INTERNATIONAL CONFERENCE OF AGRICULTURAL ECONOMISTS
ICAE
29th | Milan Italy 2015
UNIVERSITÀ DEGLI STUDI DI MILANO AUGUST 8 - 14
AGRICULTURE IN AN INTERCONNECTED WORLD

Are Farms in Less Favoured Areas Less Efficient?

Lajos Baráth[a], Imre Fertő[b], Štefan Bojnec[c]*

[a] *Research Centre for Economic and Regional Studies, Hungarian Academy of Sciences*

[b]*Research Centre for Economic and Regional Studies, Hungarian Academy of Sciences, Corvinus University of Budapest*

[c]*University of Primorska, Faculty of Management*

This paper investigates farm technical efficiency (TE), taking into account technological heterogeneity among farms in the case of the Slovenian Farm Accountancy Data Network sample of farms in the 2007-2010 period. A random parameter model is used to analyse inter- and intra-sectoral heterogeneity of farms. The empirical results confirmed that it is important to handle both inter- and intra-sectoral heterogeneity. Additionally the estimations based on propensity score matching (PSM) demonstrated that farms in less favoured areas (LFAs) are slightly technically less efficient than farms in non-LFAs. However, combined PSM and difference in difference estimator cast serious doubts that LFA farms are less efficient in terms of TE. Both groups of farms are able to adopt technologies to natural and other conditions for their operation.

Keywords: *technical efficiency, type of farming, less favoured areas, random parameter model, propensity score matching difference in differences.*

JEL codes: G22, L25, Q12, Q14

1. Introduction

The Common Agricultural Policy (CAP) of the European Union (EU) among important objectives focuses on different types of farming and particularly on farming in less favoured areas (LFAs). Farms in different types of farming and in different territorial areas, particularly in LFAs, can receive different policy attention. Therefore, the research question is whether farm technical efficiency (TE) is associated with types of farming and differences in natural agricultural factor endowments between different areas, which can influence technology used, and on direction of association between farm TE and LFA subsidies.

More specifically, this paper focuses on farm TE in association with types of farming and farm location in LFAs, and on farm TE in association with LFA subsidies. The Slovenian Farm Accountancy Data Network (FADN) sample of farms is used to answer on the set research question. Slovenia has been selected because most of the Slovenian farms are situated in LFAs (SORS, 2010), which cover 85% of Slovenian territory, of which slightly less than 72% are hilly and mountain areas (Republic of Slovenia, 2009). LFA subsidies are important to maintain the cultivation of agricultural land and for the existence of farm agricultural activity in LFAs, particularly marginal areas (e.g. Knific and Bojnec, 2010). The paper focuses on the two research issues. First, we analyse the impact of different technologies used by farms. It assumes inter-sectoral heterogeneity of farm technologies among different types of farming and intra-sectoral heterogeneity of farm technologies among farms. Second, we investigate the effect of operation in LFA on farm TE.

Therefore, the main novelties of this paper are twofold. First, random parameter model (RPM) methods are used to estimate TE for the Slovenian FADN farms. Second, propensity score matching (PSM) model and related methods are used to analyse the impacts of LFA on farms TE. Considering the importance of LFA in the Slovenian agriculture, the paper provides empirical results, which are important for research on LFAs and findings, which are important for agriculture and rural development policies.

The rest of the paper is organized as follows. In the next section is presented theoretical background, RPM and PSM model. After then are presented data and summary statistics with description of the variables used in the tested empirical models. Econometric results are based on the estimated RPM of TE for the Slovenian FADN sample of farms in association with farms situated at LFAs and non-LFAs. In addition, the impact of LFA subsidies on farms' TE is estimated using PSM approaches. Final section concludes.

2. Econometric estimation of TE

The first step of our investigation is the estimation of TE. Since the pioneering work of Knox-Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), efficiency measurement using stochastic frontier models has become a standard approach of applied economists (Tsionas, 2002). However, traditional efficiency models assume that all firms face a common frontier and the only differences result from the intensity of input use (Tsionas, 2002; Alvarez, 2012). "This implies that firms from different sectors but with the same input-output combination generate the same marginal products (Cechura and Hockmann, 2011: 4)."

However, in practice firms have different technologies for a variety of reasons (Tsionas, 2002); for instance as Xiaobing and Hockmann (2012) revealed in the Chinese agriculture: differences in resource endowment between different regions influence the technology applied in agriculture and cause location specific effects on production and technical change.

As our aim is to estimate TE for agricultural farms from different types of farming and compare farms at LFA and non LFA, the assumption of a common technology is certainly too strong. We therefore assume that heterogeneity exists both among different types of farming (inter-sectoral heterogeneity) and among farms (intra-sectoral heterogeneity) in LFA and non LFA. In order to handle both inter and intra-sectoral heterogeneity we use a RPM with types of farming dummies.

A general form of a RPM following (Greene, 2005) may be written as follows:

$$y_{it} = \alpha_i + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + v_{it} - u_{it}, \qquad (1)$$

where

$$v_{it} \sim N[0, \sigma_v^2],\ v_{it} \perp u_{it}$$

$$u_{it} = |U_{it}|, U_{it} \sim N[\mu_i, \sigma_{ui}^2],$$

$$\mu_i = \boldsymbol{\mu}_i'\boldsymbol{z}_i,$$

$$\sigma_{ui} = \sigma_u \exp(\theta_i'\boldsymbol{h}_i)$$

$$(\alpha_i, \boldsymbol{\beta}_i) = (\bar{\alpha}, \overline{\boldsymbol{\beta}}) + \Delta_{\alpha,\boldsymbol{\beta}}\boldsymbol{q}_i + \Gamma_{\alpha,\boldsymbol{\beta}}\boldsymbol{w}_{\alpha_i,\boldsymbol{\beta}_i},$$

$$\mu_i = \bar{\mu} + \Delta_\mu \boldsymbol{q}_i + \Gamma_\mu \boldsymbol{w}_{\mu_i},$$

$$\theta_i = \bar{\theta} + \Delta_\theta \boldsymbol{q}_i + \Gamma_\theta \boldsymbol{w}_{\theta_i}.$$

Each subvector of the full parameter vector, $(\alpha_i, \boldsymbol{\beta}_i)$, μ_i, θ_i allowed to vary randomly, e.g. in the case of $(\alpha_i, \boldsymbol{\beta}_i)$, with mean vector $(\bar{\alpha}, \overline{\boldsymbol{\beta}}) + \Delta_{\alpha,\boldsymbol{\beta}}\boldsymbol{q}_i$ where $\Delta_{\alpha,\boldsymbol{\beta}}$ is a matrix of parameters to be estimated and $\mathbf{q}_i$ is a set of variables that measure observable heterogeneity. Additionally,

$\boldsymbol{w}_{ki}$, k=$(\alpha, \boldsymbol{\beta}), \mu, \theta$ is an unobservable latent random term, which assumed to have mean vector zero and known diagonal covariance matrix Ω_j (usually assumed to be normally distributed); Γ_k denotes scale factor, $\boldsymbol{w}_k$ is an unobservable latent random term, u_i represents TE and v_i stands for statistical noise (Greene, 2005).

We estimated different specifications of the above model concerning the effect of observed heterogeneity. However, the model in many cases has collapsed. The specification with half-normal distribution for u_{it} and homoscedasticity in u_{it} was estimable. Furthermore, $\boldsymbol{w}_{\alpha_i,\boldsymbol{\beta}_i}$ was assumed to be normally distributed. In the general formulation this corresponds: $\mu_i = 0$; $\theta_i' = 0$ and $\boldsymbol{w}_{\alpha_i,\boldsymbol{\beta}_i} \sim N[0,1]$.

In the empirical application we assume a translog production frontier. Our empirical model was developed within a panel data methodology, with i=1,…N farms and t=1,…T observations per farm. Additionally, time variables (t), (tt) were added to the production function specification in order to capture the effect of technological change; the time trend is interacted with the input variables to allow for non-neutral technical change.
Our empirical model might be written as follows:

$$\mathrm{lny_{it}} = \beta_0 + \sum_{k=1}^{K} \beta_k \mathrm{lnx_{kit}} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \mathrm{lnx_{kit}} \mathrm{lnx_{lit}} + \sum_{d=1}^{D} \beta_d D\_TOF_{di} + \beta_t t + \frac{1}{2} \beta_{tt} t^2 + \sum_{k=1}^{K} \beta_{kt} \mathrm{lnx_{kit}} t + v_{it} - u_{it} \qquad (2)$$

where y_{it} is output and x are inputs in our case for labour, land, capital and intermediate consumption.

3. Econometric estimation of treatment effect

Our second research question is that how does LFA influence farms' TE. In standard policy analysis settings, the sample-average treatment effects cannot be calculated because we only observe one of the two possible outcomes for each individual. Thus we employ a matching estimation technique to identify the treatment effects. Following the insights of impact analysis literature we adopt a counterfactual framework developed by Rosenbaum and Rubin (1983). More specifically, farms selected into treatment and nontreatment groups have potential outcomes (TE scores) Y0, Y1 in both states (working or not in LFA) D=0,1: the one in which the outcomes are observed (E[Y1|D=1], E[Y0|D=0]) and the one in which the outcomes are not observed (E[Y1□D=0], E[Y0□D=1]). The most common evaluation parameter of interest is the 'average treatment effect on the treated' (ATT), defined:

$$ATT = E(Y_1 - Y_0|D = 1) = E[(Y_1|D = 1) - (Y_0|D = 1)] \quad (3)$$

Similarly we can derive estimators of the average treatment effect on controls (ATC) and the overall average treatment effect (ATE).

To solve the evaluator's classing problems the matching approach reproduces the treatment group among the nontreated by pairing each program participant with members of the non-treated group, controlling for observable characteristics. Estimating the treatment effects based on the propensity score matching (PSM) requires two assumptions. The first is the Conditional Independence Assumption (CIA), which states that for a given set of covariates participation is independent of potential outcomes. A second condition is that the average treatment effect for the treated (ATT) is only defined within the region of common support. This assumption ensures that treatment observations have comparison observations "nearby" in the propensity score distribution. For more comprehensive discussion of the econometric theory behind this methodology we refer the reader to Imbens and Wooldridge (2009) and Guo and Fraser (2010). However, the PSM has several limitations. First, PSM requires extensive data sets on large samples of units, and even when those are available, a lack of common support between the treatment or enrolled group and the pool of nonparticipants may appear. Second, the assumption that no selection bias has occurred arising from unobserved characteristics is very strong, and most problematic, it cannot be tested.

We employ propensity score matching (PSM) to predict the probability of working in LFA on the basis of observed covariates for both LFA and non-LFA. The method balances the observed covariates between the LFA group and non LFA farmers based on similarity of their predicted probabilities of being LFA farmers. The aim of PSM matching is to find a comparison group of LFA farmers from a sample of non-LFA farmers that is closest (in terms of observed characteristics) to the sample of LFA farmers.

Having data on LFA and non LFA farms over time can also help in accounting for some unobserved selection bias, by combining PSM and Difference-in differences estimator (conditional DID estimator). The conditional DID estimator (e.g. Smith and Todd, 2005) is highly applicable in case the outcome data on programme participants (i.e. working in LFA) and nonparticipants (working in non LFA) is available both "before" and "after"periods (2007 and 2010, respectively). In our study, the PSM-DID measures the impact of the LFA by using the differences in selected outcome indicator (ATE, or ATT) between LFA (D=1) and non LFA (D=0) in the before-after situations. The main advantage of the PSM-DID estimator is that it can relax the unconfoundedness assumption. The PSM-DID estimator also allows for quantile differences, that is assessing the effects of LFA at different points of the outcome variable's (TE scores) distributions. It means that we can compare individuals across both groups and time according to their quantile[1].

4. Data and descriptive statistics

For purposes of empirical analysis we used data from the Slovenian FADN, which was obtained from the Slovenian Ministry of Agriculture and Environment. FADN data at a farm level for Slovenia are available only for the years after Slovenia's entry into the EU in 2004. The database used consists of an unbalanced panel over the period 2007-2010. Some descriptive statistics and variables used are presented in Table 1.

Farms' total output (Y) in euro was used as an output variable, which was deflated by the producer price indices of agricultural products for agricultural goods. Four input variables were used: land input, which is expressed by utilized agricultural area (UAA) of farms in ha (X_1), labour input expressed in annual work unit (AWU) (X_2), total fixed assets in euro (X_3) and total intermediate consumption in euro (X_4) (Table 1). All values in current prices were deflated to the year 2005 using appropriate price indices obtained from the Statistical Office of the Republic of Slovenia. Total fixed assets were deflated by the agricultural input price index for goods and services contributing to agricultural investment, while total intermediate consumption was deflated by the agricultural input price index for goods and services currently consumed in agriculture.

In the FADN sample on average around 80% of farms are farming at LFAs during analysed period. Descriptive statistics of the variable presented in Table 1 reveal differences of output and inputs between farms at LFAs and at non-LFAs. The biggest difference can be observed in the case of output and intermediate input: Non-LFA farms produce more output and use less intermediate consumption.

The Slovenian farms can receive subsidies for different purposes. We divide the various subsidy forms into six major groups: total crops subsidy (SE610), total livestock subsidy (SE615), total rural development subsidy (SE624), subsidies on intermediate consumption (SE625), decoupled payment (SE630) and other subsidies (SE699). Figure 1 shows that average

[1] See Athey and Imbens (2006) and Imbens and Wooldridge (2008) for an overview on the quantile PSM-DID method.

subsidies per farms are considerably higher for non LFA than LFA farms. There are two prominent subsidy types: decoupled payment and rural development supports. The decoupled payment play dominant role following by rural development supports for non LFA farm. These subsidy forms are roughly equally distributed for LFA farms.

5. Econometric results

5.1. Technical efficiency (TE) scores

We interpret first the parameter estimates of the RPM (Table 2). The input variables have been normalized with their geometric means, so the obtained parameters can be considered as output elasticities evaluated at the mean of the sample. Most of the estimated parameters are highly significant and it can be seen that criterion of theoretical consistency is fulfilled as it holds: monotonicity ($\beta_n > 0$; $n = X_1, X_2, X_3, X_4$) and quasy-concavity ($\beta_{nn} + \beta_n^2 - \beta_n < 0$). This suggests that from theoretical point of view the RPM is applicable for further empirical analysis.

Regarding the effect of inputs on output it can be seen that the coefficient of elasticity associated with intermediate inputs is the largest, whereas, the coefficient of elasticity associated with land is the smallest. This relatively smaller impact of land on output can be explained by land fragmentation in Slovenian agriculture by farms and several parcels within a farm. The sum of the four coefficients of elasticities associated with labour, land, capital, and intermediate consumption is 1.18 suggesting increasing return to scale.

Moreover, both the dummy variables and the scale parameters were significant, indicating that there exist significant intra and inter-sectoral heterogeneity among the Slovenian FADN farms.

The regression coefficient that is associated with time trend is 0.015, which indicates on average technological development of 1.5% per year. The regression coefficient of time trend squared is positive and significant at 5% level, indicating that the rate of technical change increases at an increasing rate.

Additionally, the estimate of Lambda (λ) is high (1.89) and statistically significant, meaning that much of the variation in the composite error term is due to the inefficiency component, which show that technical (in)efficiency is an important aspect in Slovenian agriculture. Some differences are seen by type of farming from being insignificant for TF8=01 – fieldcrops and being negative and significant for TF8=06 – other grazing livestock, to being positive and significant for other types of farming when using TF8=08 – mixed farms as benchmark type of farming. In the next step of our empirical analysis we compared the obtained TE scores between farms in LFAs and non LFAs.

Figure 3 shows that TE scores have fluctuated over the analysed period, both for farms in LFAs and for farms in non-LFAs. The TE score of the Slovenian FADN sample of farms on median was for non-LFA farms higher than the TE score for LFA farms in almost every year (except 2009). Although the difference is small, there is larger variation in TE for LFA farms comparing to non-LFA farms. This is somehow expected because LFAs due to limited natural agricultural factor endowments may cause larger variation in output. However, the empirical evidence suggests that even farms in LFAs are able to adopt the technology in a similar way than other Slovenian FADN farms.

6. Impact of LFA

Descriptive analysis indicates that LFA farms in average are smaller and receive less subsidies comparing to non-LFA farms. This finding suggests that instead of LFA subsidies non-LFA farms utilized other agricultural and rural development subsidy programmes, which offset LFA subsidies. Moreover, mean comparison using Kruskal-Wallis test between two groups shows that non-LFA farms are more efficient than LFA farms. However, such results may based on a selection bias arising from the fact that non-LFA farms are higher and get more subsidy than their LFA counter partners. Thus we select total agricultural subsidy and economic farm size in terms of European Size Unit (ESU) as covariates that are likely to influence both to get subsidies and TE to ensure appropriate similarity between treated and controls without violating the common support assumption.

First issue in the PSM analysis is the choice of appropriate matching algorithm. The most commonly used matching algorithms involving propensity score are the following: Nearest Neighbour Matching, Radius Matching, Stratification Matching and Kernel Matching. As the quality of a given matching technique depends strongly on a dataset, the selection of a relevant matching technique is based on three independent criteria: i) standardized bias (Rosenbaum and Rubin, 1985); ii) t-test (Rosenbaum and Rubin, 1985); and iii) de joint significance and pseudo R^2 (Sianesi, 2004). Our estimations suggest that various methods produce very similar results, but nearest neighbours (N3) matching is the best matching algorithm for all cases[2].

In next step we employ balancing property test (t-test) to check statistically the comparability of two groups of farms in terms of observable covariates (Caliendo et al., 2008).

[2] We apply STATA psmatch2 programme developed by Leuven and Sianesi (2003)

Our estimations confirm that applied matching algorithm considerably improved comparability of two farms groups making counterfactual analysis more realistic (Table 5). After matching the differences between two groups on covariates became insignificant.

The common support condition is imposed in the estimation by matching in the region of common support. The distribution of the propensity scores and the region of common support are displayed in Figure 2. The figure shows the bias in the distribution of the propensity scores between the groups of supported and non-supported farms, and clearly confirms the significance of proper matching, as well as the imposition of the common support condition to avoid incorrect matches.

Table 6 presents our results on treatment effect using biased corrected and heteroscedastic robust estimator[3]. Negative coefficient on ATT suggests that farms working on LFA farms are less efficient then non-LFA partners. In other words, PSM estimator confirms the finding of the Kruskal-Wallis test.

To resolve some drawbacks of the PSM methodology we combined the PSM with DID methods to better match LFA and non-LFA farms on inital characteristics. Moreover, we extend the standard PSM-DID approach with quantile estimators allowing us to examine the LFA on entire distribution of TE scores[4]. Our estimations clearly show that we can reject the inequality in TE scores between LFA and non-LFA farms not only at the mean and but along entire distributions (Table 8). In other words, we do not find significant differences in TE between two farm groups. This finding does contradict our previous results. This can be explained by widespread LFAs in Slovenian agriculture, while natural and structural limitations for farming can be also present in non-LFAs. Both groups of farms are able to adopt best technologies to their heterogeneous conditions for operation. Thus differences in TE between both groups of farms are smaller than one could expect.

Finally we check the comparability of two groups of farms in terms of observable covariates. Our calculations show that after matching the differences between two groups on covariates became insignificant (Table 9).

7. Conclusion

Diversified farming structures by types of farming and a large share of UAA and farms in LFAs in Slovenia are challenging issues for research and for policy makers. While the previous

[3] We employ STATA nnmatch programme developby Abadie et al (2004).
[4] We use STATA diff programme developed by Villa (2011)

research investigated the role of subsidies on farm TE (e.g. Bojnec and Latruffe, 2013; Bojnec and Fertő, 2013), so far there has not been any study to investigate inter-sectoral heterogeneity of farms TE by type of farming and intra-sectoral heterogeneity of farms using RPM approach. As expected, the empirical results confirmed inter-sectoral heterogeneity of farms TE by types of farming and intra-sectoral heterogeneity among farms within the same types of farming. Additionally, the results revealed that farms TE in non-LFAs was a slightly higher than for farms in LFAs. However, combined PSM and difference in difference estimator cannot reject the hypothesis on equality of farms' TE between LFA and non-LFA groups of farms. Farms' TE between both groups of farms is more similar than different as both groups of farms are able to adopt technologies to their heterogeneous operational natural, structural and policy conditions. This finding provides a clear message that a given LFA conditions can be offset by adoption of technologies, which do not necessary result in lower TE than in non-LFAs. As a result, TE between both groups of farms is smaller or even more similar than different in maintaining agricultural production.

The large percentage of UAA and farms in LFAs can explain important role that natural and structural conditions for farming and subsidies can play for farms in Slovenia. Over the analysed 2007-2010 period, there has been identified a shift in the percentage of farms from being situated in non-LFAs to being situated in LFAs. Because subsidies in Slovenian agriculture in general are high, subsidies can play important role for both intra-sectoral income redistribution and factor allocation by types of farming and inter-sectoral income redistribution and factor allocation between farms situated in non-LFAs and LFAs. Subsidies have become an important factor of farm incomes, which has mitigated the exit of farms. Subsidies, can play a certain role in stabilization of farm incomes and government transfers to agriculture and rural areas for a provision of public services in keeping rural agricultural landscape cultivated also in areas, where agricultural factors endowments face certain shortcomings due to limited opportunities to use advanced agricultural machinery and technologies. Finally, the RPM and PSM methodological approaches applied in this paper are suggested to be used in the comparative cross-country research. This can provide comparisons between the Slovenian case study and possible new studies in other countries with the important role of LFA and other agricultural subsidies. The empirical results are of relevance for policy formulation towards LFAs in synergy between sustainable development of agriculture and other rural economy in the countryside.

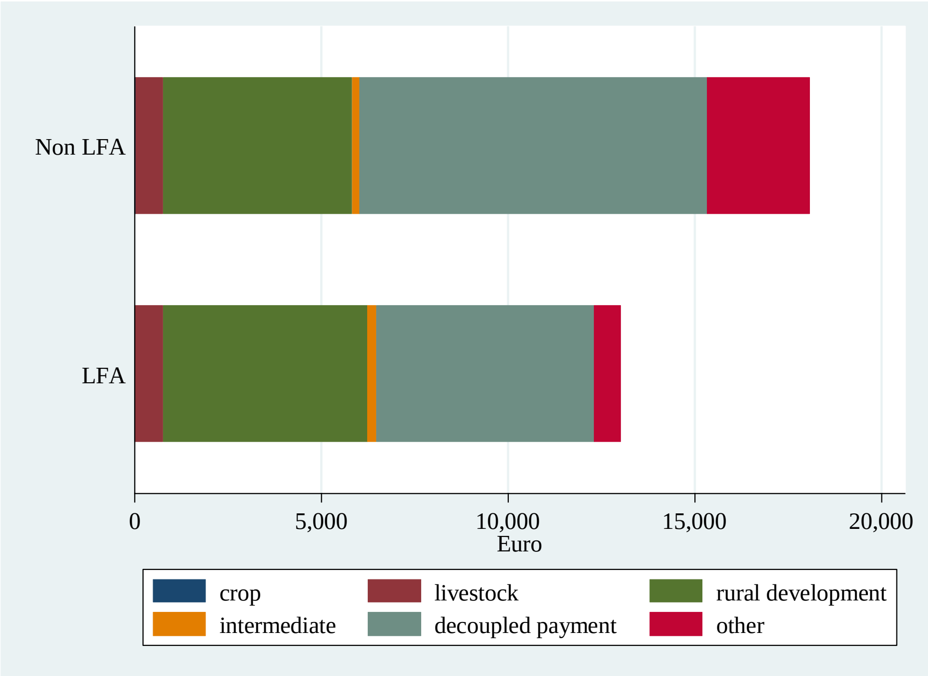
Tables and Figures

Table 1. Summary and description of the variable used

Variable	Symbol	Mean	Std. Deviation	Minimum	Maximum
		LFA farms			
total output	Y	39464.1	70660.1	-50279.6	2.43E+06
labour	X_1	2.18266	1.72077	0.12	46.0866
Land	X_2	20.4313	20.4448	1.1	325.62
Capital	X_3	268213	243542	469.722	6.51E+06
Intermediate cons.	X_4	16242.5	22876.8	0.12	231061
		Non-LFA farms			
total output	Y	55319.3	59411.7	-26495.6	593186
labour	X_1	2.32396	1.82575	0.20005	43.6173
Land	X_2	22.4178	21.5858	0.68	153.05
Capital	X_3	288837	243649	2000	1.93E+06
Intermediate cons.	X_4	22558.8	25425.8	0.15	221073
		All farms			
total output	Y	42964	68647	-50279.6	2.43E+06
labour	X_1	2.21385	1.74529	0.12	46.0866
Land	X_2	20.8698	20.7164	0.68	325.62
Capital	X_3	272765	243693	469.722	6.51E+06
Intermediate cons.	X_4	17636.8	23606.6	0.13	231061

Source: Own calculations based on FADN data

Figure 1 Mean size and distribution of agricultural subsidies between LFA and non LFA farms



Source: Own calculations based on FADN data

Table 2. Random parameter model of TE for the Slovenian FADN farms with types of farming dummies

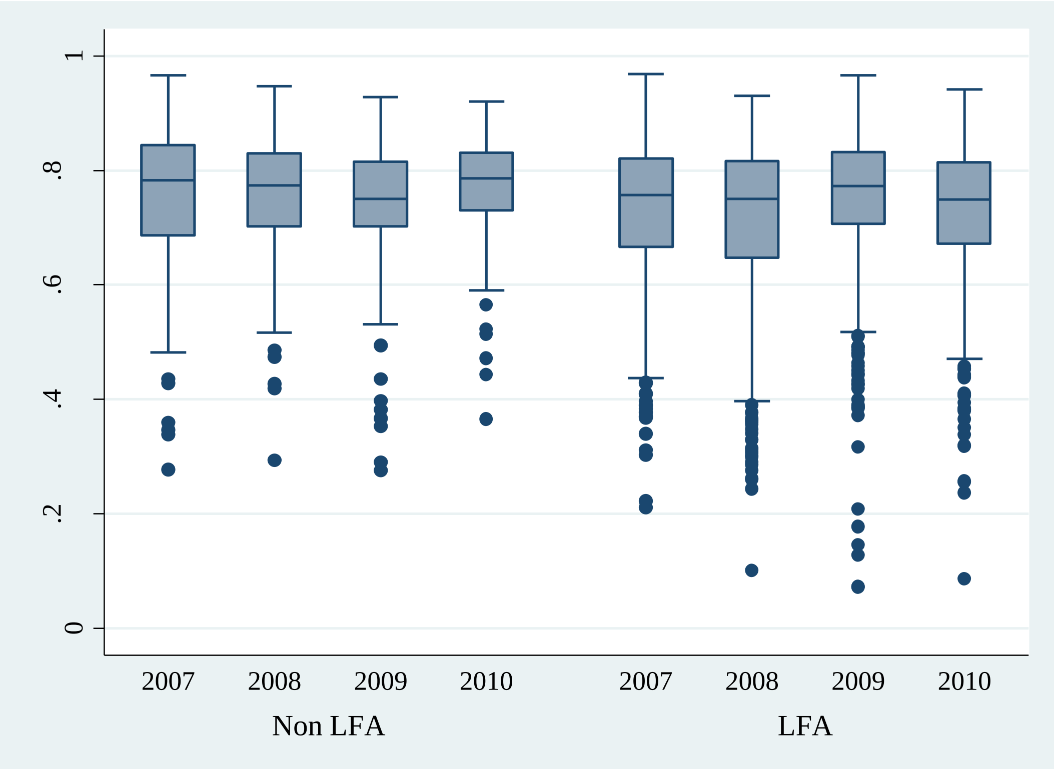
	Coefficient	Standard Error	Prob |z|>Z*
	Means for random parameters		
Constant	.18642***	0.01167	0.000
T	.01504***	0.00257	0.000
X1	.20994***	0.01004	0.000
X2	.15512***	0.01009	0.000
X3	.27761***	0.00932	0.000
X4	.53322***	0.00693	0.000
	Scale parameters for dists. of random parameters		
Constant	.23256***	0.00421	0.000
T	.02842***	0.00208	0.000
X1	.12061***	0.00787	0.000
X2	.05583***	0.00511	0.000

X3	.02398***	0.00524	0.000
X4	.13473***	0.00332	0.000
	Nonrandom parameters		
TT	.00718**	0.00297	0.0156
X1*X2	-.05184***	0.0163	0.0015
X1*X3	.08624***	0.01559	0.0000
X1*X4	-.07426***	0.0091	0.0000
X2*X3	0.00478	0.01372	0.7277
X2*X4	-.04623***	0.00838	0.0000
X3*X4	-.07672***	0.00905	0.0000
X1*X1	.16058***	0.02057	0.0000
X2*X2	.05908***	0.01777	0.0009
X3*X3	.09182***	0.01299	0.0000
X4*X4	.13363***	0.00679	0.0000
T*X1	.01787***	0.00473	0.0002
T*X2	-.00830*	0.00442	0.0604
T*X3	.01496***	0.00448	0.0008
T*X4	-.01063***	0.00302	0.0004
TF8=01	0.00311	0.01713	0.8558
TF8=02	.56988***	0.03911	0.0000
TF8=03	.59737***	0.02299	0.0000
TF8=04	.35405***	0.02017	0.0000
TF8=05	.08298***	0.01294	0.0000
TF8=06	-.18204***	0.01301	0.0000
TF8=07	.17493***	0.04488	0.0001
	Variance an asymmetry parameters		
Sigma	.45526***	0.00208	0.0000
Lambda	1.89400***	0.01873	0.0000

Source: Own calculations.

Note: ***,**,* denote significance at 1%, 5% and 10% level

Figure 2 Boxplots for TE scores over time and by farm types



Source: Own calculations.

Table 4. Comparison of matching algorithms

	Matching parameters	Sample	Pseudo R^2	p>chi^2	Mean Bias
radius caliper	0.1	Raw	0.015	0.000	26.1
		Matched	0.004	0.000	5.5
kernel (Gaussian)		Raw	0.015	0.000	26.1
		Matched	0.004	0.000	5.5
nearest neighbours	N(1)	Raw	0.015	0.000	26.1
		Matched	0.004	0.000	5.5
nearest neighbours	N(2)	Raw	0.015	0.000	26.1
		Matched	0.001	0.021	.0
nearest neighbours	N(3)	Raw	0.015	0.000	26.1
		Matched	0.001	0.036	2.8

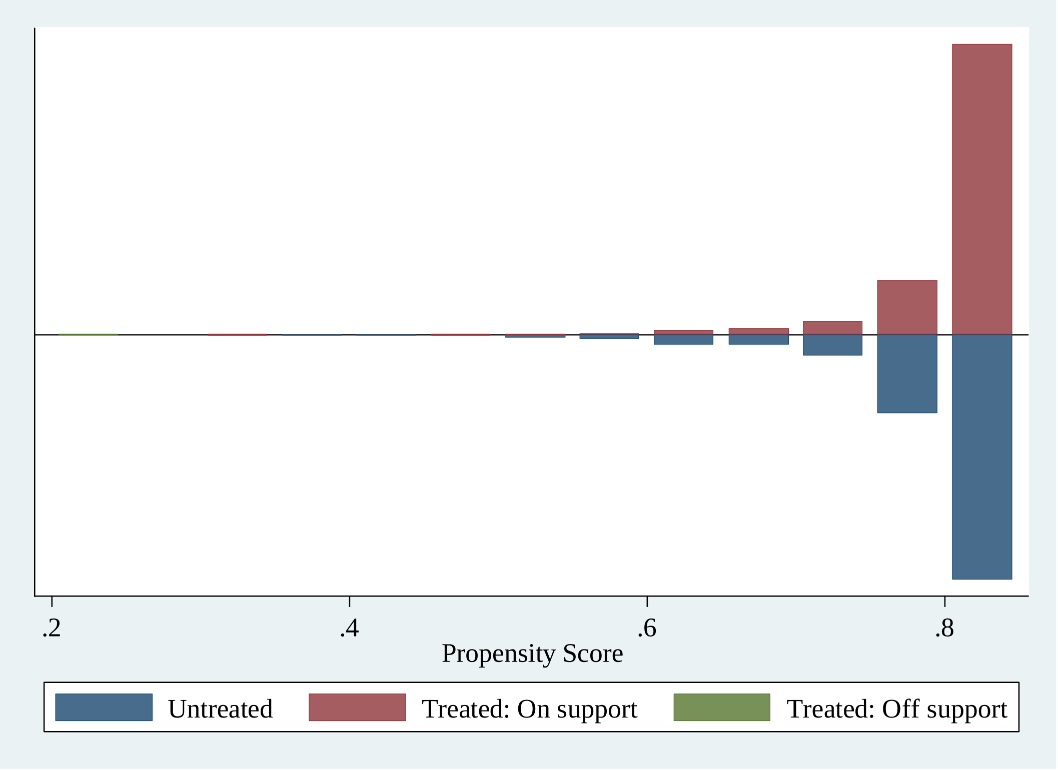
Source: Own calculations.

Table 5. Variables balancing test between supported and non supported farms (nearest neighbours matching N(3))

		Mean		% reduction		t-test	
Variable	Sample	Treated	Control	%bias	bias	t	p>t
ESU	Unmatched	28.109	38.307	-26.3		-5.97	0.000
	Matched	27.96	29.306	-3.5	86.8	-1.40	0.163
Total subsidy	Unmatched	13053	18221	-25.9		-6.85	0.000
	Matched	13000	12581	2.1	91.9	0.99	0.321

Source: Own calculations.

Figure 2. Propensity score distribution and common support for PSM



Source: Own calculations.

Table 6. Results for treatment effects

	Coef.	Std. Err.	z	P value
ATT	-0.018	0.006	-2.81	0.005

Source: Own calculations based on FADN database.

Table 8: PSM-DID and Quantile PSM-DID results

		Baseline period			End period			
		Control	Treated	Diff.	Control	Treated	Diff.	DIFF-IN-DIFF
TE	mean	0.754	0.734	-0.021	0.763	0.729	-0.034	-0.014
Std.Error		0.011	0.005	0.012	0.009	0.006	0.010	0.015
TE	Q10	0.599	0.577	-0.022	0.633	0.590	-0.044	-0.022
Std.Error		0.031	0.015	0.035	0.021	0.027	0.034	0.049
TE	Q20	0.665	0.648	-0.016	0.688	0.659	-0.029	-0.013
Std.Error		0.020	0.009	0.022	0.027	0.009	0.028	0.035
TE	Q30	0.728	0.697	-0.030	0.740	0.692	-0.048	-0.018
Std.Error		0.020	0.010	0.023	0.022	0.009	0.024	0.032
TE	Q40	0.755	0.732	-0.023	0.771	0.720	-0.051	-0.028
Std.Error		0.010	0.006	0.012	0.013	0.010	0.015	0.019
TE	Q50	0.783	0.759	-0.024	0.786	0.750	-0.037	-0.013
Std.Error		0.009	0.005	0.010	0.010	0.006	0.012	0.016
TE	Q60	0.802	0.781	-0.021	0.799	0.782	-0.017	0.004
Std.Error		0.009	0.005	0.011	0.007	0.007	0.010	0.015
TE	Q70	0.831	0.807	-0.023	0.813	0.799	-0.015	0.009
Std.Error		0.010	0.005	0.011	0.009	0.006	0.011	0.015
TE	Q80	0.853	0.837	-0.016	0.835	0.824	-0.012	0.005
Std.Error		0.008	0.005	0.010	0.010	0.005	0.011	0.014
TE	Q90	131.83	141.59	-1.03	89.31	144.35	0.10	0.73
Std.Error		0.000	0.000	0.303	0.000	0.000	0.918	0.466

Source: Own calculations based on FADN database.

Notes: Kernel Propensity Score Quantile Difference in Difference Estimation, bootstrapped standard errors (with 500 replications), N=1190

Table 9: Variables balancing test between supported and non supported farms

Weighted Variables	Mean Control	Mean Treated	Diff.	t	P value
TE scores	0.746	0.734	-0.012	1.27	0.2059
ESU	17.769	17.246	-0.523	0.38	0.7034
Total subsidy	1.1e+04	1.2e+04	855.909	0.91	0.3637

Source: Own calculations based on FADN database.

References

Abadie, A., Drukker, D., Herr, J.L. and Imbens, G.W. (2004). Implementing Matching Estimators for Average Treatment Effects in Stata. *The Stata Journal* 4(3): 290-311.

Aigner, D., Knox Lovell, C. A. and Schmidt, P. (1977). Formulation and estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6: 21-37.

Alvarez (2012). Modelling unobserved Heterogeneity in new York dairy farms: One-Stageversus Two-Stage Models. *Agricultural and Resource Economics Review* 41(3):275-285.

Athey, S., and Imbens, G. W. (2006). Identification and inference in nonlinear difference-in-differences models. *Econometrica*, *74*(2), 431-497.

Bojnec, Š. and Fertő, I. (2013). Farm income sources, farm size and farm technical efficiency in Slovenia. *Post-Communist Economies* 25(3): 343-356.

Bojnec, Š. and Latruffe, L. (2013). Farm size, agricultural subsidies and farm performance in Slovenia. *Land Use Policy* 32: 207-2017.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22(1): 31-72.

Čechura, L. and-Hockmann, H. (2011). Efficiency and heterogeneity in Czech food processing industry. Paper prepared for presentation at the EAAE 2011 Congress Change and Uncertainty Challenges for Agriculture, Food and Natural Resources August 30 to September 2, 2011 ETH Zurich, Zurich, Switzerland.

Greene. W. (2005): Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics* 126: 269-303.

Guo, S. and Fraser, M.W. (2010). *Propensity Score Analysis - Statistical Methods and Applications*. SAGE.Heckman, J., Ichimura, H. and Todd, P. (1997). Matching as an econometric evaluation estimator. *Review of Economic Studies* 65(2): 261-294.

Imbens, G. and J. Wooldridge (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature* 47: 5-86.

Knific, K. and Bojnec, Š. (2010). Agricultural households in mountain areas in pre- and post-accession Slovenia. *Journal for Geography* 5(1): 33-42.

Leuven, E. and Sianesi, B. (2003). PSMATCH2 Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. URL <http://ideas.repec. org/c/boc/bocode/s432001.html>.

Meeusen, W. and Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18(2): 435-444.

Pufahl, A. and Weiss, C.R. (2009). Evaluating the effects of farm programmes: results from propensity score matching. *European Review of Agricultural Economics* 36(1): 79-101.

Republic of Slovenia. (2009). National strategic plan of rural development. Ljubljana.

Rosenbaum, P. R. and Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica* 70(1): 41-55.

Sianesi, B. **(**2004). An evaluation of the Swedish system of active labor market programs in the 1990s, *The Review of Economics and Statistics* 86(1): 133-155.

Smith, J.A., and Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of econometrics*, *125*(1), 305-353.

SORS. (2010). Agricultural census in 2010. Ljubljana: Statistical Office of the Republic of Slovenia.

Tsionas (2002). Stochastic Frontier Models with Random Coefficients. *Journal of Applied Econometrics 17: 127-147.*

Villa, J. M. (2011). DIFF: Stata Module to Perform Differences in Differences Estimation. Statistical Software Components. Boston College Department of Economics.

Wang, X., Hockmann, H. and Bai, J. (2012). Technical Efficiency and Producers' Individual Technology: Accounting for Within and Between Regional Farm Heterogeneity. *Canadian Journal of Agricultural Economics* 60:561-576.