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LAND FRAGMENTATION AND MARKET INTEGRATION - HETEROGENEOUS TECHNOLOGIES IN KOSOVO

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Abstract

This paper empirically measures the prevalence of heterogeneous technologies in a sample of small-scale agricultural producers as an answer to structural conditions and market risks. Such risks are closely linked to the effects of land fragmentation and the degree of market integration. We use the empirical case of Kosovo as a transition country to investigate the efficiency effects of land fragmentation by simultaneously considering the effects of market integration. Different to previous studies, we assume that land fragmentation and market integration lead to the prevalence of heterogeneous technologies allowing farm households to respond more efficiently to exogenous price and policy shocks given their fragmentation and subsistence situation. The empirical work links the latent class frontier method to the estimation of a directional output distance function. We estimate beside primal technology measures also dual Morishima type elasticities of substitution investigating changes in production decisions based on relative shadow price changes.

Keywords

land fragmentation, market integration, farm households, Kosovo, JEL - O13; Q12

1 Introduction

A substantial literature exists on the relationship between land fragmentation, on the one hand, and land productivity at parcel level, or efficiency at farm level, on the other (BLAREL et al., 1992; WU et al., 2005; VAN HUNG et al., 2007; RAHMAN and RAHMAN, 2008; CHEN et al., 2009; CORRAL et al., 2011). To date, however, empirical estimations of the relationships have produced inconclusive results. For instance, while some studies found that land fragmentation is a source of inefficiency or has a negative relationship with farm profitability (e.g. Van HUNG et al., 2007; RAHMAN and RAHMAN, 2008; DI FALCO at al., 2010; CORRAL et al., 2011); WU et al. (2005) found a lack of a statistically significant relationship between land fragmentation and technical efficiency. One common drawback of these studies is that they did not account for the heterogeneity of farm households and assumed that all farms operated on the same frontier production function.

This paper investigates the effect of land fragmentation on farm efficiency in Kosovo. Kosovo has been chosen due to the importance of agriculture in rural areas and its role as the main source of income for the rural population. It possesses a mass of small scale farms supporting, by European standards, relatively large households. Whilst previous studies on the 'economics of fragmentation' presume one homogenous technology to measure the effects of fragmentation, the assumption in this paper is that when the unit of analysis are small, poor households accounting for heterogeneity is crucial.

To recognize heterogeneity among agricultural production systems in Kosovo, we estimate the technology separately for different groups or "classes" of farms, identified using latent class modeling. This approach separates the data into multiple technological "classes" accord-

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ing to estimated probabilities of class membership based on multiple specified characteristics relating in this case to land fragmentation and market integration. Each farm is assigned to a specific class based on these probabilities. This is useful for exploring the effects of fragmentation and market integration specific to technology types. To the best of our knowledge this is the first study in which the latent class frontier method is related to estimates of the effects of fragmentation. Empirically, the latent class frontier method is linked to the estimation of a multi-output multi-input production function, namely a directional output distance function, and to the estimation of Morishima elasticities of substitution, based on shadow price changes indicating allocative efficiency changes.

2 Conceptual framework

A representative agricultural household maximizes its utility *(U)* over consumption of a vector of agricultural products (c) c=1,....C and a composite vector of all other tradables (x) subject to production function and cash income constraints.

Max U*(c,x)*

The consumption of agricultural products (c) originates from two sources – from self-produced products (c^s) and from products purchased in the market (c^m) (DAVIDOVA, 2011). Following BARRETT (2008), it is assumed that each crop has a production technology expressed as a flow of private services provided by the household private quasi-fixed assets (*PA*) and public goods provided by the government (*PG*), e.g. physical road infrastructure, extension service etc.

Y = f*(PA,PG)*

where (Y) is crop output.

Agricultural output is divided into three uses: self-consumption by the farm holder's household (y^s), sales (y^m) and on-farm production use (y^f). The self-consumed output (y^s) is equal to the consumption coming from own production (c^s). The share of the self-consumed output in the total output of a product or of the marketed output in the total output is a measure of subsistence, or conversely, of market integration (*MI*). In addition, there is output lost due to diseases, flood, drought, fire etc. Each household has some availability of land, labor and capital at a point in time. However, the demand for labor and capital for a particular level of output depends on land fragmentation as the latter imposes transaction costs, e.g. time to travel or walk to and between plots; costs for monitoring labor scattered in different plots etc. One of the most widely used measures for land fragmentation is the Simpson Index (*SI*) (BLAREL et al. 1992). It is expressed as follows:

$$1 - \sum_1^i A_i^2 / A^2$$

where A_i, is the area of the i^{th} plot and A is the total farm area. *SI* is defined over the range of 0 to 1. If *SI* = 0 there is no fragmentation of farm land into spatially separated plots. The larger the index is, the larger the level of land fragmentation. Assuming that *PG* does not vary with land fragmentation, it is possible to focus on the effect of land fragmentation on the *PA* necessary to produce a level of output, *Y**. If *SI* > 0 then:

$$L_D = la + qd \qquad (1)$$

In equation (1) L_D is the total demand for labor, l_a is the labor necessary for strictly agricultural work, q is time spent walking or on transport per km per unit of labor and d is the distance (ANGELSEN et al., 2001). So that the labor requirements are larger than in the case of *SI* = 0, at least due to the time spent walking or travelling to reach dispersed plots. However, with land fragmentation there are also higher transaction costs (τc) to monitor labor working on different fields, particularly if the farm holder works for the market and has to impose some production standards. Therefore:

$$L_{D=} f(la, d, \tau c_{la}) \qquad (2)$$

Similarly, if $SI > 0$ the capital demanded K_D is larger than under $SI = 0$ due to the need to invest in means of transport, to handle and transport the output from different plots. Thus, under $SI > 0$:

$$K_D = f(ka, d, \tau c_{ka}) \quad (3)$$

where ka is the capital needed in case of $SI = 0$ to achieve Y^* and τc_{ka} are the transaction costs resulting from land fragmentation. Therefore, when $SI > 0$ there are labor and capital τc which we can sum under τc_{LF}.

Concerning the utilizable farm land area A, under land fragmentation it is decreased by A_{LF} as, for example, there are losses around the boundaries of the plots where the machinery cannot work or due to disputes with neighbors concerning the boundaries. The need to have more land, labor and capital in the conditions of land fragmentation to achieve the same level of output leads to the hypothesis that land fragmentation is negatively related to economic efficiency.

On the other hand, Y^* may not be achieved in the case of a non-fragmentation (NF) due to the higher risk of loss of output if the land is consolidated in one place in comparison to a better spread of the risk over several plots scattered in different locations. Therefore, it might be the case that $Y_{LF} > Y_{NF}$ and $U_{LF} > U_{NF}$ where Y_{LF} is the output in the case of land fragmentation and Y_{NF} is in the case of non-fragmentation; U_{LF} and U_{NF} are the respective utilities.

Considering market integration (MI), under imperfect markets households face additional τc say τc_{MI} (H, PA, PG, W, y^m) where are the household-specific characteristics, particularly education, age and gender that relate to search costs; PA as above are the private assets and PG are public goods; W is liquidity from non-agricultural sources of income and y^m is the marketed output (Barrett, 2008). A larger volume of y^m helps spread the fixed transaction costs of MI over more units and thus decrease the total transaction costs per unit. Therefore, the conceptual model suggests that important variables for the empirical analysis are SI, Y, PA, PG, H, W and MI. Some of these variables enter into the efficiency frontier; others are used as factors to explain inefficiency and to identify different classes of farms.

3 The case study area and dataset

Kosovo is a small, landlocked economy with a total area of 1.1 million hectares (ha), of which 53% is agricultural land. It has a high population density, and consequently a small amount of agricultural land per inhabitant (0.24 ha) (Riinvest, 2005). In the first half of the 2000s, 86% of the agricultural land was privately owned and operated by family farms; the remainder was under the ownership of producer cooperatives (1%) or the so-called socially owned enterprises (13%) (UNMIK, 2003). Farming accounts for 25% of GDP and between 25% and 35% of total employment (World Bank and SOK, 2007). Agriculture has been identified as one prospective area for growth and job creation (ARCOTRASS Consortium, 2006).

Overall, regarding physical infrastructure, roads are underdeveloped. However the quality of the infrastructure varies by region, imposing varying transaction costs on farmers. There are seven regions in Kosovo. Mitrovice is in the north; Prishtine is in the centre where the capital is located; Gjilan is in the east; Ferizai in the south-east close to the border with the Former Yugoslav Republic of Macedonia; Prizren is in the south near the border with Albania; Gjakove is in the south-west also near to Albania and Peje in the north-west near to Montenegro. This description is necessary for two reasons. First, due to the legacy of the military conflict, farmers located in regions near to the Serbian border may suffer from feelings of insecurity, hampering agricultural investment (Sauer et al., 2012). Second, the regions exhibit differences in climatic conditions which affect yields and production patterns.

The data employed in this study originate from the annual Agricultural Household Surveys (AHS) conducted by the Statistical Office of Kosovo (SOK) between 2005 and 2008. The surveys were based on a two-level stratified sample (SOK, 2006). The first level of stratification was by the above mentioned regions and the second level by farm size according to cultivated area. After stratification households were randomly selected for interview.

The data provides information on plot by plot land use, the number of plots per household and individual plot sizes, and outputs in quantity. Outputs included in the multi-output multi-input directional distant function are wheat, hay, potatoes, tomatoes, peppers and onions. These are the most common products in Kosovo for which a sufficiently large sample (2,217 households) could be built with all farms producing some output. Hay is included as an output although it does not have a direct market integration measure. Since livestock has not been included in the estimations, there is not a problem of endogeneity.

Regarding inputs, land, labor, seeds, fertilizers, plant protection chemicals, fuel, machinery value, and rental of land and farm buildings are used. Concerning labor, the survey contains data about the number of family members engaged on-farm for agricultural production both full- and part-time. Part-time workers are defined as family members who work at least 20 hours/week on-farm. There was also a question concerning the hours supplied by hired labor but due to very few observations this indicator was not used. Since the survey is focused on agriculture, data on the allocation of labor off-farm and off-farm income, which ideally should be taken into consideration (CHAVAS et al., 2005), are absent. Land is included in hectares. Machinery value, expressed in euro, is the expected resale value indicated by the respondents. The remaining inputs are measured as expenditure in Euro. All input values have been deflated.

Two measures of land fragmentation are included in the empirical analysis– SI and the number of plots. Two proxies for market integration are also included. The first one is the number of crops, since more subsistence oriented farmers do not pursue specialization according to their comparative advantage but rather grow a larger number of crops to satisfy household consumption needs (variable pdi - product diversity index). In the survey, the respondents were asked to indicate crop by crop how much of the harvested output they expect to use for self-consumption. The sum of these percentages over the analyzed crops per household is used as a second proxy for market integration (variable: hhups).

The surveys contain information about the head of household and members of household. Several variables were chosen to capture household-specific characteristics – age of the head of household, gender of the head of household, education level of the head of household, average age of the household members, average education level of the household members.[4] Regional dummies are used to control for agro-environmental conditions and government provided infrastructure: 1=Ferizaj, 2=Gjakove, 3=Gjilan, 4=Mitrovice, 5=Peje, 6=Prishtine, 7=Prizren.

4 Empirical modeling

The technological processes are modeled by using a directional distance function since multiple outputs are produced by Kosovo farms, precluding the estimation of the production technology by a single output production function. A farmer uses a vector of input levels $x = (x_1, \dots, x_N) \in R_+^N$ to produce a vector of output quantities $y = (y_1, \dots, y_M) \in R_+^M$. The relationship between inputs and outputs is represented by the set:

$$T = \{(x, y): x \text{ can produce } y\} \qquad (4)$$

[4] Education was recorded according to the level attained: 1 no education; 2 some primary school; 3 primary school completed; 4 some secondary; 5 secondary school completed; 6 some high school; 7 high school completed; 8 some higher education; 9 higher education completed.

where T is the set of technically feasible input and output combinations, assuming that T satisfies free disposability of inputs and outputs, and is a convex set (FÄRE and PRIMONT, 1995). A functional representation of T is the directional output distance function, defined as:

$$\overrightarrow{D_O}(x,y,g) = sup\{\beta: (x, y + \beta g) \in T\} \quad (5)$$

where $g = (g_1, \ldots, g_M) \in R_+^M$ This distance function maps the input-output vector (x,y) into a scalar of value. If free disposability holds, the distance function

$$\overrightarrow{D_O}(x,y,g) \geq 0 \quad if, and\ only\ if\ (x,y) \in T \quad (6)$$

gives a complete characterization of the technology to be approximated (CHAMBERS et al., 1996). The translation property of the directional distance function allows its use for empirical work:

$$\overrightarrow{D_O}(x, y + \mu g; g) = \overrightarrow{D_O}(x,y,g) - \mu; \mu \in R \quad (7)$$

This property states that if outputs are translated by μg, then the value of the distance function is reduced by the scalar μ. To empirically estimate the directional output distance function a quadratic functional form can be chosen which makes $\overrightarrow{D_O}(\cdot)$ a second-order approximation of the underlying technology T. Imposing symmetry in parameters, the distance function is given by:

$$\overrightarrow{D_O}(x,y;g) = \alpha_0 + \sum_{i=1}^{M}(\alpha_i y_i + 0.5\alpha_{ii}y_i^2) + \sum_{i=1}^{M}\sum_{j=i+1}^{M}\alpha_{ij}y_i y_j + \sum_{i=1}^{N}(\beta_i x_i + 0.5\beta_{ii}x_i^2) + 0.5\sum_{i=1}^{N}\sum_{j=i+1}^{N}\beta_{ij}x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{N}\gamma_{ij}y_i x_j \quad (8)$$

Translation requires then

$$\overrightarrow{D_O}(x, y + \mu g; g) = \alpha_0 + \sum_{i=1}^{M}(\alpha_i y_i + \mu g_i) + \sum_{i=1}^{M} 0.5\alpha_{ii}(y_i + \mu g_i)^2 + \sum_{i=1}^{M}\sum_{j=i+1}^{M}\alpha_{ij}(y_i + \mu g_i)\left(y_j + \mu g_j\right) + \sum_{i=1}^{N}(\beta_i x_i + 0.5\beta_{ii}x_i^2) + 0.5\sum_{i=1}^{N}\sum_{j=i+1}^{N}\beta_{ij}x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{N}\gamma_{ij}(y_i + \mu g_i)x_j - \mu \quad (9)$$

To measure an individual farms' efficiency a parametric stochastic frontier approach can be used. In this paper the BATTESE and COELLI (1995) estimator on the distance function described in (9) is applied using an unbalanced panel data specification. The corresponding likelihood function and efficiency derivations are given in KUMBHAKAR and LOVELL (2000). The stochastic specification of the directional output distance frontier takes the form:

$$0 = \overrightarrow{D_O}(x, y + \mu g; g) + \varepsilon \quad (10)$$

where $\varepsilon = v - u$; $v \sim N(0, \sigma_v^2)$ and $u \sim N^+(u, \sigma_u^2)$. To estimate (10) the translation property of the directional output distance function is exploited. Following common practice (see FÄRE et al., 2005) we set $g = 1$, resulting in:

$$\overrightarrow{D_O}(x, y + \mu; 1) + \mu = \overrightarrow{D_O}(x, y; 1) \quad (11)$$

By substituting $\overrightarrow{D_O}(x, y + \mu; 1) + \mu$ in (10) and rearranging, the following equation is obtained:

$$-\mu = \overrightarrow{D_O}(x, y + \mu; 1) + \varepsilon \quad (12)$$

Choosing $\mu = y_1$, which is farm specific, a sufficient variation on the left-hand side is obtained to estimate the specification given in (12). The output vector used is y = (wheat, hay, pepper, tomatoes, onions, and potatoes) whereas the input vector is x = (land, full-time labor, part-time labor, machinery, fuel, rented services, fertilizer, chemicals and seed). The final specification estimated is:

$$-y_w = \alpha_0 + \sum_{i=1}^{M}(\alpha_i y_i') + \sum_{i=1}^{M} 0.5\alpha_{ii}(y_i')^2 + \sum_{i=1}^{M}\sum_{j=i+1}^{M}\alpha_{ij}(y_i')(y_i') + \sum_{i=1}^{N}(\beta_i x_i + 0.5\beta_{ii}x_i^2) + 0.5\sum_{i=1}^{N}\sum_{j=i+1}^{N}\beta_{ij}x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{N}\gamma_{ij}(y_i')x_j + v - u \quad (13)$$

where $y_i' = y_i + y_w$ with y_w as the quantity of wheat produced and abstracting from farm and time related variation.

Efficiencies

The vector of technical inefficiency effects u in the stochastic frontier model outlined by (13) is specified as:

$$u = z\delta + w \qquad (14)$$

with, according to the conceptual framework, the following components of the vector z: Simpson index (SI), number of plots, the percentage of crops used for subsistence, product diversity index, region, year, average education of household members, average age of household members, educational level of the head of the household, age of the head of the household, and gender of the head of the household. The random variable w is defined by the truncation of the normal distribution with zero mean and variance, σ_w^2, such that the point of truncation is $-z\delta$, i.e. $w \geq -z\delta$ (see BATTESE and COELLI, 1995). Abstracting from farms and time variation, the technical efficiency is then defined by:

$$TE = \exp(-u) = \exp(-z\delta - w) \qquad (15)$$

The corresponding likelihood function and its partial derivatives with respect to the individual parameters is given in BATTESE and COELLI (1995) or COELLI et al. (2005).

Elasticities

To represent and evaluate the technological or production structure, the primary measures to be computed are first- and second-order elasticities of the directional distance function. The first-order elasticities in terms of primary output y_w represent the (proportional) shape of the production possibility frontier (given inputs) for all other outputs and the shape of the production function (given all other inputs) for input x_i – or output trade-offs and input contributions to secondary and other outputs respectively. That is, the estimated output elasticity with respect to the "other" outputs: $\varepsilon_{w,j} = \partial \ln y_w/\partial \ln y_j = \partial y_w/\partial y_j*(y_j/y_w)$ would be expected to be negative as they reflect the slope of the production possibility frontier, with its magnitude capturing the (proportional) marginal trade-off. The estimated output elasticity with respect to input i, $\varepsilon_{w,I} = \partial \ln y_w/\partial \ln x_i = \partial y_w/\partial x_i*(x_i/y_w)$, would be expected to be positive, with its magnitude representing the (proportional) marginal productivity of x_i. Second-order own-elasticities can also be computed to confirm that the curvature of these functions satisfies regularity conditions; the marginal productivity would be expected to be increasing at a decreasing rate, and the output trade-off decreasing at an increasing rate, so second derivatives with respect to y_j and x_i would be negative (concavity with respect to both outputs and inputs).

Returns to scale may be computed as a combination of the y_w elasticities with respect to the other outputs and inputs. For a directional output distance function such a measure must control for the other outputs (CAVES et al., 1982). For our purposes as $\varepsilon_{w,X} = \sum_i \varepsilon_{w,i} /(1 - \varepsilon_{w,Y})$ these measures may be computed for each observation and presented as an average over a subset of observations (such as for the full sample, a farm, a time period or a particular group of spatially clustered farms), or may be computed for the average values of the data for a subset of observations.[5] Further, we can compute second order or cross elasticities to evaluate output and input substitution with our flexible functional form. These elasticities involve second-order derivatives such as, for input substitution, $\varepsilon_{i,j} = \partial 2y_w/\partial x_i \partial x_j*[x_j/(\partial y_w/\partial x_i)]$. As $MP_{w,I} = \partial y_w/\partial x_i$ is the marginal product of y_w with respect to x_i, this elasticity,

[5] The latter approach, the "delta method", evaluates the elasticities at one point that represents the average value of the elasticity for a particular set of observations, allowing standard errors to be computed for inference even though the elasticity computation involves a combination of econometric estimates and data. The delta method computes standard errors using a generalization of the Central Limit Theorem, derived using Taylor series approximations, which is useful when one is interested in some function of a random variable rather than the random variable itself (OEHLERT, 1992). In this case, the method uses the parameter estimates from our model and the corresponding variance covariance matrix to evaluate the elasticities at average values of the arguments of the function.

$\varepsilon_{i,j} = \partial MP_{w,i}/\partial x_j * (x_j/MP_{w,i})$ represents the extent to which the marginal product of x_i changes when x_j changes.

To measure changes in relative output and input quantities as a consequence of changes in relative prices, Morishima Elasticities of Substitution (MES) can be used. MES can be interpreted as a measure of the percentage change in relative factors for a percentage change in price (STERN, 2011). The directional output distance function allows for the measurement of substitution or complementarity relations between different inputs and outputs via the Morishima shadow price output and input elasticities of substitution. Following BLACKORBY and RUSSELL (1978) and FÄRE et al. (2005), the ratio of shadow output prices are derived from the directional distance function as:

$$\frac{p_2'}{p_1'} = -\frac{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial y_2}}{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial y_1}} \qquad (16)$$

and the Morishima elasticity is:

$$M_{y_2 y_1} = y_1^* \left[\frac{\frac{\partial^2 \overrightarrow{D_O}(x,y;g)}{\partial y_2 \partial y_1}}{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial y_2}} - \frac{\frac{\partial^2 \overrightarrow{D_O}(x,y;g)}{\partial^2 y_1}}{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial y_1}} \right] \qquad (17)$$

with $y_1^* = y_1 + \partial \overrightarrow{D_O}(x, y; g)$. This yields in terms of the quadratic specification chosen

$$M_{y_2 y_1} = y_1^* \left[\frac{\alpha_{12}}{\alpha_2 + 0.5 \sum_{i=1}^{M} \alpha_{2i}(y_i') + \sum_{j=1}^{N} \gamma_{j2} x_j} - \frac{\alpha_{11}}{\alpha_1 + 0.5 \sum_{i=1}^{M} \alpha_{1i}(y_i') + \sum_{j=1}^{N} \gamma_{j1} x_j} \right] \qquad (18)$$

Equally, the ratio of shadow input prices are derived as:

$$\frac{w_2'}{w_1'} = -\frac{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial x_2}}{\frac{\partial \overrightarrow{D_O}(x,y;g)}{\partial x_1}} \qquad (19)$$

which gives the corresponding Morishima elasticity of

$$M_{x_2 x_1} = x_1^* \left[\frac{\beta_{12}}{\beta_2 + 0.5\beta_{22} x_2 + 0.5 \sum_{j=i+1}^{N} \beta_{2j} x_j + \sum_{i=1}^{M} \gamma_{i2}(y_i')} - \frac{\beta_{11}}{\beta_1 + 0.5\beta_{11} x_1 + 0.5 \sum_{j=i+1}^{N} \beta_{1j} x_j + \sum_{i=1}^{M} \gamma_{i1}(y_i')} \right] (20)$$

with $x_1^* = x_1 + \partial \overrightarrow{D_O}(x, y; g)$.

Technology Classes

Recent contributions demonstrate that estimating a "common" technological frontier for a group of observations is misleading if the farms in the sample are using different technologies (KUMBHAKAR et al., 2009; ALVAREZ and DEL CORRAL, 2009; SAUER and MORRISON-PAUL, 2011). With a flexible functional form, differences are partly accommodated because different netput mixes are allowed for in the production structure estimates. For example, estimated output elasticities with respect to an input will depend on all other arguments of the function and so will differ by observation. Unobserved technological heterogeneity is also partially accommodated by a standard error term for econometric estimation, but the factors underlying the heterogeneity are not directly represented and will bias parameter estimates if they are correlated with the explanatory variables (see GRILICHES, 1957). To adequately capture and evaluate heterogeneity between production systems operating in Kosovo, we explicitly distinguish technologies by estimating for different groups or "classes" of farms. This is particularly important to explore the effects of fragmentation and market integration specific to technology types. To accomplish this, the estimation of the production structure is combined with a latent class model (LCM) structure (GREENE, 2002; GREENE 2005).

It has increasingly been recognized that latent class models are desirable for representing heterogeneity (BALCOMBE et al., 2006; GREENE, 2005; OREA and KUMBHAKAR, 2004; QUIROGA and BRAVO-URETA, 1992; SAUER and MORRISON-PAUL, 2011). This approach separates the data into multiple technological "classes" according to estimated probabilities of class membership based on multiple specified characteristics, for example land fragmentation and market integration. Each farm can then be assigned to a specific class based on these probabilities. The LCM structure estimates a multinomial logit model together with the estimation of the overall technological structure. Statistical tests can be conducted to choose the number of classes or technologies that should be distinguished. The specification of multiple technologies based on multiple characteristics, outputs and inputs, along with random effects and a flexible functional form used in this study, accommodates heterogeneity in the sample of Kosovo small-scale farmers.

The latent class model in general form can be written as equation (13) for class l:

$$\vec{D}_{O_{kt}} = \overrightarrow{D_O}(\cdot)_{kt}\big|l \qquad (21)$$

where *l* denotes the class or group containing farm *k* and the vertical bar means a different function for each class *l*. As we are assuming that the error term for this function is normally distributed, the likelihood function for farm *k* at time *t* for group l, LF_{klt}, has the standard OLS form. The unconditional likelihood function for farm *k* in group l, LF_{kl} is the product of the likelihood functions in each period *t* and the likelihood function for each farm, thus LF_k, is the weighted sum of the likelihood functions for each group l (with the prior probabilities of class l membership as the weights): $LF_k = \Sigma l\ P_{kl}\ LF_{kl}$. The prior probabilities P_{kl} are typically parameterized as a multinomial logit (MNL) model, based on the farm-specific characteristics used to distinguish the technologies or determine the probabilities of class membership (called separating- or q-variables), q_k, and the parameters of the MNL to be estimated for each class (relative to one group chosen as numeraire), δ_l:

$$P_{kl} = \frac{exp(\delta_l q_k)}{[\sum_l exp(\delta_l q_k)]} = \frac{exp(\delta_{0l}+\sum_n \delta_{nl} q_{nkt})}{[\sum_l exp(\delta_{0l}+\sum_n \delta_{nl} q_{nkt})]} \qquad (22)$$

where the q_{nkt} are the N q-variables for farm *k* in time period *t*.

In this case four sets of features to distinguish technologies with respect to land fragmentation and market integration are included: fragmentation (SI and number of plots); market integration (the percentage of crops used for subsistence and a product diversity index); regional location, and year. We chose our preferred q-variables by trying different combinations of the four types of indicators and evaluating the latent class model (LCM) q-variable coefficient's estimates' significance and the resulting posterior probabilities for the individual classes. The number of classes is determined by AIC/SBIC tests suggested by GREENE (2005) that "test down" to show whether fewer classes are statistically supported. The model can be estimated in a panel or a cross-sectional specification whereas in the latter each farm is recognized as a separate entity that is assigned to a particular class allowing farms to switch between classes to identify changes in production systems over time (i.e. a cross-sectional specification):

$$\overrightarrow{D_O}(\cdot)_k\big|l = \big(\alpha_0 + \sum_{i=1}^{M}(\alpha_i y_i') + \sum_{i=1}^{M} 0.5\alpha_{ii}(y_i')^2 + \sum_{i=1}^{M}\sum_{j=i+1}^{M}\alpha_{ij}(y_i')\,(y_i') + \sum_{i=1}^{N}(\beta_i x_i + 0.5\beta_{ii}x_i^2) + 0.5\sum_{i=1}^{N}\sum_{j=i+1}^{N}\beta_{ij}x_i x_j + \sum_{i=1}^{M}\sum_{j=1}^{N}\gamma_{ij}(y_i')x_j + v - u\big)\big|l \qquad (23)$$

where $y_i' = y_i + y_w$ again with y_w as the quantity of wheat produced and abstracting from observational and time related variation. The probabilities P_{kl} are therefore functions of the parameters of the MNL model, and the likelihoods LF_{kl} are functions of the parameters of the technology for class l farms, so the likelihood function for farm k is a function of both these sets of parameters. The overall log-likelihood function for our model, defined as the sum of the individual log-likelihood functions LF_k, can be maximized using standard econometric methods.

For the purposes of this analysis, due to degree of freedom problems for the LCM model from the high number of outputs and inputs in the data, we initially characterize the classes based on an approximation to the directional output distance function that does not include all second-order interaction terms. The resulting (first-order and own second-order) elasticities thus represent the average contributions of each output and input to production for each class. To accommodate and measure the second order effects involving output and input substitution, we then estimate the full DODF form for the full sample and the separate classes. If the distinctions among classes capture key differences in technology, as we find, the elasticities for the constrained and fully flexible functional forms will be comparable but incorporating the interaction terms will allow assessment of cross effects.

5 Results

Figure 1 presents the distribution of technical efficiency scores for the full sample (by construction ranging between 0 and 1) where a larger index score indicates higher efficiency levels relative to other farms in the sample. The mean score is 0.60 with a standard deviation of 0.148. Compared to results for developing countries, the average technical efficiency score is relatively high (RIOS et al. 2008) albeit with a wide dispersion in efficiency across households. However, the efficiency scores are in line with some estimates for transition economies (see DAVIDOVA and LATRUFFE, 2007).

Table 2 presents estimation results for the determinants of inefficiency for the full sample. The estimations indicate an efficiency increasing effect of the SI but that the number of plots is associated with increases in inefficiency. This suggests that the relationships between efficiency and fragmentation may be complex. SI captures the relative size distribution of plots utilized by a household (for a given number of plots, the index will be higher the more equal the size of plots). This suggests that farming several plots of roughly equal size is more efficient than an unequal distribution of plot sizes.

Increases in efficiency are positively associated with the average education level of household members (hhavedu) but negatively associated with the level of education of the head of the household (headedu) which is counter-intuitive. Rises in the average age of household members (hhavage) are negatively associated with efficiency. The product diversity index (pdi) has no significant impact.

Table 3 presents elasticity measures for the full sample. Here qw refers to quantity of wheat, with qh, qpe, qt, qo and qpo referring to hay, peppers, tomatoes, onions and potatoes respectively. The first five elasticities listed reflect output trade-offs. For instance the elasticity of -.097 for qw/qt indicates that producing 1% more wheat given input use, on average involves about 9.7% less output of tomatoes for the farms in our data.

The (proportional) productive contributions of the inputs for the production of wheat are given by the remaining qw elasticities (k = land, labft, labpt, mach, fuel, rent, fert, chem, seed). Here labft and labpt refer to the number of full and part-time family labor workers respectively. Mach, fert and chem refer to machinery, fertilizers and chemicals respectively. The output elasticities with respect to the inputs show that seeds comprise the largest marginal input 'share' or contribution to output of wheat at about 18%, land at 12%, followed by fertilizers (6.7%) and fuel (6.3%).

In combination, these estimates point to increasing returns to scale; a 1% increase in all netputs generates an increase in production of about 2.82%. As stated previously, a premise of the study is that such average measures for the whole sample fail to reflect a farm's production patterns if the technology is heterogeneous. Four variables related to land fragmentation and market integration (SI, number of plots, hhups and pdi) were used to distinguish classes. As explained above, determining the number of classes involved 'testing down' to assess whether restricting classes is justified. This utilized AIC and SBIC tests (GREENE, 2005). For the dataset, three classes were statistically supported but two classes were not. In general, the four variables capturing fragmentation / market integration display a significant influence on defining different classes of technology, indicating that land fragmentation and market integration are associated with different production technologies.

Table 4 details the characteristics of the each class. Farms in Class 3 display the lowest average technical efficiency, while farms in Class 2 display the highest average level of efficiency. Class 2 contains by far the largest number of observations. Class 3 is characterized by the highest mean SI and highest average number of plots, indicating greater land fragmentation. From the point of view of market integration, Class 1 appears to be more subsistence oriented than Classes 2 or 3.

Table 5 presents the first-order elasticities for the three separate classes, where the output is wheat. The first order elasticities for non-wheat outputs (hay, peppers, tomatoes, onions and potatoes) for all classes are negative (as required). For Class 1, the higher absolute values of the estimates suggest that an increase in wheat production involves a greater decrease in other outputs. For Class 1, the marginal contribution of land is higher than for the other groups. For Class 2, seeds represent the largest marginal input 'share' or contribution to output of wheat. For Class 3 the marginal products of the inputs tend to be lower, confirming the relatively low efficiency of these farms. Increasing returns to scale are apparent for all three classes, and are highest for Class 3.

The determinants of technical inefficiency are investigated separately for the three classes. For Class 2, with by far the largest number of observations, neither the SI nor the number of plots are significant determinants. The measure of market integration, hhups, has a significant, efficiency decreasing effect for Class 2. This is in keeping with other studies on the relationship between market integration and efficiency (LATRUFFE et al., 2004). Other factors which are significant for Class 2 are: region, the educational level of the head of the household, age of the head of the household (all efficiency increasing effect). In contrast, the average age of the household (hhavage) has an efficiency decreasing effect.

For Class 3, the least efficient group, SI is positively associated with technical efficiency while the number of plots is not significant. This may mean that for a small group of relatively lowly efficient Kosovo farmers, the private costs of land fragmentation are more than offset by private benefits. As with Class 2, hhups has a significant efficiency decreasing effect. For Class 3, the only other significant determinants are the average age of household members and the educational level of the head of the household, both of which have efficiency decreasing effects.

For Class 1, SI is negatively associated with efficiency while the number of plots is not significant. In contrast to the other two groups, hhups has a positive impact on efficiency which may suggest that the need to satisfy household food requirements forces farmers to use their scarce resources more efficiently. It should be reminded that this is the class in which farmers expect to use a highest share of their harvest for household purposes amongst the three classes. For Class 1, the average educational level of household members is positively associated with efficiency.

Overall, Table 6 illustrates that the determinants of efficiency vary across classes. For the most efficient farms in Class 2, land fragmentation (both SI and number of plots) has no significant impact on efficiency. In contrast, subsistence (as measured by the variable hhups) has a negative impact on efficiency for both Classes 2 and 3, but a positive impact for Class 1.

6 Conclusion

This study analyzes the relationship between the farm fragmentation and market integration, on the one hand, and efficiency, on the other, for a sample of farm households in Kosovo. In contrast to previous studies on this topic, which limited the scope of their analysis to the relationship between different measures of land fragmentation and productivity or efficiency, this study considers land fragmentation simultaneously with the effects on efficiency of market integration. This approach was driven by the fact that many agricultural households with small farm endowments operate in an environment of underdeveloped factor and commodity markets are subsistence/semi-subsistence in nature. It is the first study of the effects of farm fragmentation that links the latent class model approach to the estimation of a multi-output production function and to the estimation of Morishima elasticities based on shadow price changes.

The empirical application led to the definition of three classes with heterogeneous technologies. Several conclusions can be drawn from the results. First, in general small Kosovo farmers are relatively technically efficient (a mean score for the full sample 0.6). This may reflect that most of the land in the former Federal Socialist Republic of Yugoslavia era was not collectivized and small farmers have longstanding experience and technical knowledge to perform efficiently. In addition, under imperfect labor and commodity markets there is a strong motivation to maximize the output given the level of inputs in order to cover household consumption needs.

Almost four-fifths of farm households in the sample belong to the high relative efficiency Class 2 with an average technical efficiency of 0.88. For this class there is a lack of a statistically significant relationship between land fragmentation and technical efficiency which is in agreement with WU et al. (2005). It is often assumed that land fragmentation is a major cause of inefficiency in Kosovo (ARCOTRASS CONSORTIUM, 2006). For the largest class of farm households this does not appear to be the case. The fact that several policy initiatives to promote land consolidation have faced resistance from farmers in Kosovo may not mean that they are irrational, but just the opposite, that farmers rightly do not regard land fragmentation as a major impediment.

Classes 1 and 3 incorporate a minority of farm households in the sample (8.9 and 12.6% respectively) and present interesting and to some extent counter-intuitive cases. The estimations for Class 1 are consistent with the theory presented in the conceptual framework - that fragmentation increases inefficiency. However, the puzzle comes from the result that the allocation of a higher share of crops for household consumption, thus weaker market integration, is efficiency increasing. This contradicts the mainstream belief that semi-subsistence farms in Europe impose high costs on society as they use the scarce resources inefficiently (DAVIDOVA, 2011). For Class 1 land consolidation may help, but probably most of all the members of this class need policies that can decrease the transaction costs of market integration which, as discussed in the conceptual framework, depend largely on public goods supplied by the government. For Class 3 the unexpected result is the strong pro-efficiency effect of land fragmentation. This may confirm that for specific sub-sets of farms, land fragmentation may be beneficial to the extent that it aids the production of a variety of crops and spreads risk.

References

ALVAREZ, A., J. DEL CORRAL, and , L.W. TAUER (2009): Detecting Technological Heterogeneity in New York Dairy Farms, Cornell University Working Paper.

ANGELSEN, A., VAN SOEST, D., KAIMOWITZ, D., and E. BULTE (2001): Technological change and deforestation: A theoretical overview. In: Angelsen, A., and Kaimowitz, D. (eds.): Agricultural Technologies and Tropical Deforestation, Wallingford, UK: CABI Publishing, 19-34.

ARCOTRASS CONSORTIUM (2006): Kosovo, Report for the European Commission, http://ec.europa.eu/agriculture/analysis/external/applicant/kosovo_en.pdf

BALCOMBE, K., FRASER, I. and J.H. KIM (2006): Estimating technical efficiency of Australian dairy farms using alternative frontier methodologies. In: Applied Economics 38: 2221-2236.

BARRETT, C. (2008): Smallholder market participation: Concepts and evidence from eastern and southern Africa. In: Food Policy 33: 299-317.

BATTESE, G. and T. COELLI (1995): A model for technical inefficiency effects in a stochastic frontier production function for panel data. In: Empirical Economics 20: 325-332.

BLACKORBY, C., PRIMONT, D. and R.R. RUSSELL (1978): Duality, Separability, and Functional Structure: Theory and Economic Applications. New York, Elsevier North-Holland.

BLAREL, B., HAZELL, P., PLACE, F. and J. QUIGGIN (1992): The economics of farm fragmentation: Evidence from Ghana and Rwanda. In: World Bank Economic Review 6: 233– 254.

CAVES, D.W., L.R. CHRISTENSEN and W.E. DIEWERT (1982): The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity. In: Econometrica 50: 1393-1414.

CHAMBERS, R., CHUNG, Y. and R. FÄRE (1996): Benefit and distance functions. In: Journal of Economic Theory 70: 407-419.

CHAVAS, J-P., PETRIE, R. and M. ROTH (2005): Farm household production efficiency: Evidence from the Gambia. In: American Journal of Agricultural Economics 87: 160-179.

CHEN, Z., HUFFMAN, W. and S. ROZELLE (2009): Farm technology and technical efficiency: Evidence from four regions in China. In: China Economic Review 20: 153-161.

COELLI, T., PRASADA RAO, D.S., O'DONNELL, C.J. and G.E. BATTESE (2005): An Introduction to Efficiency and Productivity Analysis. Springer, New York

CORRAL, J., PEREZ, J. and D. ROIBAS (2011): The impact of land fragmentation on milk production. In: Journal of Dairy Scienc 94: 517-525.

DAVIDOVA, S. (2011): Semi-subsistence farming: an elusive concept posing thorny policy questions. In: Journal of Agricultural Economics 62: 503-524.

DAVIDOVA, S. and L. LATRUFFE (2007): Relationship between technical efficiency and farm financial management: The example of the Czech Republic. In: Journal of Agricultural Economics 58: 1-20.

DI FALCO , S., PENOV, I., ALEKSIEV, A. and T. VAN RENSBURG (2010): Agrobiodiversity, farm profits and land fragmentation: Evidence from Bulgaria. In: Land Use Policy 27: 763-771.

FÄRE, R. and D. PRIMONT (1995): Multi-Output Production and Duality: Theory and Applications. Kluwer Academic Publishers, Boston.

FÄRE, R., GROSSKOPF, NOH, D-W. and W. WEBER (2005): Characteristics of a polluting technology: theory and practice. In: Journal of Econometrics 126: 469-492.

GREENE, W. (2002): Alternative panel data estimators for stochastic frontier models. Working Paper, Department of Economics, Stern School of Business, NYU.

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

GRILICHES, Z. (1957): Specification bias in estimates of production functions. In: Journal of Farm Economics 49: 8-20.

KUMBHAKAR, S. and C.A. KNOX-LOVELL (2000): Stochastic Frontier Analysis. University Press, Cambridge, UK.

KUMBHAKAR, S., TSIONAS, E. and T. SIPILÄINEN (2009): Joint estimation of technology choice and technical efficiency: An application to organic and conventional dairy farming. In: Journal of Productivity Analysis, 31: 151-161.

LATRUFFE, L., BALCOMBE, K., DAVIDOVA, S.M. and K. ZAWALINSKA (2004): Determinants of technical efficiency of crop and livestock farms in Poland. In: Applied Economics 36: 1255-1263.

OEHLERT, G.W. (1992): A note on the Delta method. In: American Statistician 46: 27-29.

OREA, L. and S. C. KUMBHAKAR (2004): Efficiency measurement using a Latent Class Stochastic Frontier Model. In: Empirical Economics 29: 169-183.

QUIROGA, R.E. and B.E. BRAVO-URETA (1992): Short- and long-run adjustments in dairy production: a profit function analysis. In: Applied Economics 24: 607-616.

RAHMAN, S. and R. RAHMAN (2008): Impact of land fragmentation and resource ownership on productivity and efficiency: The case of rice producers in Bangladesh. In: Land Use Policy 26: 95–103.

RIINVEST (2005): Kosovo Socio-Economic Profile and Development Challenges, Prishtina, Mimeo.

RIOS, A.R., MASTERS, W.A. and G.E. SHIVELY (2008): Linkages between Market Participation and Productivity: Results from a Multi-Country Farm Household Sample. Paper presented at the American Agricultural Economics Association Annual Meeting. Orlando, FL. July 27-29, http://ageconsearch.umn.edu/bitstream/6145/2/461840.pdf

SAUER, J. and C.M. MORRISON-PAUL (2011): The empirical identification of heterogeneous technologies and technical change. In: Applied Economics 43: 1-19.

SAUER, J., DAVIDOVA, S. and L. LATRUFFE (2012): Determinants of smallholders' decisions to leave land fallow: the case of Kosovo. In: Journal of Agricultural Economics 63; 119-141.

SOK (2006): Agricultural Household Survey. Statistical Office of Kosovo, Pristina, Kosovo.

STERN, D.I. (2011): Elasticities of substitution and complementarity. In: Journal of Productivity Analysis 36: 79-89.

UNMIK (2003): The Kosovo Green Book: A Strategy for Sustainable Agricultural and Rural Development in Kosovo. United Nations Interim Administration Mission in Kosovo, Pristina, Kosovo.

VAN HUNG, P., MACAULAY, T.G. and S. MARSH (2007): The economics of land fragmentation in the North of Vietnam. In: Australian Journal of Agricultural and Resource Economics 5: 195-211.

WORLD BANK and SOK (2007): Kosovo Poverty Assessment, Report No. 39737-XK Poverty Reduction and Economic Management Unit, Europe and Central Asia Region. Washington D.C.

WU, Z., LIU, M and J. DAVIS (2005): Land consolidation and productivity in Chinese household crop production. In: China Economic Review 16: 28–49.

Appendix

Table 1: Selected Descriptive statistics (n= 2217)

Variable	Mean	Min	Max
Average land area used for wheat production (ha)	1.25	0.0300	150.0
Average land area used for hay production (ha)	1.24	0.0050	30.7
Average land area used for pepper production (ha)	0.03	0.0003	3.0
Average land area used for tomatoes production (ha)	0.01	0.0003	0.9
Average land area used for onions production (ha)	0.02	0.0004	5.2
Average land area used for potatoes production (ha)	0.05	0.0004	10.2
Age of household head (years)	55.61	19	98
Gender of household head (1-male, 2-female)	1.02	1	2
Education of household head (level)	3.98	1	9
Average age of household members (years)	29.41	13	76.5
Average education of household members (category 1-9)	3.36	1.5	7.4
Full-time labour per year (no of household members)	1.13	0	21
Utilised land area (ha)	2.61	0.20	151.66
Machinery value (in 2005 values in Euro)	3550.64	0	101826.5
Simpson Index	0.75	0.020	0.941
Number of plots (no)	8.38	2	28
Product diversity index	14.30	6	43

Table 2: Determinants of inefficiency for the full sample

	Coefficient	Sig		Coefficient	Sig
Simpson Index (SI)	-6.359	-10.94***	hhavage	0.013	1.78*
number of plots	0.958	3.78***	headedu	0.293	8.97***
hhups	-0.002	-2.15**	headage	-0.000	-0.18
pdi	-0.013	-1.22	headg	-0.383	-0.87
region	-0.076	-3.53***	year	-0.117	-2.95
hhavedu	-0.274	-4.21**	_cons	-140.243	-0.61

*10%, **5%, ***1% significance

Table 3: First-order production structure elasticities for the full sample

Elasticity	Estimate	t-statistics	Elasticity	Estimate	t-statistics
qw/qh	-.01513768	-3.765	qw/labpt	.00607433	6.481
qw/qpe	-.29213747	-3.151	qw/mach	.05228562	3.839
qw/qt	-.09658588	-5.128	qw/fuel	.06250621	4.561
qw/qo	-.08835404	-5.008	qw/rent	.01690271	6.769
qw/qpo	-.04250834	-8.527	qw/fert	.06688338	1.841
qw/land	.12143243	4.919	qw/chem	.01194148	6.179
qw/labft	.02366067	3.385	qw/seed	.18199252	6.508
Returns to scale	2.82284783	151.656			

Table 4: Characteristics of the three classes

Class	Class 1	Class 2	Class 3
Number of farm households	198	1740	279
Average efficiency score	0.712	0.883	0.656
Range of efficiency scores	0.096 to 0.969	0.752 to 0.939	0.241 to 0.898
Average Simpson Index	0.67	0.75	0.78
Average number of plots	6.7	8.1	11.3
Average amount of cultivated crops used for subsistence purposes	472	451	362

Table 5: First order elasticities for the three classes

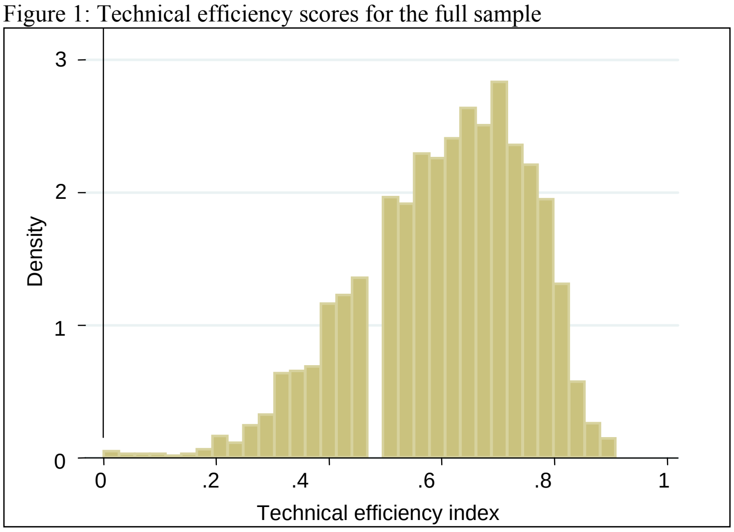
	Class 1		Class 2		Class 3	
Elasticity	Estimate	t-statistics	Estimate	t-statistics	Estimate	t-statistics
qw/qh	-.1844	-1.874	-.0478	4.181	-.0321	-8.911
qw/qpe	-.3208	-1.691	-.2314	4.259	-.2046	-2.866
qw/qt	-.2547	-1.010	-.0933	-11.801	-.1921	-1.622
qw/qo	-.0634	-2.526	-.0211	-2.677	-.0386	-3.273
qw/qpo	-.1080	-1.547	-.0963	3.992	-.0452	-13.832
qw/land	.1311	-1.693	.0334	-2.603	.0296	8.991
qw/labft	.0438	1.450	.0301	1.424	.0176	1.563
qw/labpt	.0030	10.811	.0071	2.425	.0088	5.411
qw/mach	.0485	12.830	.0156	4.231	.0363	2.133
qw/fuel	.1334	2.447	.0280	.832	.0248	2.013
qw/rent	.1147	2.461	.0562	2.182	.0161	9.055
qw/fert	.0587	10.261	.0581	.752	.0221	1.082
qw/chem	.0587	1.400	.0191	5.210	.0873	7.712
qw/seed	.1579	7.781	.2932	3.001	.0720	3.913
Returns to scale	2.575	25.095	2.755	1555.022	4.805	23.946

Table 6: Determinants of inefficiency for the three classes

	Class 1		Class 2		Class 3	
	Coefficient	Sig	Coefficient	Sig	Coefficient	Sig
Simpson Index (SI)	3.511	3.16***	1.997	1.03	-7.245	-3.34***
number of plots	0.312	0.37	-0.548	-0.76	-0.868	-0.31
hhups	-0.005	-2.14**	0.006	2.37**	6.725	1.66*
pdi	-0.023	-0.65	-0.002	0.07	1.365	0.67
region	0.103	1.68*	-0.127	-1.91*	0.432	0.52
hhavedu	-0.456	-2.15**	0.119	0.75	-0.978	-1.35
hhavage	0.029	1.42	0.131	1.72*	0.146	1.59
headedu	0.161	1.93*	-0.148	-1.66*	0.628	2.38**
headage	-0.019	-1.57	-0.020	-1.75*	0.001	0.03
headg	-0.746	-0.67	0.613	0.89	-32.447	-0.02
year	0.070	0.61	0.240	1.92*	-0.479	-1.40
_cons	-140.243	-0.61	-417.180	-1.95*	984.957	0.54

*10%, **5%, ***1% significance

Figure 1: Technical efficiency scores for the full sample



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