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Research Paper

A comparison of different full and partial non-parametric frontier models for measuring technical efficiency: With an application to Iran's cotton producing provinces

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Abstract. This study analyses the technical efficiency of Iran's 13 major cotton producing provinces over the period 2000-12. It uses two non-parametric full frontier models (Data Envelopment Analysis and Free Disposal Hull) and two partial frontier models (Order-α and Order-m with different values for α and m) to assess the technical efficiency of these cotton producing provinces. It compares the different models with respect to technical efficiency scores and the provinces' rankings. Using this method, the paper identifies the most (least) efficient provinces and follows the temporal patterns of their performance in cotton production. The study also compares the efficiency of different models according to the order of ranking using the Spearman rank order correlation. The efficiency results are sensitive to the choice of frontier model and the values of parameters m and α. According to our results, technical efficiency obtained from partial frontier models is higher than that obtained from full frontier models. Spearman rank order correlation's results indicate that the correlation between models DEA and FDH is high. As $\alpha \rightarrow 1$ and $m \rightarrow \infty$, the correlation coefficient between DEA with Order-α and Order-m increases. Our results also indicate that rank order correlation between FDH and Order-m is higher than that for Order-α.

Keywords: DEA, FDH, full frontier, Order-α, Order-m, partial frontier.

INTRODUCTION

With an area of 1,648,000 square kilometres, Iran is the 18th largest country in the world. It has wide temperature fluctuations (-30 to 50°C) which make it possible to cultivate different agricultural products like fruits, vegetables, cereals, sugarcane, cotton, sugar beet, nuts, pistachios, spices (like saffron), tea, berberis, tobacco and medical herbs. Iran also produces and exports large quantities of wool and timber. The agricultural sector accounts for 20 per cent of the country's GDP and it employs one-third of the country's workforce. Abundant and fertile land and diversity of plants make studies of agricultural production in the country interesting (World Weather and Climate Information, 2015).

The agricultural sector has an important role to play in developing societies' growth and development. However, this sector is also required to increase crop production for meeting the food and clothing needs of increasing populations in these countries. Therefore, policy priorities for the agriculture sector include a quantitative analysis of crops for increasing their production.

Cotton is an important input in Iran's textile industry. Its fabric is mostly composed of domestically produced cotton. Iran's cotton production reached its peak in 1975. However, thanks largely to the low prices that the government paid for harvested cotton and also due to government interventions in later years, the country's cotton production decreased. This downward trend continued till 1981 when it reached minimum levels (204,000 tons per annum). Eventually this decline in production forced the government to ban cotton exports to meet domestic consumption requirements. However, despite this policy, cotton production continued declining and eventually reached such low levels that the government had to import cotton.

In recent years, cotton production reached about 337,000 tons produced in different parts of the country (86,837 tons in Khorasan and 61,742 tons in the Fars provinces). The total area under cotton production in Iran is about 123,000 hectares. Most of the area devoted to cotton production is located in Khorasan (31 per cent) and Golestan (15.3 per cent) provinces. Despite the relatively high cotton production in the country, the textile industry needs to double its present production levels to meet demand. However, most of its cotton is provided through imports. This is against the government's policy of having self-sufficiency in the production of cotton. The country can increase domestic production of cotton through two ways: first, by increasing the area under cotton cultivation and second, by increasing yield per unit of land. Due to limited supply of arable land and production inputs, the first alternative is not practical. Therefore, increasing cotton production from the land already under its cultivation seems to be a better option. In other words, if Iran can increase the amount of cotton produced from one hectare of cultivated area, its total cotton production will increase. For following the second option, we first need to measure the technical efficiency of cotton production in the country.

There are two alternative measures of analysing the performance of decision making units (DMUs): technical efficiency, which measures a DMU's ability to produce the maximum amount of output from a given set of inputs and technology and allocative efficiency which measures a DMU's ability to choose an optimal set of inputs at given prices and technology. A combination of technical and allocative efficiencies is called economic efficiency (Sengupta, 1999).

Parametric and non-parametric approaches are used for measuring technical efficiency. Parametric approaches use the stochastic frontier analysis (SFA) to estimate production, cost or profit functions. According to Giannakas *et al*. (2003) parametric methods face a problem as one has to choose a functionl form for representing profit, cost and production functions. This is an important drawback of this approach because it leads to biased results when the functionl form chosen is not appropriate because its policy implications become misleading. Non-parametric approaches develop mathematical programmes for measuring efficiency like the Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH).

Considering the importance of cotton production in Iran's textile industry and the poor performance of this crop in the agricultural sector, there is a need for precise performance evaluations in different provinces in the country. For doing so, this study uses the non-parametric methodology to measure the technical efficiency of Iran's cotton producing provinces. The empirical analysis uses panel data from 13 major cotton producing provinces for the period 2000-12. The main objectives of the paper include:

- measuring the technical efficiency of Iran's cotton producing provinces and comparing the results of four alterntive models -- DEA and FDH with robust estimators of Order-α and Order-m.
- ranking the provinces and identifying the efficient ones.
- comparing different non-parametric models according to their order of ranking using the Spearman rank order correlation.

Our estimators are based on the envelopment approach, which assumes that all observed units belong to an attainable set.[1] Order-α and Order-m, which are generalized versions of the FDH approach, are also non-parametric measures for measuring technical efficiency; these are more robust in extreme observations. As a result, this paper presents the most complete set of results on the efficiency of the Iranian agricultural sector, as previous studies in this sector have limited themselves to only using DEA and FDH approaches.

LITERATURE REVIEW

Several studies evaluate the efficiency of production units in different sectors of the economy following non-parametric approaches (Afonso and Aubyn, 2005; Gabdo *et al*., 2014;[2] Řepková, 2014;[3] Aldamak and Zolfaghari, 2017;[4] Gearhart and Michieka, 2018[5]).

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[1] For a detailed review of literature, see Deprins *et al*. (1984), Charnes and Cooper (1985), Lovell and Schmidt (1988), Bauer (1990), Charnes *et al*. (1994), Coelli (1995), Kumbhakarand Lovell (2000) and Fried *et al.* (2008).

[2] Gabdo *et al.* (2014) used two full frontier (DEA and FDH) and two partial frontier (Order-alpha and Order-m) models for a comparative estimation of technical efficiency in the goat-oil palm and cattle-oil palm integration systems.

[3] Řepková (2014) applied the Data Envelopment Analysis (DEA) and the Windows Analysis to data from Czech commercial banks.

[4] Aldamak and Zolfaghari (2017) reviewed literature on rankings using the Data Envelopment Analysis to increase the discrimination power of this analytical technique.

[5] Gearhart and Michieka (2018) examined cross-county healthcare efficiency rankings using modern non-parametric estimators. Their analysis showed that the two-stage DEA was inappropriate and violated several assumptions as compared to the conditional Order-m estimation.

Daouia and Gijbels (2011) found Order-α and Order-m methods more robust as compared to the full frontier methods. They specified the Order-α method for which both partial production frontiers can be compared and showed that even one change in data was sufficient for a breakdown of non-parametric Order-m frontiers, whereas the global robustness of the Order-α frontiers attained a higher breakdown value. They concluded that Order-m frontiers are more resistant to outliers than Order-α frontiers and that Order-m frontiers have the advantage of being statistically more efficient.

Abdelaati *et al.* (2012) derived a theory of an estimator of the frontier with an asymptotic normal distribution. They used an Order-m partial frontier model and let Order-m converge to infinity when $n \rightarrow \infty$ but at a slow rate. They found that this estimator was more robust to extreme values and outliers as a regularized frontier estimator as compared to the usual non-parametric frontier estimators (FDH). They evaluated the performance of this estimator through Monte-Carlo experiments. Carvalho and Marques (2014) suggest that Order-α frontiers be linearized by the DEA frontier. Their proposed methodology uses partial frontier non-parametric methods which are more robust as compared to traditional full frontier methods. They proved the usefulness of their approach and showed that if only full frontier methods are used they would lead to different results.

Silva *et al*. (2016) used six non-parametric estimators to evaluate the efficiency of the banking sector in Brazil: DEA, FDH, bias corrected FDH (FDHC), bias corrected DEA (DEAC), Order-m and alpha-conditional quintile. Their comparison of the different models showed that there was a significant discrepancy in the estimated efficiency scores. According to their results, Order-m and alpha-conditional quintile estimators were useful in identifying extreme values and they were also more robust relative to DEA and FDH. The latter methods produced significant changes in a firm's rankings and estimated efficiencies.

Compared to the number of studies that measure the efficiency of other agricultural crops, there are very few studies that evaluate the performance of cotton production. Our analysis contributes to existing literature because it is the first comparative study of province level efficiency of cotton producers in Iran. Further, prior literature on Iran's cotton efficiency provides some controversial results; these studies are also based on a restricted number of variables. Hence, another contribution of our study is that it uses a larger number of explanatory variables which could affect the estimated technical efficiency. However, the primary contribution of our study lies in measuring the technical efficiency of cotton producing provinces in Iran over 13 years using a different range of non-parametric models and doing a sensitivity analysis of the estimated efficiency results because of the estimation method that we choose.

The rest of this paper is organized into four sections. First, we present the methodological framework that we adopt for our study. This is followed by a description of the data and specifications of the empirical models. Next we present the results. The last section gives the conclusion and policy recommendations.

NON-PARAMETRIC FRONTIER METHODOLOGIES

Most of the existing research uses Farrell's (1957) piecewise-linner convex hull approach for estimating frontiers in measuring efficiency. Boles (1966) and Afriat (1972) suggest using mathematical programming for the measurements. Charnes *et al*. (1994) propose a model in which inputs are minimixed to produce a given output (assuming constant returns to scale). Charnes *et al*. (1994) were the first to develop the term DEA (Data Envelopment Analysis). Subsequently, Banker *et al*. (1984) proposed a flexible model in which they assumed that returns to scale was a variable (VRS). The DEA technique develops an empirical frontier using observed production and then measures technical efficiency as the distance of each DMU from the frontier. This technique has the advantage of handling multiple outputs and inputs without price information and functional forms (Ruggiero, 2007).

The second non-parametric model which is used extensively in efficiency measurement studies is the Free Disposal Hull (FDH) model. This model was first formulated by Deprins *et al*. (1984) and was developed by Tulkens (1993). This model's advantage is that it is based on the principle of weak dominance and departs from the convexity assumption inherent in the DEA model. It also assigns an already existing DMU an efficient reference point, which makes the achievement of goals more credible. However, it also marks more DMUs as efficient (see, for example, Cooper *et al*., 2007 for a comprehensive discussion on DEA and FDH).

The non-parametric approaches mentioned so far in literature on technical efficiency measurement are full frontier models (DEA and FDH). Full frontier models assume that all observations belong to an attainable set and are based on the envelopment approach. Although DEA and FDH methods have some advantages over parametric methods they also have some limitations and have been criticized by econometricians for lacking a well-defined data generating process, being deterministic and being highly sensitive to measurement errors and extreme data. They also suffer from the problem of the 'curse of dimensionality' (Carvalho and Marques, 2014). Some of these objections are addressed by Cazals *et al*. (2002) and Aragon *et al*. (2005) as they introduce partial frontier approaches Order-m and Order-α. These two techniques generalize the FDH model by allowing super-efficient DMUs to be located beyond the estimated production possibility frontier. Hence, if there are some outliers and abnormal observations that might represent measurement errors, the estimated frontiers will not be shaped by them. Therefore, partial frontier models are less vulnerable to outliers as compared to DEA or FDH (Tauchmann, 2011).

Full frontier

Data envelopment analysis

The DEA method is a non-parametric mathematical programming approach used for evaluating a set of comparable decision-making units; it measures the DMUs' productive efficiency. The DMUs can be different organizations, departments, firms or provinces which have similar functions, goals and market segments (Pjevčević *et al*., 2012). This is a full frontier method which estimates the production frontier and evaluates the technical efficiency of each DMU.

If we consider a set of n DMUs, let Y_k and X_{ik} denote the level of the output and the level of the *i*th input respectively for DMU k. Charnes *et al*. (1994) present the following model to measure the efficiency of DMU k:

$$\text{(1)} \quad \begin{array}{lll} & \min \theta & \\ \text{Subject to} & \theta X_{ik} - \sum_{j=1}^{n} \lambda_j X_{ij} \geq 0, & i = 1,\ldots,m. \\ & \sum_{j-1}^{n} \lambda_j Y_{rj} \geq Y_{rk}, & r = 1,\ldots,s. \\ & \sum_{j=1}^{N} \lambda_j = 1 \ , \ \lambda_j \geq 0, & j = 1,\ldots,n. \end{array}$$

The optimal level of θ, denoted by θ^*, satisfies the condition $0 \prec \theta^* \leq 1$. If θ equals one, the DMU under measurement lies on the estimated frontier and is said to be technically fully efficient. The observed data of inefficient DMUs is said to be enveloped by the frontier.

Model (1) assumes constant returns to scale of the production function and hence, this model is often referred to as the CCR (Charnes, Cooper and Rhodes, 1978) model. The obtained scores of the CCR model determine technical efficiency (TE) and distinguish it from other types of efficiencies (such as allocative efficiency) in which no costs and prices are used (Yang and Chang, 2009).

Free disposable hull

Another model which has received a considerable amount of research attention is the Free Disposable Hull (FDH) model. This model was first formulated by Deprins *et al*. (1984). The FDH estimator is both a deterministic and a non-parametric method for measuring technical efficiency. The FDH model is deterministic as it cannot accommodate stochastic properties. The FDH estimator's non-parametric nature arises from its lack of specifications of the functional form. Like DEA, FDH is very sensitive to noise and outliers and it is also susceptible to dimensionality problems (Gabdo *et al*., 2014). The most important advantage of FDH is that efficiency evaluations are affected only by the actually observed performance (Subhash, 2004).

The FDH estimator only imposes free disposability of inputs, it does not impose convexity of the estimated technology (Silva *et al*., 2016). Following DeBorger *et al*. (1994), we derive FDH as:

Suppose $Y = Y(Y_1, Y_2, \ldots, Y_n)$ presents *n* non-negative outputs produced by *m* inputs $X = X(X_1, X_2, \ldots, X_m)$. Then, the FDH estimator is defined by the following axioms:

Axiom I: $0 \quad L(Y) \text{ for } Y \geq 0, \text{ and } L(0) = R_+^n$

This axiom assumes that it is not possible to obtain a semi-positive output from a null input vector.

Axiom II: $if \ \left|Y^l\right| \rightarrow +\infty \text{ as } l \rightarrow +\infty, \text{ then } \bigcap_{l=1}^{+\infty} L(Y^l) \text{ is empt}$

Axiom II states that for any utilization of finite inputs, finite outputs are produced.

Then we have the axiom of free disposability of inputs (Axiom III), which implies that an increase in input X cannot lead to a decrease in output Y:

Axiom III: $\text{if } X \in L(Y) \text{ and } X' \geq X, \text{ then } X' \in L(Y)$

Axiom IV: $L(y) \text{ is a closed correspondence}$

Axiom IV indicates that if an array of input vectors can each yield an output bundle Y and converge to X^*, then the same X^* can also yield output bundle Y.

Axiom V: $\text{if } Y' \geq Y, \text{ then } L(Y') \subseteq L(Y)$

Strong free disposability of output (Axiom V) provides for variable returns to scale and assumes a reduction in output with the same quantity of inputs. Therefore, the specification of the FDH input correspondence is:

$$\text{(2)} \quad L(Y)^{FDH} = \{X \left| X \in R_+^m, Z'J \geq Y, Z'N \leq X, I_k^{'} Z = \right|, Z_i \in \{0,1\}\}$$

where J represents the k×n matrix of outputs, N represents the k×1 vector of intensity, I_k indicates the k×1 vector of ones. According to all axioms, convexity assumption is not imposed on technology.

Partial frontier

DEA and FDH are particularly sensitive to outlier observations or extreme data points. These outliers may misleadingly influence the evaluation of other firms' performance. There are two solutions to this problem in full frontier models: first, identifying any outliers in the data and then perhaps deleting them. Some studies (Wilson, 1993, 1995; Porembski *et al*., 2005) suggest a number of techniques for finding out outliers in frontier models. The other alternative is using robust estimators that have been developed recently. In current case, the yield may vary by location and be related to weather conditions, irrigation infrastructure, soil condition, variety chosen or other local factors.

New estimators involve the concept of a 'partial' frontier as opposed to the traditional idea of a 'full' frontier that envelops all the data. Cazals *et al*. (2002), Aragon *et al*. (2005), Daouia and Simar (2004, 2005) and Daraio and Simar (2005) have developed the concept of partial frontier models. Order-m and Order-α quintile frontiers are two families of partial frontiers (Simar and Wilson, 2000).

An Order-m model's aim is estimating an efficiency frontier which is less sensitive to outliers and extreme values. In this model, the efficiency of each DMU is benchmarked against the average maximum output by m-number of peers which are randomly drawn from the population of observations. The principle of Order-α efficiency models is similar to the principle of Order-m efficiency models. Like Order-m models, Order-α models' aim is estimating an efficiency frontier that is less sensitive to extreme values (Hardeman and Roy, 2013).

Order-m frontiers

Order-m is a generalization of a FDH model and is a result of adding a layer of randomness to the computation of efficiency scores in the FDH model (Cazals *et al*., 2002; Daraio and Simar, 2007). It introduces a benchmark frontier which is less sensitive to extreme observations as compared to a full frontier model. This benchmark is defined as the expected minimal input value among *m* (m ≥ 1) peers:

(3) $$Q_m(y) = E[\min(X_1,...,X_m)|Y \geq y],$$

where $Q_m(y)$ is the minimal input frontier function. Then we have the equivalences in which m→∞, $Q_m(y) \rightarrow Q(y)$:

(4) $$Q_m(y) = \int_0^\infty S^m(u|y)du = Q(y) + \int_{Q(y)}^\infty S^m(u|y)du.$$

By plugging the empirical version of $S(u|y)$ in Equation 4, a non-parametric estimator of $Q_m(y)$ is given as:

(5) $$\hat{Q}_m(y) = \int_0^\infty \hat{S}^m(u|y)du.$$

According to Cazals *et al*. (2002) for a fixed *m* we have: $\sqrt{n}(\hat{Q}_m(.) - Q_m(.)) \xrightarrow{\ell} \xi(0,\Omega)$, ($\xi$ is a Gaussian process with covariance function Ω). Therefore, for a fixed value of m and any given y, as n→∞, we have:

(6) $$\frac{\sqrt{n}}{\sigma^2(m,y)}(\hat{Q}_m(y) - Q_m(y)) \xrightarrow{\ell} N(0,1)$$

where:

(7) $$\sigma^2(m,y) = E\left[\frac{m\psi(Y \geq y)}{S_Y(y)}\int_0^\infty (S^{m-1}(u|y)\psi(X \geq u) - S_m(u|y))du\right]^2$$

Therefore, $\hat{Q}_m(y)$ will converge to the FDH estimator ($\hat{Q}\ (y)$), as m→∞.[6]

Order-α frontiers

The other concept of a partial frontier model mentioned earlier is the Order-α (conditional) quintile frontier, which provides a robust estimator of the frontier function (Aragon *et al*., 2005; Daouia and Simar, 2005). According to Tauchmann (2011) Order-α generalizes the FDH estimator by employing the (100-α)th percentile approach. Order-α also minimizes input consumption among available peers for benchmarking. This model is written as:

(8) $$\hat{\theta}_{\alpha i} = \underset{j \in B_i}{\overset{P(100-\alpha)}{}} \left\{ \max_{k=1,\dots,K} \left\{ \frac{x_{kj}}{x_{ki}} \right\} \right\}$$

If $\alpha = 100$, both the Order-αand FDH models result in the

[6]For more details, please see Cazals *et al*. (2002).

Table 1. Summary statistics of the inputs and output, NT=169, Cotton production in Iran, 2000-2012.

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
Y	Output (Kilogramms per hektares)	2445.309	575.504	1092.383	4894.894
X_1	Seed (Kilogramms per hektares)	76.205	40.157	20.000	205.596
X_2	Pesticide (Kilogramms per hektares)	4.595	3.648	0.154	28.918
X_3	Fertilizer (Kilogramms per hektares)	439.183	172.240	161.090	1332.320
X_4	Labor (man-day)	76.986	31.722	16.810	162.600
X_5	Animal Fertilizer (Kilogramms per hektares)	1740.620	3284.743	2.000	24228.000
X_6	Machinery (percent)	38.6243	12.1198	7.1640	76.0130

same output, while for values of $\alpha \prec 100$ some super-efficient DMUs may result. Also, for $\alpha \prec 100$ some observations might be un-enveloped by the estimated production possibility frontier, which are called super-efficient DMUs (Gabdo *et al*., 2014).

Practical values for m and α

In Order-m and Order-α models we need to choose values for parameters m and α. Different amounts of m and α define the position of the frontier relative to the data. Therefore, the choice of m and α is critical. *m* represents the size of the artificial reference sample and the default is (m=ceil ($N^{2/3}$)), where ceil (.) stands for the ceiling function. Only integer and positive amounts are allowed for m values (Tauchmann, 2011). As the values of m and α increase, the data used in the estimation increases. Therefore, efficiency scores are dependent on the choice of m and α. The choice of practical values for m and α is a theoretical issue. We follow literature in choosing different values for these parameters in our analysis. As Silva *et al*., (2016) suggest 75, 150, 300 and 1,500 for m and 98, 98.5, 99 and 99.5for α, we use these values with m=21 (according to m=ceil ($N^{2/3}$); for empirical data of N=169.

DATA

Our research selected 2000-12 panel data on Iran's 13 main cotton producing provinces which is a balanced panel data with 169 observations. The data contains information on output and inputs. The output of cotton (Y) is measured as the provincial cotton production in kilograms. Seed (X_1) represent kilograms of seeds used for cotton production. Pesticide (X_2) is kilograms of pesticides used. The chemical fertilizer input (X_3) represents the quantity of fertilizers used for production. Labour input (X_4) is the total number of employees in different provinces. The other input variable is animal manure fertilizer (X_5). X_6 is the machinery utilization rate measured in percentage use and indicates the share of farmers in each province who use machinery. All output and input variables are measured in hectares of land. The data used for our study came from Iran's Ministry of Agriculture, which collects the data regionally through an annual survey that uses a common questionnaire across all provinces.

The summary statistics of our data is given in Table 1, which shows that cotton production varied between 1,092 and 4,895 kg per hectare in different provinces during the study period. The sample mean of cotton production was about 2,445 kg per hectare. Mean seed consumption was about 76 kg per hectare. Seed use ranged between 20 to 205 kg with a standard deviation of about 40 kg. The consumption of chemical fertilizers ranged between 161 and 1,332 kg per hectare with a standard deviation of 172. Mean chemical fertilizer usage was about 439 kg per hectare. The number of workers employed in cotton production was about 77 per hectare, which may reflect the fact that cotton production in Iran is labour intensive. Mean animal fertilizer and pesticide usage was about 1,740 and 4.5 kg per hectare respectively. Detailed information from our data confirms that use of animal fertilizers decreased over time. According to Table 1, on average, 38.62 per cent of the farmers in each province used machinery for cotton production.

Investigating the correlation between inputs and output is important when considering the robustness of the non-parametric frontier models. If there is an input which has a high correlation with other input variables, it can be excluded from the model to avoid the collinearity problem as this variable might be thought of as a proxy for the other variables. The correlation between each pair of variables is presented in Table 2. Concerning output and input variables, all input variables are positively correlated with cotton production, and only pesticides are negatively correlated with output (-0.121). This indicates that an increase in pesticide use is accompanied by a fall in cotton production. Seeds are positively correlated with fertilizers, labor, and animal fertilizers. As shown in this table, there is a negative association between pesticides and other input variables. Fertilizers are positively correlated with seeds, labor, and animal fertilizers but negatively correlated with pesticides (-0.027) and machinery (-0.158). Animal fertilizers are positively correlated with all other input variables, except pesticides

Table 2. Correlation matrix of the variables, NT=169.

Variable	Definition	Y	X_1	X_2	X_3	X_4	X_5	X_6
Y	Output	1.000						
X_1	Seed	0.311	1.000					
X_2	Pesticide	-0.121	-0.363	1.000				
X_3	Fertilizer	0.117	0.241	-0.027	1.000			
X_4	Labor	0.055	0.252	-0.065	0.231	1.000		
X_5	Animal fertilizer	0.115	0.223	-0.139	0.231	0.009	1.000	
X_6	Machinery	0.014	-0.240	-0.044	-0.158	-0.548	0.024	1.000

Table 3. Descriptive statistics and mean technical efficiency scores of provinces according to different models.

Provinces	DEA	FDH	Order-α				Order-m				
			α=98	α=98.5	α=99	α=99.5	m=21	m=75	m=150	m=300	m=1500
Markazi	0.618	0.976	1.434	1.291	1.235	0.989	1.683	1.201	1.075	1.006	0.989
Mazandaran	0.640	1.000	1.575	1.339	1.289	1.000	2.407	1.369	1.134	1.036	1.000
East Azerbaijan	0.937	1.000	1.186	1.186	1.109	1.000	1.367	1.120	1.061	1.010	1.000
Fars	0.774	0.983	1.043	1.032	0.998	0.983	1.474	1.031	0.997	0.985	0.983
Kerman	0.553	0.999	1.451	1.275	1.242	1.000	1.619	1.226	1.098	1.028	1.000
Khorasan	0.540	0.971	1.132	1.102	1.045	0.971	1.194	1.054	1.010	0.982	0.971
Isfahan	0.847	0.993	1.064	1.024	1.001	0.993	1.220	1.030	1.001	0.995	0.993
Semnan	0.676	0.949	1.253	1.233	1.048	0.949	1.363	1.100	1.011	0.963	0.949
Yazd	0.812	0.998	1.790	1.634	1.180	1.000	2.311	1.430	1.148	1.047	1.000
Tehran	0.803	0.973	1.028	0.997	0.984	0.984	1.552	1.091	1.006	0.984	0.984
Golestan	0.668	1.000	1.778	1.574	1.432	1.000	2.736	1.390	1.160	1.047	1.000
Ardebil	0.771	0.983	1.123	1.018	0.987	0.983	1.382	1.057	1.002	0.985	0.983
Qom	0.481	0.821	0.956	0.896	0.882	0.821	1.030	0.890	0.846	0.829	0.821
Mean	0.702	0.973	1.293	1.200	1.110	0.975	1.641	1.153	1.042	0.992	0.975
Std. Dev.	0.191	0.070	0.571	0.460	0.387	0.069	1.242	0.303	0.147	0.082	0.069
Min	0.245	0.654	0.726	0.699	0.699	0.654	0.767	0.700	0.676	0.657	0.654
Max	1.000	1.000	5.500	4.500	4.500	1.000	14.477	3.368	1.913	1.298	1.000

(-0.139). Table 2 shows no evidence of a very high correlation relationship between the variables. Therefore, it is a reasonable validation of our non-parametric models.

ANALYSIS OF THE RESULTS

Measuring technical efficiency using different models

As per existing considerations we ran two full frontier models (DEA and FDH) and two partial frontier models (Order-α nd Order-m with different values for α and m). Table 3 gives their efficiency scores.

The second part of Table 3 shows mean technical efficiency scores obtained by different models. Based on the DEA model, the mean technical efficiency of cotton producing provinces was 0.702. When we drop the convexity assumption (that is, move from DEA to FDH), the estimated mean technical efficiency scores become higher (this is as expected since the best practice frontier then wraps itself closer around the data). Other studies which have used DEA and FDH models on the same dataset also report higher technical efficiency scores for the FDH model as compared to the DEA model (De Borger *et al.*, 1994; Gabdo *et al.*, 2014; De Witte and Marques, 2010). Technical efficiency based on the FDH model is 0.97.3, which suggests that cotton producing provinces in Iran could increase their production by about 2.7 per cent through better use of inputs and improved productivity. One possible way of achieving this is by improving agricultural extension services, Training and education for farm managers, efficient management practices, and providing other facilities to the farmers.

Estimated technical efficiency scores become higher when we use the partial frontier approaches (Order-α and Order-m). The average Order-α_{99} efficiency estimate takes a value of 1.110, which means that on average the

Table 4. Ranking of provinces according to different models.

Provinces	DEA	FDH	Order-α				Order-m				
			α=98	α=98.5	α=99	α=99.5	m=21	m=75	m=150	m=300	m=1500
Markazi	10	9	5	4	4	7	4	5	5	6	3
Mazandaran	9	3	3	3	2	1	2	3	3	3	1
East Azerbaijan	1	1	7	7	6	2	9	6	6	5	1
Fars	5	7	11	9	10	9	7	11	12	8	5
Kerman	11	4	4	5	3	3	5	4	4	4	1
Khorasan	12	11	8	8	8	11	12	10	8	11	7
Isfahan	2	6	10	10	9	6	11	12	11	7	2
Semnan	7	12	6	6	7	12	10	7	7	12	8
Yazd	3	5	1	1	5	4	3	1	2	1	1
Tehran	4	10	12	12	12	8	6	8	9	10	4
Golestan	8	1	2	2	1	5	1	2	1	2	1
Ardebil	6	8	9	11	11	10	8	9	10	9	6
Qom	13	13	13	13	13	13	13	13	13	13	9

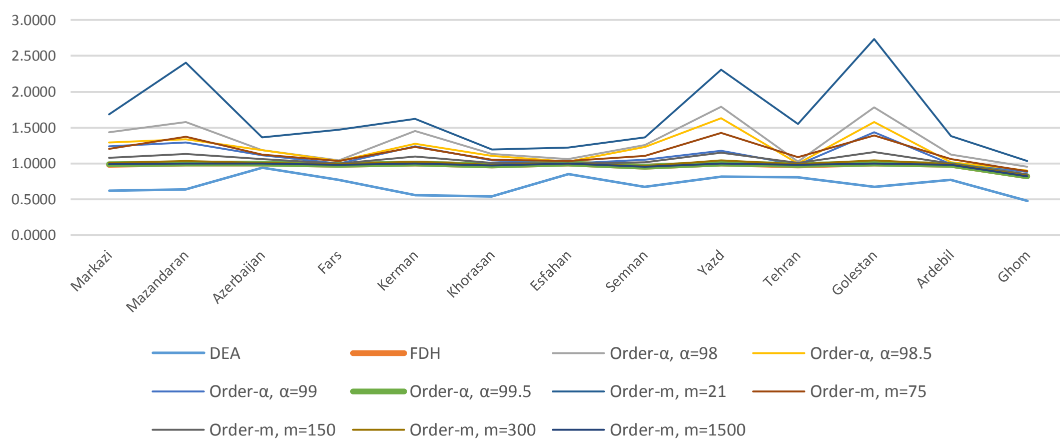

Figure 1. Average technical efficiency of provinces.

country is 11 percentage points inefficient. This value is compared to the average Order-m_{150} efficiency estimate, which takes a value of 1.042; this means that on average the country is 4.2 percentage points inefficient, or could produce 4.2 percentage points more output for its input levels to be considered fully efficient.

As expected, while α and m increased, technical efficiencies obtained from these models equalled the FDH model. Based on the results of different Order-α estimators it appears that efficiency scores are robust to the choice of α; this has also been noted by other studies (Daouia and Simmar, 2005; Gearhart, 2016; Silva *et al*., 2016; Gearhart and Michieka, 2018). Also, as the value of α approach 1.0, efficiency scores approach the full frontier estimation. For the Order-m estimator, the percentage of super-efficient observations decreases as m increases. To compare the different models, we have the following relation: *Order-m_{21}> Order-α_{98}> Order-$\alpha_{98.5}$> Order-m_{75}> Order-α_{99}> Order-m_{150}> Order-m_{300}> Order-m_{1500} = Order-$\alpha_{99.5}$>FDH> DEA.*

The most interesting results of efficiency measurements in such cases are those provided by the complete listing of the efficiency scores of each province ranked in decreasing order. Table 4 presents provinces' ranks determined by different models. According to full frontier models (DEA and FDH), East Azerbaijan was the most efficient province while Qom and Khorasan were the least efficient. Although there are differences in the exact level of efficiency depending on the approach used (Table 4 and Figure 1) efficiency rankings according to various approaches tend to support similar conclusions about the provinces' relative performance. In models Order-α_{98}, Order-$\alpha_{98.5}$, Order-α_{99}, Order-m_{21}, Order-m_{75}, Order-m_{150} and Order-m_{300}some of the provinces are super-efficient. Besides the super-efficient performers, East Azerbaijan, Mzandaran and Golestan provinces were situated on the efficiency frontier based on the FDH model.

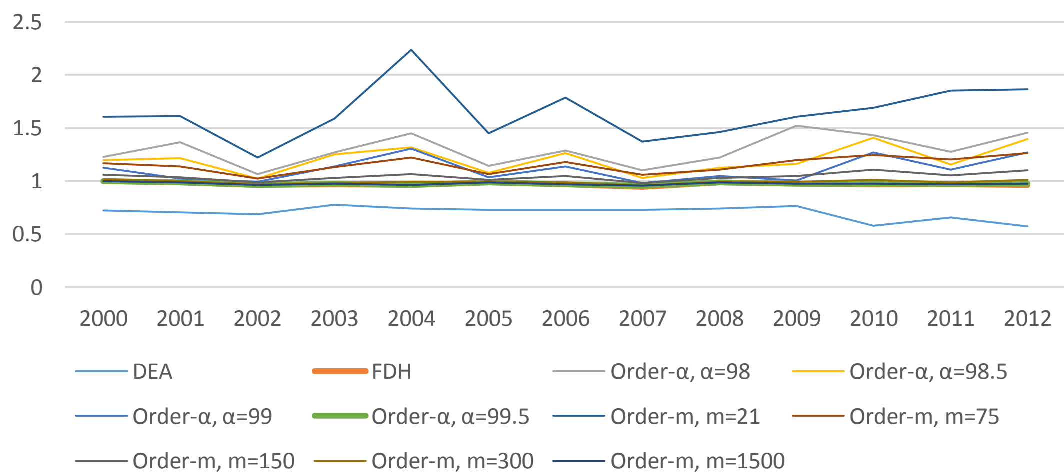

Figure 2. Average technical efficiency of different years.

Table 5. Percentage of observations in technical efficiency intervals.

Interval of efficiency scores	DEA	FDH	Order-α				Order-m				
			α=98	α=98.5	α=99	α=99.5	m=21	m=75	m=150	m=300	m=1500
%	%	%	%	%	%	%	%	%	%	%	%
> 100	0.00	0.00	59.76	49.11	31.95	0.00	94.67	78.70	69.23	55.03	0.00
= 100	13.61	78.70	31.95	40.83	55.62	84.02	1.78	7.69	14.79	28.99	84.02
90-100	6.51	9.47	4.73	5.33	4.73	5.33	1.78	5.92	6.51	6.51	5.33
80-90	11.83	5.92	1.78	1.18	2.96	4.73	1.18	5.92	4.73	3.55	4.73
70-80	14.79	4.73	1.78	2.96	4.14	4.73	0.59	1.78	4.14	5.33	4.73
60-70	17.75	1.18	0.00	0.59	0.59	1.18	0.00	0.00	0.59	0.59	1.18
50-60	21.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
40-50	8.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30-40	4.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20-30	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10-20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
00-10	0.00	0.00	0.00	0.00	0.00	.00	0.00	0.00	0.00	0.00	0.00

A graphic representation of average technical efficiencies of the provinces in the study period for different models is shown in Figure 1.

The level and time patterns of mean efficiency for each model over the 13-year period are given in Figure 2 which exhibits volatile patterns over time. Figure 2 gives us the following results: (i) Models DEA, FDH, Order-m_{1500}, Order-m_{300} and Order-$\alpha_{99.5}$have almost the same time trends. According to these models, technical efficiency decreased slightly from 2000 to 2002, increased substantially from 2002 to 2003 and then decreased from 2003 to 2007; 2010 and 2012 were the most inefficient years during the study period. (ii) Models Order-m_{21}, Order-m_{75}, Order-m_{150}, Order-α_{98}, Order-$\alpha_{98.5}$ and Order-α_{99}have almost the same time trends. According to these models 2004 was the most efficient year in the study period. Overall, most of the provinces could not improve their efficiency over time during the period of analysis. The main reasons behind decreasing technical efficiency during the study period include: (1) In recent years seed quality has deteriorated which has decreased yields and crop quality. (2) Environmental and climate constraints like lack of precipitation especially in recent years could be another reason for decreasing technical efficiency. (3) Finally, traditional and low-technology used in cotton harvesting in the country (which accounts for about 20 to 23 percent of the cost of production) has led to low crop yields and efficiency.

Table 5 shows some of the distributional characteristics of the provinces' efficiency scores using DEA, FDH, Order-α and Order-m models. It also presents the percentage of efficient and super-efficient provinces. According to the DEA model, most of provinces (about 21.89 per cent) were in the efficiency range of 50 to 60 per cent. According to Tables 3 and 5, the mean technical efficiency was about 70.2 per cent; and 39.95

Table 6. Spearman's rank-order correlation between technical efficiency different models.

		DEA	FDH	Order-α				Order-m				
				α=98	**α=98.5**	**α=99**	**α=99.5**	**m=21**	**m=75**	**m=150**	**m=300**	**m=1500**
DEA		1.000										
FDH		0.501 (0.00)	1.000									
Order-α	α=98	-0.503 (0.49)	0.390 (0.00)	1.000								
	α=98.5	-0.082 (0.29)	0.446 (0.00)	0.861 (0.00)	1.000							
	α=99	-0.058 (0.46)	0.514 (0.00)	0.740 (0.00)	0.808 (0.00)	1.000						
	α=99.5	0.435 (0.00)	0.879 (0.00)	0.475 (0.00)	0.546 (0.00)	0.609 (0.00)	1.000					
Order-m	m=21	0.189 (0.01)	0.466 (0.00)	0.757 (0.00)	0.691 (0.00)	0.596 (0.00)	0.548 (0.00)	1.000				
	m=75	0.088 (0.26)	0.507 (0.00)	0.880 (0.00)	0.829 (0.00)	0.742 (0.00)	0.601 (0.00)	0.911 (0.00)	1.000			
	m=150	0.061 (0.43)	0.538 (0.00)	0.891 (0.00)	0.878 (0.00)	0.797 (0.00)	0.639 (0.00)	0.838 (0.00)	0.965 (0.00)	1.000		
	m=300	-0.017 (0.82)	0.536 (0.00)	0.870 (0.00)	0.912 (0.00)	0.858 (0.00)	0.646 (0.00)	0.739 (0.00)	0.891 (0.00)	0.944 (0.00)	1.000	
	m=1500	0.435 (0.00)	0.879 (0.00)	0.475 (0.00)	0.546 (0.00)	0.609 (0.00)	1.000 (0.00)	0.548 (0.00)	0.601 (0.00)	0.639 (0.00)	0.464 (0.00)	1.000

Note p-values in parentheses.

per cent of the provinces had more than 80 per cent technical efficiency. The minimum efficiency was 24.5 per cent. Mean technical efficiency according to the FDH model was 97.3 per cent. When we consider the FDH model, 78.70 per cent of the provinces were efficient. This number is significantly larger than the 13.6 per cent efficient provinces obtained using the DEA model. There are two main reasons for the differences between the FDH and DEA models: (i) The convergence rate in the FDH model is slow, and (ii) Assumption of convexity in the DEA model.

Columns 4-12 of Table 5 give efficiency estimates of Order-α and Order-m with different values of α and m. These values define the position of the frontier relative to the data. As the values of these parameters increase, the number of provinces in the estimation gets higher and the efficiency scores get closer to the FDH model. According to Table 5, efficiency estimates are highly dependent on the choice of m and α. Table 5 also indicates that 40.83 per cent of the provinces were efficient when α=98.5 and 14.79 per cent were efficient when m=150. Comparing these numbers to the FDH model (78.70), partial frontier models produce a finer efficiency ranking for the provinces. Based on Order-α_{99} and Order-m_{300} models, the technical efficiency of 31.95 and 55.03 per cent of the provinces respectively was greater than unity and they are considered to be super-efficient. Silva *et al*.'s (2016) study also reported that some of the firms were super-efficient with efficiency scores larger than one.

According to Table 5 and the second part of Table 3, the technical efficiency estimates of model Order-α_{98} show that all the provinces operated between an efficiency range of 0.72 and 5.50 with a mean score of 1.29. This range in model Order-$\alpha_{98.5}$ is 0.69 to 4.5. As Table 5 shows, according to these models 59.76 and 49.11 per cent of the provinces were super-efficient respectively. As expected, by increasing the value of α and m, the number of efficient and super-efficient provinces decreased.

We calculated the Spearman rank order correlation coefficients (r) to determine how close the implied rankings of provinces were in each of the models. Coefficient r is essentially a measure of association derived from ranks of observations between two series. A value of r=1 (or –1) indicates a perfectly positive (negative) rank order correlation, while r=0 indicates that no correlation exists. Pairwise rank order correlations of different models are reported in Table 6. The main results of this table can be summed as:

1. The correlation between DEA and FDH models was relatively high at 0.50. This implies that in our study the DEA and FDH models ranked the provinces in almost the same order.

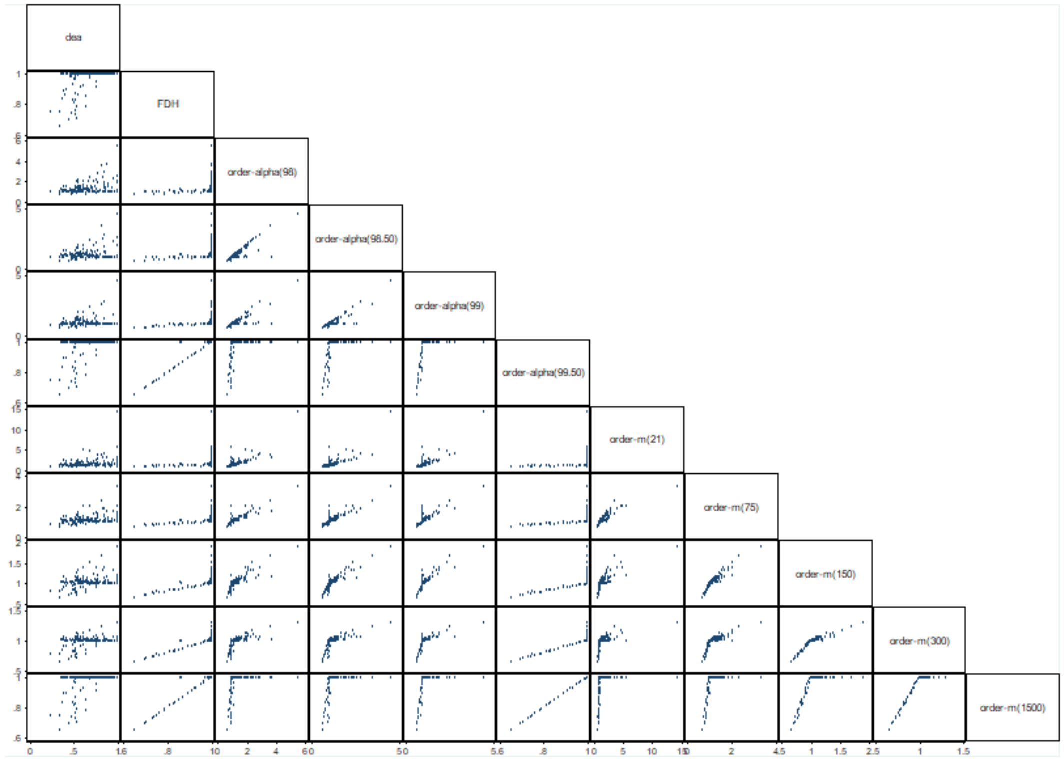

Figure 3. Scatter plot matrices of pairwise technical efficiency estimates for different models. Technical efficiency levels for each scatter plot are shown on both the horizontal and vertical axes for each pair-wise comparison.

2. Rank order correlation between FDH and Order-α_{98} was 0.39; and that between FDH and Order-α_{99} was 0.51. On the other hand, the correlations of FDH with Order-m_{21} and Order-m_{300} were 0.47 and 0.54 respectively. Therefore, while $\alpha \rightarrow 1$ and $m \rightarrow \infty$ the rank order correlations of FDH with Order-α and Order-m approached one. The rank order correlation between FDH and Order-m was higher than that for Order-α.
3. As the value of different *α*s' got closer, the rank order correlation between Order-α models increased. The highest correlation was between Order-α_{98} and Order-$\alpha_{98.5}$ models (0.86). This finding implies that these models ranked the provinces in the same order.
4. The same relationship existed between different Order-m models and as different amounts of m got closer, the rank order correlation increased. The highest rank order correlation was 0.96 (between Order-$m_{75}$and Order-m_{150}).
5. Rank order correlation between Order-m_{21} and Order-$\alpha_{99.5}$ was 0.55. The highest correlation between Order-α and Order-m was 1.00 (between Order-$\alpha_{99.5}$ and Order-m_{1500}). These models seem to be the most consistent in generating similar results in ranking the provinces.

Figure 3 provides scatter plot matrices for DEA, FDH, Order-α and Order-m models with different values for α and m. It illustrates the differences between the models in the ranking of provinces by technical efficiency estimates. The straight lines in the graph indicate a perfect match between two compared models. These results prove the findings given in Table 6.

SUMMARY AND CONCLUSION

This paper compared different non-parametric estimators for technical efficiency and used them to evaluate the efficiency of cotton producing provinces in Iran. The estimators considered were the Data Envelopment Analysis (DEA), the Free Disposal Hull (FDH), Order-m and Order-α. For this comparison, we used an identical dataset of cotton producing provinces in Iran during the period 2000-12.

After outlining the target of this study and the main concepts related to it, we addressed empirical issues concerning data requirements and the mathematical methods used for efficiency analyses. After reviewing the various methodologies that have been developed to address efficiency empirically we chose to report on four methodologies.

Our efficiency results were sensitive to the choice of the frontier model and the values of parameters m and α. According to our results, when we dropped the convexity assumption, the estimated mean technical efficiency scores became higher; the estimated technical efficiency scores became even higher when we used partial frontier approaches (Order-m and Order-α).

The mean technical efficiency of DEA, FDH, Order-α_{98} and Order-m_{21} models was 0.702, 0.973, 1.293 and 1.641 respectively. According to most of our models, the top performing provinces in this category were East Azerbaijan, Mazandaran and Golestan. Qomwas among the lowest ranked. Overall, most of the provinces could not improve their efficiency over the period of study. According to all the models, 2004 was the most inefficient year during the study period.

Finally, using the Spearman rank order correlation coefficients we explored the extent to which different models were similar in the ranking of different provinces. The correlation between models DEA and FDH was high. As $\alpha \rightarrow 1$ and $m \rightarrow \infty$, the size of the correlation coefficient between DEA with Order-α and Order-m increased. The results indicate that rank order correlation between FDH and Order-m models was higher than in the Order-α model.

FUTURE RESEARCH

This research has some limitations which can be overcome in future studies. Its first limitation is mainly due to the nature of the dataset used as we did not have access to other input variables (for example, irrigation and energy consumption). Second, considering the time variable would give a more precise assessment of technical efficiency. This provides a direction for future research for measuring technical efficiency using *Window-analysis* and using *Consistency Conditions* suggested by Bauer *et al*. (1998) to compare the scores and rankings of different models. Third, there is also a need to examine the extent to which our results can be generalized to other crops.

Policy implications

The empirical results of our research are important for policymakers as they provide detailed information about cotton production in different provinces in Iran. Our recommendations for policymakers are:

- Since cotton picking harvesters cost a lot and farmers cannot afford to buy them, subsidies for machinery should be provided to increase the technical efficiency of cotton production in the country.
- Descriptive evidence from our data indicates that low quality seeds that have been used recently might be one reason for decreasing technical efficiency. Hence, funds should be provided to help cotton producers in developing and improving both the quality and quantity of the seeds that they use.
- Different scores of technical efficiency indicate large disparities in the provinces in terms of technical efficiency which may be due to the fact that some of the provinces (for example, East Azerbaijan) have comparative advantages in producing cotton. Thus, specialization in the use of resources is recommended for increasing cotton production in the country.

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