Acta Sci. Pol.
Oeconomia 17 (1) 2018, 75–84
www.oeconomia.actapol.net ISSN 1644-0757 eISSN 2450-047X DOI: 10.22630/ASPE.2018.17.1.9

ORIGINAL PAPER

Received: 05.01.2018
Accepted: 08.03.2018

ANALYSIS OF CONTRACT FARMING EFFECTS ON EFFICIENCY AND PRODUCTIVITY OF SMALL-SCALE SUNFLOWER FARMERS IN TANZANIA – A PROPENSITY SCORE METHOD APPROACH

Daniel Mpeta[1], Joseph A. Kuzilwa✉[2], Batimo Sebyiga[2]

[1] Institute of Rural Development Planning, Tanzania
[2] Mzumbe University, Tanzania

ABSTRACT

This paper attempts to measure and compare technical efficiency (TE) levels across small scale contract and non-contract sunflowers farmers in Kongwa district, in the central agricultural zone of Tanzania. Sunflower is not the ideal contract crop; it lacks conventional characteristics of a contract crop such as high perishability, product homogeneity, high hygiene, and safety requirement at the end market and product being hard to grow. We apply propensity score method of Rosenbaum and Rubin to mitigate bias arising from observed characteristics among farmers in both groups. Participating in contract farming lead to an average increase in technical efficiency of a farmer by 4.5–7.4%, and this impact is significant at 5% level. Similarly contract participation increases land productivity of a famer by an average, in the range of 20.8–25.1 $kg \cdot ac^{-1}$. This impact is significant at 5% and the expected output(total factor productivity) per acre of an average contract farm produces 24% more sunflower per acre than non-contract farm. Participation in contract farming has a significantly positive effect on the use of high-quality seeds, which can explain a part of the higher (land) productivity of contract farmers compared to non-contract farmers. By improving service provision from contract firms to farmers (e.g. improved seed provision), there is still a room to improve efficiency, thereby increasing productivity and total output.

Key words: technical efficiency, propensity score method, contract farming, sunflower production, Tanzania

INTRODUCTION

This paper investigates the effects of contract farming on technical efficiency and productivity of small-scale sunflower farmers in Kongwa district. It is well known that agriculture production in developing countries generally has a very low productivity compared to non-agricultural production in the same country or to agricultural production in developed countries. The low agricultural productivity often has many diverse reasons, e.g. limited knowledge about productivity-enhancing production methods and highly productive technologies, limited availability of or access to highly productive varieties and productivity-enhancing inputs, limited availability of liquidity and limited access to credit, and/or reluctance to invest in productivity-enhancing measures due to production risk, output price variability, and unreliable market access combined with (rational) risk aversion of poor farmers.

✉ jakuzilwa@mzumbe.ac.tz

Contract farming is seen as a tool to increase agricultural productivity in developing countries, as it could solve some of the abovementioned problems, e.g. by improving access to knowledge, better technologies (e.g. highly productive seed varieties), productivity-enhancing inputs, and credit and by providing more predictable output prices and guaranteed market access. Vertical integration in production and marketing has often been a case for perishable products, products with technical requirements and economic importance [Bijman 2008]. Over time however, this practice is increasingly being extended to several other mundane crops [Guo and Fraser 2015].

There exist some studies in the literature [Bravo-Ureta and Pinheiro 1997, Begum et al. 2012] that compare the productivity and efficiency of contract farmers and non-contract farmers in developing countries but most of these studies on contracts involving crops considered to be ideal contract crop, i.e. crops with specific characteristics such as high perishability, product homogeneity, high hygiene and safety requirement at the end market and product being hard to grow. There are only very few studies that analyse the causal effects of contract farming in commercial production involving low value crops like sunflower as it is in this paper.

THE OBJECTIVE OF THE STUDY

The main objective of this study is to accurately measure the impact of contract farming on technical efficiency and productivity of sunflower farmers in Kongwa. The specific objectives of this study are as follows:

Technical efficiency (TE) as presented in literature [Farrell 1957, Coelli et al. 2005], is about the maximization of output for a given set of inputs. It compares the actual input combinations used to produce a unit of the output with an efficient, unobservable, but estimatable isoquant from sample observations. Technical efficiency is measured by comparing the observed output in production function against the feasible (frontier) output under the assumption of fixed input; alternatively, it is measured as the ratio between the observed input and the minimum input under the assumption of fixed output in cost functions. Technical efficiency indicates how far the firm can increase its output without employing additional resource but rather improving the level of its efficiency. It helps understanding of how farmers are operating and what factors are affecting their production. Thus, through non-price factors, contract farming may bring about a decrease in cost of production or increase in yield per unit, which in turn may enhance production efficiency, productivity and incomes of farmers involved.

MATERIAL AND METHODS

This paper uses data from a cross sectional farm survey conducted in Kongwa district of Dodoma in central agricultural zone of Tanzania. The data were collected between September and October 2012 under POLICOFA I project, the project sponsored by DANIDA Fellowship Centre through Tanzania-Denmark Pilot Research Programme. The sample included 400 small-scale sunflower farmers stratified on participation: 205 were contract farmers while 195 were non-contract farmers. Two stage sample design was used to collect the data. First, eight villages from four wards were selected purposefully on account of contract farming presence. Then, the contract farmers were randomly selected from list of contracted farmers, and non-contract farmers were also randomly selected from village households list. The data collection was carried out by face to face interview with the household head using structured questionnaire.

This study uses stochastic models as proposed by Kumbhakar et al. [1991] and extended by Battese and Coelli [1995]. The use of stochastic model is more appealing because the model allows accounting for the statistical noise and inefficiency. It provides estimators for the parameters of model linear in parameters with a disturbance term that is assumed to be a mixture of two components, which have a strictly non-negative and symmetric distribution respectively [Kumbhakar and Lovell 2000]. It generates good results for a production set-up in which there is a single output and multiple inputs.

The frontier model with Cobb–Douglas formulation fitted in this paper is of the following type:

$$\log \textit{yield} = \beta_0 + \beta_1 \log(\textit{farmsize}) + \beta_2 \log(\textit{labour}) + \beta_3 \log(\textit{implement expenditure}) + \beta_4 \log(\textit{seed}) \mid + \alpha_1 + \varepsilon \qquad (1)$$

Technical efficiency level is predicted after estimation of the frontier production model.

In order to effectively investigate the effects of contract farming on technical efficiency of sunflower production of small farmers involved in Kongwa district, this paper adopts Roy–Rubin model [Roy 1951, Rubin 1974] as cited in Caliendo and Kopeinig [2008]. According to this model, conclusion about the impact of a given treatment on outcome of interest for the individual beneficiary involves estimation of how the individual would have performed had he not received the treatment (the missing counterfactual). The frame of analysis consists of treatment which in this study refers to participation into contract farming; the treated are individual household participating in contract farming, while the effect or outcome of interest is the change; that is, increase or decrease of technical efficiency and productivity of farmers participating in contract farming.

Propensity score matching method and the treatment effects on the treated (ATT)

Let C, be a dummy variable, such that $C = 1$, if a household participates in contract farming and $C = 0$, if otherwise. And let Y_{1i} and Y_{0i} denote potential outcome (technical efficiency or productivity) of contract and non-contract farming households respectively.

The observed outcome of individual household is: $Y = C\, Y_{1i} + (C = 1)\, Y_{0i}$, rather than $Y_{1i} - Y_{0i}$ for the same individual household. Thus, the primary treatment effect of interest to be estimated is the average treatment effect on the treated that can be written as:

$$\tau = E\,(y_{1i} - y_{0i} \mid C = 1) = \mathrm{E}\,(y_{1i} \mid C = 1) - E\,(y_{1i} \mid C = 1) \tag{2}$$

The propensity score $p(X)$ is defined by Rosenbaum and Rubin [1983] as the probability of receiving a treatment or not conditional on given pre-treatment characteristics. The propensity score $p(X) \equiv \Pr(C = 1|X) = E(C|X)$. Propensity score matching is a way to correct the estimation of treatment effects controlling for the existence of the confounding factors, based on the idea that the bias is reduced when the comparison of outcome is performed using treated and control groups who are as similar as possible [Rosenbaum and Rubin 1983]. The propensity score replaces the collection of X characteristics in the observational study with just one number based on these characteristics. It reduces the dimensionality problem of matching treated and control units on the basis of the multidimensional vector of X. Then, X in equation (2) can be substituted for $p(X)$ so that:

$$\tau = E[\{y_{1i} - y_{0i} \mid C = 1\} = \mathrm{E}\,[\mathrm{E}\{\, y_{1i} - y_{0i} \mid C = 1, p(X)\}] = \\ = E[E\{\, y_{1i} \mid C = 1, p(X)\} - E\,\{\, y_{0i} \mid C = 0, \mathrm{p}(X)\} \mid C = 1] \tag{3}$$

According to Rosenbaum and Rubin [1983], however, certain assumptions need to hold. First is the balancing assumption (balancing hypothesis). It is assumed that there should be balancing of pre-treatment variables given the propensity score. That is: $X \perp C|p(X)$, implying that observations (treated and control) with the same propensity score must have the same distribution of characteristics independently of treatment status. Secondly, the assignment to treatment is unconfounded given the propensity score. That is, conditional on X; C and (Y_{1i}, Y_{0i}) are independent; by notation $Y_{1i}, Y_{0i} \perp C|p(X)$.

Common support condition

For quality matching of propensity score, proposition is further made that $0 < p(X) < 1$ to ensure common support, that is, there are treated and non-treated for each characteristic in X for which comparison is made. If the common support is not satisfied in the treatment group, e.g. if $p(X) = 1$, such households are dropped and ATT is estimated only for those households where: $p(X) < 1$. This restriction means that the test of balancing property is performed only on the observations whose propensity score belongs to the intersection of the support of the propensity score of treated and controls [Backer and Ichino 2002].

Matching estimators of the ATT based on the propensity score using different matching algorithms

This paper uses the most widely used methods, the nearest neighbour matching (NNM) where each treatment unit is matched to the comparison control unit with closest propensity score [Backer and Ichino 2002].

However, in order to check the robustness of the result of NNM, the effect of contract on technical efficiency and income using NNM method is compared to estimates using Kernel based matching method (KBM) and the ordinary least squares method (OLS).

The nearest neighbour matching (NNM)

In this method each treatment unit is matched to the comparison control unit with closest propensity score. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units and the outcome of the matched control units is calculated [Backer and Ichino 2002]. The ATT is then generated by averaging these differences and is given as:

$$ATT = \frac{1}{N_1} \sum_{i=1}^{N_1} (Y_{1i} - \sum_{j=1}^{N_0} w_{ij} Y_{0j}) \quad (4)$$

where: N_1 – number of participants;
N_0 – number of non-participants;
i – index of participants;
j – index of non-participants;
w_{ij} – weights: where $w_{ij} \in [0, 1]$ and $\sum_{j=1}^{N_0} wij = 1$;
Y_{1i}, Y_{0i} – outcome of interest on both participants and non-participants.

With NNM all treated units find a match [Backer and Ichino 2002].

RESULTS AND DISCUSSION

Table 1 compares selected variables between contract and non-contract farmers. Share of 79.3% of all households surveyed were headed by males while only 20.7% were female headed. The average age for non--contract farmers at 41.4 years is significantly lower than contract farmers at 43.7 years.

There are no significant differences in level of education between the two groups. In overall, the majority farmers (74%) have primary level education, while 23.3% have virtually no formal education. Only 2.3 and 0.5% have secondary and diploma education levels respectively. Generally the level of education among sunflower farmers is basically a primary education considered to be a low education but which can allow the needed flexibility in attitudes towards adopting new farming practices.

Comparatively as indicated in the Table 1. Contract farmers are on average not significantly different from non-contract farmers in terms of farm size and share of land allocated for sunflower production, which suggests that there is no pronounced concentration in sunflower production even among contract farmers. Yet contract farmers have significantly higher mean output and mean yield per acre. While contract farmers have mean output of 4,223 kg and mean yield per acre of 121.6 kg, mean output, and mean yield per acre among non-contract farmers are only 325.1 and 103.9 kg respectively, indicating that being in contract gives some advantages that enable farmers to produce more output per acre and more total output. Contract farmers have better access to high yielding seed variety and have higher rate of use of these improved seed at 46.3% compared to non-contract farmers' seed use at 8.7%. The mean technical efficiency for contract farmers is 68% while that of non-contract farmers is 64%, and the difference is statistically significant at 5% level of significance.

Using simple t-test results assessment was also made to see if there had been indication of self-selection bias observable among contract farmers, the idea was to speculate whether the observable gains among contract farmers are results of participating in contracts or are there just because these farmers had better conditions even before joining contracts (self-selection bias), and hence would emerge far better off than their fellow non-contract farmers even if they had not engaged themselves in contracts. This is just a preliminary investigation as the paper eventually carries out estimations of the actual effect of contracts on variable of interests namely; technical efficiency and productivity using a method of propensity score matching.

Thus, ownership of assets which are not likely to change due to contracts (pre-determined assets) is considered. Table 1 shows t-test results of the mean differences between contract and non-contract farmers. Results show that contract farming households are not significantly different from non-contract farming household in terms of household land endowment, non-agriculture assets possessed and amount of labour

Table 1. Summary statistics of socio-economic characteristics of farmers

Variables		T – sample means (N = 400)	Non-contract farmers (means) (N = 195)	Contract farmers (means) (N = 205)	t-Test of means difference
Household	age	42.55	41.36	43.67	–1.81**
	H/h size	5.38	5.44	5.33	0.50
	adults – ratio	0.49	0.48	0.506	–0.90
	dependence – ratio	0.49	0.51	0.47	1.71**
Farm	farm size	3.60	3.40	3.70	–0.29
	farm – ratio	0.48	0.47	0.49	–1.07
	land endowment	8.42	8.28	8.55	–0.36
	family labour	23.07	22.80	23.32	–0.30
	expenditure	50 337.6	48 143.75	52 424.53	–0.71
	seed (kg)	11.52	11.77	11.29	0.41
	output (kg)	374.9	325.13	422.25	–2.4**
	yield (kg·ac^{-1})	112.9	103.87	121.55	–2.17**
	tech. eff. level	0.65	0.64	0.68	–2.57**
Credit access	accesable credit (%)	4	4.1	3.9	
Extension	external service (%)	27	13.85	39.51	
Education	no education	23.25	25.13	21.46	
	primary education	74.0	73.33	74.63	
	secondary education	2.25	1.03	3.41	
	diploma	0.5	0.50	0.49	
Gender	male	79.25	75.9	82.40	
	female	20.75	24.10	17.56	

*, ** and *** represent significance at 10, 5 and 1% levels respectively.

power owned in households (given as proportion of adults in a household).

Basing on the t-test results in Table 1, it can be concluded that there is no strong evidence to suggest that there was self-selection bias among contract farmers. In other words, observable differences between contract and non-contract farmers in terms of productivity and level of total output could be attributed to contract participation.

The difference in technical efficiency score observed in the distributive statistics cannot be concluded to be a result of contract participation due to potential selection bias arising from some observable factors, which may be simultaneously influencing both participation and technical efficiency. To address selection bias, this paper adopts propensity score matching method. The paper follows the steps of Backer and Ichino [2002].

Using propensity score matching method, results in Table 2 show that, in overall, the logit model (participation model) is significant as expressed by Wald chi-square test (20) $\chi^2 = 69.18$, $P < 0.001$ and pseudo-$R^2 = 0.1010$. However, the pseudo-R^2 at 10.1% is low, indicating that although the model is significant, it only accounts for a small part of the variability of the dependent dummy variable, the contract participation. It is, however, argued in the evaluation literature that, in propensity score matching, trying to achieve balance on relevant predictors is more important than taking trouble trying to mode the selection process [Augurzky

Table 2. Logit (weighted) estimation of propensity score

Dependent variable: contract participation dummy	Coefficient	Robust *SE*	$P > \|z\|$
Explanatory variables			
Age (years)	0.023	0.011	0.04**
Household size (number of persons in the household)	0.059	0.089	0.51
Experience in growing sunflower	–0.003	0.039	0.944
P/education (1, if having primary education,0 otherwise)	0.419	0.296	0.157
S/education (1, if having secondary education,0 otherwise)	1.13	1.05	0.283
Household land endowment	–0.056	0.035	0.114
Land endowment per household member	0.350	0.208	0.092*
Value of non-agricultural assets (Tshs)	–1.85e-08	1.60e-08	0.248
Having a bank account (1 yes, 0 otherwise)	–2.26	0.636	0.000***
Savings 2 (1, if f/inst., 0 otherwise)	–0.801	0.700	0.253
Savings 3 (1, if assets, 0 otherwise)	0.702	0.243	0.004***
Dummy 1 (1, if village 1, 0 otherwise)	1.26	0.428	0.003***
Dummy 2 (1, if village 2, 0 otherwise)	1.26	0.400	0.002***
Dummy 3 (1, if village 3, 0 otherwise)	1.31	0.394	0.001***
Dummy 4 (1, if village 4, 0 otherwise)	0.731	0.391	0.062*
Dummy 5 (1, if village 5, 0 otherwise)	0.774	0.404	0.056*
Dummy 6 (1, if village 6, 0 otherwise)	–0.361	0.494	0.465
Dummy 7 (1, if village 7, 0 otherwise)	–0.651	0.525	0.214
Constant	0.048	1.49	0.974
Number of observations = 400			
Log pseudo likelihood = –159.95498			
Wald chi-square (20) = 69.18			
Prob. > χ^2 = 0.0000			
Pseudo-R^2 = 0.1010			

*,**,*** significant at the 10, 5 and 1% levels respectively.

and Schmidt 2001, Kiluve et al. 2002, Khandker et al. 2010] as cited in Venetoklis [2004]. This is also because for contracts, for example, there are explicit terms which are often reinforced by numerous unwritten rules, and implicit incentives which make it difficult to find observational data that captures every important aspect of the contract environment [Wu and Roe 2007].

Examination of the logit model indicates that, among all the predictors in the model as presented in Table 2 only age, land endowment per household member and having economic ability to make savings by means of purchasing assets including stocks of seasonal crop harvest for future resell or exchange significantly favour participation in the contract.

Having generated the propensity score, it is important to examine its distribution. The figure indicates that the propensity scores is reasonably similar in the contract and non-contract farmers. This is necessary to ensure that there are good matches as we apply propensity score matching method.

It is important to ensure that there are balancing scores within the common support region before proceeding to estimate the average effect of treatment on the treated (ATT). This is done by discarding treated individuals with a propensity score lying outside the common support restriction. The region of common support in this data is [0.01911637, 0.93316652] and its detailed summary is as described in Table 3.

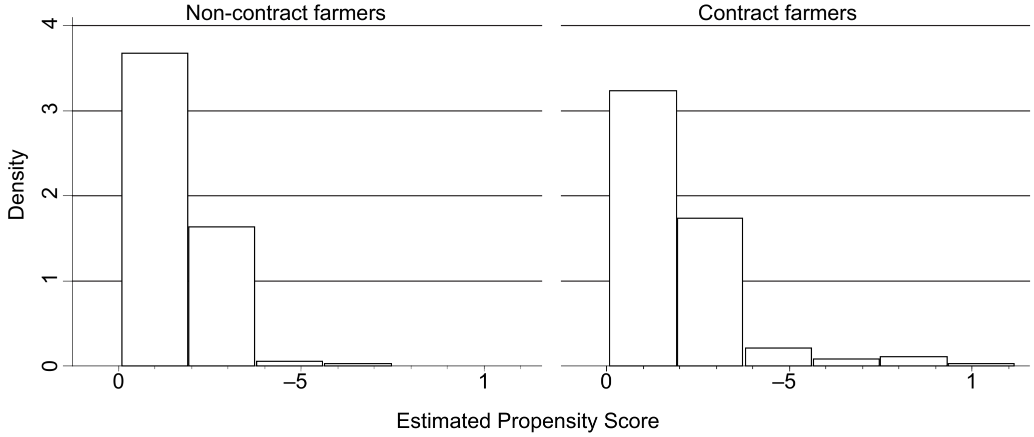

Fig. Distribution of propensity scores for non-contract and contract farmers

Table 3. Description of the estimated propensity score in region of common support

	Estimated propensity score			
	Percentiles	Smallest		
1%	0.02186	0.0191164		
5%	0.0333034	0.0199475		
10%	0.0477531	0.0215964	observations	399
25%	0.0858596	0.02186	sum of weights	399
50%	0.155941		*AVG*	0.1772523
		Largest	*SD*	0.1320227
75%	0.2351803	0.7968217		
90%	0.3154769	0.8012924	variance	0.01743
95%	0.3766117	0.8108296	skewness	2.138178
99%	0.7968217	0.9331665	kurtosis	10.23555

Table 4. Distribution of contract and non-contract farmers based on blocks of propensity score

Inferior of block of propensity score (with common support)	Whether a household is in contract or not		Total
×	0	1	×
0.0191164	135	128	263
0.2	49	37	86
0.3	7	25	32
0.4	2	8	10
0.6	1	4	5
0.8	0	3	3
Total	194	205	399

The common support option has been selected.

With skewness at 2.1 and kurtosis at 10.2, Table 3 further indicates that, the issue of normality in the distribution of propensity is score is not generally problematic. Balancing hypothesis is therefore likely to hold well.

Identification of the optimal number of blocks

The final number of blocks is 6. This is the number of blocks that ensures that the mean propensity score is not different for treated and controls in each block. This also means that each predictor used in the logit model does not differ between the two groups. Table 4 shows the inferior bound, the number of treated and the number of controls for each block. The balancing property in this analysis is satisfied. Final blocks are defined and the common support option has been selected.

Effect of contracts on technical efficiency and land productivity

Table 5 presents results of comparison between contract and non-contract farmers matched by the NNM. The 205 contract farmers are matched with 109 non--contract farmers. The ATT is shown for technical efficiency score and land productivity. With regard to technical efficiency the results in Table 5 indicate that, contract farming has significant positive effect on technical efficiency level of farmers. The ATT estimated by NNM method suggest that contract farmers are on average 7.4% higher in technical efficiency score than non-contract farmers. This difference in technical efficiency score is statistically significant at 5% level and above. Similarly, the results in Table 5 indicate that contract arming significantly increase land productivity (yield per acre) via improved technical efficiency. Contract famers have on average 25.5 kg more of sunflower yield per acre than the non-contract farmers. The result is statistically significant at 5% level or better.

To assess the robustness of the results another quite widely used technique of matching based on propensity score, the Kernel based matching method (KBM) is applied. Table 6 shows results obtained by KBM. Standard errors are obtained by bootstrapping using 100 replications because analytical standard errors could not be computed. The 205 contract farmers are matched with 194 non-contract farmers. The results obtained by KBM method for technical efficiency and productivity are statistically significant at 5% level and above, and appear to be substantively close to the results obtained by NNM method.

The results in Tables 5 and 6, taken together, present consistent evidence that contract farming has positive significant impact on technical efficiency in the range of 5.8–7.4%, and land productivity in the range of 20–25 kg.

Furthermore, based on the mean yield per acre and technical efficiency level statistics of both contract

Table 5. Average treatment effects on the treated

Matching algorithm	Outcome	ATT	*SE*	*t*	Number of treated	Control number
NNM	technical efficiency	0.074***	0.031	2.55	205	109
	land productivity	25.456**	11.533	2.20	205	109

,* significant at 5 and 1% levels respectively.

Table 6. Average treatment effects on the treated

Matching algorithm	Outcome	ATT	*SE*	*t*	Number of treated	Control number
KBM	technical efficiency	0.058***	0.018	3.290	205	194
	land productivity	20.883**	7.865	2.655	205	194

,* significant at the 5 and 1% levels respectively.

Table 7. Average effects of contracts on the treated

Matching algorithm	Outcome	Effect	Robust *SE*	*t*	Number of treated	Control number
OLS	technical efficiency	0.045**	0.01	2.30	205	195
	land productivity	15.04*	8.27	1.82	205	195

*,** significant at the 10 and 5% levels respectively.

and non-contract farmers as summarised in Table 1, the expected output (total factor productivity) per acre of an average contract farm is computed as 121.5 × × 0.68 = 82.6 kg, while that of a non-contract farm is equal to 103.8 × 0.64 = 66.4 kg. Thus, other things being equal an average contract farm produces 82.6/66.4 – 1, which is equal to 24% more sunflower per acre than non-contract farm.

Since results in descriptive statistics suggested that there was no selectivity bias, based on evaluation of time invariant characteristics. It would be reasonably right to estimate the effect of contracts on technical efficiency and land productivity by using OLS on the survey data without having to correct for selectivity bias. Results would equally be unbiased and consistent. Table 7 shows results obtained by OLS method. Standard errors indicated are robust as the sample is weighted. Compared to results from matching methods NNM and KBM, results by OLS method are similar in terms of sign, significance, though with slight difference in magnitude revealing the significance of carrying out treatment effect analysis.

CONCLUSIONS

Findings in this paper present important insights about functioning of contract farming and its effect on smallholder farming. It has been shown that contract farming of sunflower production in Kongwa district generates higher technical efficiency and increased yield (productivity) to households.

Simple comparison of treatment effects by OLS method are slightly inferior compared to results obtained by NNM and KBM procedures; this validates the robustness of the results and usefulness of the propensity score method in impact analysis. The method has the strength that, it reduces bias by matching treatment and control households on the basis of observable covariates [Khandker et al. 2010]. It assumes that selection bias is based on observed characteristics. This paper therefore, contributes to technical efficiency and productivity literature by implementing propensity matching technique, a non-experimental method with strength to address the problem of selection bias inherent in many observational data, a method that is relatively new in agricultural production economics studies.

Examining the magnitude of the estimated effects of contract on variables of interest, one might argue that the effects are not substantial enough to reflect the real potential of contract farming in raising technical efficiency as revealed in other studies, e.g. Ruben and Saenz [2008]. However, the fact that the results are positive and significant is of particular importance. Small, but significant effects could be pointing to the fact that present sunflower production contracts practiced are still confronting some problems. For example, despite that farmers need several types of inputs such as seeds, pesticides, and fertilizers for improved productivity, and only seed input is involved in present contractual agreements. Firms cannot expand their facilitation role to match farmers' basic demands they would like to have in contracts. By improving service provision from contract firms to farmers (e.g. improved seed provision), there is still a room to improve efficiency, thereby increasing productivity and total output.

REFERENCES

Augurzky, B., Schmidt, C.M. (2001). The propensity score: a means to an end. Discussion Paper 271. The Institute for the Study of Labor (IZA), Bonn.

Battese, G.E., Coelli T.J. (1995). A Model of Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. Empirical Economics, 20, 325–332.

Becker, S., Ichino, A. (2002). Estimation of average treatment effects based on Propensity Scores. The Stata Journal, 2 (4), 358–377.

Begum, I.A., Alam, M.J., Buysse, J., Frija, A., Van Huylenbroeck, G. (2012). Contract farmer and poultry farm efficiency in Bangladesh: a data envelopment analysis. Applied Economics, 44, 3737–3747.

Bijman, J. (2008). Contract Farming; An Over view: Agri--Pro Focus Expert Meeting on Contract Farming. Wageningen University, Utrecht.

Bravo-Ureta, B.E., Pinheiro, A.E. (1997). Technical, Economic and Allocative Efficiency in Peasant Farming: Evidence from the Dominican Republic. Developing Economies, 35 (1), 48–67.

Caliendo, M., Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of Economic Survey, 22 (1), 31–72.

Coelli, T., Christopher, P., Battese, G. (2005). An introduction to efficiency and productivity analysis. 2nd edn. Springer.

Farrell, M.J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A (General), 120 (3), 253–290.

Guo, S., Fraser, M.W. (2015). Propensity score analysis. Statistical Methods and Application: SAGE Publications, London.

Khandker, S.R., Koolwah, G.B., Samad, H.A. (2010). A Handbook on Impact Evaluation. Quantitative methods and practices. The World Bank, Washington, D.C.

Kiluve, J., Lehmann, H., Schmiat, C. (2002). Disentangling Treatment Effects of Polish Active Labour Market Policies; Evidence from Matched Sample. Discussion Paper 355. The Institute for Study of Labour (IZA), Bonn.

Kumbhakar, S.C., Ghosh, S., McGuckin, J.T. (1991). A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in United States Dairy Farms. Journal of Business and Economic Statistics, 9 (3), 279–286.

Kumbhakar, S.C., Lovell, C.A.K. (2000). Stochastic Frontier analysis. Cambridge University Press, Cambridge.

Rosenbaum, P., Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41–55.

Roy, A. (1951). Some thoughts on the distribution of earnings. Oxford Economic Papers, 3 (2), 135–145.

Rubin, D. (1974). Estimating causal effects to treatments in randomised and nonrandomized studies. Journal of Educational Psychology, 66 (5), 688–701.

Venetoklis, T. (2004). An evaluation of wage subsidy programs to SMEs utilizing propensity score matching. Valtion taloudellinen tukkimuskeskus (VATT), Government Institute for Economic Research, Helsinki.

Wu, S., Roe, B. (2007). Contract enforcement social efficiency and Distribution: some experimental evidence. American Journal of Agricultural Economics, 89 (2), 243–258.

ANALIZA WPŁYWU KONTRAKTACJI NA EFEKTYWNOŚĆ I WYDAJNOŚĆ MAŁOOBSZAROWYCH GOSPODARSTW PRODUCENTÓW SŁONECZNIKA W TANZANII

STRESZCZENIE

W artykule podjęto próbę pomiaru i porównania poziomów wydajności technicznej grup producentów słonecznika z małoobszarowych gospodarstw kontraktujących i tych bez kontraktacji w okręgu Kongwa, w centralnej strefie rolniczej Tanzanii. Zastosowano metodę oceny *propensity score* Rosenbauma i Rubina. Udział rolnika w kontraktacji prowadził do średniego wzrostu wydajności technicznej o 4,5–7,4%, przy znaczącym, pięcioprocentowym poziomie istotności. Podobnie większa była produktywność ziemi – średnio od 20,8 do 25,1 kg·ac^{-1}. Szacowana produkcja całkowita słonecznika w przeliczeniu na jeden akr w przeciętnym gospodarstwie kontraktującym przewyższyła o 24% poziom produkcji z grupy gospodarstw bez umowy kontraktacji. Kontraktacja miała znaczący, pozytywny wpływ na stosowanie wysokiej jakości materiału siewnego, co może częściowo wyjaśniać większą produktywność ziemi w gospodarstwach kontraktujących. Dalszy wzrost wyników produkcyjnych wciąż jest możliwy poprzez poprawę usług firm kontraktujących.

Słowa kluczowe: wydajność techniczna, metoda *propensity score*, kontraktacja w rolnictwie, produkcja słonecznika, Tanzania