Saffron Agronomy & Technology
Homepage: http://saffron.torbath.ac.ir
Vol. 13, No. 3, 2025, p. 307-322

Determinants of Bias-Corrected Technical Efficiency in Saffron Production: Evidence from a Double Bootstrap DEA Approach

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Article type:
Research Article
Article history:
Submitted: 21 November 2025
Revised: 25 December 2025
Accepted: 12 March 2026
Available Online: 16 March 2026

How to cite this article:
Morteza Yaqubi, M. (2025). Determinants of Bias-Corrected Technical Efficiency in Saffron Production: Evidence from a Double Bootstrap DEA Approach. *Saffron Agronomy & Technology*, *13*(3), 307-322. https://doi.org/10.22048/jsat.2026.520132.1577

Abstract

This study evaluates the technical efficiency of saffron farms in Torbat Heydarieh and Zaveh Counties in Northeastern Iran using a two-stage double-bootstrap Data Envelopment Analysis (DEA) approach. Cross-sectional data were collected from 108 saffron producers across six districts, and technical efficiency (TE) scores were estimated using a variable returns to scale (VRS) input-oriented DEA model. The bias-corrected double-bootstrap procedure of Simar and Wilson (2007, Algorithm 2) was applied with 1000 replications to ensure consistent inference and robust estimation. Results reveal that the Farrell efficiency estimates tend to overstate farm technical efficiency by approximately 25 percent. I detected significant regional disparities in efficiency scores ($\chi^2 = 12.74$, $p < 0.05$), with the highest mean efficiency observed in Kadkan (0.32) and the lowest in the Central district (0.17). The truncated bootstrap regression identified an inverted U-shaped relationship between farm age and efficiency, where efficiency initially increases with farm age but declines beyond a certain point. Experience in saffron cultivation had a strong positive and statistically significant effect on efficiency ($p < 0.01$), while education level and farmer's age were not significant predictors. Slack analysis revealed considerable input-specific inefficiencies and spatial heterogeneity in slacks. On average, farms could reduce water use by 706.88 $m^3.ha^{-1}$, land by 3.04 ha, corm use by 528.10 $kg.ha^{-1}$, and labor by 20 person-days.ha^{-1} without reducing output.

Keywords: Data Envelopment Analysis (DEA); Bootstrap Bias Correction; Technical Efficiency; Truncated Regression; Saffron Farming; Iran; Agricultural Productivity

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https://doi.org/10.22048/jsat.2026.520132.1577

Introduction

Saffron (*Crocus sativus* L.) stands as one of the world's most expensive spices across arid and semi-arid regions and has diverse applications in the food industry as a natural colorant and flavor enhancer (Ahmed et al., 2021; Khorasanchi et al., 2018), in pharmaceuticals for its antioxidant, anti-inflammatory, and neuroprotective properties (Frusciante, 2024; Hatziagapiou et al., 2019), and also in cosmetics for its pigmentative and skincare benefits (Damayanti & Riyanto, 2023; Mzabri et al., 2019). As the leading global producer—accounting for over 90% of worldwide output—Iran's saffron sector represents not only a vital source of export revenue but also a critical livelihood for thousands of Iranian smallholder farmers (Sardar Shahraki et al., 2025). Despite this strategic importance, productivity remains suboptimal in key producing regions, constrained by inefficient resource use, managerial limitations, and environmental pressures (Rastegaripour et al., 2025; Ramezani et al., 2022). This challenge is particularly evident in Torbat Heydarieh and Zaveh, core hubs within Iran's saffron belt, where yield gaps and input misallocation threaten both economic viability and long-term sustainability (Yaqubi et al., 2024; Nazarian et al., 2024).

Improving technical efficiency—defined as the ability of a producer to maximize output from a given set of inputs or, conversely, to minimize input use for a given level of output—is widely recognized as essential for sustainable agricultural development (Alem, 2021). It enhances food security by maximizing production from existing resources (Hakim et al., 2021). In addition, improved technical efficiency supports environmental sustainability by conserving critical inputs such as water and reducing chemical runoff (Zhen et al., 2023). It also delivers substantial economic benefits by lowering production costs and improving farm profitability (Gaviglio et al., 2021).

Several studies have applied Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA), as two of the most common methods, to assess efficiency across diverse farming systems. DEA is a nonparametric, linear-programming-based methodology for empirically measuring the relative efficiency of a set of similar decision-making units that does not require assumptions about the functional form of the production function. It constructs an empirical production possibility frontier from the observed data of the best-performing decision-making units (DMUs). Charnes et al. (1978) introduced the first classic DEA model, known as the CCR, which assumes constant returns to scale. Banker et al. (1984) modified that approach by allowing the separation of pure technical efficiency from scale efficiency, known as the BCC, which assumes variable returns to scale. The assessment of decision-making units is generally implemented through a dual-phase analytical design. Traditionally, researchers start by estimating technical efficiency (TE) scores using the CCR and BCC, or other variants derived from these foundational models. These estimated scores are then analyzed in a subsequent stage using econometric regression models to identify the effects of contextual or environmental variables, with Tobit or Logit regression. Despite its widespread application, this sequential approach has been widely criticized for several methodological weaknesses. One major concern is the lack of a well-defined data-generating process (DGP), which undermines the model's statistical coherence. Another limitation stems from sampling bias-an issue that arises when the frontier of production is constructed from only a fraction of the available data rather than from the full population. This partial representation leads to biased estimates of efficiency. Moreover, because TE scores are computed relative to the frontier determined by the most efficient DMUs, they are inherently dependent. The complexity of these interdependencies remains largely unexamined, hindering valid statistical inference. Consequently, the efficiency values obtained in the first phase seldom satisfy the independence and distributional assumptions required for conventional regression analysis in the second phase, thus calling into question the reliability of the results derived from such two-stage procedures (Daraio et al., 2018; Valiyattoor & Bhandari, 2020; Yadava, 2024). Simar and Wilson's (2007) seminal work introduced a bootstrap-based, two-stage estimator designed to address the statistical shortcomings inherent in traditional methods. However, a significant segment of the research community continues to apply the older, conventional two-stage framework. Ngo et al. (2025), Chang et al. (2025), Sultana et al. (2023), Ramezani et al. (2022), and Romagnoli et al. (2021) are just a few examples of the extensive body of work dedicated to this topic in the agricultural context. However, as mentioned, conventional DEA models can generate biased and inconsistent estimates, especially in small to moderate samples, due to the inherent dependence among efficiency scores and the bounded nature of DEA outputs.

Here, I apply Simar & Wilson's (2007) bootstrap-based bias correction to evaluate the determinants of technical efficiency of saffron farms. I employ a two-stage semi-parametric approach grounded in bias-corrected DEA, leveraging 1,000 bootstrap replications to produce accurate, statistically reliable efficiency scores. In the second stage, I apply a truncated regression to identify the key socioeconomic and farm-level determinants of efficiency, while rigorously accounting for the censored nature of efficiency data. My analysis makes three distinct contributions. First, it provides the first bias-corrected efficiency estimates for saffron farming in one of Iran's most important production zones, revealing a starkly lower mean efficiency than previously assumed. Second, it confirms the inverted U-shaped relationship between farm age and efficiency—a finding with important implications for land management and sustainability—while showing that farming experience significantly enhances performance, whereas formal education does not. Third, slack analysis uncovers substantial spatial heterogeneity in input excess, highlighting region-specific opportunities for resource optimization.

Materials and Methods

I employed a two-stage semi-parametric approach to estimate and analyze the technical efficiency of saffron farmers in Torbat Heydarieh, Iran, proposed by Simar & Wilson (2007). I used DEA for efficiency estimation in the first stage, and a regression analysis with a bootstrapping procedure for bias correction, as follows:

First Stage: DEA Efficiency Estimation

The first stage involves estimating Farrell technical efficiency scores of saffron farmers. The CCR evaluates the relative efficiency of decision-making units (DMUs) by minimizing a function that accounts for input and output slacks while ensuring non-negative weights for reference units. This model assumes a proportional relationship between inputs and outputs, reflecting constant returns to scale. The primal form of the CCR model can be expressed as follows:

$$\text{Min } \theta + \varepsilon \left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+ \right) \tag{1}$$

s.t.

$$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{rp}, \quad r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta X_{ip}, \quad i = 1, \ldots, n$$

$$\sum_{j=1}^{n} \lambda_j \geq 0, \; j = 1, \ldots, n$$

$$S_i^-, S_r^+ \geq 0, \quad r = 1, \ldots, s; \quad i = 1, \ldots, m$$

Where:

S_r^-: Slack variable corresponding to inputs (input excess).

S_r^+: Slack variable corresponding to outputs (output shortfall).

λ: A set of non-negative weights defining the reference set.

ε: A non-Archimedean infinitesimal number preventing weights from becoming zero, ensuring a lower bound for both input and output weights.

By solving this model, I determine each farmer's efficiency score. An efficiency score of one indicates that the DMU lies on the efficient frontier, whereas a score less than one implies inefficiency, requiring adjustments in inputs or outputs to achieve optimal performance.

The BCC model extends the CCR model by adding the constraint $\sum_{j=0}^{n} \lambda_j = 1$ to account for Variable returns to Scale (VRS). The efficiency score for each DMU is denoted as $d_0 = d(x_0, y_0 | P)$, where P represents the production set defined as $P = \{(x,y) | x \text{ can produce } y\}$. The primal form of the BCC model is expressed as follows:

$$\text{Min } \theta + \varepsilon\left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+\right) \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ = y_{rp}, \quad r = 1, \ldots, s$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- = \theta X_{ip}, \quad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n$$

$$S_i^-, S_r^+ \geq 0, \quad r = 1, \ldots, s; \quad i = 1, \ldots, m$$

By relaxing the CRS assumption, I provide a more nuanced analysis of technical efficiency through isolating managerial efficiency from scale effects.

Second Stage: Regression Analysis with Bootstrapping

To address potential biases and serial correlation issues inherent in traditional two-stage DEA, I adopt a bootstrapping approach that ensures valid statistical inference by correcting biases in efficiency estimates and accounting for farm-specific variables.

Underlying Data-Generating Process (DGP)

The DGP assumes that the efficiency level d_i for each farmer is determined by farm-specific variables z_i through the following relationship:

$$d_i = c(z_i, \beta) + e_i \geq 1, \qquad (3)$$

Where $c(z_i, \beta)$ is a smooth function representing the effect of farm-specific variables, β is a vector of parameters, and e_i is an independent random variable distributed as $N \sim (0, \sigma_e^2)$ with left-truncation at $1 - c(z_i, \beta)$.

Bias Correction

The estimated efficiency scores, $\hat{d}_i$ obtained from the DEA are biased downward due to finite sample effects. To correct for this bias, based on Simar and Wilson's approach, I apply the following formula:

$$\tilde{d}_i = \hat{d}_i - \text{BIAS}(\hat{d}_i), \qquad (4)$$

Where $\text{BIAS}(\hat{d}_i)$ is the estimated bias term derived through bootstrapping.

The bias term is estimated as:

$$\text{BIAS}(\hat{d}_i) = \text{BIAS}(\hat{d}_i) + v_i. \qquad (5)$$

Where v_i represents the residual error that diminishes as the sample size increases. The variance of the residual v_i diminishes as $n \to \infty$, and hence v_i is typically of smaller magnitude than for reasonable sample sizes.

Bootstrapping Procedures

I implement two bootstrap algorithms to enhance the robustness of the analysis: the single and the double bootstrap algorithms. The single bootstrap algorithm involves three steps: first, computing DEA efficiency scores, $\hat{d}_i$, for all DMUs; second, estimating the truncated regression model, $\hat{d}_i = z_i \beta + \xi_i$, using maximum likelihood estimation (MLE); and third, generating L bootstrap samples to construct confidence intervals for the regression parameters β and the error term σ_e. The double bootstrap algorithm builds upon the single bootstrap by adding a parametric bootstrap step to generate bias-corrected efficiency scores, which are then used to re-estimate the truncated regression model and construct improved confidence intervals. Compared to the single bootstrap, as Simar and Wilson show, the double bootstrap offers better coverage probabilities and reduces root-mean-square-error (RMSE) for moderate sample sizes.

Regression Model

In the next step, I regress the corrected efficiency scores $\tilde{d}_i$ on farm-specific variables z_i to identify factors influencing technical efficiency:

$$\hat{d}_i = z_i \beta + \xi_i \qquad (6)$$

Where ϵ_i is the error term assumed to follow a truncated normal distribution.

To validate the robustness of the bootstrapping procedures, I conduct Monte Carlo simulations. These simulations assess the performance of the single and double bootstrap methods under various conditions, including different sample sizes and model dimensions.

I construct confidence intervals for the regression coefficients using percentile bootstrap methods. The double bootstrap algorithm mentioned is particularly effective in reducing bias and improving the precision of estimates, even in high-dimensional settings.

To estimate practical technical efficiency and analyze its determinants, I first calculate efficiency scores for saffron farmers in the first stage. Inputs include water consumption (W) in m^3.ha$^{١-}$, farm size (FS) in hectares, labor days (LD) in hectares, corm weight (C) in kg.ha^{-1}, and chemical fertilizer (F) in kg.ha^{-1}. I consider the output to be dry saffron yield (TP_{dry}) in g.ha^{-1}. After calculating efficiency scores ($\hat{d}_i$), in the second stage, I regress efficiency scores on farm-management variables to identify factors influencing efficiency.

In the second stage, I include in the regression model education level (*Edu*), farming experience (*Exp*), farm age (*FA*), farm age squared (*FA*2), and farmer age (*Age*) as independent variables. Note, I consider not only the mean-centered variable representing the age of the farm but also its quadratic mean-centered term to capture the inverted U-shaped relationship between farm age and efficiency. The literature shows that farm productivity per hectare tends to increase initially with farm age (Koocheki et al., 2006). However, beyond a certain age, productivity declines due to factors such as soil degradation, reduced resource quality, or diminishing returns from prolonged cultivation of the same land (Colla & Rouphael, 2009). This inverted U-shaped relationship can be effectively modeled by incorporating both the linear and quadratic terms of farm age into the regression equation.

As Simar & Wilson indicate, I apply bootstrapping procedures to account for biases and serial correlation issues inherent in traditional two-stage approaches to estimate the efficiency score for each farmer (*d*0) using the following linear program:

$$\hat{d}_0 = \max \left\{ \begin{array}{l} \theta | \, TP_{dry} \leq \sum_{j=1}^{n} \lambda_j TP_{dry,j}, \\ W + FS + LD + C + F + P \geq \sum_{j=1}^{n} \lambda_j (W_j + FS_j + LD_j + C_j + F_j + P_j), \\ \sum_{j=1}^{n} \lambda_j = 1, \\ \lambda_j \geq 0 \end{array} \right\}. \qquad (7)$$

Then, I regress the corrected efficiency scores ($\tilde{d}_i$) on farm-specific variables to determine their impact on efficiency as follows:

$$\tilde{d}_i = \beta_0 + \beta_1 Edu + \beta_2 Exp + \beta_3 FA + \beta_4 FA^2 + \beta_5 Age + {}_{\epsilon i}, \qquad (8)$$

Where $\beta 0$ is the intercept, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, and $\beta 5$ are coefficients representing the marginal effects of education, experience, farm age, farm age squared, and farmer age, respectively, and ϵi is the error term assumed to follow a truncated normal distribution with left-truncation at $Z_i^T \hat{\beta}$.

Study Area and Population

The study's case is Torbat Heydarieh and Zaveh counties in Razavi Khorasan Province, Iran, two of the country's most prominent saffron-producing regions. Torbat Heydarieh County, covering approximately 371.8 km², is geographically located at 59°12′ E longitude and 34°17′ N latitude, at an elevation of 1,451 meters above sea level. This area has a cold, arid climate, with an average annual precipitation of 113.8 mm. The mean annual maximum and minimum temperatures are 21.4°C and 7.6°C, respectively. The demographic characteristics of the study area are summarized in Table 1.

Table 1. Demographic Characteristics of the Study Area

Counties	District	Number of Village Districts	Number of Villages	Number of Families	Population
Torbat Heydarieh	*Bayg*	1	46	1270	3392
	Jolgeh Rokh	4	141	11588	37706
	Kadkan	2	87	3752	12225
	Central	3	104	43029	140019
Zaveh	*Central*	4	83	20063	67695

Source: Yaqubi et al (2024)

Torbat Heydarieh and Zaveh together account for the largest share of saffron production in Razavi Khorasan Province, in recent years (Yaqubi et al., 2024). The study population consisted of saffron farmers located in the central districts of these counties, including Zaveh, Feyzabad, Jolgeh Rokh, Bayg, and Kadkan.

Data Collection

Given the wide geographical distribution of saffron farms across the study area, I adopted a non-probability convenience sampling approach. In total, 108 questionnaires were completed in the selected regions during the 2023–2024 growing season, using a researcher-designed, structured questionnaire and face-to-face interviews with farmers, through purposive sampling. The adoption of a non-probability sampling method impacts the statistical generalizability of the findings to the entire population of saffron farmers in Torbat Heydarieh and Zaveh counties, Khorasan Razavi, Iran. While the extensive geographical dispersion of farms and practical constraints necessitated this sampling, it potentially introduces selection bias, as more accessible or willing farmers may not fully represent the diversity of the farming community. Due to these sampling limitations, employing the double-bootstrap DEA procedure is not merely a choice but a methodological necessity to ensure the robustness and validity of this study's results. Conventional DEA estimates are susceptible to sampling variation, especially in small to medium samples, leading to upward bias in efficiency scores and invalid statistical properties for the second-stage regression. Our approach explicitly corrects for finite-sample bias. Furthermore, by simulating the sampling distribution via 1000 bootstrap replications, the method produces reliable confidence intervals for both the efficiency scores and the second-stage regression coefficients.

The questionnaire collected data on geographical location, farm age (year), and farm size (in hectares), water consumption (m^3 per hectare), quantity of saffron corms planted ($kg.ha^{-1}$), labor input (man-days per hectare), chemical fertilizer use ($kg.ha^{-1}$), pesticide use ($l.ha^{-1}$), and saffron yield, measured as the dry weight of saffron produced ($g.ha^{-1}$).

Results and Discussion

Technical Efficiency Estimates

I estimated technical efficiency (TE) scores for the saffron farms using the bias-corrected double bootstrap procedure proposed by Simar and Wilson (2007, Algorithm 2) under the assumption of variable returns to scale (VRS) and an input-oriented DEA model. This orientation was selected because farmers are more likely to control input quantities (e.g., water, labor, fertilizer) than output levels. A total of 1000 bootstrap replications were employed to ensure robust bias correction and consistent inference.

Table 2 presents the descriptive statistics of the original Farrell efficiency scores, the bootstrap bias estimates, and the bias-corrected efficiency scores.

Table 2. Farrell Efficiency, Bootstrap Bias, and Bias-Corrected Efficiency Scores among Saffron Farmers (n = 108)

Variable	Observations	Mean	Std. Dev.	Min	Max
FE[1]	108	0.47	0.230	0.167	1.00
BB[2]	108	0.29	0.367	0.067	2.88
BCE[3]	108	0.22	0.125	0.006	0.73

[1]FE: Farrel Efficiency; [2]*BB*: Bootstrap Bias; [3]*BCE*: Bias Corrected Efficiency

The mean bias-corrected efficiency is approximately 0.22, indicating that, on average, the sampled farms are operating at only 21.7% of their potential efficiency. In other words, output could increase by nearly 78% without additional inputs if we adopt best-practice techniques. This finding indicates substantial technical inefficiency in the study area. The substantial difference between the Farrell and bias-corrected means shows that conventional DEA tends to overestimate efficiency, underscoring the need for bias adjustment via bootstrapping.

The range of bias-corrected efficiencies (0.006–0.73) is wider than that of the unadjusted scores, implying that bias correction affects farms heterogeneously, depending on their proximity to the efficiency frontier.

Table 3. Mean efficiency scores by location

Location	Mean Farrell	Mean Bias	Mean BCE	SD (BCE)	Min (BCE)	Max (BCE)
Central	0.397	0.225	0.172	0.079	0.006	0.338
Zaveh	0.517	0.331	0.252	0.131	0.043	0.636
Bayg	0.621	0.357	0.264	0.145	0.112	0.568
Feyzabad	0.334	0.139	0.195	0.098	0.081	0.361
Kadkan	0.511	0.441	0.316	0.212	0.163	0.735
Rokh	0.679	0.680	0.277	0.162	0.101	0.418
Other	0.350	0.281	0.069	0.027	0.043	0.096

[1]*BB*: Bootstrap Bias; [2]*BCE*: Bias Corrected Efficiency

While the descriptive patterns are informative, the mean differences across districts were further examined using the Kruskal–Wallis nonparametric test, which confirmed significant regional disparities in efficiency ($\chi^2 = 12.74, p < 0.05$). These findings imply that contextual factors—such as soil fertility, irrigation methods, and access to extension services—are likely contributing to performance heterogeneity across the regions.

Figure 1 illustrates the distribution of the Farrell efficiency scores, which exhibit a pronounced right skew, with most farms clustered between 0.2 and 0.4. Only 11 farmers (10.2%) lie on the frontier (TE = 1).

The most frequent bias estimates for Farrell efficiency scores range from 0.1 to 0.4, as shown in Figure 2.

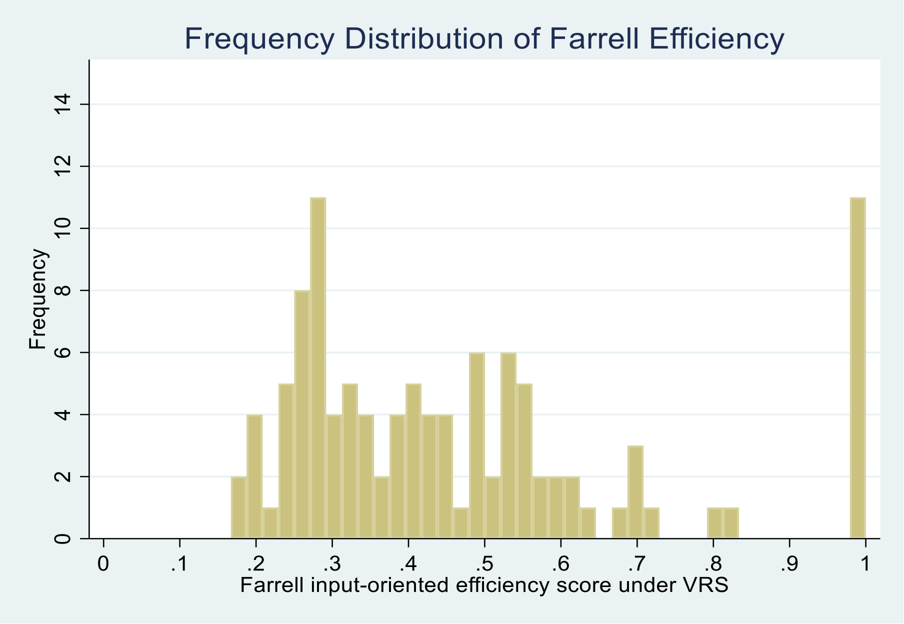

Figure 1. Histogram of Farrell efficiency scores

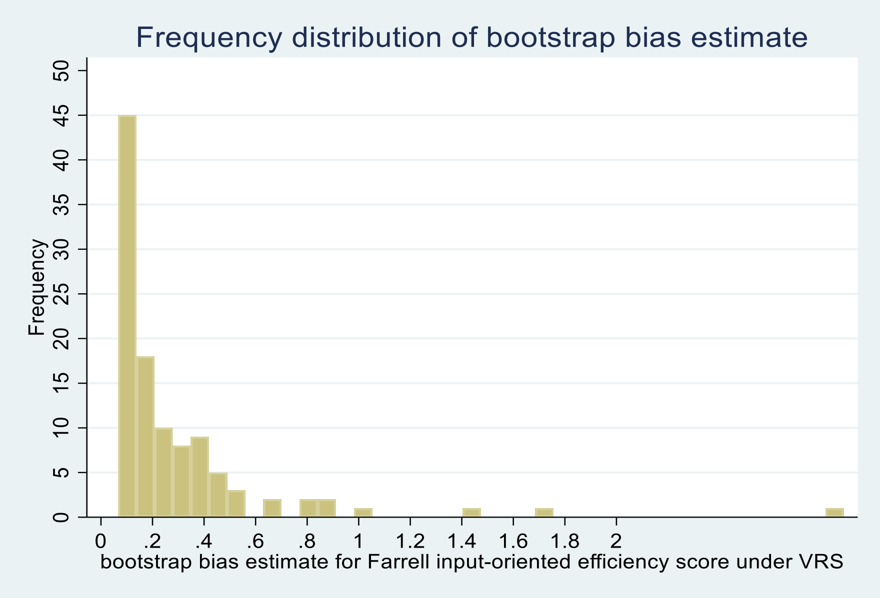

Figure 2. Histogram of bias estimates of Farrell efficiency scores

Table 4. Truncated Regression Results (Simar & Wilson, 2007 Double Bootstrap Approach)

Variable	Coefficient	Std. Error	z	p-value	95% Confidence Interval
Farm Age	2.086	0.896	2.33	0.020	[0.474, 3.920]
Farm Age²	-0.252	0.097	-2.60	0.009	[-0.459, -0.075]
Farmer's Age	-0.284	0.215	-1.32	0.187	[-0.697, 0.121]
Experience	0.999	0.317	3.15	0.002	[0.391, 1.630]
Education	0.024	0.246	0.10	0.922	[-0.443, 0.520]
Constant	0.033	2.775	0.01	0.991	[-5.890, 4.809]
σ (sigma)	2.786	0.207	13.49	0.000	[2.316, 3.114]

Wald $\chi^2(5) = 16.13$, p = 0.0065; n = 108; Bootstrap replications = 1,000.

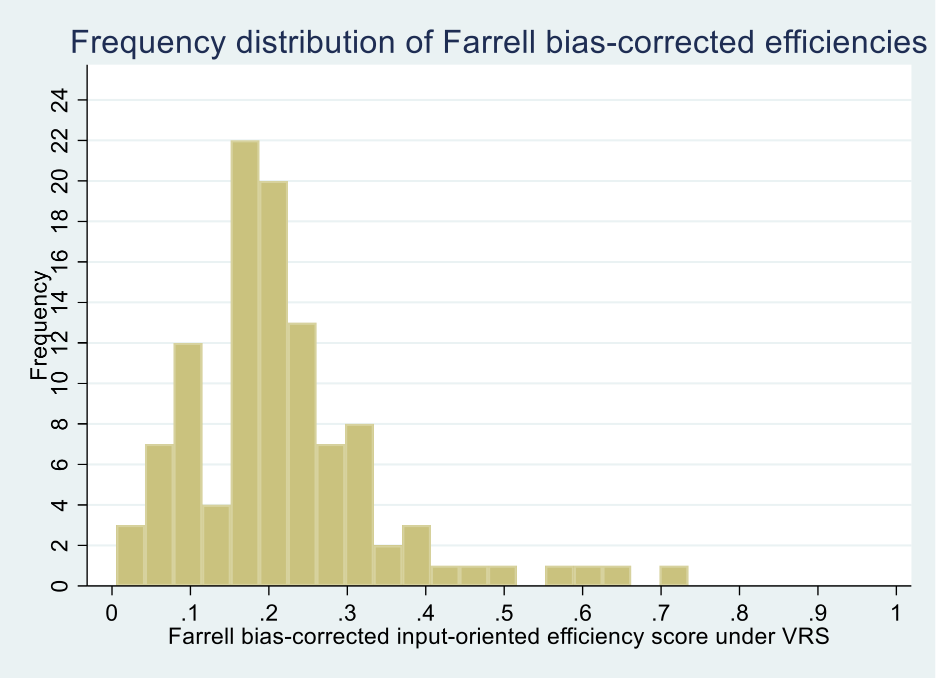

Figure 3. Histogram of bias-corrected Farrell efficiency scores

The histogram of bootstrap bias estimates (Figure 2) shows that the most frequent bias values lie between 0.1 and 0.4, confirming the presence of non-negligible bias in the initial DEA results. After correction (Figure 3), the majority of efficiency scores are below 0.4, reaffirming pervasive inefficiency across the sample.

Determinants of Inefficiency: Truncated Bootstrap Regression

In the second stage, I analyze the influence of farm- and farmer-specific variables on inefficiency using the truncated regression model embedded within the double bootstrap algorithm (Simar & Wilson, 2007). The dependent variable represents the bias-corrected inefficiency scores (1 − BCE) to maintain consistency with the original framework. Independent variables included *farm age*, *farm age squared*, *farmer's age*, *experience in saffron cultivation*, and *education level* (measured in years of schooling). All continuous variables were mean-centered before introducing the squared term to minimize multicollinearity.

Although some variables exhibit relatively high standard errors, particularly the constant term and education level, this is consistent with the truncated regression methodology and bootstrap approach (Simar & Wilson, 2007), which accounts for the two-stage estimation process and bias correction. The key variables of theoretical interest—farm age, farm age squared, and farming experience—maintain statistical significance at conventional levels ($p < 0.05$), indicating that the core relationships in the model are robust despite the precision limitations associated with the sample size and estimation technique.

The regression results reveal an inverted U-shaped relationship between farm age and efficiency. Initially, older farms exhibit higher efficiency, but beyond a threshold, efficiency declines. This pattern shows that as farms mature, accumulated managerial experience and soil adaptation initially improve performance, but over time, soil nutrient depletion and declining productivity may offset these gains. Similar patterns have been observed in other perennial crops (Colla & Rouphael, 2009).

The coefficient for farmers' age is negative but not statistically significant, suggesting that older farmers do not necessarily perform less efficiently after controlling for experience and other factors. Experience in saffron cultivation, however, has a strong and statistically significant positive impact on efficiency, underscoring the role of experiential learning and adaptation to local agronomic conditions. Conversely, education level does not exert a significant effect on efficiency, consistent with earlier findings suggesting that formal education alone may not directly translate into improved farm management efficiency in traditional or specialized crops like saffron.

The σ parameter represents the standard deviation of the inefficiency component within the stochastic frontier model. A value of 2.79 indicates substantial dispersion in inefficiency levels across the sampled saffron farms; that is, there is unobserved heterogeneity in production conditions and management practices that are not fully captured by the explanatory variables. This interpretation aligns with the stochastic frontier methodology, in which elevated σ values indicate greater variation in farm-level efficiency. The Wald χ^2 statistic ($\chi^2 = 16.13$, $p = 0.0065$) further corroborates the model's overall significance, showing that the included farm management variables collectively account for a meaningful portion of the efficiency variation among saffron producers in the study region.

Slack Analysis

In addition to the bias-corrected technical efficiency results, I performed an input slack analysis to identify sources of inefficiency across the regions. Input slacks represent the excess amounts of inputs used by inefficient decision-making units relative to the efficient frontier. Accordingly, higher slack values indicate greater potential for input reduction without affecting output levels. I consider four primary inputs: water consumption (m³), land area (ha), saffron corms (kg), and labor (person-days). The results are summarized in Table 5.

Table 5. Average input slacks across regions in the study area

Location	Observations	Water Slack ($m^3.ha^{-1}$)	Farm Size Slack (ha)	Corm Slack ($kg.ha^{-1}$)	Labor Slack (person-days.ha^{-1})
Central	43	963.30	3.80	463.82	25.81
Zaveh	36	807.01	2.60	324.76	15.13
Bayg	10	495.89	2.57	1112.61	13.07
Feyzabad	7	929.13	3.87	589.20	27.99
Kadkan	6	557.63	2.36	489.66	16.57
Rokh Plain	3	602.89	1.58	297.52	11.86
Other	3	592.32	4.49	418.19	27.62
Average	–	706.88	3.04	528.10	20.01

Note: Higher slack values indicate greater potential for input reduction (inefficiency).

The mean water slack implies that, on average, farmers could reduce their water consumption by 706.88 m³ per hectare without affecting yield. The central area shows the highest water slack (963.30 $m^3.ha^{-1}$), indicating significant water overuse relative to the efficiency frontier. In contrast, Bayg exhibits the lowest water slack (495.89 $m^3.ha^{-1}$), showing more efficient water use, due to limited irrigation availability. The average land (farm size) slack is 3.04 hectares, with Kadkan showing the lowest value (2.36 ha), showing that farms there operate closer to their optimal land utilization levels. By contrast, Feyzabad and other districts exhibit greater land slack, suggesting underutilized or fragmented land resources. Regarding biological inputs, the mean corm slack of 528.1 $kg.ha^{-1}$ indicates overuse of planting densities among many farmers. Bayg shows the highest corm slack (1112.6 $kg.ha^{-1}$), which may indicate excessive planting densities or poor corm management practices, whereas Rokh Plain demonstrates more efficient corm use (2,975 $kg.ha^{-1}$).

Labor slack averages 20 person-days.ha^{-1}, highlighting potential labor underutilization. Feyzabad exhibits the highest labor slack (about 28 person-days.ha^{-1}), possibly due to seasonal underemployment or inefficient labor allocation, while Rokh Plain has the lowest (about 12 person-days.ha^{-1}), showing tighter labor utilization and potentially higher mechanization.

Generally, findings show that inefficiency is input-specific and spatially heterogeneous. The results complement the bias-corrected efficiency estimates reported earlier (Sections 3.1–3.2) by showing that regions with higher slacks generally correspond to lower efficiency scores.

The observed patterns are consistent with previous studies on saffron efficiency in Iran. For example, Rastegaripour et al. (2025) found widespread overconsumption of inputs in saffron farms. Similarly, Saeidi et al. (2022) reported that optimizing input use significantly reduced production costs in Iranian saffron farms during the 2019–2020 season. Ramezani et al. (2022) also highlighted technical inefficiencies driven by excessive use of inputs, particularly water and corm density.

Key Findings

This paper contributes to the empirical literature on farm efficiency by showing that applying a bootstrap bias-correction to DEA scores substantially alters the interpretation of farmers' performance. Using the Simar & Wilson (2007) double-bootstrap algorithm (Algorithm 2), the bias-corrected estimates are markedly lower than the raw Farrell scores: the unadjusted mean Farrell score was ≈0.47, while the bias-corrected mean was ≈0.22. The magnitude of this adjustment underscores the potential for conventional DEA to produce overly optimistic performance assessments when sampling noise and small sample sizes are present. In the present study, we used a small sample size (108 DMUs). Implementing the double-bootstrap method provides a suitable corrective mechanism, reducing related statistical issues and securing the internal validity and reliability of the principal findings regarding efficiency scores and their determinants. In fact, these methodological concerns are well recognized in the literature and motivate the use of the double-bootstrap procedure for valid inference. This finding is methodologically consistent with the work of Simar & Wilson (2007) and aligns with empirical applications in agriculture, such as López-Penabad et al. (2020), who also reported significant reductions in average efficiency scores after bias correction. Importantly, the mean level of bias correction I observe is larger than that reported in some other saffron studies that did not adopt the same inference procedure. For example, recent studies of saffron producers in Gonabad and Ghaen report substantially higher mean technical efficiency (e.g., Ramezani et al., 2022; Mardani Najafabadi et al., 2023), which likely reflects differences in region, input/output specification, and the absence of the same bias-correction procedure in those studies. In fact, previous related studies have used conventional approaches, whereas the Simar & Wilson double-bootstrap procedure corrects for the inherent upward bias in DEA estimates. Consequently, the lower efficiency level reported here does not necessarily indicate poorer farm performance, but rather reflects a more statistically conservative and accurate estimation method. Furthermore, the observed differences can also be attributed to regional characteristics. Variations in soil fertility, water availability, local extension services, and predominant farming practices in the present study area, compared to other regions such as Ghaen or Gonabad, can lead to different baseline efficiency levels. Studies from other major producing countries, including India (Tariq, 2020) and Morocco (Lambarraa-Lehnhardt et al., 2022), also report differing efficiency scores, reflecting contrasts in agro-climatic zones, farm scale, technology adoption rates, and institutional support systems. For instance, different rainfall patterns or more developed cooperative structures can significantly alter the production frontier.

Despite the differences in efficiency levels, findings regarding the determinants of efficiency are consistent with the broader literature. The truncated bootstrap regression (Simar & Wilson, 2007) identifies a quadratic relationship between farm age and technical efficiency: farm age is positively associated with efficiency up to an inflection point, after which efficiency declines (an inverted-U pattern). This finding is consistent with agronomic evidence that some management gains accrue early in the life of a saffron stand, but that prolonged monocropping and dense corm planting can lead to declines in productivity (e.g., Ramezani et al., 2022; Colla & Rouphael, 2009).

I also find that practical farming experience (years of saffron cultivation) is strongly and positively associated with higher efficiency, whereas formal years of schooling are not statistically significant once experience and other covariates are controlled for. This pattern - a robust effect of experiential knowledge but mixed or weak effects of formal education - is reported in several agricultural efficiency studies (e.g., Ramezani et al., 2022) and likely reflects the importance of tacit, crop-specific skills and extension or training on the farm. I therefore recommend policies focused on hands-on training (farmer field workshops, demonstration plots, and peer-to-peer exchanges) rather than relying solely on formal education as a route to improved technical performance.

Finally, the slack analysis demonstrates pronounced spatial heterogeneity in input excesses. For instance, the central area shows the largest average water slack, while Bayg displays the smallest; Bayg also has the highest corm slack; Feyzabad records the greatest labor slack. These spatial patterns are consistent with other regional studies that document localized overconsumption of specific inputs (e.g., water, corms, fuel) and argue for place-based resource management (e.g., Balcombe et al., 2008). The heterogeneity I observed supports targeted interventions such as precision irrigation in high-water-slack zones, corm-density training in areas with high corm slack, and labor-use optimization where labor is under-utilized.

Implications for Policy and Practice

Given that experience is the strongest predictor of efficiency, targeted extension programs should prioritize hands-on training, farmer field workshops, and knowledge-sharing networks. These programs can help bridge the gap between novice and veteran farmers by disseminating proven techniques in irrigation management, labor allocation, and optimal corm density.

The slack analysis demonstrated notable spatial heterogeneity in input utilization. For instance, the Central area exhibited high-water slack, reflecting inefficient irrigation practices, while Bayg faced potential water scarcity. Similarly, Feyzabad showed labor surpluses, and Bayg recorded the highest corm slack. These patterns imply that a one-size-fits-all policy approach would be ineffective. Region-specific interventions—such as introducing drip irrigation in over-irrigated areas or optimizing planting densities in areas with corm overuse—can enhance efficiency while conserving scarce resources.

Modern technologies such as precision irrigation systems and mechanized harvesting can substantially reduce inefficiencies. However, their adoption is often hindered by credit constraints. Policymakers should therefore expand access to affordable financing through specialized agricultural credit lines, cooperative lending schemes, and public–private partnerships that support innovation in smallholder systems. Enhanced access to finance will empower farmers to invest in efficiency-enhancing inputs and sustainable production methods.

The observed decline in efficiency with increasing farm age signals the risk of soil degradation from prolonged monocropping.

Implementing crop rotation, organic matter replenishment, and integrated pest management programs can mitigate these effects. Encouraging organic and eco-friendly production methods would not only maintain soil fertility but also improve market competitiveness, aligning with the growing global demand for sustainably produced saffron.

Although formal education was not directly linked to production efficiency, it may indirectly improve farmers' market participation and negotiation power. Training programs on marketing skills, contract farming, and e-commerce platforms can help farmers capture greater value within the supply chain.

In summary, this study demonstrates that technical efficiency in saffron production is shaped by both managerial factors (experience, farm age) and contextual conditions (regional resource endowments). Integrating bias-corrected efficiency measurement with locally tailored interventions can provide a more accurate basis for policymaking and enhance the long-term sustainability of Iran's saffron sector.

Finally, it should be noted that the efficiency outcomes discussed above are conditional on the set of explanatory variables included in the analysis. Due to data availability constraints, the second-stage regression focused primarily on farm-level managerial characteristics, while potentially influential institutional, infrastructural, and natural factors could not be explicitly incorporated. Variables such as access to agricultural credit, membership in cooperatives, proximity to all-season roads and major markets, soil quality, rainfall patterns, and irrigation water quality are known to shape farmers' production environments and may significantly affect technical efficiency. The absence of these variables implies that the estimated effects of experience, farm age, and education should be interpreted as partial effects, conditional on unobserved heterogeneity in broader contextual conditions. Future research could address this limitation by integrating geo-referenced environmental data and institutional indicators within conditional or meta-frontier efficiency frameworks to provide a more comprehensive understanding of efficiency drivers.

Acknowledgement

This work has been financially supported by the University of Torbat Heydarieh. The grant number was UTH: 1404.09.04-278. The author would like to express sincere gratitude to Moein Tosan for his valuable assistance in data collection.

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