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DISTORTED PRICES AND PRODUCER EFFICIENCY – ROMANIAN MAIZE

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Abstract

This research aims at shedding empirical light on the relative efficiency of small-scale maize producers in Romania. Farmers in transition countries still face heavily distorted price systems resulting from imperfect market conditions and socioeconomic and institutional constraints. To capture such distortions we formulate a stochastic shadow-cost frontier model 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 and the effects on the individual efficiency estimates are shown. The empirical results show a relative high technical efficiency of the small-scale farmers but relatively poor scores on systematic input price efficiency. The usage of extension services as well as agricultural training on the farm level are found to have a positive effect on the technical efficiency level of the farms. All model specifications further agree on the negative effect on efficiency with respect to the use of insecticides. The imposition of functional concavity on the shadow cost frontier leads to relative differences in the efficiency estimates of up to 240 %.

Keywords

Efficiency, Shadow Cost Frontier, Functional Consistency, Maize, Romania

1 Introduction

Profound structural changes are still taking place in the process of transition from a command to a market oriented economy in Romania. This is especially true for the agricultural sector where the structural reforms are concentrated on the privatization of land and the downsizing of agricultural enterprises and led to the emergence of numerous small farms (LERMAN, 1999; OECD, 2000). These farmers – so-called individual farmers – are currently the most important actors with respect to land and output markets (OECD, 2000; LEONTE, 2002). However, they are still heavily constrained with respect to an insufficient factor endowment and the lack of developed input and output markets. As a result, most technology intensive crops have been substituted by the cultivation of more traditional crops and the importance of subsistence farming 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). This research aims to assess the relative efficiency of small-scale maize production and tries to determine different factors for maize farms' inefficiency. To the background of the restructuring in the 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, 1984 and 1986; KUMBHAKAR and BHATTACHARYYA, 1992; 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. After briefly outlining the case of small-scale maize production in Romania subsequently the

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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 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 aiming at changing collective agriculture to individual agriculture as well as on the downsizing of the farms (LERMAN, 1999). 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 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.

Furthermore the new individual producers lacked the necessary know-how to cultivate their land. They had no cash to invest and rarely access to credit as well as 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. 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 by non-commercial crops, technical crops by traditional crops and increased subsistence production. 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.

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. Despite some studies on the economic efficiency of farming in transitional countries (see e.g. HUGHES, 1998; MATHIJS and SWINNEN, 2000) none considers the effects of distorted input and output price relations with respect to the relative efficiency of agricultural production in Romania. Due to the vast literature on shadow prices (see for an overview e.g. KUMBHAKAR and LOVELL, 2000) non-observable shadow price ratios have to be considered as the relevant ones for producer decisions in distorted agricultural 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. Alternatively shadow prices can be modeled by multiplicatively scaling observed prices into shadow ones (LAU and YOTOPOULOS, 1971). We follow the latter approach here and define the relationship between the normalized shadow prices for the inputs w^* and the normalized market prices w as

$$w^*_i = \theta_i w_i \tag{1}$$

where θ_i are (non-negative) price efficiency parameters and i is an index for inputs. If no bending market restrictions are the case then θ_i equal unity, if market distortions 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 mar-

ket prices reflect the farmer's opportunity cost with respect to inputs. It has to be considered that the price efficiency parameters θ_i may reflect both effects of market distortions as well as optimization errors.

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

We start our modeling efforts by assuming a simple single-output translog cost function and its associated cost-minimizing input cost share equations (see e.g. ATKINSON and HALVORSEN, 1980, 1984 and 1986; KUMBHAKAR, 1989; WANG et al., 1996; KUMBHAKAR and BHATTACHARYYA, 1992). Incorporating shadow prices and following the input-oriented approach with respect to technical efficiency, observed expenditure and observed input cost shares can be expressed in terms of shadow cost and shadow input cost shares as

$$\ln C = \alpha_0 - \sum_{n=1}^6 \chi_n D_n + \gamma_y \ln y + \frac{1}{2} \gamma_{yy} (\ln y)^2 + \sum_{i=1}^2 \alpha_i \ln(\theta_i w_i) + \frac{1}{2} \sum_{i=1}^2 \sum_{k=1, i \neq k}^2 \beta_{ik} \ln(\theta_i w_i) \ln(\theta_k w_k) + \sum_{i=1}^2 \beta_{yi} \ln y \ln(\theta_i w_i) + \ln \left\{ \sum_{i=1}^2 (\theta_i)^{-1} \left[\beta_i + \sum_{i=1}^2 \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right] \right\} \quad [2]$$

and

$$S_i = \frac{(\theta_i)^{-1} \left[\beta_i + \sum_{k=1}^2 \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right]}{\sum_{i=1}^2 (\theta_i)^{-1} \left[\beta_i + \sum_{k=1}^2 \beta_{ik} \ln(\theta_k w_k) + \beta_{yi} \ln y \right]} \quad i = 1, \dots, 4 \quad [3]$$

respectively, where symmetry and homogeneity of degree +1 in input prices are imposed and where y = maize output; the inputs' prices w = labour, fertilizer, land, organic fertilizer; and the control variables herbicide used, insecticides used, seed applied, subsidies received, extension services used, agricultural training received. Hence, total expenditure is expressed as the sum of the original translog cost function, the cost differential due to input oriented technical efficiency, and the cost of systematic allocative inefficiency (the last term in equation [2]) depending on data as well as parameters. The shadow input cost shares in [3] are obtained by applying the usual derivation procedure as well as adjusting for input specific allocative inefficiency (see KUMBHAKAR and LOVELL, 2000). Classical error terms are appended, one input cost share equation is deleted, and the remaining system of 3 equations is estimated. χ includes the relative technical inefficiency with respect to a group of farmers defined along different characteristics following the control variables, θ gives the systematic allocative inefficiency for the respective input.

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 RYAN and WALES, 1998; and the more technical discussion in SAUER, 2006). 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 and FRAUMENI (1981) and RYAN and WALES (1998). By this procedure the bordered Hessian 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

$$\beta(\delta)_{rs} = -(\Delta\Delta')_{rs} + \alpha(\delta)_r \lambda_{rs} + \alpha(\delta)_s \alpha(\delta)_r \quad [4]$$

where $r = i, l$ and $s = k, m$ and $\lambda_{rs} = 1$ if $r = s$ and 0 otherwise and $(\Delta\Delta^*)_{rs}$ as the rs -th element of $\Delta\Delta^*$ with Δ as a lower triangular matrix (see in detail Sauer 2006). 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 \mathbf{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:

$$\begin{aligned} \ln\left(\frac{C}{C'}\right) = & \alpha_0 - \sum_{n=1}^6 \chi_n \left(\frac{D_n}{D'}\right) + \gamma_y \ln\left(\frac{y}{y'}\right) + \frac{1}{2} \gamma_{yy} \ln\left(\frac{y}{y'}\right)^2 + \sum_{i=1}^2 \alpha_i \ln\left(\theta_i \frac{w_i}{w'_i}\right) \\ & + \frac{1}{2} \sum_{i=1}^2 (h_{ii} + \alpha_i - \alpha_i \alpha_i) \ln\left(\theta_i \frac{w_i}{w'_i}\right)^2 + \frac{1}{2} \sum_{i=1}^2 \sum_{k=1, i \neq k}^2 (h_{ik} - \alpha_i \alpha_k) \ln\left(\theta_i \frac{w_i}{w'_i}\right) \ln\left(\theta_k \frac{w_k}{w'_k}\right) \\ & + \sum_{i=1}^2 \beta_{yi} \ln\left(\frac{y}{y'}\right) \ln\left(\theta_i \frac{w_i}{w'_i}\right) + \ln\left\{ \sum_{i=1}^2 (\theta_i)^{-1} \left[\alpha_i + \sum_{i=1}^2 (h_{ik} - \alpha_i \alpha_k) \ln\left(\theta_k \frac{w_k}{w'_k}\right) + \beta_{yi} \ln\left(\frac{y}{y'}\right) \right] \right\} + \varepsilon_i \end{aligned} \quad [5]$$

However, the elements of Δ are nonlinear functions of the decomposed matrix 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 [5] 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 and 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.

In a second step the behavioural (shadow price) cost function in its constrained and unconstrained version 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

$$\xi_i = v_i + u_i \quad [6]$$

where v_i is the inefficiency component and u_i as the usual stochastic noise 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; KHUMBHAKAR and LOVELL, 2000). As the price efficiency parameters θ_i 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 one-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 (the stochastic details are readily available in the relevant literature, see e.g. BATTESI and COELLI, 1995). 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 and LOVELL, 2000).

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 farm level result from the error components model and finally such of 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

$$\frac{(eff_i^{in} - eff_i^{con})}{eff_i^{in}} * 100 \quad [7]$$

where eff_i^{in} and eff_i^{con} are the efficiency scores by the inconsistent and the consistent model respectively. To test for the robustness of our estimates by the adjusted shadow cost model (based on [5]) we further apply a simple stochastic resampling procedure based on bootstrapping techniques (see e.g. EFRON, 1979; EFRON and TIBSHIRANI, 1993).

4 Data and Estimation

We use data on 64 maize farmers based on a survey among agricultural households in 15 Romanian villages in 2003. 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 most frequently produced crop was maize, cultivated by about 92 % of the households and only less than a quarter of all households cultivated technical more demanding crops as sunflower, soya or sugar beet. Table 1 gives the summary statistics on the sample data.

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/month)	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)	0.594	0.495	0	1
Insecticides used (binary)	0.937	0.244	0	1
Commercial Seed used (binary)	0.406	0.495	0	1
Subsidies received (binary)	0.297	0.460	0	1
Extension Services used (binary)	0.5	0.504	0	1
Training used (binary)	0.187	0.393	0	1

Source: Own Calculations

The estimation procedure is as follows: In a first step the translog cost system given by [5] is estimated (without imposing curvature correctness) using the cost function as well as the cost shares s_i derived from the non-distorted translog cost function $\ln C$ to obtain estimates for the allocative efficiency parameters θ with respect to the individual inputs as well as group-wise technical efficiency effects χ . By using the estimates of the former and after adding the usual error components, in a second step the adjusted translog cost frontier is estimated by applying the usual decomposition formula to obtain estimates of producer-specific technical efficiency

(see e.g. BATTESE and COELLI, 1995). As we ‘corrected’ the cost frontier for price distortions 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 . The two-stage model is estimated using a non-linear iterative seemingly unrelated regression (ITSURE) technique with symmetry and homogeneity conditions imposed.

This two-stage model is then estimated again (model 2) by imposing curvature correctness (i.e. functional concavity) on the cost function in [5] by basically following the decomposition shown by [4]. By this we go beyond similar modelling efforts (see ATKINSON and HALVORSEN, 1980; KUMBHAKAR, 1989; KUMBHAKAR and BHATTACHARYYA, 1992; WANG et al., 1996) and also incorporate considerations on the consistency of the estimated frontier with basic microeconomic principles (i.e. cost minimisation). Finally the estimation results of the unconstrained and the constrained models are compared with respect to the relative differences in the individual efficiency scores.

5 Results and Discussion

All estimated cost systems show a relatively good overall fit with respect to the usual statistical criteria. However, in the unconstrained model I only 27 % of all observations adhere to functional concavity contrasting to 80 % in the constrained model II (due to space limitations the estimation results are not shown here but can be obtained from the author). The estimated shadow price parameters show a high significance over the models. Table 2 and 3 summarize the estimation results with respect to systematic input-specific allocative, producer-specific overall technical and producer- and input-specific cost efficiency.

Table 2: Systematic Input-Specific Allocative Efficiency

Efficiency ¹	Model I		Model II	
	Mean	Std. Err. ²	Mean	Std. Err.
AE Labor	0.476	0.007***	0.320	0.010***
AE Fertilizer	0.138	0.006***	0.585	0.009***
AE Land	0.380	0.001***	0.503	0.001***
AE Organic Fertilizer	0.260	0.001***	0.292	0.001***

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

Source: Own Calculations

The systematic allocative efficiencies with respect to the inputs labour, fertilizer, land, and organic fertilizer were found to be moderately higher with respect to the constrained model II.

Table 3: Producer-Specific Technical and Cost Efficiency

Efficiency	Model I				Model II			
	Mean	Std. Err. ¹	Min	Max	Mean	Std. Err.	Min	Max
TE	0.938	0.074***	0.606	0.999	0.869	0.131***	0.488	0.999
CE Labour	0.447	0.035***	0.289	0.476	0.278	0.042***	0.156	0.320
CE Fertilizer	0.129	0.010***	0.084	0.138	0.509	0.077***	0.285	0.585
CE Land	0.357	0.028***	0.230	0.380	0.438	0.066***	0.245	0.503
CE Organic Fertilizer	0.244	0.019***	0.157	0.260	0.254	0.038***	0.142	0.292

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

Source: Own Calculations

However, in the unconstrained model the input labour shows the highest efficiency (about 48 %) whereas the same holds for the use of the input fertilizer in the constrained model

(about 59 %). On the other side the lowest allocative efficiency was found for fertilizer in the unconstrained (about 14 %) and for the input organic fertilizer in the constrained model (about 29 %). What can be generally concluded from these results is that price distortions prevail in the agricultural input markets for labour and inorganic fertilizer.

Hence, the underlying modelling assumption that maize producers optimize their production decisions with respect to unobservable shadow price ratios does hold for the sample. This indicates that 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 values for the shadow prices indicate that ‘prices’ actually paid by the farmers for the inputs used are far less than the observed market prices because of the existence of market distortions. These findings strongly suggest that there is a considerable gap between agricultural input market prices and farm input prices. Different factors could account for such a price gap with respect to labour and fertilizer: 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 leads to a decrease in the average individual shadow price at the farm level for the input labour. As with respect to fertilizer the price increases as a consequence of the availability of commercially produced and marketed high quality fertilizers in the market, the scope and demand for black market fertilizer increases also. Consequently the quantity of available ‘underpriced’ fertilizer increases leading to a lower shadow price for fertilizer with respect to the individual farmer. The estimated shadow parameters for the inputs land and organic fertilizer show that the farms’ resource endowment – i.e. land endowment as well as livestock size – crucially influences its relative allocative performance. In the case of land the evidence of the two models is mixed: for model I it was found evidence that increasing the amount of cultivated land leads to an increase in allocative efficiency, for model II the opposite holds. In the case of organic fertilizer the models show evidence for an efficiency gain as the farmers apply more of it in producing maize.

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 4 contains the frequency distributions for the producer-specific technical efficiencies.

The mean of the estimated technical efficiency is about 94 % (model I) and about 87 % (model II) whereas the least technically efficient farm shows a value of about 61 % (model I) and about 49 % (model II). This implies that at average up to 13 % 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 in the level among the farms in the sample: For both models the majority of farmers show a relative technical efficiency of more than 90 %. 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 3). With the exception of labour the cost efficiency levels are moderately higher for the constrained model (model II) compared to those for the unconstrained model (model I). For model I maize farmers most efficiently used the input labour and on the other side least efficiently the input fertilizer with respect to costs. For model II farmers in the sample most efficiently used fertilizer and least efficiently the input organic fertilizer. These cost efficiency results hence reveal partly mixed evidence for the different model specifications.

With regard to the effects of different production settings, institutional as well as policy related factors both estimation stages by construction delivered evidence, 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).

Table 4: Frequency Distribution – Producer-Specific Technical Efficiency I and II

Efficiency Index	Frequency ¹		Percentage		Cumulative Frequency		Cumulative Percentage	
	I	II	I	II	I	II	I	II
Model								
0.4 – 0.5	-	1	-	1.56		1		1.56
0.5 – 0.6	-	4	-	6.25		5		7.81
0.6 – 0.7	1	4	1.56	6.25	1	9	1.56	14.06
0.7 – 0.8	2	6	3.12	9.37	3	15	4.69	23.44
0.8 – 0.9	9	9	14.06	14.06	12	24	18.75	37.50
0.9 – 1.0	52	40	81.25	62.50	64	64	100	100
Mean	0.938	0.869						
St.Err.	0.074* **	0.131* **						
Min	0.606	0.488						
Max	0.999	1.000						

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

Source: Own Calculations

In the latter case 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’ efficiencies. Table 5 and 6 summarize the different effects found.

Table 5: Group-Wise Technical Efficiency Effects

Factor	Model I		Model II	
	Mean	Std. Err. ¹	Mean	Std. Err.
TE Difference Herbicide	-0.024	0.011**	-0.042	0.016***
TE Difference Insecticide	-0.022	0.014	-0.008	0.020
TE Difference Seed	-0.013	0.009	-0.024	0.013*
TE Difference Subsidies	+0.018	0.007**	-0.036	0.038
TE Difference Extension	+0.025	0.009***	+0.051	0.015***
TE Difference Training	+0.029	0.013**	+0.087	0.019***

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

Source: Own Calculations

The results for the shadow frontier show that the use of herbicides, the use of insecticides, and the application of commercial seeds are negatively correlated with the technical efficiency of the maize producing farms for both models. The use of extension services and agricultural training were found to be positively correlated to technical efficiency for both models, however, mixed evidence was found for receiving subsidies. These correlations are only partly confirmed by the results of the error components estimation: Here both the unconstrained as well constrained model specification agree on a negative effect on efficiency by the use of insecticides, the use of extension services, and receiving subsidies. Mixed evidence was found for the use of herbicides, the application of commercial seeds, and the use of agricultural

training. It can be concluded for this part of the analysis that only with respect to the use of insecticides all model specifications agree on the negative efficiency effect.

Table 6: Producer-Specific Technical Efficiency Effects

Factor	Model I ^{1,2}	Model II
Herbicide	_*	+**
Insecticide	_***	_***
Seed	-	+
Subsidies	-	_***
Extension	_***	_***
Training	_***	+*

1: *,**,*** significance at the 1, 5, and 10 % level, 2: - negative correlation with TE, + positive correlation
Source: Own Calculations

Table 7: Relative Difference in Efficiency Scores Unconstrained vs. Constrained Specification

Measure	Mean (%) ²	Std. Err. ¹	Min	Max
Technical Efficiency	7.36	12.14	-18.06	41.45
Cost Efficiency Labour	30.52	8.15***	13.25	53.00
CE Fertilizer	-131.41	51.49**	-239.19	11.85
CE Land	-94.09	16.06***	-127.71	-49.41
CE Organic Fertilizer	-86.62	13.63***	-115.14	-48.70

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

Source: Own Calculations

The reported efficiency results of the unconstrained as well as constrained model specification point to the relevance of theoretical consistency of the estimated frontier. Table 7 delivers the relative differences in the efficiency scores for the unconstrained and the constrained specification.

The relative difference in the efficiency scores in absolute terms ranges at average from about 7.4 % (producer-specific technical efficiency measure) to about 131.4 % (producer- and input-specific cost efficiency measure for organic fertilizer). Hence, this is empirical evidence for the validity of our concerns about the appropriate functional form and its theoretical consistency (see SAUER, 2006). Finally the results of the applied bootstrapp procedure confirmed the estimates for the theoretically consistent model (model II) on the estimation stage of the error-components specification.

6 Summary and Implications

This study focuses on the relative efficiency of small-scale maize farmers in Romania by using a cost function modelling framework combining the stochastic frontier approach of shadow prices as well as the mainstream error components model. Various market distortions are adressed by adopting the concept of a shadow cost frontier delivering insights in the systematic input specific allocative efficiency. After correcting for shadow prices we subsequently reveal evidence on farm specific technical efficiency and develop an efficiency index for a sample of Romanian maize producers in 2002. Finally different transition policy relevant factors are investigated with respect to their impact on technical efficiency on group as well as individual farm level. 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 system by means of iterated seemingly unrelated regression techniques (ITSURE).

The empirical results show that price distortions prevail in the agricultural input markets in the Romanian economy and that a model incorporating such market distortions seems to be more suitable in an agricultural transition context than one solely based on observable market price ratios. The revealed relative difference in the efficiency scores of up to 240 % 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. The empirical applications hence document the need for a posteriori checking 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).

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