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Improving greenhouse vegetable competitiveness through grants program from government in Kosovo

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Abstract

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Greenhouse vegetable cultivation is considered a priority sector for the Kosovo government based on employment potential, income, and export. Based on this, we assess the impact of the grant programs from the Ministry of Agriculture, Forestry and Rural Development (MAFRD) using genetic matching on improving the greenhouse vegetable sector in Kosovo. The main purpose of the study was to assess whether grants have an impact on the farmers' gross seasonal revenue after matching similar grantees to non-grantees. Results showed that greenhouse vegetable grantees make EUR 2 950.04 more per growing season in comparison to the non-grantees (95% confidence interval EUR 2 359.20 to EUR 3 540.25). We use propensity score matching (PSM) to estimate important matching variables that affect a farmer to be a grantee. The study identified that younger farmers, farmers with more years of education, and farmers from the rural area are more likely to be grantees.

Keywords: competitiveness; genetic matching; Kosovo; PSM; vegetable

Introduction

Agriculture is one of the main sectors of the Kosovo economy in terms of employment and contribution to GDP and is considered a priority sector by the Government of Kosovo. This sector was characterized for a long time by an unsuitable structure of crops, primitive equipment, and deficient performance (Muriqi et al., 2019). The last conflict in 1999 caused significant damage to the entire economy, including agriculture. Additionally, Kosovo has unfavorable farm structures, with an average Utilized Agricultural Area (UAA) per holding of 1.5 ha, fragmented into seven plots, and most of the crop farms are not performing efficiently despite the huge potential for technical efficiency improvement. The total number of persons involved in agriculture in Kosovo is 362 700, and the agricultural farmers who are registered in Kosovo are 130 775 (Miftari et al., 2017). Since 2007 there has been a significant improvement of financial support from the Government of Kosovo and the international donor community for the agriculture sector (Miftari, 2017). The financial support of MAFRD has marked an improvement in the performance of the vegetable sector, especially in the case of greenhouse vegetable. These grants have helped support desperately needed upgrades in farm facilities (Frangu, et al., 2018). Grants give positive effects in improving the performance of a farm, labor, and market organization. Grants are also a reflection that agriculture is developed not only by technology and good agricultural practices, but also by the organization and institutional support (Jacqueline et al., 2008; Ton et al., 2013). The purpose of this study was to identify the impact of MAFRD grants for the purchase of new greenhouses (grantees) in gross seasonal revenue that differs from non-grantees. Kosovo is a vegetable net importer country. Large quantities of fresh vegetable are continuously imported. Imports of fresh vegetable for 2019 were 56 589 tons, while it exported only 12

975 tons (KAS, 2020). The most cultivated greenhouse vegetable over the years in Kosovo remain peppers, tomatoes, and cucumbers (Balliu & Kaçiu, 2008). Although some empirical studies have been conducted regarding the impact of MAFRD grant programs (Frangu et al., 2018; Gjokaj et al., 2018; Bajrami et al., 2019), there are still gaps that show the effects of these grants on agriculture in general, and on greenhouses in particular. The survey data are analyzed using R Studio. In the study, we have included some factors that can influence a farmer to win a grant. One approach to understanding the gross revenue differences between the grantee and non-grantee farmers is the use of matching to compare grantees to similar non-grantees. A matching method known as genetic matching was selected to estimate the causal treatment effects of the farmers who received a MAFRD grant. We also used a propensity score matching model. The analysis used allows us to assess the influence of factors on the selection of a farmer to be the winner of the grant. Recognizing the potential of greenhouse vegetable would have positive effects in creating appropriate policies to reduce the trade deficit in this sector.

Material and Methods

Kosovo is a small country with a total area of 10 908 km^2, situated in the center of the Balkan, between the Mediterranean Sea and the mountainous regions of Southeast Europe. The data for the study were obtained from a survey in 150 agricultural economies from June to August 2019. The data included age in years, education in years, the experience of cultivation in years, and living area that takes values of 0 or 1. The farmers were from all seven regions of Kosovo.

Data

Propensity score approaches were first introduced by Rosenbaum and Rubin in 1983, and their use to control for confounding has been increasing in the previous decade (Sanni et al., 2019). The propensity score allows one to design and analyze an observational (non-randomized) study so that it mimics some of the particular characteristics of a randomized controlled trial. In particular, the propensity score is a balancing score: conditional on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects (Austin, 2011). Matching methods are commonly used in two types of settings (Stuart, 2010). One method includes genetic matching as a multivariate matching method (Frangu et al., 2018). Genetic matching is an algorithm that iteratively checks propensity scores. In this study, the genetic matching algorithm is used to find covariate balance after matching between MAFRD grantees and non-grantees. The implementation of this method enables us to estimate the average treatment effect on the treated (ATT), which we use to assess the average differences in the farmers' gross seasonal revenue between grantees and non-grantees. The genetic matching (Diamond & Sekhon, 2013) minimizes a multivariate weighted distance on covariates between treated and untreated cases, where a genetic algorithm is used to choose weights that optimize post-matching covariate balance. The distance minimized by the genetic matching algorithm is the generalized Mahalanobis distance (GMD).

$$\mathrm{GMD}\ (X_i, X_j, W) = \sqrt{(X_i - X_j)^{\mathrm{T}} (S^{-1/2})^{\mathrm{T}} W S^{-1/2} (X_i - X_j)}, \quad (1)$$

where X_i – covariates from farmers i; X_j – covariates from farmers j; and W – is a diagonal weight matrix with rows and columns equal to the number of covariates and is included to reflect the relative importance of each covariate to optimize overall covariate balance. The matrix from the model contains the covariates described in Table 1. $S^{-1/2}$ – is the Cholesky decomposition of S (Sekhon & Grieve, 2012) and T – indicates the transpose (Diamond & Sekhon 2013). The replacement was used to ensure that a farmer who received a grant (treatment group) has a proper match with a non-grantee (control group).

Considerations in covariate selection

Four factors that we measure may have an influence on a MAFRD grantee's ability to match with a non-grantee. The first covariate is age. According to Tauer (1995), the productivity of a farmer increases with age, reaches some mid-age peak, and then decreases with further age. An increase and then decrease in efficiency as a farmer age has implications for the survival of beginning farmers, for successful succession planning, and even for the competitiveness of the nation's farmers with farmers of other countries. Agriculture education enhances the farming skills and productive capabilities of the farmers (Weir, 1999). It enables them to follow some written instructions about the application of adequate and recommended doses of chemical and other inputs (Huang & Luh, 2009). Again, numeracy helps them to calculate the costs and benefits of adopting a particular farming technology (Paltasingh & Goyari, 2018). An earlier study that used propensity score matching found that education was positive and significant for cherry production (Ali et al., 2013). Based on these previous studies, we concluded that education was an important matching variable (Frangu et al., 2018). It is starting to become widely recognized that farmers' knowledge has an important role to play in bringing about sustainable innovations in agriculture (Chambers, 1989; Röling, 1996).

Based on this farm experience, is included as a matching variable. Farmers' years of experience vary by region in Kosovo. For example, farmers in the Prizren region have a long tradition of cultivating tomatoes and peppers (Frangu et al., 2018). Lastly, we consider that the living area may be an important variable in matching MAFRD grantees to non-grantees. In Kosovo, farmers living in rural areas are more likely to be grantees than farmers living in urban areas (MAFRD, 2020). Considering the fact that almost 62% of Kosovo's population lives in rural areas, we concluded that the living area would also be a significant variable.

Specification of the PSM Impact Evaluation Model

The assessment of the impact of a program (or a development intervention) requires a model of causal inference (Essama-Nssah, 2006). A number of evaluation techniques can be utilized to estimate treatment effects (Bajrami et al., 2019). Holland (1986) specifies such a statistical model. He starts from the fundamental observation that the effect of a cause can be understood only in relation to another cause. Thus, we can assess the effect of a MAFRD program of grants only if we know what would have happened without such an intervention. Our PSM impact evaluation model estimates the mean effect (impact) of the MAFRD program of grants on age, education, experience, and living area. The most common impact indicator of interest is the mean impact of treatment on the treated. Let $g = (y_1 - y_0)$, then the mean impact on the treated can be written as a conditional mean Heckman and Smith (1995):

$$ATT = E\,(g \mid x, d_i = 1) = E\,(y_{1i} \mid x, d_i = 1) - E\,(y_{0i} \mid x, d_i = 1), \qquad (2)$$

where E – is the expectations operator, y_{1i} – is the observed outcome of farmer i (participant), y_{0i} – is the observed outcome of the same farmer i (non-participant) and $d_i = 1/0$ denotes whether the farmer participated in grantees or not.

The missing data here relates to the counterfactual mean $E\,(y_{0i} \mid x, d_i = 1)$. One might be tempted to use the mean outcome for nonparticipants $E\,(y_{0i} \mid x, d_i = 0)$ as a proxy for the above counterfactual mean (Essama-Nssah, 2006). However, Heckman & Smith (1995) caution that subtracting the mean response for nonparticipants from the mean outcome of participants yields an estimate which is equal to the average treatment effect on the treated (the parameter of interest) plus selection bias. Selection bias stems from the failure of the assumption of unit homogeneity. In general, nonparticipants differ from participants in the nonparticipation state. This heterogeneity may be due to observable or unobservable characteristics (Heckman & Smith, 1995). The impact of grants was measured in two phases (Kabunga, 2014). In the first phase, a probit model was created for each farmer $P\,(x_i)$. The propensity score indicates the probability of a greenhouse vegetable farmer joining the program of grants given the covariates observed. The equation is as follows:

$$Pr\,(P_1 = 1 \mid x_i) = p\,(x_i) \qquad (3)$$

The control (non-participants) group was constructed by matching the participants with non-participant farmers based on their propensity score values. Observations without an appropriate match were dropped from further analysis (Bryson et al., 2002). To yield consistent estimates of program impact, matching methods rely on a fundamental assumption known as "conditional independence" or "selection on observables". This assumption can be formally stated as:

$$(y_0, y_1) \perp d \mid x \qquad (3.1)$$

The above expression states that potential outcomes are orthogonal to treatment status, given the observable covariates x are not affected by treatment. In other terms, potential outcomes y are independent of treatment assignment d (Imbens, 2004). This assumption reduces bias when the untreated units are constructed (Bajrami et al., 2019). For matching to be feasible, there must be individuals in the comparison group with the same values of the covariates as the participant of interest. This requires an overlap in the distribution of observables between the treated and the comparison groups (Essama-Nssah, 2006). The overlap assumption is usually stated as:

$$0 < Pr\,(d = 1 \mid x) < 1 \qquad (3.2)$$

This implies the possible existence of a nonparticipant analogue for each participant. This is all that is required for the estimation of the mean impact on the treated (Smith & Todd, 2005). When this condition is not met, then it would be impossible to find matches for a fraction of program participants.

Results and Discussion

Table 1 reports the statistical characteristics of the farmers included in the study. The average age of farmers receiving grants remains 41 years, while that of non-grantees is 43.52 years. Grantees have average education and experience in vegetable cultivation, 9.57 years, and 2.89 years. Non-grantees have average education of 8.12 years and experience in vegetable cultivation of about 3 years. Respondents' responses show that farmers living in rural areas show a higher tendency to receive grants from MAFRD than farm-

Table 1. Descriptive statistics of the covariates by grant status

Variable	Grantees (N = 47)				Non Grantees (N = 103)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Age (in years)	41	8.88	23	55	43.52	7.82	21	55
Education (in years)	9.57	1. 48	5	11	8.12	2.67	0	13
Experience (in years)	2.89	0.63	2	5	3.17	0.86	2	5
Living Area (Urban = 1)	0.19	0.40	0	1	0.45	0.50	0	1

ers living in urban areas. The main vegetable grown in the greenhouse were peppers around 59.4%, tomatoes at 22.5%, and cucumbers at 9.2%. Other vegetable were spinach, lettuce, and melon. The largest number of cultivated vegetable farmers are from the region of Prizren, followed by the region of Ferizaj. As expected, because the sites in "Rrafshi i Dukagjinit" (Prizren) and Ferizaj, have better climates for greenhouse production (Balliu & Kaçiu, 2008).

The box plot analysis from Figure 1 shows farmers producing greenhouse vegetable who reserved grants have realized a mean of EUR 6 952.90, while farmers who have not received grants have a lower mean of EUR 1 123.5. From the results, it is noticed that most non-grantees have generated seasonal revenue lower than EUR 5 000, while grantees higher than EUR 5 000 and only a few higher than EUR 15 000.

Considering that grants could have a positive impact on farmers' gross seasonal revenue, we estimated possible differences using gross seasonal revenue as the outcome variable in the model (Frangu et al., 2018). The average effect of treatment on the assessments treated (ATT) is indicated in Table 2. These results show a significant difference in seasonal gross revenue between grantees and non-grantees. There was a significant impact of grants in increasing farm income ($P < 0.05$). The estimate of a difference of EUR 2 950.04 in gross revenue per growing season was estimated for grantees relative to non-grantees. The 95% confidence interval is EUR 2 359.20 to EUR 3 540.25 per growing season.

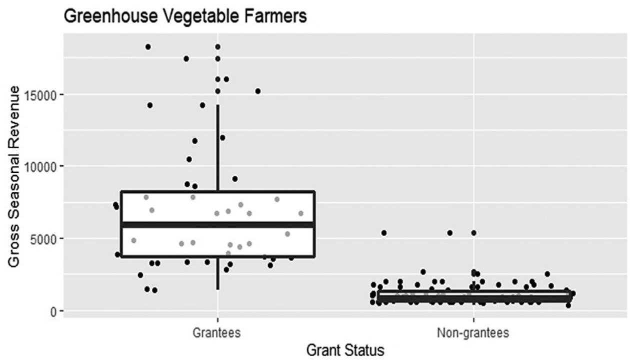

Fig. 1. Vegetable farmers' gross seasonal revenue levels

The standardized mean difference (SMD) is the most commonly used statistic to examine the balance of covariate distribution between treatment groups. Borestein (2009) recommends calculating the SMD for the study as the difference in means between the post-test and pre-test, scaled by the pooled (across pre-and post-test measurements) standard deviation. The genetic matching algorithm searches amongst a range of distance metrics to find the particular measure that optimizes post-matching covariate balance. Each potential distance metric considered corresponds to a particular assignment of weights for all matching variables (Diamond & Sekhon, 2013). These weights are used in the matching estimate of the ATT. There has been an improvement in the

Table 2. Greenhouse vegetable grantees' average treatment effect on the treated

Greenhouse Vegetable Grantees						
					95% CI	
Outcome Variable	Unit	Mean	T –stat	p-value	Lower	Upper
Gross Seasonal Revenue ESTIMATE	EUR	2 950.04	9.8704	2.2e-16***	2 359.20	3 540.25

Note: Significance levels: '***'0.001 '**' 0.01 '*' 0.05 '.'0.1

Table 3. Greenhouse vegetable covariate balance results

Covariate	Pre –Match (N = 103)			Post-Match (N = 47)		
	Grantees	Non – Grantees	d	Grantees	Non – Grantees	d
Age	41	43.52	- 28.42	41	40.71	- 6.31
Education	9.57	8.11	98.16	9.57	9.59	8.59
Experience	2.89	3.17	- 44.37	2.89	2.96	3.36
Living area	0.19	0.46	- 66.58	0.19	0.19	0

mean of age. This covariate's SMD went from – 28.42 to – 6.31. Age had a weight of 63. Educational showed a mean improvement of roughly a year and four months of education. Its SMD was reduced from 98.16 to 8.59, with a largest weight (337). Although experience had a relatively an improvement in the mean difference from – 44.37 to 3.36, yet had the lowest weight of only 24. The living area marked SMD improvements from – 66.58 to 0, with the relatively high weight of 290 (Table 3).

Estimated coefficients and standard errors indicate which factors influence the receipt of grants by farmers. A statistically significant coefficient suggests that the likelihood of a farmer receiving grants will increase/decrease as the response of the explanatory variable increases/decreases (Winship, 2003). Table 4 presents results estimated from the binary probit model. The ratio test statistic results of the model indicate that three variables are statistically significant at 0.001, 0.01, and 0.05 levels of significance. Elder farmers, farmers with fewer years of education, and farmers who live in an urban area are less likely to win grants from MAFRD. While experience is not statistically significant. For the estimated binary probit model, the pseudo-R^2 is about 0.25, indicating a good model fit (Domencich & McFadden 1974).

Table 4. Probit coefficient estimates for the SAC

Dependent variable	Coefficients		S.E.[1]
Age in years	- 0.05 *		0.02
Education in years	0.30 ***		0.09
Experience in years	-0.42		0.26
Living Area	-1.33**		0.45
Constant	0.34		1.51
N		150	
LR χ2		29.96	
Pseudo- R^2		0.25	

Note: Significance levels: '***'0.001 '**' 0.01 '*' 0.05 '.'0.1
[1] S.E. – Standard Error

The presence of the government grant programs as an agricultural policy may provide the opportunity to promote Kosovo's greenhouse production given that each year more and more farmers apply to the MAFRD grant programs (Frangu, et al., 2018). The impact of grants on gross seasonal revenue was estimated using genetic matching. From the results presented in the study, there is a significant impact of grants in increasing seasonal revenue for farmers who received grants. Grantee farmers who grow vegetable in greenhouses are expected to earn more than farmers who have not received a grant from the MAFRD ($P < 0.05$). The difference in gross seasonal revenue between grantees and non-grantees is EUR 2 950.04. In this study, important matching variables for greenhouse vegetable farmers were age, education, and living area. Variables included in the model have the expected signs (Bajrami et al., 2019). The MAFRD regulation says that younger farmers, with more years of education, and farmers from rural areas have the advantage of being grantees, compared to farmers who do not meet these criteria. Although experience had a relatively an improvement in the mean difference, had the lowest weight (only 24). From this, we conclude that experience is not statistically significant ($P > 0.05$). The estimated model pseudo-R^2 of the current study was fairly low (0.25). This indicates the covariates were well-fitted (balanced) with the model. In agreement (Pradhan & Rawlings, 2002; Caliendo & Kopeinig 2008) revealed that low pseudo-R^2 value indicates that the allocation of the treatment has been fairly random, and the result suggests that greenhouse grantees do not have diverse characteristics overall and hence obtaining a good match between treatment and control.

Conclusions

Agriculture plays a multifunctional role related to the economic, environmental, and social dimension of Kosovar families. The government grants program as an agricultural policy can provide good opportunities for farmers to encourage farmers to engage in greenhouse vegetable cultivation. This will be the best way to reduce imports, reduce poverty and increase fnarm incomes. Based on the importance of grants, we measured their impact on gross seasonal revenue for vegetable farmers in greenhouses. According to the results from the study, grantee farmers generate gross seasonal revenue of EUR 2 950.04 more than non-grantee farmers. Regarding the impact estimates, this study found the genetic matching method with a good convergence of the results with our sample of surveyed farmers (Frangu et al., 2018).

From this, we conclude that genetic matching can improve balance on measured covariates between the grantee and non-grantee farmers. A propensity score matching approach with three matching algorithms was age, education, and living area. While cultivation experience in years was not a significant variable. Additionally, the number of observations used in the study is small, and ATT results could vary with a larger sample. In conclusion, our findings suggest that grants from the MAFRD had a significant impact on increasing gross seasonal revenue for greenhouse vegetable farmers. The study results may help the MAFRD to promote the development of the vegetable greenhouse industry in the country. Through agricultural research, policymakers create the best choice of which sector promises employment, income growth and economic development. Considering balance on the covariates, it was found that based on the farmers' age, education, and living area balance was possible to be MAFRD grantees and non-grantees.

References

Ali, A., Sharif, M., Mahmood, K. & Akmal, N. (2013). Determinants of cherry production and marketing in Pakistan: A propensity score matching approach. *Agricultural Economics Review, 14(1),* 45-58.

Austin, P. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46(3),* 399-424. doi:10.1080/00273171.2011.568786

Bajrami, E., Wailes, E. J., Dixon, B. L., Musliu, A. & Durand-Morat, A. (2019). Do coupled subsidies increase milk productivity, land use, herd, size and income? Evidence from Kosovo. *Studies in Agricultural Economics, 121(3),* 134-143. doi:https://doi.org/10.7896/j.1913

Balliu, A. & Kaçiu, S. (2008). Potential of the greenhouse industry in Kosovo, 1st ed. Prishtine: Project funded by the governments of Switzerland and Denmark. doi:10.13140/RG.2.2.14793.54887

Bryson, A., Dorsett, R. & Purdon, S. (2002). The use of propensity score matching in the evaluation of active labour market policies. London: Policy Studies Institute and National Centre for Social Research.

Caliendo, M. & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal Economic Surveys, 22*, 37-72.

Chambers, R. (1989). Farmer first, farmer innovation and agricultural research. London: Intermediate Technology Productions.

Diamond, A. & Sekhon, J. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *The Review of Economics and Statistics, 95(3),* 932-945.

Domencich, T. & McFadden, D. L. (1974). Conditional logit analysis of qualitative choice behavior (2nd ed.). New York: Academic Press.

Essama-Nssah, B. (2006). Propensity score matching and policy impact analysis: A demonstration in EViews. Washington, DC: Policy Research Working Paper. Retrieved from openknowledge.worldbank.org/handle/10986/8730

Frangu, B., Popp, J. S., Thomsen, M. & Musliu , A. (2018). Assessing government grants: evidence from greenhouse tomato and pepper farmers in Kosovo. *Acta agriculturae Slovenica, 111(3),* 691-698. doi:doi:10.14720/aas.2018.111.3.17

Gjokaj, E., Leeds, S. & Halimi, K. (2018). The impact of financial support program in creation on farm jobs, Kosovo's case. *Bulgarian Journal of Agricultural Science, 24(6),* 933-941.

Heckman, J. & Smith, J. A. (1995). Assessing the case for social experiments. *Journal of Economic Perspectives, 9(2),* 85-110.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association, 81*(*396),* 945-960.

Huang, F. & Luh, Y. (2009). The economic value of education in agricultural production: a switching regression analysis of selected East-Asian countries. Bejining: International Association of Agricultural Economists Conference.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics, 86(1),* 4-29. doi:10.3386/t0294

Jacqueline, A. A., Ann, B. R., Gracia, T., Guerrero, M. d., Hernandez, L. A., Quiros, C. A. & Roa, J. I. (2008). Investing in farmers as researchers – Experience with local agricultural research committees in Latin America. In: *Investing in farmers as researchers,* 199. Cali, Columbia: Centro Internacional de Agricultura Tropical.

Kabunga, N. (2014). Improved dairy cows in Uganda: Pathways to poverty alleviation and improved child nutrition. Washington DC, USA: International Food Policy Research Institute (IFPRI).

KAS (2020). Kosovo Agency of Statistics. Retrieved February 3, 2021, from https://ask.rks-gov.net/

MAFRD (2020, March). Green Report. Prishtinë: Ministry of Agriculture, Forestry and Rural Development. Retrieved from https://www.mbpzhr-ks.net/repository/docs/PZHR_202021_final_7.pdf

Miftari, I. (2017). Efficiency analysis of alternative production systems in Kosovo – an ecosystem services approach. Gießen, Hesse: University Giessen.

Miftari, I., Gjokaj, E. & Zvyagintsev, D. (2017). Efficiency measurement of Kosovo crop farms data envelopment analysis, Parma, Italy. In: Proceedings of the XV EAAE Congress – Towards Sustainable Sustainable Agri-Food Systems: Balancing between Markets and Society.

Muriqi, S., Fekete-Farkas, M. & Baranyai, Z. (2019). Drivers of cooperation activity in Kosovo's agriculture. *Agriculture, 9(96).* doi:https://doi.org/10.3390/agriculture9050096

Paltasingh, K. R. & Goyari, P. (2018). Impact of farmer education on farm productivity under varying technologies: case of paddy growers in India. *Agricultural and Food Economics, 6(7).* doi:doi.org/10.1186/s40100-018-0101-9

Pradhan, M., & Rawlings, L. B. (2002). The impact and targeting of social infrastructure investments: Lessons from the Nicaraguan Social Fund. *The World Bank Economic Review, 16*, 275-295.

Röling, N. (1996). Towards an interactive agricultural science. *European Journal of Agricultural Education and Extension, 2(4),* 35-48.

Sanni, A. M., Prieto-Alhambra, D., Lopes, C. L., Ramos, D., Bispo, N., Ichihara, M.Y., Pescarini, J.M., Williamson, E., Fiaccone, R.L., Barreto, M.L., Smeeth, L. (2019). Propensity score methods in health technology assessment: Principles, extended applications, and recent advances. *Frontiers in Pharmacology*, 973. doi:10.3389/fphar.2019.00973

Sekhon, J. S. & Grieve, R. D. (2012). A matching method for improving covariate balance in cost-effectiveness analyses. *Health Economics, 21(6),* 695-714. doi:10.1002/hec.1748

Smith, J. A. & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Jour-*

nal of Econometrics, 125(1-2), 305-353. doi:10.1016/j.jeconom.2004.04.011

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science: a Review Journal of the Institute of Mathematical Statistics, 25(1),* 1-21. doi:10.1214/09-STS313

Tauer, L. (1995). Age and farmer productivity. *Review of Agricultural Economics, 17(1),* 69-69.

Ton, G., de Grip, K., Klerkx, L., Rau, M.-L. & Douma, M. (2013). Effectiveness of innovation grants to smallholder agricultural producers: An explorative systematic review. London: EPPI-Centre, Social Science Research Unit, Institute of Education.

Weir, S. (1999). The effects of education on farmer productivity in rural Ethiopia. Oxford: Oxford University.

Winship, C. (2003). Logit and Probit: Ordered and multinomial models. *Journal of The American Statistical Association, 98*, 775-776. doi:10.1198/jasa.2003.s301

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