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4.3 Assessing Efficiency of input Utilization in Wheat Production in Uzbekistan

Abstract

Increased technical and scale efficiency in the production of wheat has been of major interest for farmers and administrators alike in Uzbekistan particularly since wheat became a strategic crop to achieve the goal of food self-sufficiency soon after the country's independence in 1991. A pioneer approach was adopted to estimate technical and scale efficiencies among wheat producing farms in the Khorezm and Fergana regions of Uzbekistan. A method was developed that consists of extending a nonparametric, output-based Data Envelopment Analysis (DEA) in two stages to allow the use of double bootstrapping techniques to produce bias-corrected estimates. The findings show that while most farmers have achieved scale efficiency under the current state of agricultural technology, there is room for increasing wheat production via enhanced technical efficiency. Interestingly, findings also show that the higher efficiency estimated for arable land with lower bonitet (soil fertility) scores indicates that farmers with better land quality use their resources less efficiently. It is argued that this in turn implies that under non-competitive market conditions, farmers have little incentives to use resources more efficiently.

Keywords: wheat production, technical efficiency, data envelopment analysis, Central Asia

4.3.1 Background

The efficient use of resources plays a fundamental role in maximizing grain productivity. In an era marked by major vulnerabilities associated with food insecurity, the efficient use of resources becomes critical for present and future agricultural policy. The resource-use efficiency of wheat production was examined in the context of Uzbekistan, where grain crops became central after the country gained sovereignty from the Soviet Union in 1991. Crucial changes in cropping patterns began with the Decree of the Cabinet of Ministries (*CMD*) No. 400 "*On measures of increasing grain production in irrigated lands starting from 1995"*. It promoted significant increases in wheat production for achieving self-sufficiency in grain consumption (Kienzler et al. 2011). The allocation of arable land for wheat production was achieved largely at the expense of reducing land designated to other crops, including cotton[1], the main agricultural export commodity in the country. Irrigated land for wheat increased consequently from 626,900 hectares (ha) in 1992 to approximately 1.4 million ha in 2010, pushing the overall wheat production from 964,000 tons in 1992 to 6.7 million tons in 2010 (FAO, 2011).

Following independence, irrigated winter wheat became part of the state quota system next to cotton (Rudenko et al. 2012). The state quota system for wheat requires individual farms[2] to sell half of the produced wheat to the state at fixed prices in exchange for loans with below-market rates of interest, and subsidized agricultural inputs (Abdullaev et al. 2009). The remaining wheat is either home-consumed, traded at local markets, or in some cases, sold to the state at negotiated prices (Rudenko et al. 2012). Individual farms are presently the main wheat producers, producing nearly 82 % of *total wheat* in 2007 (State Statistical Committee of Uzbekistan, 2008).

Despite recent improvements in productivity, wheat yields have remained low in Uzbekistan *vis-à-vis* other countries with similar climatic conditions (ADB 2009). Studies conducted in developing countries by, *inter alia*, Hopper (1965), Getu et al. (1998), and Coelli et al. (2002), suggest that grain yields can be increased by a more efficient use of production factors. These studies explored whether or not there is a need for the adoption of new technologies, or if it is still possible to achieve higher yields with the current technologies. This is a major challenge to Uzbekistan given its only recent involvement in domestic, irrigated wheat production. Therefore, technical and scale efficiencies[3] of wheat production based on farm-level surveys conducted in two regions of Uzbekistan were analyzed. Technical and scale-efficiency estimations were obtained from a

1 About 30 – 35 % of the cotton areas were freed to grow irrigated wheat (Aminova and Abdullaev, 2012).

2 These refer to the "private" farmers who work on land leased from the state (Rudenko et al. 2012).

3 We use the term technical efficiency (*TE*) to measure farm capacity to utilize resources, including production technologies, in the most efficient way.

two-step output-oriented Data Envelopment Analysis (DEA) model[4] (Charnes et al. 1978, 1979, 1981), which allows estimating to what extent production can be increased given the level of utilized resources. In addition, the traditional *DEA* model has been extended by an application of the double bootstrapping method to improve the estimates (Simar and Wilson 2007).

4.3.2 Methodological Approach

The adopted *DEA* model has its theoretical foundations in the work of Farrell (1957), and relies on linear programming techniques initially developed by Charnes et al. *(1978). The method has been extensively used in efficiency studies, including those by Wadud and White (2000), Coelli et al. (2002), and Latruffe et al. (2005).* The use of the *DEA* method is justified for various reasons. First, the model enables division of the overall technical efficiency[5] into pure technical efficiency (TE) and scale efficiency (SE). This clarifies whether or not resource-use inefficiencies arise from diseconomies of scale due to SE or from factors associated with deficient farming techniques due to a low TE. Second, with the model there is no need for the specification of a functional form. Third, variables in the model (inputs and outputs) can be measured in different units and dimensions (e. g., continuous or categorical variables).

In a two-stage *DEA* model, the sampling variations, measurement errors and sample size can increase the bias in the efficiency estimators. Simar and Wilson (2007) proposed therefore a double bootstrapping technique to improve the consistency and reliability of the *DEA* estimators.[6] An advantage of this improvement is that it allows the use of bootstrapping measures of *TE* in the first stage, and via non-parametric statistics, to generate standard errors and confidence intervals for exogenous variables in the second step (Charnes 1978). Both single and double bootstrapping techniques were therefore used. The results were compared with those of the traditional *DEA* model, which relies on a *Tobit* regression in the second stage.[7] Single and double bootstrapping techni-

4 With this output-oriented approach, it can be estimated how much production is increased for a given level of utilized input resources.

5 The term overall technical efficiency is used for those farms that operate under constant returns to scale (*CRS*), while pure technical efficiency (TE) is utilized for the farms that operate under variable returns to scale (*VRS*). The difference between *CRS* and *VRS* technologies is that *CRS* also takes into account scale effects, and scale efficiency (*SE*) can thus indicate farm size optimality. Moreover, we can also determine farms operating under different returns to scale (constant, increasing and decreasing).

6 Bootstrapping allows estimating properties of an estimator by assigning measures of accuracy to sample estimates.

7 In the second stage of *DEA*, where we included explanatory factors which impact on *TE*, a

ques are similar in algorithms, except that in the case of double bootstrapping, efficiency scores obtained from the second stage are also bootstrapped.

4.3.2.1 Estimation of Technical Efficiency via a Double Bootstrapping Procedure

Initially, the standard *DEA* model is used to estimate *TE* scores for each individual farm (i) under variable returns to scale (*TEvrs*) as follows:

$$\hat{\tau}_i = max\left\{\tau > 0|\tau y_i \leq \sum_{i=1}^{n}\lambda_i Y; x_i \geq \sum_{i=1}^{n}\lambda_i X; \sum_{i=1}^{n}\lambda_i = 1; \lambda_i \geq 0, i = 1, \ldots n\right\} \tag{1}$$

where, $\hat{\tau}_i$ is the *TEvrs* score for each (i); y_i and x_i as well as Y and X denote the input and output matrices of individual farms i's and their corresponding sample mean, respectively. The symbol λ captures a non-negative intensity variable that reflects returns to scale.

Secondly, the *TEvrs* scores estimated in the first stage are used as a dependent variable in a truncated maximum likelihood regression that takes the form:

$$\tau_i = \varepsilon_i \geq 1 - z_i\beta \tag{2}$$

where z_i is a vector of exogenous variables, $\beta$is a vector of parameters to be estimated, and ε_i, a continuous independent and identically distributed random variable.

Thirdly, several steps are needed for each individual farm (*i=1,…, n*) $S_n$times to obtain the

$$\left\{\hat{t}^*_{i,s} = 1, \ \ldots \ S_n\right\}\text{bootstrap estimates:}$$

a. For each individual farm, *i=1,…, n*, ε_i is obtained from the normal distribution function, and $\tau_i^* = \beta z_i + \varepsilon_i$ is computed.
b. A new pseudo data set (x_i^*, y_i^*), where $x_i^* = x_i$ and $y_i^* = y_i\,\hat{\tau}_i \,/\, \hat{\tau}_i^*$, is constructed and used to compute the *TEvrs* scores.

censored (Tobit) regression is usually employed. With single and double bootstrapping methods, truncated regression is used as recommended by Simar and Wilson (2007).

Fourthly, (bias corrected) for each individual farm is calculated as follows:

$$\hat{\tau}_i = \hat{\tau}_i - \widehat{bias}_i \qquad (3)$$

$$\text{where } \widehat{bias}_i = \left(\frac{1}{S_n \sum_{s=1}^{S_n} \hat{\tau}^*_{i,s}}\right) - \hat{\delta}_i \qquad (4)$$

Fifthly, bias-corrected *TEvrs* scores are used as a dependent variable to estimate a truncated regression function employing a maximum likelihood framework. Then steps (a) and (b) below are repeated *S2* times to obtain $\{(\beta^*_s, \sigma^*_s)s = 1, \ldots, S_2\}$:

a. For each individual farm, $\varepsilon_i$is obtained from $N\ (0,\ \sigma^2_\varepsilon)$ and $\tau^{**}_i = \beta z_i + \varepsilon_i$ is computed, and then
b. A second bootstrapping is employed on the truncated regression.

Lastly, bootstrap-based 95 % confidence intervals are computed for each parameter estimate. The $(1 - \alpha)\%$ confidence interval of the *j-th* element of vector β is constructed as

$$\Pr\left(-b_{\frac{\alpha}{2}} \leq \widehat{\hat{\beta}}^*_j - \widehat{\hat{\beta}}_j \leq -\alpha_{\frac{\alpha}{2}}\right) \approx 1 - \alpha \qquad (5)$$

such that the estimated confidence interval is $Higher_{\alpha,j} = \widehat{\hat{\beta}}_j + \hat{b}_\alpha$ and $Lower_{\alpha,j} = \widehat{\hat{\beta}}_j + \hat{\alpha}_\alpha$.

4.3.2.2 Scale Efficiency Estimation

To estimate *SE* for each individual farm (*i*), the following expression is computed:

$$SE = TEcrs\ /\ TEvrs \qquad (6)$$

TEvrs is obtained from Eq. 1, whereas *TEcrs* (*TE* under constant returns to scale) is also calculated from the Eq.1 but without the convexity constraint ($\sum_{i=1}^{n} \lambda_i = 1$). Note that scale-inefficient farms may be operating under constant (*CRS*), increasing (*IRS*) or decreasing (DRS) returns to scale. Estimates of technical efficiency under non-increasing returns to scale (or *TEnirs*) need to be obtained by changing the convexity constraint to. If ($\sum_{i=1}^{n} \lambda_i \leq 1$) two scores are different from each other, and *SE* is less than one, then the farm is operating under *IRS.* In contrast, if the scores are equal and *SE* is lesser than one, the farm displays the *DRS* in its operation.

4.3.3 Data

This study was conducted in the Khorezm and Fergana regions of Uzbekistan with individual farms that grow wheat on land leased from the state (see Figure 4.3.1). The Khorezm region is located in the northern climatic zone according to the classification by FAO (2003) for agro-ecological zones. It is situated in the north-western part of the country, bordering the Karakalpakstan region and Turkmenistan. The main water source for irrigation is the Amudarya river. Soils belonging to this zone are hard and loamy, and have been partly influenced by human interventions since the introduction of a large-scale irrigated agriculture (Akramkhanov et al. 2012). The Fergana region is situated in the eastern part of Uzbekistan and, based on the FAO (2003) classification, in the central climatic zone. Fergana's main water providing river is the Syrdarya, which is formed from the joining of the Naryn and Kara-Darya rivers. The region comprises gley and meadow soils characterized by initial low salinity levels. It has better hydro-physical infrastructures in comparison to Khorezm.

Figure 4.3.1: Map of Uzbekistan in Central Asia indicating (squares) the two study regions Khorezm and Fergana. *Source: GIS laboratory of the ZEF/UNESCO Khorezm Project*

A farm-level survey was conducted among randomly selected individual farms, recollecting information about use of resource endowments in wheat production for the 2007 agricultural season. The input-output dataset was constructed such as to capture information on agricultural production activities from a sample of 180 farms representative of 8 districts in Khorezm and 164 farms from 9 districts in Fergana. The survey also collected qualitative information on farm activities as well as on socio-economic, demographic and location-specific characteristics to account for possible sources of efficiency differentials.[8] A statistical summary of input and output variables used in the *DEA* model is given in Table 4.3.1.

Table 4.3.1: Descriptive statistics of variables used in the analysis

Variable	Unit	Khorezm Region N=180		Fergana Region N=164	
		Mean	Standard Deviation	Mean	Standard Deviation
Output variable					
Yield	tons h^{-1}	4.2	1.04	4.8	1.01
Input variables					
Land	ha	11.7	12.1	11.7	12.0
Labor	man-days ha^{-1}	184	55	172	57
Seeds	kg ha^{-1}	224	19	222	19
Nitrogen fertilizer	kg ha^{-1}	175	30	170	32
Diesel fuel	kg ha^{-1}	172	34	170	31
Other expenses	1,000 UZS ha^{-1}	101.7	12.7	101.6	13.0
Farm Characteristics					
Bonitet score*	Index (1 – 100)	58	10	56	13
Farm size	ha	23	13	32	20
Water availability	Dummy (Enough Water = 1; Not Enough = 0)	0.54	0.50	0.54	0.50
Diversification index	Index	0.34	0.44	0.42	0.46
Dependency ratio	Ratio	1.13	0.84	1.26	1.42
Potential to work in larger land area	Dummy (Yes = 1; No = 0)	0.48	0.50	0.40	0.49
Obsolete canal	Dummy (Yes = 1; No = 0)	0.57	0.50	0.51	0.50
Distance to market	Km	9.7	2.5	9.5	2.2

*A *bonitet* score is on a scale 1 – 100 and is calculated based on several indicators for soil quality. Land with a higher *bonitet* score is considered more fertile and hence attractive.

In the first stage analysis of *DEA*, we included one output and six production factors. Output consisted of quantities of wheat both sold and kept for self-consumption. Inputs used in the analysis were land, labor, seeds, nitrogen fertilizer, diesel and 'other expenses'. Land input was defined as the total cultivated land utilized for growing wheat measured in hectares (ha). The labor input variable was specified in man-days where labor was divided into thirteen

8 For a more detailed discussion on the sampling frame see Karimov (2012)

agronomic activities (e.g., land preparation, planting, fertilizer application, and weeding etc.). One man-day consisted of eight hours. Since information was based on recollection of farmers, it was not always possible to distinguish the labor used in wheat production by sex and age. The seeds variable was measured in kilograms (kg), and consisted of seeds purchased at the market or produced by the farmer. Nitrogen fertilizer is the most important nutrient necessary for wheat growth (Kienzler et al. 2011). This variable was calculated by estimating the share of nitrogen (in kg) in each fertilizer. Diesel fuel was included as a proxy for machinery services and was measured in kg. "Other expenses" is an aggregated variable that consists of the sum of expenses farmers paid to the Water User Associations (WUAs)[9] for the membership fee, for obtaining chemicals (other than chemical fertilizers), organic manure and machinery services, which all were measured in monetary values.

The second-stage analysis of the *DEA* model included eight independent variables and one dependent variable (*TE*), which was obtained from the first stage analysis. The first variable is a *bonitet* score, which captures land productivity. The second variable, farm size (in ha), is the whole-farm operating area. The third variable, water availability, is expressed as a dummy indicator. Since water usage was not directly observed, it was not possible to provide information on the intensity of water utilization during the survey. Instead, a water-related dummy variable was included under the assumption that farmers who reported adequate water sources were more efficient in the use of other inputs. The fourth variable is the Shannon diversity index (SHDI) that captures farmers' crop diversification (Eilu, et al. 2003, Shaxson and Tauer, 1992). It was calculated as:

$$SHDI = -\sum_{i=1}^{J}(P_i * lnP_i) \qquad (7)$$

where J stands for the number of grown crops, and the term P_i is the proportion of the area used for a particular crop. When there is only one crop, the index in Equation 7 equals zero and increases with the number of cultivated crops. The fifth variable is the dependency ratio, which is calculated as the ratio of family dependents aged 15 and younger and 60 and older to the number of adults of working age. The sixth indicator is a dummy variable that captures information on whether or not a farmer is interested in working on a larger cropping area. The seventh variable is a dummy, which is used as a proxy for the condition of the irrigation canals. Those farmers who reported a poor canal system were

9 Renamed to Water Consumers Associations in 2009

recorded as 1. Finally, the eighth variable indicates the mean distance between the farm and the nearest local market.

The output-oriented *DEA* model produces *TE* values starting from score 1, in other words they are bounded to 1 from below. However, for convenience, the inverse of the initial and bias-corrected average values of *TE* are calculated. As a result, *TE* values were between 0 and 1. With the model it was possible to estimate efficiency scores under different categories, although it should be noted that for each classification under each category, a frontier needed to be constructed separately. In this way, additional information for assessing policy implications was obtained. The *DEA* model is categorized by location (pooled sample, and regions), by cropped area, and by bonitet scores under two types of technologies: (1) assuming constant returns to scale (*CRS)* and (2) variable returns to scale (*VRS*). Efficiency results obtained from the model were estimated using the *FEAR* package developed by Wilson (2008) for the R, and Stata 12 statistical software.

4.3.4 Results and Discussion

Findings from the pooled results show that estimated values for the *TE* coefficient under *CRS* are 0.72, and 0.75 under *VRS* (Table 4.3.2). Since the highest efficiency in the use of resources is achieved at the score of 1.0, model results indicate room for technical efficiency gains with the current production technologies. A similar conclusion can be drawn when the *DEA* model is constructed for each region, but with varying efficiency scores. Individual farms in the Fergana region had a higher *TE* under *CRS* and *VRS* technologies in comparison to those in the Khorezm region. This suggests a regional divide in terms of efficient use of resources. Given minor differences between *CRS* and *VRS* technologies, we postulate that most of the productivity gaps monitored arose not from scale differences between farms but rather from farm-level factors (e. g., mismanagement, delay in agronomic activities, farm characteristics) and exogenous determinants such as location, and institutional and socio-economic attributes that are associated with farm activities.

TE scores were also highest for farms that had the largest wheat fields (e. g., group of farms with wheat areas of 30.1 ha and above); however, when the sample was grouped by *bonitet* levels, differences between the three farm size groups were not significant. It should be noted that the highest efficiency score was achieved in lands with *bonitet* scores below 50. This is an interesting finding, as it suggests that farms that operate in low-fertility lands were relatively more efficient in terms of resource endowment.

To verify the initial results from the *DEA* model, the single bootstrapping method was employed to obtain bias-corrected *TEvrs* estimates (column 4 of Table 4.3.2), illustrating that the uncorrected initial results were considerably biased. For instance, the initial for the Khorezm sample suggests farms could increase their production by 28.2 % (((1/0.78)-1)*100) if full efficiency were to be achieved, whereas the bias-corrected *TEvrs* estimates suggested a production increase in the order of even 41 %(((1/0.71 – 1)*100). Furthermore, in the case of Khorezm, the lower and upper bounds of the 95 % confidence interval for the bias-corrected *TE* obtained from the single bootstrapping suggests that an 'average' farm could increase its production by 30 % (((1/0.77 – 1)*100) to 47 % (((1/0.68 – 1)*100) by improving the use of existing resources.

Table 4.3.2: Estimates of Technical Efficiency

	Initial TE_{CRS}	Initial TE_{VRS}	% of farms with TE_{VRS}=1	Bias – Corrected TE_{VRS} Single	Lower -Bound 95 % CI Single	Higher -Bound 95 % CI Single
			Categorized by Location			
Pooled sample	0.72	0.75	0.12	0.69	0.66	0.74
Khorezm region (north-western)	0.75	0.78	0.12	0.71	0.68	0.77
Fergana region (eastern)	0.78	0.82	0.24	0.74	0.71	0.81
			Categorized by Wheat Area			
up to 10.0 ha	0.73	0.76	0.15	0.68	0.66	0.75
10.1 – 30.0 ha	0.75	0.81	0.25	0.72	0.68	0.81
30.1 ha and above	0.83	0.94	0.41	0.88	0.81	0.93
			Categorized by Bonitet Score			
Up to 50.0 ha	0.76	0.81	0.26	0.71	0.67	0.80
50.1 – 60.0 ha	0.74	0.77	0.15	0.69	0.67	0.76
60.1 ha and above	0.75	0.77	0.20	0.70	0.67	0.78

Note: In the first and second column, TE under CRS and VRS technologies, respectively, are presented. Even though the analysis concentrates on the VRS technology, calculation of CRS helps to visualize scale efficiency immediately when efficiency scores from two technologies are compared. The third column lists the percent of those farms that constitute frontier under VRS. The bias-corrected efficiency scores in the fourth column are calculated based on the method suggested by Simar and Wilson (1998). Confidence intervals in columns 5 and 6 are related not for the initial efficiency scores but for those, which are bias-corrected. In all cases, biased-corrected efficiency scores are less than the original ones. This shows that initial average TE coefficients are overestimated, e.g., upwardly biased.

The width of the 95 % confidence intervals obtained by the single bootstrap approach for *TE* estimates is 0.09, which reflects a relatively higher statistical variability for the *TE* efficiency scores. Similar results can be found in other socio-economic environments (e.g., Brümmer 2001; Latruffe et al. 2005; Olson and Vu 2009). When farms were ranked by the bias-corrected *TEvrs*, from the lowest to highest scores, the quantitative differences were much more obvious. Figure 4.3.2 shows that the initial *TEvrs* does not provide such a smooth line as the bias-corrected *TEvrs*. A visible variability is also noticeable in the lower and upper bounds of the bias corrected *TEvrs*, even with similar efficiency scores.

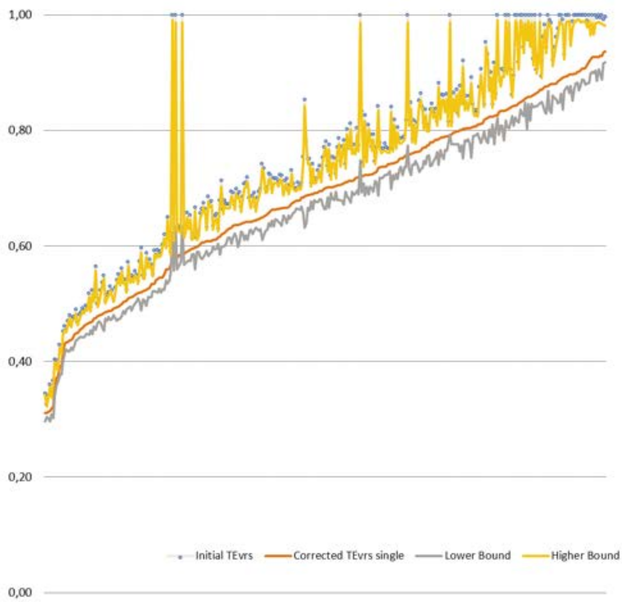

Figure 4.3.2: Distribution of TE with confidence intervals (single bootstrap)

As mentioned earlier, an increase in output appears to be possible by a more efficient use of resources. This can be further analyzed by calculating slack values[10] for all farms monitored (Table 4.3.3). Based on the slack values, the necessary input adjustment values to achieve 100 % efficiency can be estimated. The findings indicate that an average increase in production of 28 % (((1/0.78)-1)*100) in the Khorezm sample would be achieved if the technically inefficient farms optimally adjusted their input use by around 12, 15, 13, 10, 19 and 14 % of land, seeds, fertilizer N, diesel, labor and other expenses, respectively (Table 4.3.3). There would be an average increase in production of 22 % (((1/0.82)-1)*100) in the Fergana sample if the technically inefficient farms optimally

10 Zhu's *DEA* Excel Solver algorithm is used for the computation of 'slacks'. A 'slack' provides information on the inputs that are in excess supply and those that are effectively constraining production. Fully efficient farms would have no slacks.

adjusted their input use by 9, 11, 10, 16, 21 and 14 % of land, seeds, fertilizer N, diesel, labor and other expenses, respectively (Table 4.3.3).

On average, labor was the most inefficiently used input in both regions. For example, in Khorezm, 43 % of the farms on average could reduce ca. 19 % of their labor to achieve full efficiency. The least inefficiently used input was diesel (10.1 %) in the case of Khorezm, while it was land (8.5 %) in the Fergana sample (Table 4.3.3). This example indicates that 38 % of the farms in Khorezm would achieve full efficiency when reducing only 10 % of the diesel use.

Table 4.3.3: Potential percent of input adjustments needed to reach 100 % technical efficiency in two study regions

Study region	Input	Farms with slacks		Percent of input adjustments to give 100 % efficiency			
		N	% of total	Mean	Standard deviation	Minimum	Maximum
Khorezm (N=180)	Land	136	76	12.2	9.7	0.01	44.3
	Seeds	126	70	15.0	10.9	0.2	45.9
	Fertilizer N	91	51	13.4	11.0	0.5	52.0
	Diesel	69	38	10.1	7.8	0.2	34.6
	Labor	77	43	18.9	11.7	0.7	55.9
	Other expenses	80	44	13.7	10.6	0.1	38.6
Fergana (N=164)	Land	96	59	8.5	6.2	0.2	25.7
	Seeds	84	51	10.8	7.3	0.1	28.5
	Fertilizer N	76	46	10.3	8.8	0.2	44.1
	Diesel	70	43	15.8	10.5	0.01	48.2
	Labor	56	34	20.8	12.9	0.9	46.6
	Other expenses	70	43	13.8	9.1	0.1	36.2

Efficient farms attained higher crop yields in all cases. For example, while inefficient farms achieved wheat yields of 4.0 tons ha^{-1} and 4.5 tons ha^{-1} in the Khorezm and Fergana samples, respectively (Figure 4.3.3), efficient farms achieved 5.3 tons ha^{-1} and 5.7 tons ha^{-1}, respectively. Figure 4.3.3 depicts *TE* scores for six farm size intervals. The technically most efficient farms were those with the largest farm size in both regions. The technically least efficient farms in Khorezm were those in the second interval (farm sizes 5.1 – 10.0 ha). In the Fergana region, these farms were in the third group (farm sizes 10.1 – 15.0 ha).

4.3.4.1. Scale Efficiency

The results from the scale efficiency assessment (Table 4.3.4) show the percentage of farms with increasing (*IRS*), decreasing (*DRS*), and constant (*CRS*)

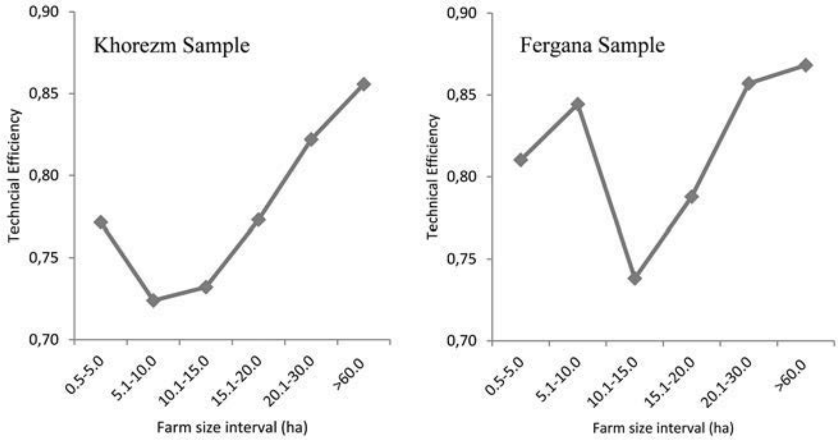

Figure 4.3.3: Technical efficiency in Khorezm and Fergana regions according to farm size

returns to scale. High scale efficiency *(SE)* was noted in both regions, thus leaving only little room for scale improvements. For example, in the case of Khorezm, *SE* was equal to 0.97, leaving room for only 3 % scale improvements in the production process. Moreover, the findings show that wheat producers operate mostly under *IRS*, thus indicating an underutilization of input resources. In contrast, farms that exhibited *DRS* would need to decrease the use of input resources to increase efficiency. In general, findings show no particular indication that wheat producing farms are too large or too small in their scale of operations. From the results, it can be confirmed that overall inefficiency mostly comes from the inefficient use of resources and not from ill-scaled production.

Table 4.3.4: Indicators of Scale Efficiencies

	Khorezm region (north-western)	Fergana region (eastern)
SE	0.97	0.95
SE=1	29.4	34.1
DRS	32.8	37.2
IRS	37.8	28.7

Farms were ranked by the bias-corrected efficiency levels using the double bootstrapping procedure (Figure 4.3.4). The double bootstrapped bias-corrected *TEvrs* ranged from 0.31 to 0.95, with average scores of 0.69. The scores for Khorezm and Fergana were 0.65 and 0.74, respectively. This suggests that wheat producers in both regions could significantly increase yield productivity even with the presently existing technologies.

Scale-inefficient farms are thus functioning at decreasing returns to scale, which reflects an overuse of input resources. This means that the initiated land consolidation process (cf. Djanibekov et al. 2014) should be carried out parallel to training programs for farmers while providing these with agricultural extension services to help them manage larger crop areas (Bekchanov 2009; Niyazmetov 2012).

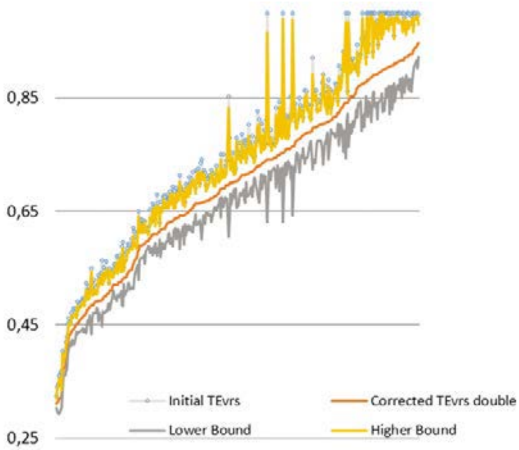

Figure 4.3.4: Distribution of TE with confidence intervals (double bootstrapping)

4.3.4.2 Factors explaining differences in technical efficiencies

The results from the second-stage analysis[11] show that comparisons of the *Tobit* and the truncated regression results are consistent with each other. The signs and statistical significance levels of the coefficients are similar with the exemption of *bonitet* scores, which turn out to be significant in the truncated regression. Our results support the recent findings by Latruffe et al. (2008) and Larsen (2010), who conclude that the *Tobit* and double bootstrap methods do not substantially differ with respect to sign and statistical significance.

11 The *Tobit* regression uses *TE* scores, while the truncated regression under the single and double bootstrap method utilizes technical inefficiency as a response variable. Because of this, their signs are opposite to each other, although they provide the same information. Table 4.3.5 also includes standard errors and confidence intervals that make non-parametric models as valuable as econometric models.

Table 4.3.5: Results from the truncated maximum likelihood regression in single and double bootstrap methods for the case of wheat production

Variable	Tobit regression		Bootstrap procedure I				Bootstrap procedure II
	Parameter estimate (S.E.) (95 % C.I.)		Parameter estimate (S.E.) (95 % C.I.)		Parameter estimate (S.E.) (95 % C.I.)		
Constant	0.672	***		0.881	**		1.072 ***
	0.054		0.380		0.338		
	0.566	0.776	0.021	1.468	0.525	5.279	
Region	-0.088	***	0.464	***	0.523	***	
	0.015		0.124		0.113		
	-0.117	-0.058	0.224	0.691	-1.629	0.777	
Bonitet score	-0.001		0.009	*	0.008	*	
	0.001		0.005		0.004		
	-0.002	0.0003	0.0002	0.018	-0.014	0.019	
Farm size	0.0005		-0.002		-0.002		
	0.0004		0.003		0.003		
	-0.003	0.001	-0.007	0.005	-0.009	0.011	
Water availability	0.044	***	-0.404	***	-0.358	***	
	0.015		0.112		0.099		
	0.014	0.073	-0.642	-0.186	-0.579	0.920	
Diversification index	0.012		-0.070		-0.086		
	0.017		0.116		0.105		
	-0.021	0.045	-0.298	0.140	-0.328	0.774	
Dependency ratio	-0.013	*	0.069	*	0.070	**	
	0.007		0.041		0.038		
	-0.027	0.001	0.022	0.191	-0.167	0.168	
Potential to work in larger land area	0.063	***	-0.295	***	-0.340	***	
	0.014		0.110		0.100		
	0.035	0.089	-0.254	0.122	-0.555	0.679	
Obsolete canal	-0.043	***	0.290	***	0.265	*	
	0.014		0.108		0.096		
	-0.071	-0.015	0.116	0.507	-0.721	0.498	
Distance to market	0.009	***	-0.046	**	-0.050	***	
	0.003		0.023		0.021		
	0.003	0.016	-0.104	0.004	-0.084	0.080	

Note 1: ***, **, * indicate significance at 1, 5 and 10 % respectively.
Note 2: Negative sign in bootstrap procedures must be read as factors positively influencing efficiency levels

Most of the variables used in the second stage regression are significant (Table 4.3.5), proving the following remarkable findings.

First, region had a positive influence on technical inefficiency (Table 4.3.5). Farmers located in Fergana were more efficient in the use of existing resources compared to those in the Khorezm region. This difference was statistically significant. Since lands in Fergana are more fertile than lands in Khorezm, this might be an influencing factor affecting efficiency scores. Differences in efficiency may also reflect the fact that input markets seem to be more developed in Fergana, perhaps because this region is more closely located to the capital city of Tashkent with the highest population in the country. This plays an important role in the delivery of farm resources, which in return affects efficient use of inputs and consequently crop productivity. Furthermore, virtually all cropland in the Khorezm region suffers from salinity (Tischbein et al. 2012), which negatively impacts crop yields. Indeed, Conliffe (this book) argues that in the Khorezm region, the spatial location is an important and often overlooked determinant influencing livelihood opportunities.

Empirical results also reveal a significant effect of *bonitet* score on *TE* (Table 4.3.5); however, the sign of the *technical inefficiency* is positive, which signals a higher inefficiency in more fertile lands. It should be noted here that under the state quota system, farmers receive soft credit and subsidized inputs for wheat production in exchange for supplying a minimum volume (or quota) of grains (Rudenko et al. 2012). Farmers with good-quality land might not be forced to use subsidized inputs very efficiently to achieve reasonably good wheat yields. Interestingly, while the crop diversification index is statistically insignificant, it is negatively correlated with technical inefficiency. This seems to reflect that farmers with lower land quality diversify crop production and use resources more efficiently. These farmers pay careful attention to the way agricultural inputs are used in order to meet the imposed quota and to avoid sanctions by the government.[12]

The correlation matrix between the *bonitet* scores and the diversification index is negative, which supports the argument that farmers operating in less fertile lands are more involved in crop diversification strategies than those that have fertile lands. Higher technical inefficiency in the more fertile lands can be explained through ratchet effects as introduced by Berliner (1952). Although there are incentives for farmers who manage to ratchet up the volume of wheat production beyond the established quota (e. g., remunerations, social bonuses, and the outstanding farmer award), they tend to avoid over-fulfilling the quotas, simply due to the fact that if they over-fulfill expectations, they are likely to have to increase the volume of production even more in subsequent crop seasons. Moreover, since farmers do not have property rights, and rewards are too small in comparison to the very high costs of future increased production plans, farmers operating in higher *bonitet* lands will aim to produce around the corresponding quota. Our explanation is in line with the evidence reported in Chertovitsky et al. (2007). In their study, the authors find that 80 % of the farmers operating in the Syrdarya region produced a volume of cotton close to

12 For a discussion on this particular issue, cf. Djanibekov et al. 2014

the state quota. They argued that the farmers were unwilling to increase the production of cotton above the quota threshold to avoid the expectation of having to meet even higher quotas in the future.

The effect of farm size is found to be negatively correlated with *TE* in the case of wheat production, which indicates that farmers with larger plots are more efficient in the use of resources than those farmers with smaller plots (Table 4.3.5). Not surprisingly, farmers who report a negative relationship with technical inefficiency also show a negatively significant result when the willingness to work in larger farmland areas is measured. Results suggest that these farmers are interested in working on larger farms to develop the necessary skills to improve production, which may open options for institutionalized farm-to-farm collaboration (cf. Djanibekov et al. 2014). They also seem to have sufficient financial resources and technologies at hand, although this recurrently has been denied (e.g., Djanibekov et al. 2012), which help them to use resources efficiently in larger plots.

Another variable is 'Obsolete Canal', which is significant and indicates that those farmers who reported that their water-canal systems were obsolete attained lower efficiency scores than those who reported access to good systems (Table 4.3.5). This spatial differentiation has been postulated before (e.g., Bekchanov et al. 2012, Conrad et al. 2007) and reflects the importance of irrigation infrastructure in influencing the better use of input resources. In general, the Water User Associations (WUAs) are responsible for maintaining the canal systems. However, due to financial constraints, the farmers use their own financial sources to clean and maintain adjacent canal systems.[13] It is therefore worth pointing out that there is a need for further investments in the maintenance and repair of canals and drainage systems to sustain crop productivity in the future.

In the case of the Shannon diversification index, which captures farm crop portfolio, the results show a negative correlation of the index with *technical inefficiency*, although the strength of the association was statistically insignificant (Table 4.3.5). Farmers who reported a higher crop diversification index were more efficient in the use of resource endowments. As mentioned earlier, additional cash from other crops could be spent on the production of strategic crops to meet the state quota. Crop diversification seems thus to reduce the risk of not meeting the planned target for wheat production.

Farmers with higher dependency ratios exhibited a more inefficient use of resources in wheat production, suggesting that family composition plays a critical role in time allocation (Table 4.3.5). In particular, farmers with young families seem to generate earnings from non-farming activities to meet house-

13 For a discussion, see cf. Saravanan et al. 2014.

hold needs, which is confirmed by Conliffe (cf. Conliffe 2014). The fact that under the quota system wheat is sold by farmers at prices below the market rate (Rudenko et al. 2012) also reduces the incentives for farmers to allocate resources evenly.

The findings also show that water accessibility is a highly significant factor in determining crop productivity as was concluded by Tischbein et al. (2012). Farmers who reported that they had sufficient access to water for crop production were more efficient in the use of resources. This is not surprising, as water plays a crucial role in decision making at all levels of agricultural production (Bekchanov et al. 2012). Prompt delivery of water must therefore be appropriately executed by the WUAs and monitored at regional levels. Since there is a private interest in the use of water, charges based on the excessive use of irrigation water could be introduced, although the effect is often disputed (Djanibekov et al. 2012). Appropriate attention is thus required to improve water use efficiency at canal and field levels, which is currently seen as a crucial step (Tischbein et al. 2012). Concessional lending schemes available to farmers could be extended to cover WUA fees and other expenses necessary for maintaining and repairing canals and drainage systems. All these aspects positively influence technical efficiency in crop production, which in return increases crop productivity at provincial and national levels.

Finally, the exogenous variable that captures the distance to key commodity markets indicates that as the market distance decreases, farmers display a more inefficient use of resources in the production of wheat (Table 4.3.5). Inefficiency came from at least two sources. First, farmers located in close proximity to local markets experience greater incentives to diversify their crop portfolio to meet the demand for agricultural goods that are not constrained by price ceilings. Second, closer locations to markets create job opportunities, which divert time for wheat production to other activities. The correlation matrix between dependency ratio and market distance is positive, which suggests that farms with high dependency ratios are also involved in off-farm activities.

4.3.5 Concluding Remarks

By extending the traditional *DEA* method, this study is a pioneer in the use of the double bootstrapping method in the field of agricultural economics and, in particular, in the context of the Central Asian region. It reveals that *TEvrs* estimates obtained from bootstrapping are lower than those in the traditional *DEA* method of estimating *TEvrs*, which reflects the bias of the *DEA* method. The extended methodology also shows that the use of *DEA* (with bootstrapping) as a benchmark to set up frontier farmers for a given sample is a useful approach to improve resource-use efficiency and increase competitiveness in crop production.

The results demonstrate that the level of *TE* among farmers differs across crop growing areas, location and *bonitet* scores, and that consequently crop producers could increase their technical efficiency considerably. Hence, there is room for potential increases in *TEvrs* even with the current state of technology in the production of wheat, although in terms of scale of operations, most of the farmers have achieved scale efficiency. Higher efficiency in arable land with lower *bonitet* scores implies that farmers with better land use resources *less* efficiently. Crop diversification seems to improve farm *TEvrs*, although this finding requires further research. Regional differences also show a geographical divide in terms of resource-use efficiency, with farmers in Khorezm being less efficient in wheat production, which could also call for an improvement via farmer-to-farmer exchange of experience. Access to adequate amounts of irrigated water is critical, as it substantially increases *TEvrs* in the production of wheat. To the extent that market-based reforms could take place, inefficient farmers could learn from best-farming practices and adopt explicit agronomic and innovative approaches.

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