Romanian Maize – Distorted Prices and Producer Efficiency

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Abstract

This study tackles the decomposition of efficiency with respect to agricultural production in transition economies by using a case study on small scale maize farmers in Romania. The underlying modelling assumption is that farmers in transition countries still face heavily distorted price systems. To capture such distortions a stochastic shadow cost frontier model is formulated to investigate the systematic input specific allocative inefficiency. We further adjust the underlying cost frontier by incorporating shadow price corrections and subsequently reveal evidence on farm specific technical inefficiency. Different models are estimated due to the imposition of curvature correctness. The empirical results confirm the underlying hypothesis of enduring price distortions.

Key Words Efficiency, Shadow Cost Frontier, Transitional Agriculture, Functional Consistency

JEL C40, D24, O33

1 - INTRODUCTION

Profound structural changes are still taking place in the process of transition from a command to a market oriented economy in most Eastern European countries and New Independent States (NIS). As a consequence, farmers in these countries still face heavily distorted price systems. As Barrett (1997) notes, given that such farm specific failures in input and output markets are a fundamental characteristic of low-income agriculture, the relevant measurement of efficiency might differ from one farm to another, with crucial variables, such as shadow prices, unobservable for to the researcher. This is especially true for the agricultural sector in Romania where the structural reforms have been concentrated on the privatization of land and the downsizing of agricultural enterprises leading to the emergence of numerous small farms (Lerman 1999, OECD 2000). These farmers – socalled individual farmers – are currently the most important actors with respect to land and output markets (OECD 2000, Leonte 2002). However, they are still constrained with respect to an insufficient factor endowment and the lack of developed input and output markets (Rizov et al 2001). As a result, most technology intensive crops have been substituted by the cultivation of more traditional crops and the importance of subsistence farming has increased (Tesliuc 2000).

The production of maize, as one of the main traditional crops in Romania, increased in its importance, which is also related to its relatively simple way of production and storage (Tesliuc 2000). Hence, this crop currently plays a central role in agricultural production being cultivated on a relatively large area and providing a relatively large proportion of output (NIS 2004). According to Gorton et al (2003), maize shows a comparative advantage in Romania. Given the importance of maize production for agricultural transition and rural development, this research aims to assess the relative efficiency of small-scale maize production and tries to determine different factors for the inefficiency of maize. In the background of the restructuring of Romanian agriculture, the individual farmers' decisions are often made with respect to shadow prices, as the prices the decision maker actually has to pay, rather than those observed as prevailing market prices (see Toda 1976, Atkinson and Halvorsen 1980, Kumbhakar and Bhattacharyya 1992 and Wang et al. 1996). The following study therefore uses such shadow prices to model and analyze the relative efficiency of small-scale Romanian maize producers. With respect to policy relevant empirical based productivity studies, Gorton and Davidova realized in 2004 that "(…) there is a lack of evidence on the Baltic States and Romania." This deficiency still exists with respect to Romanian agricultural production.

After briefly outlining the case of small-scale maize production in Romania, the applied model is described as a combination of the shadow price approach, to reveal systematic allocative efficiency, and the error components approach, to obtain producer specific technical efficiency estimates. The estimated models are tested and corrected for theoretical consistency and further bias corrected bootstrapping techniques are applied to investigate the statistical robustness of the most consistent model. Finally the relative efficiency scores and possible factors for their variance over the sample are discussed.

2 – The Case Study – Small-Scale Maize Production in Romania

The majority of the restructuring measures in the Romanian agricultural sector since 1989 were concentrated on the privatization of land aimed at changing collective agriculture to individual agriculture, as well as on the downsizing of the farms (Lerman 1999, Cartwright 2001, Rizov et al 2001). The future owners could choose among the following options: individual farming, joining a family based association, joining a formal association and pursuing a mixed strategy (Sabates-Wheeler 2001). The majority of farmers chose individual farming and thus, in 2002, 4.7 million individual farms cultivated 62% of the arable land with an average size of 1.6 hectares per farm (NIS 2004). However, by reestablishing the situation before collectivization, the privatization hence led to the fragmentation of the agricultural land and consequently the new individual farmers were constrained in their business development by the fragmented structure and small size of the land holdings (Macours/Swinnen 2000, Rizov et al 2001). Initially, the farms could not be adjusted to their efficient size because the restituted land was banned from selling till the year 1998 and a simplification of the complex law on leasing was only conducted in the same year. Due to this structure, the renting of agricultural land was not attractive to those farmers as obtaining a large piece of land implied substantial transaction costs as a consequence of the need to coordinate with several different land owners (Trzeciak-Duval 1976, Mathijs/Swinnen 1998, Tesliuc 2000).

Furthermore, the new individual producers lacked the necessary know-how to cultivate their land. They had no cash to invest and rarely had access to credit or agricultural equipment. Up and downstream sectors had not been restructured to suit the needs of the small farmers, which led to high transactions costs by using the different input and output markets. However, Rizov et al (2001) found that these input constraints differ with respect to regional location pointing to the importance of pre-reform tradition with individual farming or collective farming. Such transaction costs and the lack of capital reinforced the decline in the use of inputs like fertilizer and certified seed (Kenneth 2003, OECD 2000, Tesliuc 2000). By responding to these difficulties, producers diversified their production, substituted commercial with non-commercial crops, technical crops by traditional crops and increased subsistence production (see Sarris et al. 1999). The latter finally further promoted the stagnation in the development of input and output markets and led to a kind of vicious circle. The increase in maize cultivation in Romania during this period is basically linked to these developments in the agricultural sector. Maize production is one of the traditional agricultural activities and the area devoted to maize production increased from about 26% (1990) to about 36% (2003) of the arable land (NIS 2004). The cultivation of maize shows the relative advantage of low input intensity: no certified and commercially distributed seed is needed; the crop can be simply harvested by hand and easily stored without the need for sophisticated facilities. Maize can be consumed in the household as well as in the process of animal production. The latter leads finally to relatively less dependence on the purchase of additional fodder (Tesliuc 2000).

Although the economic reforms in Romanian agriculture have reduced direct state control over production decisions, various interferences in the input and output markets still distort farmers' production decisions (Rizov et al. 2001). Despite the focus of some studies on the economic efficiency of individual farms in transitional countries (see e.g. Mathijs/Swinnen 2001, Hughes 1998, Piesse/Thirtle 2000, Lerman 2000, Mathijs/Swinnen 2000, Christoiu 2001, and Swinnen/Vranken 2005, for an excellent compilation see Gorton/Davidova 2004) none consider the effects of distorted input and output price relations with respect to the relative efficiency of agricultural production in Romania. The following analysis aims at filling this gap by attempting to decompose farm efficiency in transition countries with respect to such market distortions, as well as farm specific factors.

3 – The Analytical Challenge - Decomposing Inefficiency

As Barrett already noted a decade ago: "Policy-induced price distortions are problematic if they induce peasants to allocate resources in a socially suboptimal manner, and market-oriented correctives are fully effective only if producers reallocate factors rationally." (Barrett 1997, p. 221). The underlying assumption of this study is that such policy-induced distortions are still the case for transitional agriculture hampering the production decisions of small scale farmers, like the Romanian maize farmers in the chosen empirical case. While the quantitative decomposition of overall economic efficiency into its technical and allocative related components is more or less easily reached by using the dual approach of cost or profit function based modelling, a further decomposition of allocative inefficiency still remains an analytical challenge. This is basically related to the definition of an appropriate concept of allocative efficiency taking into account the farmer's objectives and the constraints and prices faced by the farm enterprise, as well as the decomposition of the allocative efficiency into its components. To tackle this challenge, the economic concept of shadow prices is applied here. According to the common concept of shadow prices: when determining the optimal input vector, farms compare the benefits of using an additional unit of each input to its cost, the purchase (or 'observed') price. Depending on whether a production function approach or a cost function approach is taken, these marginal benefits – referred to as the shadow price of the input – can be measured either in terms of the input's value marginal product, or as the reductions in expenditures on other inputs that can be achieved by using one additional unit of the input (while keeping output constant). In the absence of market distortions, the optimal amount of input use is intuitive: use an input up to the point where the shadow price and the purchase price are equivalent. If market distortions are present, farms are unable to equate their shadow price to the undistorted input price. For this analysis, the shadow price of an input is defined as the potential reduction in expenditures on other variable inputs that can be achieved by using an additional unit of the input under consideration while maintaining the level of output. However, the observed prices used in the analysis are prices reported by the farmers. Due to the vast literature on shadow prices (for an overview see e.g. Khumbhakar/Lovell 2000), non-observable shadow price ratios have to be considered as the relevant ones for producer decisions in distorted markets. The divergence between the analysed (i.e. estimated) shadow prices and the observed market prices can be interpreted as the sum of allocative inefficiency due to the prevalence of various market constraints, as well as optimization failure by the farm management. Different approaches to model this divergence can be found in the literature: The usual method consists of additively translating observed prices to create shadow prices (see Kumbhakar/Lovell 2000). Alternatively, shadow prices can be modeled by multiplicatively scaling observed prices into shadow ones (Lau/Yotopoulos 1971). We follow the latter approach here and define the relationship between the normalized shadow prices for the variable and fixed inputs w^*, f^* and the normalized market prices w, f as

$$w^*_i = \theta_i w_i \qquad f^*_l = \theta_l f_l \qquad [1]$$

where θ_i, θ_l are (non-negative) price efficiency parameters and i, l are indices for variable and fixed inputs respectively. If no market restrictions and optimization errors are the case then θ_i, θ_l equal unity, if market distortions and/or management failure restrict optimizing behaviour then $\theta \geq 0 \wedge \theta \neq 1$. Consequently, a Romanian maize farmer can be regarded as allocatively efficient with respect to observed market prices only if observed market prices reflect the farmer's opportunity cost with respect to inputs. It has to be considered, however, that the price efficiency parameters θ_i, θ_l may still reflect both effects of market distortions as well as farm specific optimization failures. As we have only observed prices for the variable inputs labor and fertilizer, we treat the remaining inputs, land and organic fertilizer, as quasi-fixed, thus including the relevant quantity in the shadow cost function instead of its price (see also e.g. Morrison 1988 and Morrison/Schwartz 1996). It has to be kept in mind that by modelling allocative efficiency, as outlined above, a further decomposition is not reached. However, an approximative decomposition is attempted by the following modelling efforts.

4 – The Model – A Combination of Shadow Prices and Error Components

We start our modeling efforts by formulating a simple single-output translog cost function and its associated cost-minimizing input cost share equations (see e.g. Atkinson/Halvorsen 1980, Kumbhakar 1989, Wang et al., 1996, Kumbhakar/Bhattacharyya, 1992). Incorporating shadow prices according to [1] and following the input-oriented approach with respect to technical efficiency, observed expenditure (C) and observed input cost shares (S_i) can be expressed in terms of normalized shadow cost and normalized shadow input cost shares as

$$\ln C = \alpha_0 - \sum_{n=1}^{6} \chi_n D_n + \gamma_y \ln y + \frac{1}{2}\gamma_{yy}\left(\ln y\right)^2 + \sum_{i=1}^{2}\alpha_i \ln\left(\theta_i w_i\right) + \frac{1}{2}\sum_{i=1}^{2}\sum_{k=1}^{2}\beta_{ik}\ln\left(\theta_i w_i\right)\ln\left(\theta_k w_k\right)$$
$$+\sum_{i=1}^{2}\beta_{yi}\ln y \ln\left(\theta_i w_i\right) + \sum_{l=1}^{2}\delta_l \ln\left(\theta_l f_l\right) + \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2}\delta_{lm}\ln\left(\theta_l f_l\right)\ln\left(\theta_m f_m\right)$$
$$+\sum_{i=1}^{2}\sum_{l=1}^{2}\delta_{il}\ln\left(\theta_i w_i\right)\ln\left(\theta_l f_l\right) + \sum_{l=1}^{2}\delta_{yl}\ln y \ln\left(\theta_l f_l\right) + \ln\left\{\sum_{i=1}^{2}\left(\theta_i\right)^{-1}\left[\beta_i + \sum_{i=1}^{2}\beta_{ik}\ln\left(\theta_k w_k\right) + \beta_{yi}\ln y\right]\right\}$$

[2]

and

$$S_i = \frac{\left(\theta_i\right)^{-1}\left[\beta_i + \sum_{k=1}^{2}\beta_{ik}\ln\left(\theta_k w_k\right) + \beta_{yi}\ln y\right]}{\sum_{i=1}^{2}\left(\theta_i\right)^{-1}\left[\beta_i + \sum_{k=1}^{2}\beta_{ik}\ln\left(\theta_k w_k\right) + \beta_{yi}\ln y\right]} \qquad i = 1,2 \qquad [3]$$

respectively, where symmetry and homogeneity of degree +1 in input prices are imposed through the parameter restrictions $\beta_{ik} = \beta_{ki},\ i \neq k,\ \sum_{i=1}^{2}\beta_i = 1,\ \sum_{k=1}^{2}\beta_{ik} = 0,\ k = 1,2;\ \sum_{i=1}^{2}\beta_{yi} = 0$ and where y = maize output; the variable inputs' prices w = labor, fertilizer; the quasi-fixed inputs f = land, organic fertilizer; and the variables e = herbicide used, insecticides used, seed applied, subsidies received, extension services used, agricultural training received, slope of the land cultivated, relative amount of precipitation, soil moisture, vegetation vigor/density, and livestock units. Classical error terms are appended, one input cost share equation is deleted, and the remaining system of *I* input equations is estimated. χ includes the relative technical inefficiency, with respect to a group of farmers, defined along different characteristics *n* and denoted by *D* for dummy variable and θ gives the systematic allocative inefficiency for the respective input.

Rizov et al (2001) point to the importance of human capital matters for the productive development of individual farming in transition countries and especially in Romania. Accordingly, farmers' education and farming experience do affect the development of larger production units and the initiation of cross farm cooperation. However, the small sample size leads to an aggregation across all forms of labor used on the farm by imposing the strong assumption that all labor is equally productive, regardless of certain characteristics and irrespective of whether it is hired or family labor. By simultaneously modelling the shadow price for labor as a function of gender and age of the household head, the level of education, the relative amount of hired labor, the amount of working hours spent outside agriculture as well as the size of the household, we are at least able to control for some of these differences and examine whether they have any influence on the shadow price fluctuation. Hence, we model the parameter for the shadow price of labor θ_{lab} as follows:

$$\theta_{lab} = \varphi_{l\_g} D_{gender} + \varphi_{l\_a} \ln X_{age} + \varphi_{l\_e} \ln X_{edu} + \varphi_{l\_h} \ln X_{hf} + \varphi_{l\_out} \ln X_{out} + \varphi_{l\_hh} \ln X_{hh} \qquad [4]$$

where D_{gender} is a binary variable for the gender of the household head, X_{age} as the age of the household head in years, X_{edu} as the years of education of the household head, X_{hf} is the ratio for hired to family labor, X_{out} as the amount of labor spent outside agriculture, and X_{hh} as the number of household members.

Sherlund et al. (2002) impressively document how smallholder agricultural production depends heavily on environmental production conditions that are largely exogenously determined. By neglecting the influence of such production conditions, an omitted variables bias is likely to occur. Following their findings it can be expected that beside others the shadow price of land is affected by the quality of the land, the prevailing climatic conditions, as well as the geological characteristics of the landscape. By simultaneously modelling the shadow price for land as a function of relative precipitation, soil moisture, and the vigor and density of the vegetation in the area, we are at least able to control for some of these influences and examine whether they have any significant impact on the shadow price fluctuation in the period observed. The shadow price parameter for land θ_{land} is modelled according to the equality in [5]:

$$\theta_{land} = \eta_{land\_p} \ln X_{precip} + \eta_{land\_s} \ln X_{soil} + \eta_{land\_v} \ln X_{vege} \qquad [5]$$

where X_{precip} is a variable for the relative precipitation, X_{soil} as the soil moisture in the area and X_{vege} as a vegetation index.

Different recent contributions point to the crucial importance of considering the consistency of the estimated frontier with basic microeconomic requirements as monotonicity with respect to inputs as well as concavity of the function (see e.g. Ryan/Wales 1998 and Sauer 2006). Monotonicity of the estimated cost function – i.e. positive first derivatives with respect to all input prices - holds as all variable inputs W and quasi-fixed inputs F are positive for all observations in the sample. The necessary and sufficient condition for a specific curvature consists of the definiteness of the bordered Hessian matrix as the Jacobian of the derivatives $\partial C / \partial w_i$ with respect to w_i and $\partial C / \partial f_l$ with respect to f_l: if $\nabla^2 C(y,w,f)$ is negative definite, C is concave, where ∇^2 denotes the matrix of second order partial derivatives with respect to the shadow translog cost model defined by [2]. The Hessian matrix is negative definite at every unconstrained local maximum. Hence, the underlying function is concave and an interior extreme point will be a global maximum. The condition of concavity is related to the fact that this property implies a quasi-concave production function and consequently a convex input requirement set (see in detail e.g. Chambers 1988). Hence, a point on the isoquant is tested, i.e. the properties of the corresponding production function are evaluated subject to the condition that the amount of production remains constant. With respect to the translog shadow cost function, model curvature depends on the specific variable input price and quasi-fixed input bundle, as the corresponding Hessian **H** for our 4 input case shows:

$$H = \begin{pmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{21} & h_{22} & h_{23} & h_{24} \\ h_{31} & h_{32} & h_{33} & h_{34} \\ h_{41} & h_{42} & h_{43} & h_{44} \end{pmatrix} \qquad [6]$$

where h_{ii} is given by

$$\frac{d^2C}{d(w_i,f_l)^2}=\frac{d}{d\ln(w_i,f_l)}\left(\frac{d\ln C}{d\ln(w_i,f_l)}\right)=(w_i,f_l)^{-2}\left(\beta(\delta)_{rr}+S_r(S_r-1)\right) \qquad [7]$$

for r = i, l and S_r as the cost share of input r, and h_{ij} is given by

$$\frac{d^2C}{d(w_i,f_l)^2}=\frac{d}{d\ln(w_i,f_l)}\left(\frac{d\ln C}{d\ln(w_k,f_m)}\right)=\left[(w_i,f_l)(w_k,f_m)\right]^{-1}\left(\beta(\delta)_{rs}+S_rS_s\right) \qquad [8]$$

for r = i, l and s = k, m. Given a point x^0, what is necessary and sufficient for curvature correctness is that at this point $v'Hv \leq 0$ and **v's** = 0 where **v** denotes the direction of change. For some input bundles concavity may be satisfied but for others not and hence what can be expected is that the condition of negative definiteness of the Hessian is met only locally or with respect to a range of input bundles. The respective Hessian is negative definite if the determinants of all of its principal submatrices are negative in sign (i.e. $D_j < 0$ where D is the determinant of the leading principal minors and j = 1, 2, …, n). Hence, with respect to our translog shadow cost model, it has to be checked a posteriori for every input bundle that monotonicity and concavity hold. If these theoretical criteria are jointly fulfilled the obtained estimates are consistent with microeconomic theory and consequently can serve as empirical evidence for possible policy measures.

Concavity can be imposed on our translog shadow cost model at a reference point (usually at the sample mean) following Jorgenson/Fraumeni (1981) and Ryan/Wales (1998). By this procedure the bordered Hessian in [6] is replaced by the negative product of a lower triangular matrix **Δ** times its transpose **Δ'**. Imposing curvature at the sample mean is then attained by setting

$$\beta(\delta)_{rs}=-(\Delta\Delta')_{rs}+\alpha(\delta)_r\lambda_{rs}+\alpha(\delta)_r\alpha(\delta)_s \qquad [9]$$

where r = i, l and s = k, m and λ_{rs} = 1 if r = s and 0 otherwise and $(\mathbf{\Delta\Delta'})_{rs}$ as the rs-th element of **ΔΔ'** with **Δ** as a lower triangular matrix:

$$H=-(\Delta\Delta')=-\begin{pmatrix} d_{11}d_{11} & d_{11}d_{12} & d_{11}d_{13} & d_{11}d_{14} \\ d_{11}d_{21} & d_{12}d_{12}+d_{22}d_{22} & d_{12}d_{13}+d_{22}d_{23} & d_{21}d_{14}+d_{22}d_{24} \\ d_{11}d_{31} & d_{31}d_{12}+d_{32}d_{22} & d_{31}d_{13}+d_{23}d_{23}+d_{33}d_{33} & d_{31}d_{14}+d_{23}d_{24}+d_{33}d_{34} \\ d_{11}d_{41} & d_{41}d_{12}+d_{42}d_{22} & d_{41}d_{13}+d_{42}d_{23}+d_{34}d_{33} & d_{41}d_{14}+d_{24}d_{24}+d_{34}d_{34}+d_{44}d_{44} \end{pmatrix} \quad [10]$$

As our point of approximation is the sample mean, all data points are divided by their mean transferring the approximation point to an (n + 1)-dimensional vector of ones. At this point the elements of **H** do not depend on the specific input price bundle. The estimation model of the normalized translog shadow cost frontier is then reformulated as follows:

$$\begin{aligned} \ln\left(\frac{C}{C'}\right) &= \alpha_0 - \sum_{n=1}^{6}\chi_n\left(\frac{D_n}{D_n^{'}}\right) + \gamma_y \ln\left(\frac{y}{y'}\right) + \frac{1}{2}\gamma_{yy}\ln\left(\frac{y}{y'}\right)^2 + \sum_{i=1}^{2}\alpha_i \ln\left(\theta_i \frac{w_i}{w'_i}\right) \\ &+ \frac{1}{2}\sum_{i=1}^{2}\left(h_{ii}+\alpha_i-\alpha_i\alpha_i\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)^2 + \frac{1}{2}\sum_{i=1}^{2}\sum_{k=1}^{2}\left(h_{ik}-\alpha_i\alpha_k\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)\ln\left(\theta_k\frac{w_k}{w'_k}\right) \\ &+ \sum_{i=1}^{2}\beta_{yi}\ln\left(\frac{y}{y'}\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right) + \sum_{l=1}^{2}\delta_l\ln\left(\theta_l\frac{w_l}{w'_l}\right) + \frac{1}{2}\sum_{i=1}^{2}\left(h_{ll}+\delta_l-\delta_l\delta_l\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)^2 \\ &+ \frac{1}{2}\sum_{l=1}^{2}\sum_{m=1}^{2}\left(h_{lm}-\delta_l\delta_m\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right)\ln\left(\theta_m\frac{w_m}{w'_m}\right) + \sum_{i=1}^{2}\sum_{l=1}^{2}\left(h_{il}-\delta_i\delta_l\right)\ln\left(\theta_i\frac{w_i}{w'_i}\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right) \\ &+ \sum_{l=1}^{2}\delta_{yl}\ln\left(\frac{y}{y'}\right)\ln\left(\theta_l\frac{w_l}{w'_l}\right) + \ln\left\{\sum_{i=1}^{2}\left(\theta_i\right)^{-1}\left[\alpha_i + \sum_{i=1}^{2}\left(h_{ik}-\alpha_i\alpha_k\right)\ln\left(\theta_k\frac{w_k}{w'_k}\right) + \beta_{yi}\ln\left(\frac{y}{y'}\right)\right]\right\} + \varepsilon_i \end{aligned}$$

[11]

However, the elements of **Δ** are nonlinear functions of the decomposed matrix in [10], and consequently the resulting normalized translog model becomes nonlinear in parameters. Hence, linear estimation algorithms are ruled out even if the original function is linear in parameters. By this “local” procedure a satisfaction of consistency at most, or even all, data points in the sample can be reached. The transformation in [11] moves the observations towards the approximation point and thus increases the likelihood of getting theoretically consistent results at least for a range of observations (see Ryan/Wales 2000). However, by imposing global consistency on the translog functional form Diewert and Wales (1987) note that the parameter matrix is restricted leading to seriously biased elasticity estimates. Hence, the translog function would lose its flexibility. By a second analytical step we finally (a posteriori) check the theoretical consistency of our estimated model by verifying that the Hessian is negative semi-definite (i.e. functional concavity).

Tackling the general presumption of homogeneous prices, the estimated shadow price parameters nevertheless contain both input specific allocative inefficiency, due to market distortions, as well as input specific allocative inefficiency resulting from farm specific factors besides residual stochastic influences. Barrett (1997) points to the methodological shortcomings of most efficiency estimations in a developing context due to an unsatisfactory discussion of the problems involved in neglecting the decomposition of peasant (in)efficiency resulting from binding market constraints causing peasant decision-makers' shadow prices to deviate from market prices, or resulting from allocative inefficiency, or both. In order to address such a decomposition of the allocative inefficiency estimates found, the input specific economic loss ($-ISE_i$) or gain ($+ISE_i$) is computed based on the estimated shadow price deviations according to [12]:

$$\pm ISE_i = \pm\left|ISC_i - ISC'_i\right| = \pm\left|w_i * q_i - w'_i * q_i\right| \qquad [12]$$

where ISC_i and ISC'_i denote the input specific costs and shadow costs respectively for the use of input i. These input specific economic losses (or gains) are then simultaneously regressed on different farm specific explanatory variables by applying a multiple equations model following [13]:

$$\begin{aligned}
\ln ISE_{lab} &= \sum_u \kappa_{lab_u} D_u + \sum_v \omega_{lab_v} \ln X_v + \varepsilon_{lab} \\
\ln ISE_{fert} &= \sum_u \kappa_{fert_u} D_u + \sum_v \omega_{fert_v} \ln X_v + \varepsilon_{fert} \\
\ln ISE_{land} &= \sum_u \kappa_{land_u} D_u + \sum_v \omega_{land_v} \ln X_v + \varepsilon_{land} \\
\ln ISE_{orgfert} &= \sum_u \kappa_{orgfert_u} D_u + \sum_v \omega_{orgfert_v} \ln X_v + \varepsilon_{orgfert}
\end{aligned} \qquad [13]$$

where u is an index for the following variables: D_{seed}, D_{herbi}, and D_{insect} are binary variables for the use (or not) of commercial seed, herbicides and insecticides respectively. D_{sub}

indicates whether the farm received subsidies, D_{coop} is a binary variable for cooperation with other farms, D_{gender} is a binary variable for the gender of the household head, D_{ext} indicates whether the farm made use of extension services offered, D_{tr} shows if agricultural training has been received in the study period, D_{car} describes if the farm owned a car, thus indicating the degree of mobility and linkage to other relevant input and output markets, D_{iasi}, $D_{\mathrm{mehedinti}}$, D_{braila}, D_{vrancea}, $D_{ialomita}$, $D_{oltenia}$, D_{bihor}, D_{mures}, D_{arad}, D_{hargita}, D_{valcea}, and D_{alba} are county dummies[1] indicating the relevance of location specific factors. v is an index for: X_{precip} as the relative rainfall in the area, X_{soil} as the soil moisture in the area, X_{size} as the total size of the farm, X_{mach} as the amount of machinery used in maize cultivation as a proxy for the state of technology, X_{hfl} as a ratio for hired to family labor, X_{age} as the age of the household head in years, X_{out} as the amount of labour spent outside agriculture, X_{vege} indicating the vegetation index in the area, X_{livest} showing whether the farm is also engaged in livestock production, X_{build} as a proxy for the buildings used on the farm (i.e. input and output storage facilities, garages etc.), X_{slope} indicates the relative slope of the agricultural land used for maize production, X_{dist} reflects the average distance between the farm's plots, and X_{edu} indicates the level of the farmer's education. A simultaneous equation approach seems adequate as the relative price ratios are assumed to be affected by the same farm specific factors as well as stochastic residuals at the same point in time. Consequently, the variations in the unexplained error term are somehow linked over the different single regressions. A Breusch-Pagan test is applied to test for the significance of this underlying modelling hypothesis.

As the included regressors represent potential factors for farm specific allocative inefficiency, the explained share of the variation in the dependent variables of [13] can be (at least) considered as an approximation to the real share of allocative inefficiency due to farm

[1] To avoid the threat of perfect collinearity between the m regional dummies only (m-1) of them are incorporated as is common econometric practice.

specific variation (AIE_{farm_i}). Consequently, the remaining part of unexplained variation in the dependent variables are, by definition, regarded as allocative inefficiency stemming from market constraints (AIE_{market_i}) as well as residual stochastic influences (ξ_i). Equation [14] describes this decomposition attempt:

$$\begin{aligned} AIE_i &= AIE_{farm\_i} + AIE_{market\_i} \\ &= \left(\kappa^*_{i\_u} D_u + \omega^*_{i\_v} \ln X_v\right) + \varepsilon_i \\ &= \left(\kappa^*_{i\_u} D_u + \omega^*_{i\_v} \ln X_v\right) + AIE_{market\_i} + \xi_i \end{aligned} \qquad [14]$$

with i = labor, fertilizer, land, and organic fertilizer, the estimated parameter values $\kappa^*_{i\_u}, \omega^*_{i\_v}$. By this modelling procedure we try to attempt the decomposition of allocative inefficiency on the farm level into its market related and farm related components. Needless to say, because of neglected explanatory variables in [13], as a consequence of lacking data, the problem of omitted variables bias has to be kept in mind when interpreting the decomposition results. According to this serious specification problem, the discussion of the estimation results based on [12] to [14] is based on the relative share of the explained sum of variation leaving aside the individual inefficiency factors' coefficients. However, another specification problem noted by Kumbhakar/Lovell (2000) with respect to the inconsistency of the two-step estimation of the effects of inefficiency explaining factors is avoided here. By simultaneously modelling shadow prices, following [2] to [5] in the first estimation step of the chosen econometric procedure, the estimated variances of the shadow price parameters in [11] are conditional on the variances of most of the explanatory factors chosen in the multiple equations model in [13] and hence consistently estimated.

By a third estimation step the behavioural (shadow price) cost function in its constrained and unconstrained version (eq. [2] and [11]) is 'adjusted' by the estimated shadow price parameters θ and hence corrected for systematic allocative inefficiency by using these shadow prices as direct arguments in the cost function. An adjusted cost frontier is then modeled by simply adding the error components

$$\xi_i = v_i + u_i \qquad [15]$$

and applying stochastic frontier techniques to obtain the shadow-cost frontier and finally estimates of relative cost efficiency on the farm level (see e.g. Coelli et al., 1998 and Khumbhakar/Lovell 2000). As the price efficiency parameters θ_i, θ_l reflect both allocative effects of market distortions as well as optimization errors, the relative inefficiency measured by the adjusted cost frontier consists solely of technical inefficiency (systematic and/or farm specific).

The stochastic frontier decomposes the error term into a two-sided random error that captures the inefficiency component and the effects of factors outside the control of the farmer. The theoretical foundation of such a model was first proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The two-sided random error is assumed to be identically and independently distributed with zero mean and constant variance and is independent of the one-sided error. The distribution of the inefficiency component of the error is assumed to be asymmetrical. Following Battesse and Coelli (1995), the maximum likelihood estimation for equation 1 is obtained from the following log-likelihood function:

$$\ln L = -\frac{N}{2}\ln\left(\frac{\theta}{2}\right) - \frac{N}{2}\ln\sigma^2 + \sum_{j=1}^{N}\ln\left[1 - F\left(\frac{\varepsilon_j\sqrt{\delta}}{\sigma\sqrt{1-\delta}}\right)\right] - \frac{1}{2\sigma^2}\sum_{j=1}^{N}\varepsilon_j^2 \qquad [16]$$

where L is the log-likelihood function, N is the number of observations and $F(.)$ is the standard normal distribution function. σ^2 is the overall standard deviation equal to the sum of the standard deviations of the two error terms and δ is the proportion of the overall error term that is explained by the one-sided error. Assuming the half-normal distribution of the one-sided error term, the relative efficiency score defined at the mean is given as:

$$E\left[\exp\left(-u_j\right)\right] = 2\left[\exp\left(-\delta\sigma^2/2\right)\right]\left[1 - F\left(\sigma\sqrt{\delta}\right)\right] \qquad [17]$$

The measurement of farm level efficiency requires the estimation of the non-negative one-sided error that also depends on the assumptions regarding the distribution of the two and one-sided error terms. Based on Battesse and Coelli (1988), the best predictor of the relative efficiency of farmer i is given as:

$$E\left[\exp\left(-u_j \backslash \varepsilon_j\right)\right] = \left[\frac{1-F\left(\sigma_w - \frac{\delta\varepsilon_j}{\sigma_w}\right)}{1-F\left(\frac{-\delta\varepsilon_j}{\sigma_w}\right)}\right]\exp\left(-\delta\varepsilon_j + \frac{\sigma_w^2}{2}\right) \qquad [18]$$

where $\sigma_w = \sqrt{\delta(1-\delta)\sigma^2}$. The likelihood function is expressed in terms of the variance parameters i.e. $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\delta = \sigma_u^2 / \sigma^2$. By following a single-equation cost frontier approach on this estimation stage we are able to avoid the 'Greene'-problem with respect to the consistent specification of the individual error components (see Kumbhakar/Lovell 2000).[2]

Systematic allocative input-specific efficiency measures, as well as group-wise technical efficiency measures, are obtained by the translog shadow cost model. Measures of technical efficiency on the farm level result from the error components model and finally farm-specific radial cost efficiency measures are obtained by simple calculation. As we are also interested in the effects of imposing theoretical consistency on the translog cost frontier, we investigate the relative effect of such correction by using the simple index formula

$$\frac{\left(eff_i^{in} - eff_i^{con}\right)}{eff_i^{in}} * 100 \qquad [19]$$

To test for the robustness of our estimates by the adjusted shadow cost model (based on [2] and [11]) we further apply a simple stochastic resampling procedure based on bootstrapping techniques (see e.g. Efron 1979 or Efron/Tibshirani 1993). This seems to be necessary as our cross-sectional data sample consists of a (rather) limited number of observations. If we suppose that $\hat{\Psi}_n$ is an estimator of the parameter vector ψ_n including all parameters obtained by estimating [19] based on our original sample of 64 Romanian maize farmers $X = (x_1, ..., x_n)$, then we are able to approximate the statistical properties of $\hat{\Psi}_n$ by studying a

[2] This procedure takes care of the econometric estimation problem with respect to the frontier models. However, this comes at the cost of a residual inconsistency between the specified shadow cost models and the frontier models.

sample of 1000 bootstrap estimators $\hat{\Psi}_n(c)_m, c = 1,...,C$. These are obtained by resampling our 64 observations – with replacement – from X and recomputing $\hat{\Psi}_n$ by using each generated sample. Finally the sampling characteristics of our vector of parameters is obtained from

$$\hat{\Psi} = \left[\hat{\Psi}_{(1)m},...,\hat{\Psi}_{(1000)m} \right] \quad [20]$$

As is extensively discussed by Horowitz (2001) or Efron/Tibshirani (1993), the bias of the bootstrap as an estimator of $\hat{\Psi}_n$, $B_{\tilde{\psi}} = \tilde{\Psi}_n - \hat{\Psi}_n$, is itself a feasible estimator of the bias of the asymptotic estimator of the true population parameter ψ_n.[3] This holds also for the standard deviation of the bootstrapped empirical distribution providing a natural estimator of the standard error for each initial parameter estimate. By using a bias corrected boostrap we aim to reduce the likely small sample bias in the frontier initial estimates.

5 – DATA AND ESTIMATION

Data is used on 64 maize farmers based on a survey among agricultural households in 15 Romanian villages in 2003 (see Balint/Wobst 2006). The sample villages were chosen by a multistage representative random sampling procedure focused on seven regions defined by historical borders, landscape structure and distance to relevant input and output markets. The overall survey focused on data for 2002 with regard to various outputs, inputs and other household characteristics. The validity of the survey results were cross checked by discussions with local agricultural experts. The most frequently produced crop was maize, cultivated by about 92% of the households, whilst less than a quarter of all households cultivated technically more demanding crops such as sunflower, soya or sugar beet. The average farm in the sample shows a total acreage of about 3.70 ha and uses about 957 man days of total labor per year. The share of maize in total production was about 56% for the

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[3] Hence the bias-corrected estimator of ψ_n can be computed by $\hat{\psi}_n - B_{\tilde{\psi}} = 2\hat{\psi} - \tilde{\psi}$.

average farm and the sample year (see also EC 2002 and FAO 2000). Table 1 gives the summary statistics on the sample data:

(TABLE 1: DESCRIPTIVE STATISTICS)

The total costs of maize production are used as the dependent variable for the cost function estimations. They vary quite significantly over the sample of small-scale farmers (a mean of about 286 Euro p.a. but a maximum of about 3,627 Euro p.a.). The total output of maize produced, the price of maize and the prices for the variable inputs labor and fertilizer as well as the quantities of the fixed variables land and organic fertilizers are applied as explanatory variables. The prices in the survey are therefore real observed prices and as such can deviate from officially reported prices. Land can be considered as quasi-fixed as due to the aforementioned inflexibilities in the land market it can not be expected to be adjusted in a short-term perspective by the individual farmer. Organic fertilizer can be considered as quasi-fixed as small-scale Romanian farmers can not be expected to flexibly adjust the size of their livestock production as a response to crop input needs. Further binary variables for the use of herbicides, insecticides, commercial seeds, received subsidies, extension services used and finally agricultural training and advice received are applied. The variable livestock accounts for the livestock units on the individual farm, other variables reflect the age of the household head, the education of the household head (in years of schooling), whether additional income was generated outside the agricultural business measured in man days, the size of the household linked to the farm, the average distance of the respective farm's plots from the farmyard and the total farm size in hectares. Other binary variables are included to approximate the cost and efficiency effect of the gender of the farmer, whether the farm participated in any kind of (formal and/or informal) institutionalised cross farm cooperation and the degree of mobilisation proxied by the car dummy variable. The machinery variable attempts to capture the relative value of the machinery used for the farm's operations by giving a subjective valuation of the farm's motor pool (i.e. own truck, tractor, plough, combine, carriage, harvester etc.), the same applies for the variable buildings reflecting the farm's relative endowment of storage facilities, barns, stalls, estate buildings etc.

The average slope of the the farm's cultivated plots is reflected by the variable slope. With respect to other environmental conditions of maize production, the relative amount of precipitation (measured in percentage of the seasonal average normal rainfall per region) as well as the relative moisture of the soil in the region (measured in percentage water present in the soil) are indicators of the immediate store of infiltrating rainfall before it either evapotranspires or contributes to groundwater recharge. Further, a vegetation index (the normalized difference vegetation index NDVI as the most commonly used index for satellite imagery) is used as a proxy for the likelihood of the occurrence of pests and weeds in the respective farm environment. The data on these environmental variables were obtained from the Foreign Agricultural Service of the USDA (see USDA 2004). The relative change in the share of individual farming in the respective county is reflected by the proxy variable change in individual farming. The latter covers the percentage increase in the share of total agricultural land used in individual farms by county in the period 1985 to 2002. Finally, the variable county reflects the regional location of the farm: Farms in the survey were located in 15 different Romanian counties. All monetary variables are in Euro.

The estimation procedure is as follows: Firstly the translog cost system given by [2], [3], [4] and [5] is estimated using the cost function, the cost shares s_i derived from the non-distorted translog cost function lnC, and the parameter equations to obtain estimates for the allocative efficiency parameters θ with respect to the individual inputs as well as group-wise technical efficiency effects χ. The estimates of the former are subsequently substituted in [2] and after adding the error components given by [15] in a second step the adjusted translog cost frontier is estimated by applying the usual decomposition formula given in [16] and [17] to obtain estimates of producer-specific technical efficiency. As we 'corrected' the cost frontier for allocative inefficiency the resulting efficiency estimates u are solely technical ones. Finally, producer and input specific estimates of cost efficiency are obtained by simple calculation using the estimates for θ and u. This two-stage model is estimated using a non-linear iterative seemingly unrelated regression (ITSURE) technique with symmetry and homogeneity conditions imposed. As Greene (2000) notes, the Oberhofer-Kmenta (1974) conditions are met for the SURE model, so efficient maximum likelihood estimates can be obtained by iterating the basic feasible generalized least square (FGLS) procedure. The model is then estimated again (model II) by imposing curvature correctness (i.e. functional concavity) on the cost function in [11] by basically following the Hessian decomposition shown by [9]. In this way we go beyond similar modelling efforts (see Atkinson/Halvorsen 1980, Kumbhakar 1989, Kumbhakar/Bhattacharyya 1992, Wang et al. 1996, Barrett et al. 2005) and also incorporate considerations of the consistency of the estimated frontier with basic microeconomic principles (i.e. cost minimisation). The estimation results of the unconstrained and the constrained models are compared with respect to the relative differences in the individual efficiency scores.

Finally, a third estimation model is added to attempt a further decomposition of allocative inefficiency in farm specific as well as market specific (including stochastics) components by estimating the input related multiple equations system in [13] again by applying a non-linear iterative seemingly unrelated regression (ITSURE) technique. However, we statistically test for the underlying assumption of correlated disturbances by using a Bresuch-Pagan test for heteroscedasticity.

6 – Results and Discussion

All estimated cost systems, cost frontiers as well as multiple equation systems show a relatively good overall fit with respect to the usual statistical criteria. The Breusch-Pagan test statistics reject the null hypothesis of homoscedastic error terms and hence confirms the underlying assumption of heteroscedastic error terms for the multiple equations models. However, in the unconstrained model I, only about 16% of all observations adhere to functional concavity contrasting to 70% in the constrained model II (see appendix). A tradeoff between the statistical significance and the theoretical consistency of the estimated function, as documented by earlier studies (see e.g. Sauer 2006), is not confirmed by the results here. The estimated shadow price parameters show a high significance over all models.

Allocative Efficiency

Table 2 summarizes the estimation results with respect to systematic input-specific allocative efficiency whereas table 3 shows the estimation results with respect to the decomposition of such input-specific allocative inefficiency into its farm-specific and market as well as stochastic related components.

(TABLE 2: SYSTEMATIC INPUT-SPECIFIC ALLOCATIVE EFFICIENCY)

(TABLE 3: APPROXIMATED RELATIVE SHARES OF INPUT SPECIFIC ALLOCATIVE INEFFICIENCY)

The systematic allocative efficiencies with respect to the inputs labour, land, and organic fertilizer were found to be moderately lower with respect to the constrained model II. In the case of fertilizer no significant difference between the two model specifications was found. However, in both models the variable input labour shows the highest efficiency (about 74% and 52% respectively) over all inputs. On the other hand, the lowest allocative efficiency was found for fertilizer in the unconstrained model (about 47%) and for the quasi-fixed input organic fertilizer in the constrained model (about 36%). The farm specific component of allocative inefficiency was found to account for more than 50% of the total allocative inefficiency in the unconstrained model (model I) with respect to all variable and quasi-fixed inputs. Beside the quasi-fixed input land the same holds for the constrained model specification (model II). Table 4 summarizes the effects of different potentially allocative inefficiency explaining factors with respect to labour and land.

(TABLE 4: ALLOCATIVE EFFICIENCY EFFECTS)

The two models are consistent with respect to the negative efficiency effect of the male gender of the household head and the size of the household, and on the other hand the positive efficiency effect of the education of the farmer, the share of hired labour and the fact that household members generate additional income outside agriculture. However, the models disagree with respect to the influence of the farmer's age on the allocative efficiency of labour. The relative amount of precipitation in the farming period was shown to have a negative effect on the allocative efficiency of the quasi-fixed input land for both models estimated. Nevertheless, no consistent effects could be found for the average soil moisture as well as the vegetation index in the region. The statistical significance of the incorporated control variables confirmed earlier findings of the importance of moral hazard and adverse selection mechanisms in rural labour markets (e.g. Barrett et al. 2005), as well as the importance of environmental and climatic variables for the shadow price of land (Sherlund et al. 2002).

In general it can be concluded that price distortions still prevail in the investigated agricultural input markets for labour, fertilizer, land and inorganic fertilizer. Hence, the underlying modelling assumption that maize producers optimize their production decisions with respect to unobservable shadow price ratios holds for the sample. This indicates that modelling cost minimization based on observable market prices may be inappropriate, and thus, a model incorporating market distortions is more suitable in an agricultural transition context. The estimated parameter values for the shadow prices for fertilizer (2.142 and 2.111 respectively) and land (1.234 and 1.944 respectively) are for both model specifications greater than one, indicating that the small scale farmers in the sample optimize the use of these inputs with respect to higher shadow prices. These findings correspond to the results of previous studies investigating price distortions in transitional economies and concluding in a considerable gap between agricultural input market prices and farm input prices (see e.g. Khumbhakar/Bhattacharyya 1992 or Wang et al. 1996). As a consequence of distorted market mechanisms, the relative scarcity of chemical fertilizer, as well as land, is much higher than indicated by observed prices and hence the opportunity costs of chemical fertilizer and land are significantly higher than market price based costs would suggest. The estimated shadow parameter for the quasi-fixed input land shows that the farms' resource endowment crucially influences its relative allocative performance. The results of the approximated decomposition of input specific allocative inefficiency revealed that market related factors (as well as residual random effects) still play a significant role with respect to the divergent shadow prices of commercial fertilizer and land (see table 3). Policy consequences could imply additional measures to promote the supply of these inputs and to eliminate the shortage premium paid by the farmers. A higher degree of market liberalization with respect to fertilizer and land would maize production profit enable to move towards the efficient frontier. With respect to the transition goal of well functioning efficient local land markets, the evidence found in this study sheds further empirical light on earlier findings by confirming that land markets are not yet sufficiently developed and continue to constrain potential individual farmers in initiating and developing profitable farm enterprises (see Brooks/Meurs 1994, Rizov et al 2001).

The estimated values for the shadow prices of labour (0.741 and 0.539 respectively) and organic fertilizer (0.516 and 0.359 respectively) indicate, on the other hand, that 'prices' actually paid by the farmers for these inputs are far less than the observed market prices. Different factors could account for such a price gap with respect to labour: As the price for hired labour rises farmers tend to substitute family for hired labour. Due to a lack of data, labour is used here as an aggregated measure consisting of hired and family labour, hence, an increasing amount of family labour could lead to a decrease in the average individual shadow price at the farm level for the variable input labour. However, the latter should not be interpreted as a causality since shadow prices are by definition endogenous to household self-provision of labour services to the farm. Nevertheless, intrahousehold mechanisms to lower search and transaction costs by responding with effective labour allocation could be the main reason for the estimated lower unobservable wages and allocative inefficiency with respect to the use of labour (Barrett et al. 2005). Hence this empirical evidence confirms the results found e.g. by Barrett et al 2005 most recently with respect to developing countries. Referring finally to the approximated decomposition of input specific allocative inefficiency, it can be again assumed that market related factors (as well as residual random effects) still play a significant role with respect to the divergent shadow prices of labour and organic fertilizer (see table 3).

Technical and Cost Efficiency

Based on the estimated allocative efficiency parameters from the first step, a maximum-likelihood estimate of the corrected cost frontier is obtained and a technical efficiency index is derived for both models. Table 5 summarizes the estimation results with respect to producer-specific overall technical and producer- and input-specific cost efficiency.

(TABLE 5: PRODUCER-SPECIFIC TECHNICAL AND COST EFFICIENCY)

Table 6 contains the frequency distributions for the producer-specific technical efficiencies. The corresponding kernel densities for both models are illustrated in the appendix by figure A1 and A2.

(TABLE 6: FREQUENCY DISTRIBUTION – PRODUCER-SPECIFIC TECHNICAL EFFICIENCY)

The mean of the estimated technical efficiency is about 81% (model I) and about 82% (model II) whereas the least technically efficient farm shows a value of approximately 17% (model I) and approximately 42% (model II). This implies that on average up to 19% of the profit is lost due to technical inefficiency, which is rather moderate compared to the revealed levels of allocative inefficiency. The frequency distributions of the individual farm's technical efficiency indices show that there is a moderate variation among the farms in the sample: For both models, the majority of farmers show a relative technical efficiency of more than 80% (see also figure A1 and A2). Based on the estimated systematic input-specific allocative efficiency, as well as the estimated producer-specific technical efficiency, finally producer- and input-specific cost efficiency levels are computed (see table 5). With the exception of fertilizer, the cost efficiency levels are moderately higher for the unconstrained model (model I) compared to those for the constrained model (model II). For model I, maize farmers used the variable inputs land and labour most efficiently and the variable input fertilizer least efficiently, with respect to costs. The same was found for model II with respect to the most efficient used inputs but here the quasi-fixed input organic fertilizer showed to be least efficiently applied. Therefore, these cost efficiency results reveal more or less the same evidence for the different model specifications.

Both estimation stages delivered evidence with regard to the technical efficiency effects of different production settings, institutional as well as policy related factors - either with respect to groups of producers defined along such factors (shadow cost estimation stage) or with respect to individual producers (error components estimation stage). The derived farm-specific efficiency index facilitates the decomposition of the efficiency performance at the individual maize farm level and allows for the identification of the factors that influence farmers' technical efficiencies. Table 7 and 8 summarize the different effects found.

(TABLE 7: GROUP-WISE TECHNICAL EFFICIENCY EFFECTS)

(TABLE 8: PRODUCER-SPECIFIC TECHNICAL EFFICIENCY EFFECTS)

The results for the shadow frontier show that the use of herbicides, the use of insecticides and the application of commercial seeds are positively correlated with the technical efficiency of the maize producing farms for both models. However, the producer-specific error components frontier confirmed these positive effects only for the use of insecticides. The slope of the land was found to positively influence the technical efficiency of small-scale maize production, which could be due to a more effective use of inputs in geographically unfavourable areas. As generally expected, the relative moisture of the soil was found to have a positive effect on production efficiency. However, with respect to the efficiency influence of relative precipitation in the area, a generally expected positive effect was found only for the group-wise estimations. The producer-specific estimations revealed both a significant negative effect of the relative amount of rainfall in the maize production period. In line with the group-wise positive efficiency effects of herbicide, use is the negative efficiency effect of the vegetation index (i.e. vegetation vigour and density) in the respective geographical area. Mixed technical efficiency effects were found for the farmers' education, agricultural training received as well as the use of extension services: whereas the group-wise shadow frontier resulted in more or less insignificant negative efficiency effects, revealed the producer-specific frontiers significant positive efficiency effects. So overall, a positive effect of knowledge accumulation on the individual farm level can be concluded on significant statistical grounds. Maize farmers also engaged in livestock production were found to be less technically efficient than those without livestock production. The efficiency effect of subsidies was found to be mixed over all model specifications. Statistical significance can only be reported for the negative efficiency effect revealed by the group-wise model I and the producer-specific model I. The average distance between the plots cultivated per farm was found to have a significant negative effect on producer-specific technical efficiency: the related transaction costs (i.e. transport of seed, chemicals, fertilizer and machinery) obviously increase at a crucial rate as distance rises. The negative efficiency effect of machinery (i.e. tractor, plough, weeding and seeding facilities) applied could be due to the small-scale of the operations (at average about 1.9 ha out of 5.7 ha were used for maize production in the sample) and the fact that the production of maize in Romania requires very basic technology, as well as storage facilities (see FAO 2000). The empirical evidence found on the positive effect on technical efficiency by the share of hired labour in model I, confirms those found for the farms' allocative efficiency. However, a negative effect has to be reported for model II. The same holds for the technical efficiency effects by the fact that additional income was available for the farm created outside of agricultural operations: the positive efficiency effect was confirmed for model II, a negative one was found for model I. The various results for human capital suggest an important positive influence on the different kinds of individual farming efficiency which are in line with past findings on Romanian farming (see e.g. Rizov et al. 2001). Education, experience and training do significantly affect the successful development of individual farming. Mixed efficiency effects were finally found for the farmer's participation in cross farm cooperation with respect to input purchases and/or product marketing: whereas model I revealed a significant negative effect on the farms' technical efficiency, the opposite effect was revealed by model II. Hence, this mixed evidence only partly follows the results found by Mathijs/Swinnen (2001) and Sabates-Wheeler (2001, 2002) both concluding substantial production advantages by small 'partnerships' rather than individual farming for lower levels of resource endowment.

The error component frontiers finally showed a significant positive efficiency effect by the share of total agricultural land used in individual farms on county level. The higher the change in the share of individual farming in the period 1985 to 2002 for the respective county, the more technically efficient the small scale farms in the sample proved to be. Interpreting the relative change in the share of individual farms on county level as a proxy for the commercial orientation of the institutional environment the farmers face, as well as the commercial orientation of the farmers themselves, one can conclude in substantial economic benefits by an ongoing agricultural commercialisation (see also Balint/Wobst 2006 and Dawidson 2005). By investigating a larger period of individual farm development, this extends, and in a way contradicts, the findings of Rizov et al. (2001) concluding in less constrained variable input markets for farmers in regions where collective farms dominated and where there has been no pre-reform tradition of individual farming. The significant positive effects of the relative positive change in the share of individual farming on technical efficiency suggest that the negative effects of such pre-reform structural patterns documented by earlier studies have been partly compensated for by ongoing institutionally backed-up privatisation and commercialisation in different Romanian counties.

Model Consistency

The reported efficiency results of the unconstrained, as well as constrained model, specification point to the relevance of theoretical consistency of the estimated frontier. As outlined in section 4, model II differs from model I by applying a matrix decomposition technique to impose concavity on the translog cost frontier to ensure functional regularity and finally the adherence to the basic microeconomic principle of cost minimization (see

Sauer 2006). Table 9 delivers the relative differences in the efficiency scores for the unconstrained and the constrained specification.

(TABLE 9: RELATIVE DIFFERENCE IN EFFICIENCY SCORES UNCONSTRAINED VS. CONSTRAINED SPECIFICATION)

The relative difference in the efficiency scores ranges from about 181% (producer- and input-specific cost efficiency measure for land) to about 349.2% (producer- and input-specific cost efficiency measure for fertilizer). Hence, this is empirical evidence for the validity of our concerns about the appropriate functional form and its theoretical consistency (see Sauer 2006). Figure 1 clearly illustrates these differences with respect to the measure of technical efficiency.

(FIGURE 1: DIFFERENCES IN TECHNICAL EFFICIENCY BY IMPOSING CURVATURE CORRECTNESS)

Finally, the results of the applied bias corrected bootstrap procedure confirmed the estimates for the theoretically consistent model (model II) on the estimation stage of the error-components specification (see also table A5).

7 – SUMMARY

This study tackles the decomposition of efficiency with respect to agricultural production in transition economies by using a case study on small-scale maize farmers in Romania. A cost function framework is applied combining the stochastic frontier approach of shadow prices as well as the mainstream error components model. Assumed market distortions, as well as farm optimization failure, are addressed by adopting the concept of a shadow cost frontier, which delivers insights into systematic input specific allocative efficiency. After correcting for shadow prices, we subsequently reveal evidence for farm specific technical efficiency and develop an efficiency index for the sample of Romanian maize producers in 2002. Different policy relevant factors are investigated with respect to their impact on technical efficiency on a group, as well as the individual farm level. By regressing economic loss/gain (based on the estimated shadow prices) on different farm related factors, we finally attempt to further decompose such allocative efficiency in farm related, as well as market and stochastic related components. By referring to the ongoing discussion on functional consistency of the stochastic frontier with respect to microeconomic theory, we formulated two basic model specifications – one without and one with functional concavity imposed - and estimated the individual cost systems and multiple equation systems by means of iterated seemingly unrelated regression techniques (ITSURE).

The empirical results suggest that after 15 years of economic transition, price distortions still prevail in the agricultural input markets. Consequently, a model incorporating such market distortions seems to be more suitable in an agricultural transition context than one exclusively based on observed variable input price ratios. The estimated shadow parameters for the quasi-fixed inputs revealed that the farms' resource endowment – i.e. land endowment as well as livestock size – crucially influences its relative allocative performance. A relatively high technical efficiency on farm level with a moderate variation over the sample but relatively moderate scores on systematic allocative efficiency were found. However, the inefficiency effects aspect of the error components estimations only partly confirm the empirical results found for the group-wise technical efficiency based on the shadow frontier model. The revealed relative difference in the efficiency scores of up to 349% on the individual farm level, as a consequence of the imposition of curvature correctness, confirmed the relevance of theoretically consistent modelling with respect to the stochastic measurement of efficiency. Hence the empirical applications document the need for a posteriori checking of the regularity of the estimated frontiers by the researcher and, if necessary, the a priori imposition of the theoretical requirements on the estimation models (see Sauer 2006). Besides various specific policy implications with respect to different farm specific sources of allocative and technical inefficiency, the major policy message by this analysis refers to a prevailing need for eliminating market structures and processes which distort the functioning of price signals and cause severe allocative inefficiency. This finally describes the line for future research in the field.

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9 - APPENDIX

(TABLE A1: PARAMETER ESTIMATES SHADOW COST FRONTIER – MODEL I)

(TABLE A2: PARAMETER ESTIMATES ERROR COMPONENTS FRONTIER – MODEL I)

(TABLE A3: PARAMETER ESTIMATES SHADOW COST FRONTIER – MODEL II)

(TABLE A4: PARAMETER ESTIMATES ERROR COMPONENTS FRONTIER – MODEL II)

(TABLE A5: BIAS CORRECTED BOOTSTRAP ESTIMATES ERROR COMPONENTS FRONTIER II)

(TABLE A6: MULTIPLE EQUATION SYSTEM I – ALLOCATIVE INEFFICIENCY COMPONENTS)

(TABLE A7: MULTIPLE EQUATION SYSTEM II – ALLOCATIVE INEFFICIENCY COMPONENTS)

(FIGURE A1: PRODUCER-SPECIFIC TECHNICAL EFFICIENCY I – KERNEL DENSITY)

(FIGURE A2: PRODUCER-SPECIFIC TECHNICAL EFFICIENCY II – KERNEL DENSITY)

TABLE 1: DESCRIPTIVE STATISTICS

VARIABLE	MEAN	STDERR	MIN	MAX
TOTAL COSTS (IN EURO)	285.728	641.857	11.01	3,626.525
OUTPUT MAIZE (IN KG)	4,696.313	8,510.552	56	42,000
PRICE OF MAIZE (IN EURO/KG)	0.103	0.017	0.056	0.130
QUANTITY OF LABOUR (IN MANDAYS)	563.125	314.864	15	1,506.286
PRICE OF LABOUR (IN EURO/MANDAYS)	0.699	1.259	0.0138	6.399
QUANTITY OF FERTILIZER (IN KG)	18.198	37.083	1.176	264.706
PRICE OF FERTILIZER (IN EURO/KG)	0.187	0.052	0.004	0.320
QUANTITY OF LAND (IN HA)	1.909	3.921	0.08	30
QUANTITY OF ORG. FERTILIZER (IN KG/HA)	3,527.145	7,202.45	0	34,188
HERBICIDES USED (BINARY: 1: YES, 0: NO)	0.594	0.495	0	1
INSECTICIDES USED (BINARY: 1: YES, 0: NO)	0.937	0.244	0	1
COMMERCIAL SEED USED (BINARY: 1: YES, 0: NO)	0.406	0.495	0	1
SUBSIDIES RECEIVED (BINARY: 1: YES, 0: NO)	0.297	0.460	0	1
EXTENSION SERVICES USED (BINARY: 1: YES, 0: NO)	0.50	0.504	0	1
TRAINING USED (BINARY: 1: YES, 0: NO)	0.187	0.393	0	1
PRECIPITATION (IN % OF AVERAGE)	147.266	33.664	125	200
SOIL MOISTURE (IN %)	54.098	5.679	46.083	62.333
VEGETATION INDEX (NDVI * 100%)	78.706	25.329	39.333	97.5
LIVESTOCK (IN LV UNITS)	5.869	5.644	0	35
GENDER (BINARY: 1: MALE, 0: FEMALE)	0.812	0.393	0	1
AGE OF HOUSEHOLD HEAD (IN YEARS)	61.516	11.611	36	86
EDUCATION OF HOUSEHOLD HEAD (IN YEARS)	8.469	3.187	4	16
RATIO HIRED/FAMILY LABOUR	0.154	0.334	0	2.078
ADDITIONAL INCOME / WORK OUTSIDE OF HH (IN MANDAYS)	11.466	17.713	0	82.5
HOUSEHOLD SIZE (IN PERSONS PER HH)	2.859	1.344	1	6
SLOPE AVERAGE (1-PLAIN, 2-HILL, 3-MOUNTAIN)	1.891	0.715	1	3
CROSS FARM COOPERATION (BINARY: 1: YES, 0: NO)	0.484	0.504	0	1
MACHINERY (IN RELATIVE SCALE)	0.630	0.777	0	2.7
BUILDINGS (IN RELATIVE SCALE)	2.765	0.831	0	4
PLOTS' DISTANCE (IN KM)	1.636	1.649	0	9
TOTAL FARM SIZE (IN HA)	5.732	5.856	0.5	30
CAR (BINARY: 1: YES, 0: NO)	0.375	0.488	0	1
CHANGE IN INDIVIDUAL FARMING PER COUNTY 1985 - 2002 (% INCREASE)	72.103	12.165	45.85	92.73
COUNTY (1: CLUIJ, 2: BIHOR, 3: MURES, 4: CONSTANTA, 5: IALOMITA, 6: OLTENIA, 7: ALBA, 8: IASI, 9: VRANCEA, 10: VASLUI, 11: BRAILA, 12: ARAD, 13: HARGHITA, 14: MEHEDINTI, 15: VALCEA)	11.031	3.677	1	15

1: all variables are based on the Agricultural Household Survey 2003 part of the PASAD project (Balint/Wobst 2006); the variables Precipitation, Soil Moisture and Vegetation Index are based on USDA (2004); the variable Share of Individual Farming is based on own calculations by using Romanian Statistical Institute (1986, 1996, 2004).

TABLE 2: SYSTEMATIC INPUT-SPECIFIC ALLOCATIVE EFFICIENCY

	MODEL I		MODEL II	
EFFICIENCY[1]	MEAN	STD. ERR.[2]	MEAN	STD. ERR.
AE LABOR	0.741	9.659E-05***	0.516	0.001***
AE FERTILIZER	0.467	2.68E-04***	0.474	0.002***
AE LAND	0.810	1.76E-04***	0.514	0.001***
AE ORGANIC FERTILIZER	0.539	0.002***	0.359	0.013***

1: allocative efficiency estimates are parameter based: no min and max values are available
2: *,**,*** significance at the 10, 5, and 1% level

TABLE 3: APPROXIMATED RELATIVE SHARE OF INPUT SPECIFIC ALLOCATIVE INEFFICIENCY

Input	**Labour**		**Fertilizer**		**Land**		**Organic Fertilizer**	
Model	I	II	I	II	I	II	I	II
Mean (in %)								
Farm Specific	50.7*	57.9**	55.0**	56.6***	62.3***	49.9**	64.6***	56.3***
Rest (Market & Random)	49.3*	42.1*	44.9*	43.4**	37.7*	50.0**	35.4*	43.7**
Maximum (in %)								
Farm Specific	99.5	93.9	97.8	89.9	93.4	98.4	87.6	89.3
Rest (Market & Random)	93.8	88.8	88.9	89.1	87.5	97.5	80.8	72.9
Minimum (in %)								
Farm Specific	6.20	11.2	11.0	10.8	12.5	2.50	19.2	27.1
Rest (Market & Random)	0.50	6.10	2.20	10.1	6.60	1.60	12.4	10.6

1: *,**,*** significance at the 10, 5, and 1% level

TABLE 4: ALLOCATIVE EFFICIENCY EFFECTS

	MODEL I		MODEL II	
FACTOR	MEAN	STD. ERR.[1]	MEAN	STD. ERR.
AE LABOUR				
GENDER OF HOUSEHOLD HEAD	-0.011	2.68E-04***	-0.075	0.002***
AGE OF HOUSEHOLD HEAD	-0.025	1.76E-04***	0.063	0.001***
EDUCATION OF HOUSEHOLD HEAD	0.161	0.002***	0.133	0.013***
SHARE OF HIRED LABOUR	0.146	0.016***	0.152	0.121
ADDITIONAL INCOME OUTSIDE AGRICULTURE	0.035	2.33E-04***	0.013	0.002***
SIZE OF HOUSEHOLD	-0.168	0.002***	-0.235	0.012***
AE LAND				
PRECIPITATION	-0.095	0.039*	-0.178	0.298
SOIL MOISTURE	-0.031	6.95E-04***	0.633	0.005***
VEGETATION INDEX	0.046	0.005***	-0.282	0.034***

1: *,**,*** significance at the 10, 5, and 1% level

TABLE 5: PRODUCER-SPECIFIC TECHNICAL AND COST EFFICIENCY

	MODEL I				MODEL II			
EFFICIENCY	MEAN	STD. ERR.[1]	MIN	MAX	MEAN	STD. ERR.	MIN	MAX
TE	0.815	0.211***	0.168	0.999	0.823	0.162***	0.423	0.999
CE LABOUR	0.604	0.157***	0.124	0.741	0.425	0.083***	0.218	0.516
CE FERTILIZER	0.380	0.099***	0.078	0.467	0.390	0.077***	0.201	0.474
CE LAND	0.660	0.171***	0.136	0.810	0.424	0.083***	0.218	0.514
CE ORGANIC FERTILIZER	0.439	0.114***	0.091	0.539	0.296	0.058***	0.152	0.359

1: *,**,*** significance at the 10, 5, and 1% level

TABLE 6: FREQUENCY DISTRIBUTION – PRODUCER-SPECIFIC TECHNICAL EFFICIENCY

EFFICIENCY INDEX	PERCENTAGE		CUMULATIVE FREQUENCY		CUMULATIVE PERCENTAGE	
	MODEL I	MODEL II	MODEL I	MODEL II	MODEL I	MODEL II
0.1-0.2	1.56	-	1	-	1.56	-
0.2-0.3	1.56	-	2	-	3.12	-
0.3-0.4	1.56	-	3	-	4.69	-
0.4-0.5	3.12	1.56	5	1	7.81	1.56
0.5-0.6	12.50	9.37	13	7	20.31	10.94
0.6 – 0.7	3.12	10.94	15	14	23.44	21.87
0.7 – 0.8	15.62	26.56	25	31	39.06	48.44
0.8 – 0.9	10.94	14.06	32	40	50	62.50
0.9 – 1.0	50.00	37.50	64	64	100	100
Mean	0.815	0.824				
Std.Err.[1]	0.211***	0.162***				
Min	0.168	0.423				
Max	0.999	0.998				

1: *,**,*** significance at the 10, 5, and 1% level

Table 7: Group-Wise Technical Efficiency Effects

	Model I		Model II	
Factor	**Mean**	**Std. Err.**[1]	**Mean**	**Std. Err.**
TE Difference Herbicide	+1.93E-04	0.011	+0.332	0.084***
TE Difference Insecticide	+0.055	0.014***	+0.113	0.105
TE Difference Seed	+0.032	0.009***	+0.050	0.069
TE Difference Slope	+0.013	0.008*	+0.031	0.058
TE Difference Subsidies	-0.052	0.009***	+0.073	0.068
TE Difference Extension	-4.77E-04	0.010	-0.096	0.077
TE Difference Training	-0.053	0.013***	-0.097	0.098
TE Difference Precipitation	+0.001	0.007	+0.001	0.053**
TE Difference Soil	-0.002	0.006	+0.007	0.048
TE Difference Vegetation	+0.001	8.61E-04*	-0.015	0.006
TE Difference Livestock	-0.008	9.33E-04***	-0.004	0.007

1: *,**,*** significance at the 10, 5, and 1% level

Table 8: Producer-Specific Technical Efficiency Effects

Factor	**Model I**[1]		**Model II**	
	Mean	**Std. Err.**[1]	**Mean**	**Std. Err.**
Herbicide	-7.44	1.297***	-4.609	0.836***
Insecticide	+24.290	5.042***	+25.501	2.546***
Seed	-6.414	1.719***	-1.003	0.654*
Extension	+7.282	2.119***	+4.083	0.741***
Training	+13.861	2.224***	+19.706	2.062***
Precipitation	-0.272	0.062***	-0.104	0.031***
Soil	+1.024	0.281***	+0.037	0.127
Vegetation	-0.213	0.047***	-0.272	0.032***
Education	+0.474	0.129***	+0.126	0.115
Hired Labour	+2.458	1.593*	-2.359	1.633*
Subsidies	-1.801	1.071*	+0.519	0.617
Additional Income	-0.076	0.025***	+0.133	0.024***
Cooperation	-2.228	0.821***	+8.137	1.581***
Machinery	-3.713	0.878***	-1.282	0.456***
Distance	-1.311	0.257***	-1.306	0.224***
Individual Farming	+0.182	0.029***	+0.141	0.034***

1: *,**,*** significance at the 10, 5, and 1% level

TABLE 9: RELATIVE DIFFERENCE IN EFFICIENCY SCORES - UNCONSTRAINED VS. CONSTRAINED SPECIFICATION

MEASURE	MEAN (%)[2]	STDERR[1]	MIN	MAX
TECHNICAL EFFICIENCY	11.45	12.14	-45.79	342.55
COST EFFICIENCY LABOUR	-22.38	8.15***	-62.24	208.21
CE FERTILIZER	13.12	60.42	-44.98	349.16
CE LAND	-29.23	16.06**	-65.58	181.02
CE ORGANIC FERTILIZER	-25.66	13.63**	-63.84	195.20

1: *,**,*** significance at the 10, 5, and 1% level
2: '+' means underestimation of real efficiency, '-' overestimation of real efficiency

FIGURE 1: DIFFERENCES IN TECHNICAL EFFICIENCY BY IMPOSING CURVATURE CORRECTNESS

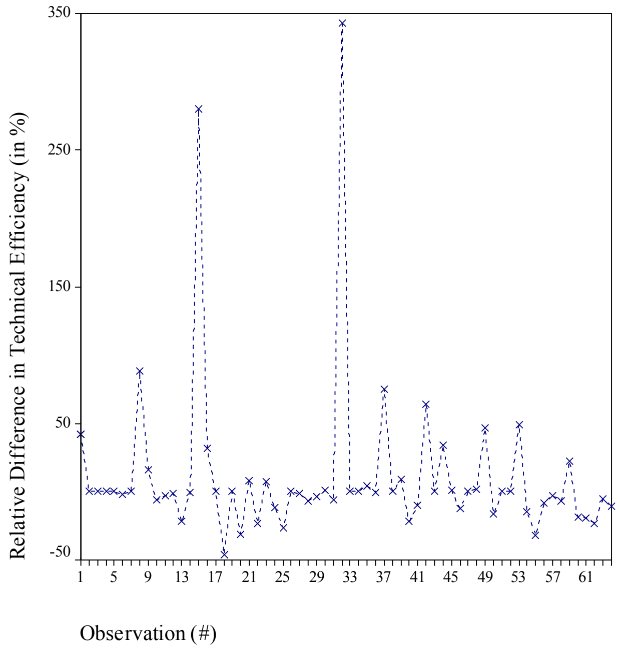

TABLE A1: PARAMETER ESTIMATES SHADOW COST FRONTIER – MODEL I

COST FUNCTION

PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	2.660	0.015***	χ_{subs}	0.013	0.008*
α_{lab}	-0.013	0.007*	χ_{ext}	-0.052	0.009***
α_{fert}	1.013	0.006***	χ_{train}	-4.771E-04	0.963
γ_y	0.027	0.007***	χ_{slope}	-0.052	0.013***
α_{lablab}	-0.072	0.010***	χ_{precip}	0.001	0.007
$\alpha_{fertfert}$	-0.073	0.011***	χ_{soil}	-0.002	0.006
γ_{yy}	-2.374	0.014***	χ_{vege}	0.001	8.607E-04*
$\beta_{labfert}$	0.145	0.009***	χ_{livest}	-0.007	9.331E-04***
β_{ylab}	-0.043	0.011***	φ_{lab_gender}	-0.010	2.682E-04***
β_{yfert}	0.043	0.012***	φ_{lab_age}	-0.025	1.765E-04***
δ_{land}	0.436	0.006***	φ_{lab_edu}	0.161	0.002***
δ_{orgf}	0.019	0.006***	φ_{lab_hire}	0.146	0.016***
$\delta_{landland}$	1.387	0.006***	φ_{lab_hhout}	0.035	2.331E-04***
$\delta_{orgforgf}$	0.002	0.014	φ_{lab_hhsize}	-0.168	0.002***
$\delta_{landorgf}$	-0.156	0.001***	η_{land_precip}	-0.095	0.039**
$\delta_{labland}$	-0.867	0.001***	η_{land_soil}	-0.031	6.951E-04***
$\delta_{laborgf}$	0.004	4.084E-05***	η_{land_vege}	0.046	4.623E-04***
$\delta_{fertland}$	4.420	0.004***	θ_{lab}	0.741	9.659E-05***
$\delta_{fertorgf}$	0.042	4.085E-05***	θ_{fert}	2.142	2.682E-04***
δ_{yland}	-0.505	0.002***	θ_{land}	1.234	1.765E-04***
δ_{yorgf}	-0.013	0.001***	θ_{orgf}	0.539	0.002***
χ_{herb}	1.934E-04	0.011			
χ_{insect}	0.055	0.014***			
χ_{seed}	0.033	0.009***			
ADJR^2	0.485				
F-VALUE	582.189				
P>|F|	9.069E-68				
CONCAVITY (%)	15.63				

*,**,***: significance at 10,5, and 1 % -level

LABOR SHARE

PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_{lab}	1.643	0.053***	φ_{lab_gender}	-0.010	2.682E-04***
α_{fert}	0.772	0.048***	φ_{lab_age}	-0.025	1.765E-04***
$\beta_{labfert}$	0.160	0.070***	φ_{lab_edu}	0.161	0.002***
β_{ylab}	0.175	0.075***	φ_{lab_hire}	0.146	0.016***
β_{yfert}	0.027	0.093	φ_{lab_hhout}	0.035	2.331E-04***
δ_{land}	5.206	0.048***	φ_{lab_hhsize}	-0.168	0.002***
δ_{orgf}	1.017	0.047***	η_{land_precip}	-0.095	0.039**
$\delta_{landorgf}$	2.915	0.009***	η_{land_soil}	-0.031	6.951E-04***
$\delta_{labland}$	0.979	0.030***	η_{land_vege}	0.046	4.623E-04***
$\delta_{laborgf}$	0.042	0.000***			
δ_{yland}	1.000	0.017***			
$\delta_{fertland}$	0.458	0.030***			
$\delta_{fertorgf}$	0.024	0.106***			
δ_{yorgf}	0.879	0.053			
θ_{lab}	0.741	0.054***			
θ_{fert}	2.142	0.048***			
θ_{land}	1.234	0.006***			
θ_{orgf}	0.539	0.007***			
ADJR^2	0.848				
F-VALUE	1516.944				
P>|F|	4.145E-76				

*,**,***: significance at 10,5, and 1 % -level

TABLE A2: PARAMETER ESTIMATES ERROR COMPONENTS FRONTIER – MODEL I

PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	1.672	0.001***	δ_{orgf}	0.164	4.21E-04***
α_{lab}	-0.1283	4.43E-04***	$\delta_{landland}$	-0.347	2.78E-04***
α_{fert}	0.0667	0.0022***	$\delta_{orgforgf}$	0.018	4.91E-06***
γ_y	0.2751	0.001***	$\delta_{landorgf}$	0.014	2.97E-05***
α_{lablab}	-0.0879	2.07E-04***	$\delta_{labland}$	0.005	3.85E-06***
$\alpha_{fertfert}$	0.196	0.229	$\delta_{laborgf}$	-0.016	4.81E-06***
γ_{yy}	0.134	4.67E-06***	$\delta_{fertland}$	-0.159	0.298
$\beta_{labfert}$	-0.047	0.001***	$\delta_{fertorgf}$	-0.058	9.18E-04***
β_{ylab}	-0.058	7.22E-06***	δ_{yland}	-0.121	8.80E-05***
β_{yfert}	0.785	0.002***	δ_{yorgf}	0 .036	6.91E-06***
δ_{land}	0.189	1.01E-04***			
$\ln\sigma^2_v$	-30.261	5.613***			
$\ln\sigma^2_u$					
β_0	21.745	9.952**	χ_{vege}	0.212	0.047***
χ_{herb}	7.444	1.297***	χ_{edu}	-0.474	0.128***
χ_{insect}	-24.290	5.042***	χ_{hire}	-2.458	1.592*
χ_{seed}	6.414	1.719***	χ_{subs}	1.800	1.071**
χ_{ext}	-7.282	2.119***	χ_{hhout}	0.076	0.025***
χ_{train}	-13.861	2.224***	χ_{coop}	2.228	0.820***
χ_{precip}	0.272	0.062***	χ_m	3.713	0.878***
χ_{soil}	-1.024	0.280***	χ_{dist}	1.310	0.257***
χ_{ifch}	-0.182	0.029***			
σ_v	2.68E-07	7.53e-07***			
WALDCHI^2(20)	1721.18				
LL	160.833				
P>CHI^2	0.000				

*,**,***: significance at 10,5, and 1 % -level

Table A3: Parameter Estimates Shadow Cost Frontier – Model II

COST FUNCTION

Parameter	Estimate	StErr	Parameter	Estimate	StErr
α_0	1.849	0.109***	χ_{subs}	0.031	0.058
α_{lab}	0.189	0.053***	χ_{ext}	0.073	0.068
α_{fert}	0.811	0.048***	χ_{train}	-0.096	0.077
γ_y	-2.080	0.053***	χ_{slope}	-0.097	0.098
α_{lablab}	0.146	0.077**	χ_{precip}	0.001	0.053
$\alpha_{fertfert}$	-0.003	0.080	χ_{soil}	0.007	0.048
γ_{yy}	2.041	0.104***	χ_{vege}	-0.015	0.006**
$\beta_{labfert}$	-0.143	0.070**	χ_{livest}	-0.004	0.007
β_{ylab}	0.079	0.076	φ_{lab_gender}	-0.075	0.002***
β_{yfert}	-0.079	0.094	φ_{lab_age}	0.063	0.001***
δ_{land}	0.562	0.048***	φ_{lab_edu}	0.133	0.013***
δ_{orgf}	0.265	0.047***	φ_{lab_hire}	0.152	0.121
$\delta_{landland}$	-6.726	0.048***	φ_{lab_hhout}	0.013	0.002***
$\delta_{orgforgf}$	0.040	0.106	φ_{lab_hhsize}	-0.235	0.012***
$\delta_{landorgf}$	0.606	0.009***	η_{land_precip}	-0.178	0.298
$\delta_{labland}$	-0.260	0.003***	η_{land_soil}	0.633	0.005***
$\delta_{laborgf}$	-0.049	0.000***	η_{land_vege}	-0.282	0.034***
$\delta_{fertland}$	-0.869	0.030***	θ_{lab}	0.516	0.001***
$\delta_{fertorgf}$	-0.074	0.000***	θ_{fert}	2.111	0.002***
δ_{yland}	2.161	0.017***	θ_{land}	1.944	0.001***
δ_{yorgf}	-0.003	0.002	θ_{orgf}	0.359	0.013***
χ_{herb}	0.332	0.084***	h_{12}	0.010	0.070**
χ_{insect}	0.113	0.105	h_{13}	-0.154	0.003***
χ_{seed}	0.050	0.069	h_{14}	0.001	0.000***
h_{11}	-0.007	0.077**	h_{23}	-0.413	0.030***
h_{22}	-0.157	0.080	h_{24}	0.141	0.000***
h_{33}	-6.972	0.048***	h_{34}	0.755	0.009***
h_{44}	-0.155	0.106			

ADJR^2	0.703
F-Value	330.448
P>|F|	4.084E-59
Concavity (%)	70.31

*,**,***: significance at 10,5, and 1 % -level

LABOR SHARE

PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_{lab}	2.264	0.061***	φ_{lab_gender}	-0.075	0.002***
α_{fert}	0.026	0.056	φ_{lab_age}	0.063	0.001***
$\beta_{labfert}$	-2.781	0.081***	φ_{lab_edu}	0.133	0.013***
β_{ylab}	-0.942	0.087***	φ_{lab_hire}	0.152	0.121
β_{yfert}	0.188	0.108*	φ_{lab_hhout}	0.013	0.002***
δ_{land}	1.442	0.055***	φ_{lab_hhsize}	-0.235	0.012***
δ_{orgf}	0.533	0.055***	η_{land_precip}	-0.178	0.298
$\delta_{landorgf}$	1.277	0.011***	η_{land_soil}	0.633	0.005***
$\delta_{labland}$	3.820	0.035***	η_{land_vege}	-0.282	0.034***
$\delta_{laborgf}$	0.575	0.000***			
δ_{yland}	1.000	0.020***			
$\delta_{fertland}$	4.601	0.035***			
$\delta_{fertorgf}$	0.083	0.122			
δ_{yorgf}	0.160	4.27E-04***			
θ_{lab}	0.516	0.061***			
θ_{fert}	2.111	0.056***			
θ_{land}	1.944	0.007***			
θ_{orgf}	0.359	0.008***			
ADJ R^2	0.571				
F-VALUE	1.025				
P>|F|	0.444				

*,**,***: significance at 10,5, and 1 % -level

TABLE A4: PARAMETER ESTIMATES ERROR COMPONENTS FRONTIER – MODEL II

PARAMETER	ESTIMATE	STERR	PARAMETER	ESTIMATE	STERR
α_0	1.418	0.002***	δ_{orgf}	0.004	0.003
α_{lab}	-0.012	8.35E-04***	$\delta_{landland}$	-0.061	7.64E-04***
α_{fert}	-0.152	0.011***	$\delta_{orgforgf}$	-0.230	0.003***
γ_y	-0.213	4.78E-04***	$\delta_{landorgf}$	0.004	0.002**
α_{lablab}	-0.061	7.64E-04***	$\delta_{labland}$	0.078	0.002***
$\alpha_{fertfert}$	0.034	0.012***	$\delta_{laborgf}$	-0.003	7.56E-04***
γ_{yy}	0.086	0.012***	$\delta_{fertland}$	-0.021	0.003***
$\beta_{labfert}$	-0.136	0.008***	$\delta_{fertorgf}$	0.004	0.003***
β_{ylab}	-0.021	1.03E-04***	δ_{yland}	0.201	1.95E-04***
β_{yfert}	0.054	0.001***	δ_{yorgf}	0.016	2.15E-04***
δ_{land}	0.779	0.006***			
$\ln \sigma^2_v$	-30.523	5.614***			
$\ln \sigma^2_u$					
β_0	10.843	6.704*	χ_{vege}	0.271	0.032***
χ_{herb}	4.609	0.836***	χ_{edu}	-0.125	0.115
χ_{insect}	-25.501	2.546***	χ_{hire}	2.359	1.632*
χ_{seed}	1.003	0.653*	χ_{subs}	-0.519	0.617
χ_{ext}	-4.083	0.741***	χ_{hhout}	-0.133	0.024***
χ_{train}	-19.706	2.062***	χ_{coop}	-8.137	1.581***
χ_{precip}	0.104	0.031***	χ_m	1.282	0.456***
χ_{soil}	-0.037	0.126	χ_{dist}	1.306	0.224***
χ_{ifch}	-0.141	0.034***			
σ_v	9.04E-09	2.95e-06***			
WALDCHI²(20)	1.554E+12				
LL	93.803				
P>CHI²	0.000				

*,**,***: significance at 10,5, and 1 % -level

TABLE A5: BIAS CORRECTED BOOTSTRAP ESTIMATES ERROR COMPONENTS FRONTIER II

PARAMETER	ESTIMATE	STERR	BIAS CORRECTED CONF. INTERVAL	PARAMETER	ESTIMATE	STERR	BIAS CORRECTED CONF. INTERVAL
α_0	1.418	0.162***	[1.172, 1.641]	δ_{orgf}	-0.231	0.291	[-0.677, 0.182]
α_{lab}	-0.0123	0.138	[-0.201, 0.169]	$\delta_{landland}$	-0.419	0.301*	[-0.874, -0.389]
α_{fert}	-0.153	0.158	[-0.526, 0.221]	$\delta_{orgforgf}$	-0.045	0.051	[-0.122, 0.028]
γ_y	-0.213	0.268	[-0.599, 0.055]	$\delta_{landorgf}$	-0.021	0.561	[-0.343, 0.356]
α_{lablab}	-0.061	0.012***	[-0.082, -0.057]	$\delta_{labland}$	0.078	0.133	[-0.041, 0.388]
$\alpha_{fertfert}$	0.034	0.585	[-0.836, 0.645]	$\delta_{laborgf}$	-0.003	0.024	[-0.049, 0.021]
γ_{yy}	0.085	0.056*	[-0.029, 0.198]	$\delta_{fertland}$	-0.021	0.561	[-0.343, 0.356]
$\beta_{labfert}$	-0.136	0.199	[-0.503, -0.019]	$\delta_{fertorgf}$	0.004	0.137	[-0.022, 0.129]
β_{ylab}	-0.022	0.067	[-0.123, 0.099]	δ_{yland}	-0.022	0.067	[-0.123, 0.099]
β_{yfert}	0.054	0.789	[-1.432, 0.806]	δ_{yorgf}	0.016	0.017	[0.001, 0.052]
δ_{land}	0.779	0.337**	[0.209, 1.208]				
β_0	10.843	21.531	[-12.509, 43.109]	χ_{vege}	0.272	2.147	[-2.718, 5.133]
χ_{herb}	4.609	28.237	[-20.027, 69.081]	χ_{edu}	-0.126	2.111	[-5.166, 1.502]
χ_{insect}	-25.501	37.255	[-54.058, 4.034]	χ_{hire}	2.359	7.691	[-13.049, 12.569]
χ_{seed}	1.003	14.290	[-20.884, 25.346]	χ_{subs}	-0.519	13.766	[-13.821, 31.526]
χ_{ext}	-4.083	14.984	[-23.347, 19.154]	χ_{hhout}	-0.133	0.279	[-0.795, 0.529]
χ_{train}	-19.706	17.506	[-48.646, 2.675]	χ_{coop}	-8.137	15.833	[-32.614, 2.728]
χ_{precip}	0.104	3.203	[-3.534, 7.924]	χ_m	1.282	23.709	[-12.993, 9.911]
χ_{soil}	-0.037	11.574	[-1.145, 8.779]	χ_{dist}	1.306	14.053	[-11.065, 8.124]

*,**,***: significance at 10,5, and 1 % -level; replications = 1000.

TABLE A6: MULTIPLE EQUATION SYSTEM I – ALLOCATIVE INEFFICIENCY COMPONENTS

	LABOR		FERTILIZER		LAND		ORGANIC FERTILIZER	
PARAMETER	ESTIMATE	STERR	ESTIMATE	STERR	ESTIMATE	STERR	ESTIMATE	STERR
ω_{precip}	5.198	0.311***	0.014	0.003***	-	-	21.576	12.504**
ω_{vege}	2.134	0.438***	-	-	-	-	-	-
ω_{livest}	7.282	1.245***	0.033	0.014***	-	-	-	-
ω_{age}	1.259	0.593**	-	-	-	-	-	-
ω_{size}	3.639	1.308***	0.195	0.021***	0.025	0.003***	-99.752	68.336*
ω_{build}	-13.559	8.065*	-	-	0.029	0.013**	-	-
ω_{slope}	-490.686	32.058***	-	-	-0.820	0.053***	-	-
ω_{hfl}	-	-	1.479	0.466***	0.174	0.062***	-	-
ω_{out}	-	-	0.024	0.006***	0.004	0.001***	20.441	18.669*
ω_{dist}	-	-	0.520	0.063***	0.064	0.009***	-	-
ω_{soil}	-	-	-	-	0.037	0.002***	-	-
ω_{edu}	-	-	-	-	-	-	-163.569	114.343*
ω_{mach}	-	-	-	-	-	-	2592.855	474.544***
κ_{ext}	-	-	-0.464	0.199**	0.162	0.029***	-	-
κ_{herbi}	-	-	0.371	0.268*	0.083	0.037**	-1158.819	961.204*
κ_{insect}	-	-	-1.502	0.335***	-0.216	0.051***	-	-
κ_{seed}	-	-	-0.167	0.174*	-	-	-	-
κ_{sub}	24.978	14.023*	-	-	0.069	0.023***	-	-
κ_{tr}	27.545	18.457*	-0.997	0.262***	0.131	0.039***	-	-
κ_{gender}	44.157	18.329**	0.397	0.232*	0.062	0.033**	-1472.555	845.427**
κ_{car}	-	-	0.849	0.247***	0.092	0.033***	-	-
κ_{coop}	-	-	0.375	0.203**	0.071	0.027***	-	-
κ_{iasi}	-704.298	43.716***	-1.459	0.3901***	-1.325	0.089***	-	-
$\kappa_{mehedinti}$	527.482	36.178***	-	-	0.719	0.062***	2572.538	1025.339***
κ_{braila}	-489.698	38.369***	-	-	-0.788	0.064***	-	-
$\kappa_{vrancea}$	-193.845	35.401***	-	-	-0.334	0.047***	-	-
$\kappa_{ialomita}$	-752.827	46.088***	-1.287	0.484***	-1.298	0.093***	-	-
$\kappa_{oltenia}$	-	-	45.179	1.114***	4.550	0.158***	-	-
κ_{bihor}	-	-	-2.249	0.753***	0.338	0.102***	-	-
κ_{mures}	-	-	-1.794	0.423***	-	-	-	-
κ_{arad}	-	-	-	-	-0.113	0.048**	2847.12	1606.909**
$\kappa_{hargita}$	-	-	-	-	-	-	4999.618	1307.038***
κ_{valcea}	-	-	-	-	-	-	2994.782	993.572***
κ_{alba}	-	-	-	-	-	-	-4165.854	2789.074
R^2	0.935		0.988		0.989		0.521	
Chi^2	906.09***		5158.29***		5627.00***		71.44***	
BP-test	31.181***							

*,**,***: significance at 10,5, and 1 % -level;
inclusion of the most significant regressors.

TABLE A7: MULTIPLE EQUATION SYSTEM II – ALLOCATIVE INEFFICIENCY COMPONENTS

	LABOR		FERTILIZER		LAND		ORGANIC FERTILIZER	
PARAMETER	ESTIMATE	STERR	ESTIMATE	STERR	ESTIMATE	STERR	ESTIMATE	STERR
ω_{precip}	17.442	1.454***	0.612	0.019***	0.031	0.005***	-	-
ω_{vege}	6.718	0.757***	-0.221	0.008***	-0.0256	0.002***	-	-
ω_{livest}	-	-	0.079	0.021***	-	-	-	-
ω_{size}	7.745	2.571***	0.166	0.021***	0.062	0.007***	-201.626	86.381***
ω_{build}	-	-	-	-	0.101	0.032***	848.615	454.947**
ω_{hfl}	93.434	43.533**	-1.222	0.477***	-0.427	0.159***	-	-
ω_{out}	-	-	-0.023	0.008***	-0.008	0.003***	72.657	32.953**
ω_{dist}	8.027	7.991*	0.491	0.069***	0.167	0.024***	-	-
ω_{soil}	-32.082	3.705***	-1.039	0.044***	-0.022	0.013***	-	-
ω_{edu}	6.579	3.794**	-	-	-	-	-	-
ω_{mach}	-	-	-	-	-	-	3297.106	721.437***
κ_{ext}	57.727	24.048***	-0.411	0.215**	-0.359	0.076***	1512.279	959.344*
κ_{herbi}	35.983	33.429*	-	-	0.210	0.079***	-	-
κ_{insect}	-	-	-1.429	0.410***	-0.561	0.145***	-	-
κ_{seed}	-	-	-0.204	0.171*	-	-	1025.666	790.525*
κ_{sub}	60.434	25.327***	-0.421	0.238**	0.105	0.079*	-	-
κ_{tr}	75.513	33.465**	-1.135	0.283**	-0.312	0.104***	2173.314	1314.663**
κ_{gender}	70.301	28.605***	0.287	0.249*	0.135	0.084*	-2515.855	1171.277**
κ_{car}	-	-	0.933	0.258***	0.195	0.089***	-1927.378	1308.391*
κ_{coop}	38.435	22.619*	0.381	0.205**	0.174	0.068***	-3013.971	986.614***
κ_{iasi}	-1268.307	91.181***	-45.518	1.207***	-3.387	0.299***	-	-
κ_{braila}	-72.659	41.720**	-	-	0.381	0.093***	-	-
$\kappa_{vrancea}$	-1190.647	88.255***	-44.146	1.166***	-2.919	0.296***	-2273.914	1630.556*
$\kappa_{ialomita}$	-1329.538	91.247***	-45.368	1.221***	-3.255	0.302***	-	-
$\kappa_{oltenia}$	-	-	-	-	11.778	0.422***	-	-
κ_{bihor}	-973.875	95.606***	-35.128	1.116***	-1.623	0.301***	-	-
κ_{mures}	-1080.585	82.746***	-34.003	1.048***	-2.459	0.261***	-	-
$\kappa_{hargita}$	-93.876	43.439**	-	-	0.114	0.099*	-	-
κ_{valcea}	-58.114	38.523*	-	-	0.307	0.093***	-	-
κ_{alba}	-	-	-44.414	1.222***	-	-	-4287.545	3817.395*
R^2	0.952		0.988		0.989		0.533	
Chi^2	1225.38***		5301.61***		6006.41***		70.24***	
BP-test	31.570***							

*,**,***: significance at 10,5, and 1 % -level;
inclusion of the most significant regressors.

FIGURE A1: PRODUCER-SPECIFIC TECHNICAL EFFICIENCY I – KERNEL DENSITY

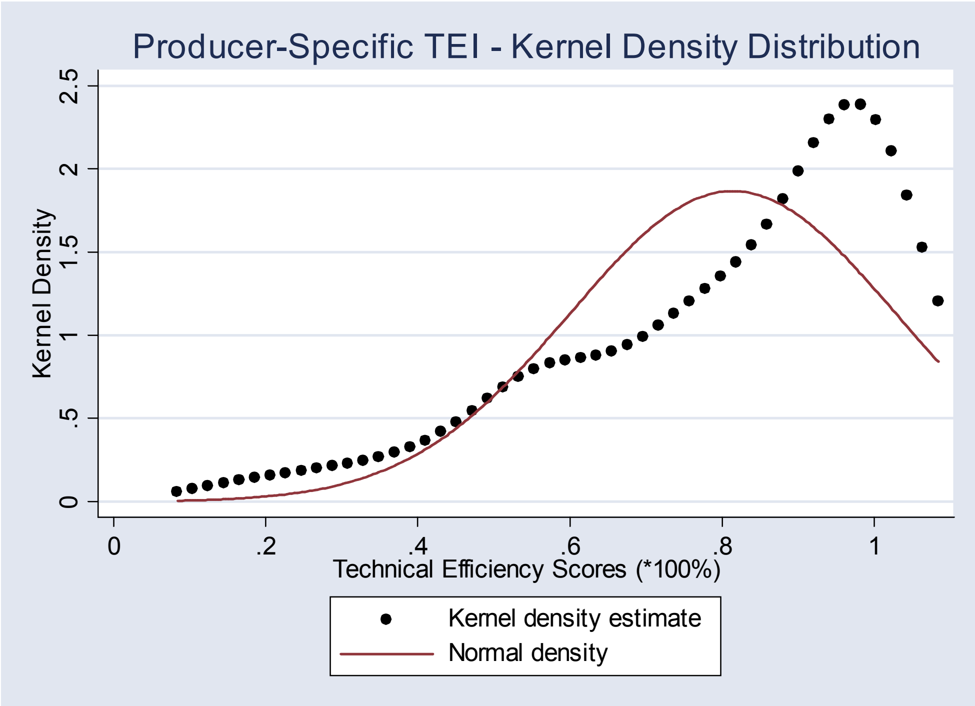

FIGURE A2: PRODUCER-SPECIFIC TECHNICAL EFFICIENCY II – KERNEL DENSITY