure the contribution (%) of each input to output change (%). As expected, output responded positively and to land and cost. The results show that cultivated farmland (Land) makes the highest contribution to TVAP; i.e., a 1 % change in cultivated farmland produces a larger percent growth (around 0.80% for the poor dataset both before and after matching, 0.78% for the BENF and 0.87% for unmatched CONF, 0.86% for matched CONF) in output compared to labor and cost inputs, indicating the importance of farmland as a scarce resource for agricultural production in China. Feng (2008) reported similar results in her analysis of technical efficiency of rice producing of farm households in Jiangxi Province. In addition, the elasticity of output with respect to cost was different between BENF (0.18) and CONF (0.13) in the full sample, with CONF (0.15) in the matched sample. To our surprise, the output responses to labor is negative and statistically significant in the full sample for non-renters.
Before matching, the contribution of renting farmland is significantly positive, 1% increase in farmland renting, 0.02% increase in output. But after matching, we did not find the contribution of renting farmland on output.

Table4. Parameter estimates for the conventional SPF models: unmatched and matched sample

	Unmatched sample			Matched sample		
Variables	PF-U	BF-U	CF-U	PF-U	BF-U	CF-U
Land (log)	0.84***	0.78***	0.87***	0.81***	0.78***	0.86***
Labor (log)	-0.01	0.01	-0.02**	0.00	0.01	-0.01
Cost (log)	0.15***	0.18***	0.13***	0.17***	0.18***	0.15***
Rent	0.02*			0.01		
Jiangxi	-0.06***	-0.07**	-0.06***	-0.06***	-0.07**	-0.05**
Liaoning	-0.09***	-0.11***	-0.09***	-0.09***	-0.11***	-0.08***
Chongqing	-0.10***	-0.13***	-0.10***	-0.10***	-0.13***	-0.07**
Constant	2.81***	2.76***	2.85***	2.74***	2.76***	2.77***
lambda	0.57	0.37	0.69	0.48	0.37	0.64
sigma2	0.02	0.03	0.02	0.02	0.03	0.02
L.Likehood	761.42	140.44	645.31	332.69	140.44	200.41
Sample no.	1363	361	1002	722	361	361

Note: *** $p < 0.01$;** $p < 0.05$; * $p < 0.01$.
Source: Authors' calculation.

4.4. Efficiency estimates

Table 5 presents a summary of average TE scores coming from the SPF and the meta-frontier models, as well as the MTRs. we present results obtained from unmatched and matched samples, for conventional SPFs. In order to make a meaningful comparison of TE across different groups, we need to use a common benchmark technology, which is the reason why we estimate meta-frontiers. In addition, meta-frontiers make it possible to examine MTRs, a measure of the distance of the group frontier with respect to the meta-frontier (O'Donnell et al., 2008).

Table 5. Descriptive statistics of TE scores from alternative models

	Full sample			Matched sample		
Item	Mean	Min	Max	Mean	Min	Max
TE-group[a]	0.94	0.56	0.99	0.94	0.62	0.99
MTR[b]	0.97	0.92	1.00	0.97	0.89	1.00
TE-meta-frontier[c]	0.91	0.52	0.99	0.91	0.55	0.99

Notes: a technical efficiency with respect to the group frontier. b MTR: Meta-technology ratio. c Technical efficiency with respect to the meta-frontier. *** $p < 0.01$;** $p < 0.05$; * $p < 0.01$.
Source: Authors' calculation.

5. Conclusions

In this study, an emerging framework that combines stochastic production frontier (SPF) model with propensity score matching (PSM) was applied to disentangle the effects of technology and managerial gaps on technical efficiency (TE), and thereby on household productivity. We use cross-sectional data for beneficiary and control groups in four regions. A group of renters was matched with non-renters of farmland using PSM to reduce biases from observed variables. Initial model diagnostics confirmed that selection bias was present while implemented matching procedures were adequate to mitigate bias from observable variables.

The results of this study confirm the important role that several variables play on participation in farmland rental markets. In order to enhance farmland renting, there is a need to broaden the delivery of extension-related activities, including encourage the old generation to rent out their farmland to the young. On the other hand, there is a need to offset factors that constrain the farmland renting including giving more information to farmers suffering from less education.

Finally, analyses of the impact of participation in farmland rental markets suggest that there are significant differences in performance between renters and non-renters. These differences are in terms of output and TE and in both cases renters perform better. In other words, we uncover significant technological and managerial gaps both favoring renters and these gaps are more pronounced after correcting for selection bias. Moreover, we find that the participation of farmland renting can have a significant positive impact on the total output of farmers and thus on poverty alleviation.

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