Impact of Off-farm Income on Farm Efficiency in Slovenia

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Abstract:
The paper investigates the impact of off-farm income on farm technical efficiency for the Slovenian Farm Accountancy Data Network farms in the years 2004-2008. Farm stochastic frontier time-varying decay inefficiency is positively associated with total utilised agricultural areas and total labour input, and vice versa with intermediate consumption and fixed assets. We find a positive association between farm technical efficiency and the off-farm income. Farm technical efficiency has increased steadily over time, the process, which was led by the off-farm spill over effect and most efficient farms. Farm technical efficiency is also positively associated with economic farm size, while association with subsidies is mixed depending on the estimation procedure. Quantile regression confirms the positive and significant associations between farm technical efficiency and off-farm income, and between farm technical efficiency and farm economic size, as well as the positive association between farm technical efficiency and subsidies, but the results are sensitive by quantiles.

Key words:

Off-farm income, Stochastic frontier analysis, Panel regression, Quantile regression, Slovenia

Introduction

Recent literature on rural development explains multifunctional and synergistic function of agricultural households in combination with other sources of employment. The role of off-farm income has increased in the total income of farm households in several of developed countries (e.g. Woldehanna et al., 2000; Lien et al., 2010). Income diversification of rural households can be driven by different determinants such as higher returns to labour and/or capital in off-farm economy as well as by risks pertaining to farm input market imperfections. Literature provides evidence on a positive association between off-farm income and farm performance (e.g. Rizov et al., 2001; Rizov and Swinnen, 2004; Hertz, 2009).

Therefore, the motivation for this paper is to investigate the impact of off-farm income on farm efficiency. We use data from the Slovenian Farm Accountancy Data Network (FADN) for farms above two European Size Units (ESUs). We analyse the impact of off-farm income on farm performance, which is proxied by technical efficiency (TE). By identifying the determinants explaining the increase in farm TE or decrease in farm TE, we aim at investigating the causalities between possible off-farm income and farm TE, which refers to the ability of farms to use at best the existing technology, in terms of input or output quantities.

The previous studies on TE of Slovenian farms show differences in TE by agricultural production branches with variations over time (Brümmer, 2001; Bojnec and Latruffe, 2008, 2009a, 2009b). Similarly, literature for other transition countries in Central and Eastern Europe (CEE) provides evidence on differentiations in farm TE by production branches with crops farm in general being more efficient than livestock farms (e.g. Gorton and Davidova, 2004).

We use Stochastic Frontier Analysis (SFA) model for panel data using translog specifications, which is tested against Cobb-Douglas specification form. In the second stage, the TE scores estimates are regressed on various explanatory variables including subsidy and off-farm income using pooled ordinary least square (OLS) method, random and fixed effects panel models, and a bootstrapped quantile regression approach.

We find that on average horticultural type of farms is the most TE, while other grazing livestock farms are the least TE. Empirical results suggest that the government support and off-farm income significantly influence farm TE, but the results are sensitive to different quantiles.

Methodology

The SFA is developed by Aigner at al. (1977) and Meeusen and Van den Broeck (1977) simultaneously yet independently in efficiency analysis. The main idea is to decompose the error term of the production function into two components, first, a pure random term (v_i) accounting for measurement errors and effects that cannot be influenced by the firm or farm such as weather, trade issues, and access to materials, and second, a non-negative term, measuring the technical inefficiency, i.e. the systematic departures from the frontier (u_i):

$$Y_i = f(x_i)\exp(v_i - u_i) \quad \text{or, equivalently:} \quad \ln(Y)_i = \beta x_i + (v_i - u_i) \qquad (1)$$

where Yi is the output of the i_{th} firm or farm, x_i a vector of inputs used in the production, f(·) the production function, u_i and v_i are the error terms explained above, and finally, β is a column vector of parameters to be estimated. The output orientated TE is actually the ratio between the observed output of firm or farm i to the frontier, i.e. the maximum possible output using the same input mix x_i.

Arithmetically, TE is equivalent with:

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{\exp(x_i\beta + v_i - u_i)}{\exp(x_i\beta + v_i)} = \exp(-u_i), \quad 0 \le TE_i \le 1. \qquad (2)$$

Contrary to the non-parametric Data Envelopment Analysis (DEA) approach, where all production TE score are located on, or below the frontier, in SFA they are allowed to be above the frontier, if the random error v is larger than the non-negative u.

Applying SFA methods requires distributional and functional form assumptions. First, because only the w_i=v_i - u_i error term can be observed, one needs to have specific assumptions about the distribution of the composing error terms. The random term v_i, is usually assumed to be identically and independently distributed drawn from the normal distribution, $N(0,\sigma_v^2)$, independent of u_i. There are a number of possible assumptions regarding the distribution of the non-negative error term u_i associated with TE. However most often it is considered to be identically distributed as a half normal random variable, $N^+(0,\sigma_u^2)$ or a normal variable truncated from below zero, $N^+(\mu,\sigma_u^2)$.

Second, SFA being a parametric approach, we need to specify the underlying functional form of the Data Generating Process (DGP). There are a number of possible functional form specifications available, however most studies employ either Cobb-Douglas (CD):

$$f(x_i) = e^{\beta_0}\prod_{k=1}^{K} x_{ik}^{\beta_k} \qquad (3)$$

or TRANSLOG (TL) specification:

$$\ln f(x_i) = \sum_{k=1}^{K} \beta_k \ln x_{ik} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} \ln x_{ik} \ln x_{jk} \quad . \qquad (4)$$

Because the two models are nested, it is possible to test the correct functional form by a Likelihood Ratio (LR) test. The TL is the more flexible functional form, whilst the CD restricts the elasticities of substitution to 1.

The production function coefficients (β) and the inefficiency model parameters (δ) are estimated by maximum likelihood together with the variance parameters: $\sigma_s^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2/\sigma_v^2$.

With panel data, TE can be chosen to be time invariant, or to vary systematically with time. To incorporate time effects, Battese and Coelli (1995) define the non-negative error term as exponential function of time:

$$u_{it} = \exp[(-\eta(t-T)]u_i \qquad (5)$$

where t is the actual period, T is the final period, and η a parameter to be estimated. TE either increases (η>0), decreases (η<0) or it is constant over time, i.e. invariant (η=0). LR tests can be applied to test the inclusion of time in the model.

In the second stage we use various models to explain the TE scores. First, we apply pooled OLS. Pooled OLS estimation is motivated by the weaker exogeneity assumptions made on the idiosyncratic error term: both random and fixed effects estimation use the strong exogeneity assumption that the unobservable component is in each period uncorrelated with explanatory variables in each other period. However, pooled OLS turn out to be inefficient if the error term in the second stage equation does contain unobserved individual components. Thus, we apply both random and fixed effects models to get more efficient estimations. But panel regression analysis estimates the relation between the mean value of the dependent variable (firm or farm growth) and variations in the explanatory variables. It is possible, however, that marginal effects of changes in some of the variables in our model are not equal across the whole distribution of TE scores. In other words, the estimated coefficients may be a poor estimate of the relation between some of the explanatory variables and firm or farm growth, at different quantiles of its distribution. Quantile regression, introduced by Koenker and Bassett (1978), is a useful way to overcome this problem, by providing estimates of the regression coefficients at different quantiles of the dependent variable. Furthermore, two additional features of quantile regression fit our data better than traditional OLS or fixed-effect estimations. First, the classical properties of efficiency and minimum variance of the OLS estimator are obtained under the restrictive assumption of independently, identically and normally distributed error terms. When the distribution of errors deviates from normality, the quantile regression estimator may be more efficient than the OLS (Buchinsky, 1998). Second, because the quantile regression estimator is derived by minimizing a weighted sum of absolute deviations, the parameter estimates are less sensitive to outliers and long tails in the data distribution. This makes the quantile regression estimator relatively robust to heteroskedasticity of the residuals.

Following Buchinsky (1998) the θ_{th} sample quantile, where 0 <θ <1, can be defined as:

$$\min_{b \in R}\left[\sum_{i \in \{i: y_i \geq b\}} \theta |y_i - b| + \sum_{i \in \{i: y_i < b\}} (1-\theta)|y_i - b|\right] \qquad (6)$$

For a linear model $y_i = \beta' x_i + \varepsilon_i$, the θ_{th} regression quantile is the solution of the minimization problem, similar to equation (1):

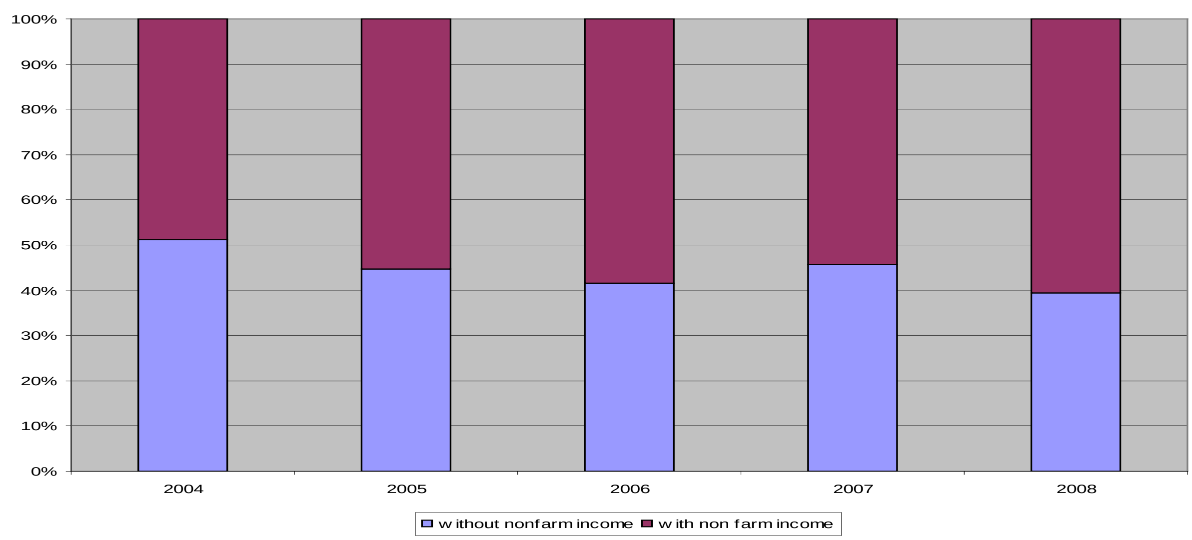
$$\min_{b \in R^k} \left[\sum_{i \in \{i: y_i \geq x_i b\}} \theta |y_i - x_i b| + \sum_{i \in \{i: y_i < x_i b\}} (1-\theta) |y_i - x_i b| \right] \tag{7}$$

Solving (7) for b results a robust estimates, and thus by changing θ from 0 to 1 any quantile of the conditional distribution may be considered, more, the constant change of θ relaxes the independent and identically distributed (IID) assumption of the error terms. As pointed out by Koenker and Hallock (2001), both asymptotic standard error and bootstrap methods could be used to estimate the covariance matrix of the regression parameter matrix, and hence to derive standard errors. But the bootstrap methods are recommended by Buchinsky (1998) due to its better performance in small samples.

Data

The data analysis is based on Slovenian FADN that includes farms above two ESU; one ESU is equivalent to 1,200 euros of gross margin. All nominal aggregates have been deflated by statistical price indices to obtain their real values over time in 2004 prices. Total value of output was deflated by harmonized consumer price index, fixed assets by agricultural input price index for goods and services contributing to agricultural investment (input 2), while intermediate consumption by agricultural input price index for goods and services currently consumed in agriculture (input 1). The time span used for analysis is 2004-2008.

Figure 1. Share of farms with and without off-farm income in the Slovenian FADN sample



Not all analysed Slovenian FADN farms have off-farm sources of income. Out of all number of observations in the FADN sample in the period 2004-2008, there are 40.2% of observations of farms with off-farm income. The percentage of FADN farms with off-farm income varies by individual years, but it tends to increase over the years from 2004 to 2008 (Figure 1).

The share of farms with off-farm income varies also by agricultural sectors by type of farming. The percentage of farms with off-farm incomes is above the Slovenian FADN average for milk and other grazing livestock farms, but below this average for wine, livestock using cereals (pigs and poultry), horticulture, field crops, other permanent crops, and mixed farms (Figure 2). This implies that on average more specialised into farm income activates with the lower percentage of off-farm incomes are in Slovenia traditional more labour intensive milk and grazing livestock farms, which can also be situated in more remote hilly areas with less off-farm employment opportunities.

Figure 2. Share of farms with and without off-farm income by type of farming

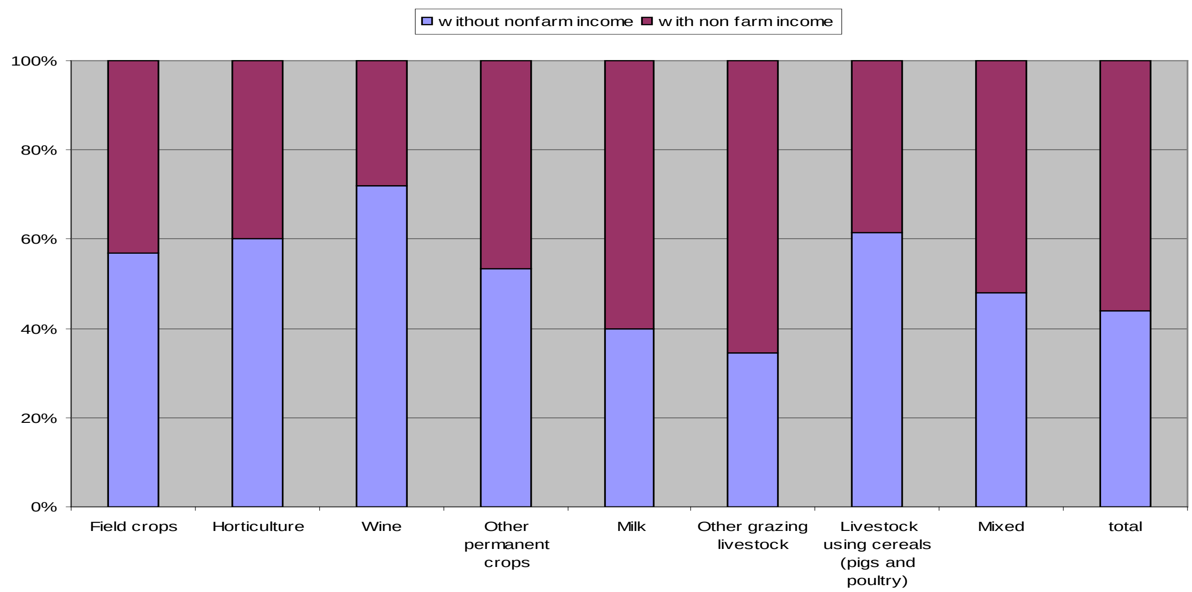


Table 1. Summary Statistics, 2004-2008

Variables	Number of Observations	Mean	Std. Dev.	Minimum	Maximum
Real output	3358	40010.48	62562.11	-50279.97	2278904
Real intermediate consumption	3358	23814.91	28381.87	290.3001	283065.7
Real fixed assets	3358	300767	563678	532.1267	1.93e+07
Total utilised agricultural area	3358	20.25901	20.3980	0.68	325.62
Total labour input	3358	2.207782	1.7663	0.12	46.08
Off-farm income	1350	0.0232	0.1927	0.000016	7.017
Economic size in ESU	3358	17.998	19.9096	2.005	314.194

Source: Own calculations based on the Slovenian FADN data

Table 1 presents descriptive statistics of the FADN data used in the empirical analysis. The off-farm income varies considerable between this kind of farms as can be seen from the comparison of the minimum and maximum values. On average, the Slovenian FADN farms are of the small economic size (18 ESU), but there are also considerable differences between them in terms of ESU and output size, level of intermediate consumption, size of real fixed assets, total utilised agricultural area used, and total labour input at the FADN farm.

Empirical results

We present our results in following steps. First, we provide an overview of the SFA estimations. Second, we focus on the stability of SFA scores during analysed period. Finally, we try to explain the TE scores using various estimation methods starting from a simple pooled OLS model, moving to panel models and quantile regressions.

Stochastic frontier analysis (SFA)

The functional specification of the stochastic production frontier was determined by testing the adequacy of the TL specification to the data relative to the more restrictive CD specification. The generalised LR test shows that the TL specification fits the data better than the CD specification. Table 2 shows the estimations based on TL specification.

Table2. Stochastic Frontier Time-Varying Decay Inefficiency Model, 2004-2008

Variable	Coefficient
Constant	-2.687
$\ln x_1$	-0.632*
$\ln x_2$	-0.538
$\ln x_3$	0.952***
$\ln x_4$	0.704***
$½\ln x_1^2$	0.098**
$½\ln x_2^2$	0.218***
$½\ln x_3^2$	0.092***
$½\ln x_4^2$	0.016
$\ln x_1 \ln x_2$	-0.102***
$\ln x_1 \ln x_3$	-0.016
$\ln x_1 \ln x_4$	0.042
$\ln x_2 \ln x_3$	-0.026
$\ln x_2 \ln x_4$	0.094***
$\ln x_3 \ln x_4$	-0.084***
$\ln \sigma_v$	-0.102***
Number of observations	3353

Source: Own calculations based on the Slovenian FADN data.
Note: x1 = real total intermediate consumption, x2 = real total fixed assets, x3 = total utilised agricultural area, and x4 = total labour input.

The variance parameter, γ, which lies between 0 and 1, indicates that technical inefficiency is stochastic and that it is relevant to obtaining an adequate representation of the data. The value of γ picks up the part of the distance to the frontier explained for the inefficiency. In our estimation, the value of the variance parameter γ is around 0.98. That means that the variance of the inefficiency effects is a significant component of the total error term variance and then, farms' deviations from the optimal behaviour are not only due to random factors. The stochastic frontier is a more appropriate representation than the standard OLS estimation of the production function.

Stochastic frontier time-varying decay inefficiency model indicates a positive and significant association of the stochastic frontier time-varying decay inefficiency in terms of real total output, which is used as the dependent variable, with the traditional agricultural inputs, i.e., total utilised agricultural area and total labour input, respectively. The negative association is found with real total fixed assets, which the regression coefficient is insignificant, and real total intermediary consumption, which is significant, but at 10% significance level. Except for total labour input, all regression coefficients for the square explanatory variables are of a positive sign and significant. The regression coefficients for the interaction effects of the explanatory variables are mixed. A positive and significant association is for the regression coefficient of the interaction effect of the real total fixed assets and total labour input, while of a negative sign and statistically significant is for the regression coefficient of two interaction effects: real total intermediate consumption and real total fixed assets, and total utilised agricultural area and total labour input. These results indicates that more utilised agricultural area and more labour input the farm employs, more inefficient it is, and vice versa for intermediate consumption and to a lesser extent for total fixed assets. The farm inefficiency is mitigated in a combination of intermediate consumption and fixed assets, and agricultural area and labour input, and vice versa for fixed assets and labour input.

Technical efficiency (TE)

First, we present the results of TE scores by the analysed years 2004-2008 (Table 3). Except on average stagnation in TE in 2006, the TE scores tend to increase from year to year, which confirms a pattern of an increase in FADN farm TE. At the same time the gap between the minimum and maximum TE scores by individual farms has been reduced particularly due to a more rapid increase in the TE scores for the least technically efficient FADN farm.

Table 3. Technical Efficiency Scores and Their Changes, 2004-2008

technical efficiency scores					
	Number of observations	Mean	Std. Dev.	Minimum	Maximum
2004	494	0.706	0.178	0.088	0.960
2005	659	0.715	0.178	0.111	0.964
2006	634	0.719	0.180	0.138	0.967
2007	746	0.742	0.166	0.168	0.971
2008	820	0.760	0.156	0.123	0.973
changes in technical efficiency scores					
2005	455	1.038	0.035	1.003	1.271
2006	528	1.038	0.036	1.003	1.2418
2007	566	1.036	0.033	1.003	1.215
2008	680	1.032	0.0288	1.002	1.192

Source: Own calculations based on the Slovenian FADN data.

Second, we present the results for the changes in TE scores between the consecutive years. The rate of growth in TE varied between 3.2% and 3.8% in the analysed period. The positive rates of growth in TE are also confirmed for the least and particularly for most efficient Slovenian FADN farms. These results confirm a steady and particularly fast growth in TE over time for the most efficient Slovenian FADN farms.

Table 4. Mean Technical Efficiency Scores by Agricultural Sectors by Type of Farming, 2004-2008

	Obs	Mean	Std. Dev.	Min	Max
1 Field crops	326	0.680	0.200	0.140	0.955
2 Horticulture	45	0.865	0.079	0.594	0.952
3 Wine	128	0.824	0.144	0.378	0.973
4 Other permanent crops	167	0.751	0.194	0.157	0.964
5 Milk	1220	0.762	0.105	0.248	0.966
6 Other grazing livestock	817	0.598	0.178	0.113	0.951
7 Livestock using cereals (pigs and poultry)	26	0.822	0.105	0.522	0.950
8 Mixed	624	0.661	0.170	0.186	0.946

Source: Own calculations based on the Slovenian FADN data.

By type of farming, other grazing livestock farms are the least TE (Table 4). Among less TE are also mixed farms and field crops farms. Close to average TE are other permanent crops farms and milk farms. Horticultural farms are found to have the highest TE scores. Among more TE are also wine farms and livestock farms using cereals (pigs and poultry farms). Horticultural farms and livestock farms using cereals (pigs and poultry) experienced also the greatest similarity in TE with the smallest differential between the least minimum and the most maximum TE farms. This differential is particularly large for other grazing livestock farms, field crops farms, other permanent crops farms, and mixed farms.

Panel regression analysis

Preliminary analysis shows that the pooled OLS and panel models are subject to heteroscedasticitiy. Thus, Table 5 presents the results of the panel regression model results of TE with correction of heteroscedasticitiy for the Slovenian FADN sample. The Breusch and Pagan test statistic, which was calculated after random effects estimation, does reject the hypothesis of absence of individual unobserved effects. Both random and fixed effects account for the presence of individual unobserved effects in the model. Although Hausman test suggests that fixed effects estimation has to be preferred, random effect results are also reported. Indeed, fixed effect estimation may lead to imprecise estimates due to the low variations of explanatory variables over time of the (Woolridge, 2002).

Table 5. Panel Regression Results of Technical Efficiency, 2004-2008

	Pooled OLS	Random effect	Fixed effect
Off-farm income	0.022***	0.001	0.001
Total subsidy	0.144***	-0.020***	-0.022***
Farm size	0.065***	0.012***	0.008***
Constant	0.527***	0.649***	0.668***
Number of observations	3353	3353	3353
Within R^2		0.8237	0.8257
Between R^2		0.0762	0.0144
Overall R^2	0.3082	0.0913	0.0398
Time fix effect	Yes	yes	Yes
Sector fix effect	Yes	yes	Yes
F-test (p-value)	0.0000		0.0000
Wald test (p-value)		0.0000	

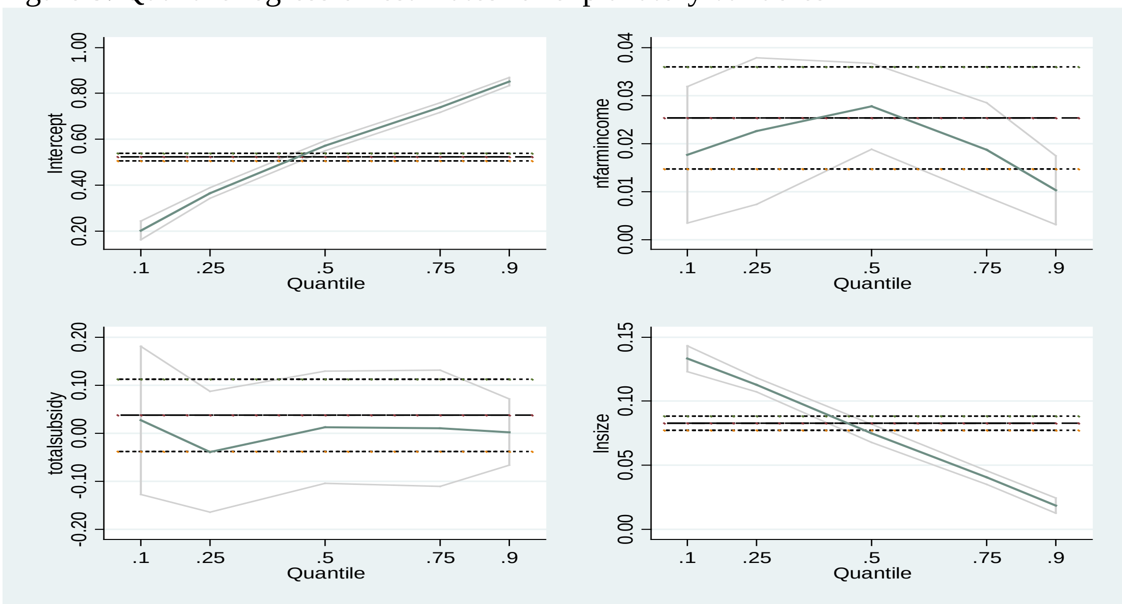
Source: Own calculations based on the Slovenian FADN data.
Note: All estimation procedures account for heteroskedasticity at the firm level and autocorrelation of the error term.

Our special focus is on the association between the farm TE and the off-farm income, which is controlled by total subsidies the farm received and the farm economic size. For the farm with the off-farm income we create a dummy variable, which is equal 1 if the farm has the off-farm income and 0 otherwise. We found a positive association between the farm TE and the farm with the off-farm income. This spill-over effect of off-farm income on farm TE might be due to relaxation of surplus of farm labour and its remaining more efficient use on the farm due to possible investment in more advanced technology, which in turn provides a higher farm TE. This argument is also in a line with the positive association between the farm TE and total farm subsidies on one hand, and between the farm TE and the farm economic size on the other. More subsidies receive larger farms, which are likely to use subsidies for investment and farm growth that is consistent with their contributions to the improvement in the farm TE. However, these findings hold only for the pooled OLS regression. The results of the random and fixed effect models are mixed. While the regression coefficient for the off-farm income is of a positive sign, it is insignificant. In these two regression models total subsidies reduce, while farm economic size increases the FADN farm TE. The contradiction results for total subsidies imply that farmers become more convenient on government transfer payments, which distort factor allocation and more likely reduces farm TE. In addition to the problem of heteroscedasticitiy, the regression residuals, however, in all cases significantly depart from normal distribution as the Shapiro–Wilk and Shapiro–Francia test results reject the null hypothesis of normality distribution at a percentage level. While those slope coefficients may represent a plausible relationship between the farm TE and control variables, the failure to pass miss-specification tests indicates that it is worth going beyond the average tendency and investigating the separate responses of TE to other variables at different quantiles of the TE.

Quantile regression analysis

Panel regression analysis estimates the relation between the farm TE score as dependent variable and variations in the explanatory variables. It is possible, however, that marginal effects of changes in some of the variables are not equal across the whole distribution of TE scores and the estimated panel regression coefficients may be a poor estimate of the relation between some of the explanatory variables and farm TE score at different quantiles of its distribution. Quantile regression is a way to overcome this problem, by providing estimates of the regression coefficients at different quantiles of the dependent variable.

Figure 3. Quantile regression estimates for explanatory variables



With the quantile regressions we test the association between a farm TE and a farm off-farm income using control explanatory variables for total subsidies and economic farm size. Figure 3 presents quantile regression estimates and OLS coefficients with confidence interval for explanatory variables with the intercept, which increases with the quantile increases. The average value for the increasing intercept value is a bit more than 0.5 at the quantile less than 0.5. The estimated quantile regression and OLS coefficient with confidence interval for off-farm income experienced first increasing, and then declining patterns with the quantile increases. In the first increasing phase between quantiles 0.1 and 0.5, with the higher farm TE, the stronger is association with off-farm income and the large gap between the quantile regression and OLS coefficient with confidence interval a slightly converges. With the further quantile increases from the average 0.5 quantile, with higher farm TE the weaker is the association with off-farm income, which curves tend to decline with a slightly converging gap between the quantile regression and OLS coefficient confidence intervals. This a roof type curve distribution between farm TE and off-farm income suggests that the least TE efficient farms to a lesser extent experience off-farm income, while over a certain level of farm TE efficiency farms less use off-farm income. Total subsidies took a lower relative scale, including a negative average value since 0.25 quantile and minimum values. They tend to increase between 0.25 and 0.5 quantiles, and after that they on average stabilised. The estimates for economic farm size clearly confirm declining and converging patterns between the quantile regressions and OLS confidence intervals with the quantile increases.

Table 6. Quantile Regression of Technical Efficiency, 2004-2008

	Q10	Q25	Q50	q75	q90	Wald test (p-value)
Off-farm income	0.028***	0.023***	0.021***	0.015***	0.019***	0.6494
Total subsidies	0.148	0.108	0.068*	0.021	0.015	0.6357
Economic size	0.098***	0.089***	0.061***	0.034***	0.020***	0.0000
Constant	0.215***	0.361***	0.588***	0.742***	0.843***	0.0000
Time fix effect	Yes	yes	Yes	yes	Yes	
Sector fix effect	Yes	yes	Yes	yes	Yes	
N	3314	3314	3314	3314	3314	
Pseudo R^2	0.2799	0.2557	0.1859	0.1127	0.0699	

Source: Own calculations based on the Slovenian FADN data.
Note: Level of significance: * $p<0.1$; ** $p<0.05$; *** $p<0.01$ based on bootstrapped standard errors with 1000 replications. Wald test of equality of the coefficient from quantile regression when: q = 0.10, q = 0.25, q = 0.50, q = 0.75, and q = 0.90 (probability).

Table 6 reports the results for a sequence quantile regression estimation for the 0.10, 0.25, 0.50, 0.75 and 0.90 quantiles of the farm TE distribution and tests for equality of coefficients across quantiles were performed. The estimation results confirm that the relation between the Slovenian FADN farm TE and explanatory variables is changing across the whole distribution of the farm TE scores. We found a positive and significant association between the farm TE and the off-farm income. The partial regression coefficient for the off-farm income a steady decreases between 0.10 quantile and 0.75 quantile, but a slightly increases for the 0.90 quantile of the farm TE distribution. This confirms that sensitivity of the farm TE on the farm off-farm income is different for farms having lower or having higher TE than the median farm TE in the sample of the Slovenian FADN farms. Farms having lower TE scores than the median value (50th percentile) show a significantly larger sensitivity to off-farm income. Interestingly, the Wald test confirms the null hypothesis of equality of the coefficient across quantiles for the off-farm income. We control the off-farm income explanatory role in quantile regression by total subsidies that are received by a farm and by farm economic size, and by time fix effect and sector fix effect. The association between the farm TE and the farm economic size is of a positive sign and significant for the each quantiles. The absolute size of the partial regression coefficient declines with the quantile increases. This implies that the increase in farm economic size improves farm TE more for smaller than larger farms vis-à-vis the median value (50^{th} percentile). In general, larger farms are more efficient, but this farm size effect decreases with increasing farm size. The Wald test confirms statistical significant association between the farm TE and farm economic size across quantiles. The association between the farm TE and total subsidies is of a positive sign, but only significant for the median 0.50 quantile. The statistical insignificant association between the farm TE and total subsidies by quantiles is also confirmed by the Wald test.

Conclusions

Slovenian agricultural farm structures are typical by off-farm employment and off-farm incomes. While on average the Slovenian farms are of relatively a small size, they are largely engaged in off-farm employment. This holds also for the Slovenian FADN farms, which on average are larger and more economically vital than the average Slovenian farms. More than 40% of the Slovenian FADN farms have the off-farm income sources.

We confirm that the off-farm income improves the FADN farm TE, which implies spill-over effect's spread of the off-farm income on farm TE. On one hand the off-farm income provides cash flow into a farm, which can be also invested in farm's technological advancements, which improve farm TE. On the other hand the off-farm employment, which is associated with the off-farm incomes, relaxes possible farm labour surpluses outside the main seasonal work, which in turn gives to farm an opportunity that a maximum possible farm output at given technology is achieved with less at the farm labour employment. Looking dynamically over time, average farm TE scores have increased and the off-farm income is found to have a positive role in this farm TE improvements.

Both the panel regression models and the quantile regressions of TE confirm the positive association between farm TE and the off-farm income. This further reinforces farm managerial and policy implications on the positive role of off-farm employment and off-farm income, when farms on average are of relatively a small technical operational and economic size giving them to relax a surplus of labour and at the same time giving them an opportunity for additional farm households' incomes that can be invested in farm advancements, farm growth, and farm survival, as well as they can improve economic well being of the farm households' members. The off-farm income is important for farm TE by different quantiles, a bit more important for smaller than for greater quantiles. This is further reinforced by the positive association between the farm TE and the economic farm size implying the importance of economic farm size growth, particularly for a smaller quantiles of farms. The association of farm TE and farm subsidies is found to be mixed depending on the estimation procedure: it is of a positive sign in the pooled OLS regression, but of a negative sign in the random and fixed effect panel models. Moreover, the quantile regression of TE suggests a positive association between farm TE and farm subsidies, which is significant only for the median value (50th percentile) quantile. This implies that farm subsidies do not necessary improve farm TE and thus their targeting objectives should be clearly defined within the reform of Common Agricultural Policy and particularly within implementation objectives and measures.

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