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Production Cost Efficiency in Indonesian Soybean Farming: Evidence from a Stochastic Frontier Analysis

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Abstract

The widening gap between domestic soybean demand and local production has raised concerns over the economic sustainability of soybean farming in Indonesia. This study examines the determinants of production cost, cost efficiency, and cost inefficiency in soybean farming in Central Java Province, focusing on Grobogan and Blora Regencies. Using farm-level data from 200 soybean farmers, the study applies a stochastic cost frontier model and a second-stage regression of predicted cost inefficiency. The results show that output and labor wage significantly increase total production cost, while fertilizer price is weakly significant and seed price is not statistically significant. The mean cost efficiency score is 0.8904, indicating that farmers could reduce production costs by approximately 10.96 percent while maintaining the same output and input-price conditions. The second-stage results show that planting frequency and irrigation access are significantly associated with lower cost inefficiency, while age, farming experience, and education are not statistically significant. These findings suggest that cost inefficiency in soybean farming is more closely related to production routines and water access than to general farmer characteristics. Policy support should therefore focus on improving input timing, labor management, irrigation access, and repeated production learning among smallholder soybean farmers.

Keywords: cost efficiency, inefficiency, soybean, farming, stochastic frontier

JEL Classification: Q12, D24, C51, Q18

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1. INTRODUCTION

Soybeans are one of Indonesia's main agricultural commodities, particularly for producing tofu, tempeh, and various soybean-based products. Despite the government's efforts to increase soybean production as part of its program to strengthen food security and reduce import dependence, data from the Directorate General of Food Security show that soybean production in Indonesia a significant decline between 2015 and 2019. The sharpest drop occurred in 2017, reaching 37,33% (Directorate General of Food Crops, 2020). One of the main obstacles contributing to the downward trend in productivity occurred in 2020, when Indonesia's soybean yield reached only 14,88 quintals per hectare, far below the global benchmark target of 29 quintals per hectare. This data indicates that Indonesia is lagging behind other countries such as Turkey, which achieved 43,55 quintals per hectare, followed by the United States with 33,44 quintals per hectare, and Brazil with 31,14 quintals per hectare (Directorate General of Food Crops, 2020).

These productivity gaps hinder Indonesia's capacity to achieve self-sufficiency and exacerbate its structural dependence on imports, with over 90% of domestic soybean demand fulfilled through foreign supply channels (Purnamasari et al., 2023). Such disparities reflect deeper inefficiencies in the domestic production system, including limited adoption of high-yielding varieties (Krisdiana et al., 2021), suboptimal land use and input management (Geo et al., 2020), and persistent structural and institutional constraints (Sayaka et al., 2021). The volatility of global supply chains, geopolitical tensions, and climate-induced risks further exacerbate the situation, reinforcing the urgency of enhancing domestic productivity (Hisjam et al., 2020).

Based on data from the (Ministry of Agriculture, 2023), ten provinces serve as Indonesia's main soybean-producing regions, collectively contributing 87.71% to the national output. East Java remains the leading producer (27.96%), followed by Central Java (21.86%) and West Java (16.18%). While Central Java continues to hold a strategic position in the national soybean supply chain, owing to the sustained use of local varieties and relatively consistent planting intensity, the province has experienced notable output fluctuations, echoing a nationwide pattern of production instability. This stagnation underscores persistent structural inefficiencies, particularly in key regions like Central Java, where constraints such as limited mechanization, fragmented landholdings, and input-related challenges continue to suppress yield potential (Krisdiana et al., 2021; Purnamasari et al., 2023).

Wang et al. (2024) stated that total production cost serves as a key indicator in measuring cost efficiency. The higher the output achieved at a relatively constant cost, the more efficient the production process becomes. However, soybean production efficiency at the farmer level does not always operate uniformly. This condition is influenced by variations in input prices and differences in land characteristics across regions and among farmers. Viana et al. (2022) emphasized that agricultural land system and input allocation directly affect the resilience and sustainability of food systems. Similarly, Tao et al. (2023) argued that efficiency and resilience must be addressed in an integrated manner, particularly in ecologically vulnerable areas where production system are increasingly exposed to clime shock, resource limitations and market fluctuations. In the context, strengthening the use of soybean production resource becomes essential, not only to enhance microeconomic outcomes in Central Java Province but also to ensure equitable, efficient, and sustainable soybean food availability (Baffoe et al., 2021; Bizikova et al., 2020).

Previous studies investigating cost efficiency in agriculture such as those by Akhilomen et al. (2015) and Antriyandarti (2015) demonstrated that technical efficiency in the agricultural sector in Southeast Sulawesi is significantly influenced by land use, seed quality, fertilizer, and labor input. Meanwhile, Purnamasari et al. (2023) found that government policy interventions, such as input subsidies under the Upsus Pajale program, had no significant impact on improving soybean production efficiency.

These differing conditions cause variation in production cost structures among farmers, both in terms of fixed costs such as land rent and variable costs such as labor, fertilizer, and pesticides. Moreover, external factors such as price fluctuations, the availability of seasonal labor, and changes in land rental rates further widen efficiency gaps between regions. In other words, two farmers incurring similar production costs may not necessarily produce the same output, depending on land conditions and input-use effectiveness.

This study is theoretically grounded in the stochastic frontier analysis (SFA) framework, initially introduced by Aigner et al. (1977) and subsequently developed by Battese & Coelli (1992, 1995). This framework incorporates inefficiency effects within the stochastic production frontier, allowing for the simultaneous estimation of technical efficiency while accounting for random disturbances that commonly affect agricultural production systems. The approach is further strengthened by the principle of production–cost duality, as articulated by Coelli et al. (2005), enabling the derivation of a cost function from the underlying production function. Through this transformation, cost efficiency can be assessed by examining the extent to which producers minimize input costs relative to a best-practice benchmark under similar production conditions. The stochastic frontier model is particularly suitable for capturing variability in producer behavior and environmental conditions characteristic of smallholder farming systems in developing countries.

While previous studies have examined technical and allocative efficiency among Indonesian farms (Kagona, 2021; A. B. Setiawan & Bowo, 2017; I. Setiawan et al., 2019; Sulaiman et al., 2019), evidence on soybean farming remains more limited from the cost side, particularly at the farm level in Grobogan and Blora. Existing studies on soybean farming have commonly focused on financial feasibility, input-output relationships, gross margin analysis, cost-benefit ratios, or general farm performance (Ayalew et al., 2018; Krisdiana et al., 2021; Purdy & Langemeier, 2020; Sultan et al., 2021). These approaches are useful for evaluating profitability and production performance, but they do not fully explain whether farmers are operating close to the minimum-cost frontier or why some farmers deviate more from that frontier than others.

This distinction is important because farmers with similar output levels may still face different cost burdens depending on input prices, labor arrangements, production routines, and access to irrigation. Therefore, estimating cost efficiency alone is not sufficient. It is also necessary to identify farm-level conditions associated with cost inefficiency. This study applies a stochastic cost frontier model to estimate production cost efficiency among soybean farmers in Grobogan and Blora. The analysis is extended by estimating a second-stage inefficiency model using irrigation access, planting frequency, age, farming experience, and education as explanatory variables. By combining cost frontier estimation with an inefficiency determinant model, this study contributes empirical evidence on both the main cost drivers and the farm-management conditions associated with deviations from the minimum-cost frontier in smallholder soybean farming.

2. RESEARCH METHOD

Soybean production in Indonesia is predominantly concentrated on Java Island, with Central Java Province recognized as the second-largest producer at the national level. In 2022, the province recorded a total soybean production of 106.09 thousand tons, supported by the country's largest harvested area for soybean cultivation (Ministry of Agriculture, 2023). Given its strategic role, Central Java serves as a representative region for examining the dynamics of soybean cultivation.

This study specifically focuses on the Grobogan and Blora Regencies, among the key production zones within the province. These locations were selected based on their consistent planting activities, comparable agroecological conditions, and homogeneity in farming practices. These characteristics make both regencies suitable for assessing cost efficiency and formulating evidence-based recommendations to improve soybean farming performance.

The population of this study comprises soybean farmers located in the Grobogan and Blora Regencies. Farmers in both regions exhibit relatively homogeneous characteristics in terms of input usage, production techniques, and daily cultivation practices. According to data from the Department of Agriculture of Central Java Province, the number of soybean farmers in Blora Regency in 2021 was recorded at 20,968 individuals, while Grobogan Regency accounted for 269,731 individuals. Accordingly, the total population targeted in this study amounts to 290,699 soybean farmers. Based on the known cumulative population of soybean farmers in both Grobogan and Blora Regencies, the sample size was determined using Slovin's formula (Lubis, 2018), with a margin of error of 5%, as follows:

$$\text{Sample Size (n)} = N / (1 + Ne^2)$$
$$= 290{,}699 / (1 + 290{,}699 \times 0.0025)$$
$$= 290{,}699 / 1{,}454.495 \approx 199.86 \approx 200 \text{ respondents (rounded)}$$

The sample proportion for the Grobogan and Blora Regencies was determined based on the percentage of the farmer population in each district. Grobogan Regency, with a farming population of 269,731, accounts for approximately 92.8% (rounded to 93%) of the total population under study, whereas Blora Regency, with 20,968 farmers, represents around 7.2% (rounded to 7%). Accordingly, out of a total research sample of 200 respondents, 186 farmers were selected from the Grobogan Regency and 14 from the Blora Regency, reflecting their respective population proportions. The operational definitions of the variables employed in this study are presented in Table 1 below.

Table 1. The Variable Definitions

No	Variables	Definition	Unit
1	Total production cost	The total cost of all inputs used during one planting period, reflecting both the unit cost and quantity of each input used	IDR
2	Fertilizer price	The weighted average price of fertilizer used during one planting period, calculated from total fertilizer expenditure divided by the total quantity of fertilizer used.	IDR/Kg
3	Labor wage	The average wage rate for farm labor during one planting period, calculated from total labor expenditure divided by total labor use.	IDR/ person
4	Seed price	The average price of soybean seed used during one planting period, calculated from total seed expenditure divided by the quantity of seed used.	IDR/Kg
5	Production	Total production of soybeans	Kg
Ineficiency analysis			
1	Irrigation	Dummy variable: 1 if the farmer has access to irrigation water during the planting season, 0 otherwise	Dummy (0/1)
2	Age	Age of the farmer at the time of survey	Years
3	Farming Experience	Number of years the farmer has been cultivating soybeans	Years
4	Education	Number of years of formal education completed by the farmer	Years
5	Planting Frequency	Number of soybean planting cycles undertaken by the farmer in one calendar year	Times/ 3 year

Source: Processed Data, 2026

The stochastic frontier production function for measuring cost efficiency in producers compiled by Farrell (1957) is as follows:

$$CE_i = \ln \frac{TC\,(xi,wi)}{C\,(yi,wi)} = \ln \text{TC}\,(x_i + y_i) - \ln \text{C}\,(y_i, w_i) \geq 0 \quad (1)$$

Using first-order conditions, the optimal total cost is TC $= \sum l\, w_j x_j^* = \lambda\ \eta\ y$, where $\eta = \sum_j \eta_j$. Taking the total derivation of the production function, it shows that η is a measure of economic return to scale (Battese & Coelli, 1988). The cost efficiency estimation model derived from equation 1 can be written in the equation below:

$$\text{LnCost} = \Upsilon_0 + \Upsilon_1 \ln\text{Fertilizer} + \Upsilon_2 \ln\text{SeedCost} + \Upsilon_3 \ln\text{LaborWages} + \Upsilon_4 \ln\text{Production} + v_i + u_i \quad (2)$$

The cost efficiency equation of the frontier stochastic production function produces two error components, namely *vi* which is a random error, and ui which is a cost inefficiency error. The residuals of the frontier stochastic efficiency model will produce an estimated efficiency value.

This study estimates cost efficiency using a stochastic frontier model. In the cost frontier framework, observed production cost is modeled as a function of output and input prices, while the error term is decomposed into random noise and non-negative cost inefficiency. After estimating the stochastic cost frontier, the predicted cost inefficiency term ($\hat{u}_i$)was obtained for each farmer. To identify the factors associated with cost inefficiency, this study estimates a second-stage regression model in which the predicted inefficiency score is regressed on farmer and farm-management characteristics. The second-stage model is specified as follows:

$$\hat{u}_i = \delta_0 + \delta_1 \mathrm{Irrigation}_i + \delta_2 \mathrm{Age}_i + \delta_3 \mathrm{Experience}_i + \delta_4 \mathrm{Education}_i + \delta_5 \mathrm{PlantingFrequency}_i + \varepsilon_i \quad (3)$$

The model is used to identify variables associated with higher or lower cost inefficiency. Since the data are cross-sectional, the estimated coefficients are interpreted as associations rather than causal effects.

3.1 RESULTS AND DISCUSSIONS

This study estimates the stochastic cost frontier using output, fertilizer price, seed price, and labor wage as explanatory variables. Land cost and pesticide price are not included in the price vector due to data limitations and lack of cross-sectional variation, although they remain part of the observed production cost where applicable. Based on observations made to 200 farmers, data on the descriptive statistics costs for each input used in the operational process of soybean production are shown in Table 2 as follows:

Table 2. Descriptive Statistics of Input Cost Components

Variable	Unit	Mean	Std. Dev.	Min – Max
Total Cost (TC)	IDR/Farmer	1,138,141	436,877	582,500 – 3,162,820
Output (y)	Kg	615	291	200 – 1,836
Fertilizer Price (w_1)	IDR/Kg	2,812	287	2,100 – 5,045
Seed Price (w_2)	IDR/Kg	15,100	724	13,333 – 17,500
Labor Wage (w_3)	IDR/Person	40,745	6,657	17,778 – 60,000

N = 200. Input prices represent weighted average price per unit paid by each farmer during one planting season.

Source: Primary data processed, 2026

Average total production cost per farmer stood at IDR 1,138,141 per planting season, with a standard deviation of IDR 436,877, reflecting meaningful variation in farm-level expenditure driven primarily by differences in cultivated area and output scale. Average soybean output was 615 kg per farmer, ranging from 200 to 1,836 kg, consistent with the smallholder scale typical of the study area.

Input prices exhibit relatively low variation across farmers. Fertilizer price averaged IDR 2,812 per kg, seed price averaged IDR 15,100 per kg, and labor wage averaged IDR 40,745 per person. The limited price dispersion reflects the homogeneous market structure in both regencies, where farmers source inputs from a small number of local suppliers operating under similar pricing conditions. This characteristic is important for interpreting the efficiency results reported in subsequent sections.

The variation in farmers' management capacity contributes to differences in the level of cost efficiency achieved. Economic efficiency also referred to as cost efficiency reflects a farmer's ability to minimize production costs while maintaining a given output level. The degree of economic efficiency is determined by the ratio of the marginal value product to the marginal cost for each input. Maximum efficiency is achieved when this ratio equals one, indicating that input use is economically optimal. Input costs are measured using prevailing unit prices in the study area.

This study estimates cost efficiency using the Maximum Likelihood Estimation (MLE) approach, with cost variables converted into a uniform currency (IDR). The estimators used in the cost efficiency model include yield, fertilizer price, seed price, and labor wages. Table 3 presents the results of the cost efficiency estimation based on the stochastic frontier regression function.

Table 3. Stochastic Frontier Analysis for Cost Efficiency

Variable	Coefficient	Standards Error	Prob
LnYield	0.6267	0.0306	0.000***
LnFertilizer	0.2537	0.1486	0.088*
LnSeed	0.1718	0.2494	0.491
LnLabor	0.2655	0.0686	0.000***
Constant	3.3285	2.8235	0.238
	Value		Value
Number of observations	200	Lambda	1.0153
Sigma v	0.1411	Log-likelihood	76.408
Sigma u	0.1432		
Sigma 2	0.0404		

Note: ***significance of > 1%; ** significance > 5%; *significance of >10%.

Source: Primary data processed, 2026

The stochastic cost frontier estimation shows positive coefficients for all explanatory variables, although not all are statistically significant. Output and labor wage are significant at the one-percent level and therefore represent the main cost drivers in soybean farming. Fertilizer price is positive but only weakly significant, while seed price does not show a statistically meaningful effect. This indicates that production cost differences are driven more by output scale and labor wage than by seed price variation.

Among the input price variables, labor wage has the strongest and most statistically robust association with total production cost, where an increase in labor wages is associated with an increase in total production cost, and is significant at the 1% level. Fertilizer costs follow closely, with a coefficient of 0.2537, indicating that an increase in fertilizer expenditure is associated with raises in production cost. Labor wage is statistically significant at the 1% level, reflecting the substantial role of hired labor in soybean production costs across the sample. Seed price, while positively signed, does not reach conventional significance levels, consistent with the limited price variation observed across farmers in the study area. These findings are broadly consistent with those of Antriyandarti (2015) and Maurice et al. (2014), who highlight the critical role of input expenditure in determining production cost dynamics. Maurice et al. (2014) and Siagian and Widyono (2020), reported an insignificant effect of seed costs, the present study identifies an insignificant impact of seed price on total cost.

The stochastic cost frontier yields sigma_v = 0.141 and sigma_u = 0.143, with lambda = 1.015. The near-unity lambda indicates that the estimated magnitudes of random noise and inefficiency are relatively similar. This suggests that soybean production costs in the study area are shaped not only by farm-level allocation decisions, but also by random disturbances that farmers cannot fully control. However, the likelihood ratio test (chibar^2(01) = 0.29, p = 0.295) does not reject the null hypothesis of no inefficiency component at conventional significance levels. Therefore, the cost efficiency scores should be interpreted cautiously as indicative measures rather than as strong evidence of systematic inefficiency across all farmers. The output coefficient is below unity, indicating that total cost increases less than proportionally as output rises. This pattern suggests the presence of cost economies in soybean farming, although the interpretation should be treated carefully because the model uses a restricted set of observed input prices.

Mean cost efficiency across 200 farmers is 0.890 (median = 0.900), implying that farmers on average operate approximately 11 percent above the minimum cost frontier. The interquartile range spans 0.863 to 0.923, confirming a narrow but meaningful efficiency distribution consistent with the homogeneous production structure of soybean farming in Grobogan and Blora.

The use of a stochastic cost frontier allows this study to distinguish random shocks from deviations associated with cost inefficiency. This is useful in the context of smallholder soybean farming, where production costs are influenced not only by input prices and output scale, but also by field-level management conditions and uncontrollable disturbances, as proposed by Battese and Coelli (1995). This framework allows for the decomposition of deviations from optimal cost into inefficiency effects and random errors, providing a more comprehensive understanding of cost behavior in heterogeneous agricultural settings. The model demonstrates statistical robustness, as evidenced by the log-likelihood and Wald chi-square values, confirming its suitability for analyzing smallholder soybean farming systems. The significance of input variables such as labor wages, fertilizer price, and yield supports the theoretical assertion that production costs are a function of input application and managerial decisions under resource constraints. These results align with efficiency modeling frameworks proposed by Coelli et al. (2005) and reaffirm the relevance of stochastic frontier theory in developing country contexts characterized by input variability and environmental uncertainty (Roessali et al., 2019; Sayaka et al., 2021).

Empirical findings underscore the dominant role of labor and fertilizer prices in determining soybean production costs, consistent with Antriyandarti (2015) and Milotić & Hoffmann (2016) who identified these inputs as primary cost drivers in food crop cultivation. Seed price, by contrast, does not significantly influence total production cost in this study, aligning with (Milotić & Hoffmann, 2016; Siagian & Soetjipto, 2020). The estimated mean cost efficiency of 0.890 suggests that soybean farming in Grobogan and Blora is relatively efficient, though an average gap of approximately 11% from the minimum cost frontier indicates room for improvement through better input allocation at the farm level. Rinaldi et al. (2023) reported similar findings, where efficient farming operations showed moderate inefficiencies, often due to institutional gaps and suboptimal input allocation strategies. This pattern aligns with Setiadi et al. (2021), who identified barriers such as discrepancies in farmer decision-making and access to inputs as obstacles to achieving full efficiency.

Purnamasari et al. (2023) argue that despite government support through programs such as *Upsus Pajale*, inefficiencies persist due to inconsistent adoption of input recommendations and inadequate monitoring. The relatively narrow cost efficiency distribution observed in this study interquartile range 0.863 to 0.923, suggests a uniform production environment where standardized efficiency-enhancement strategies, particularly around fertilizer use and labor scheduling, could yield meaningful aggregate gains.

Integrating stochastic frontier theory with localized empirical data makes a valuable contribution to theoretical refinement and practical application in agricultural economics. This study reinforces the relevance of frontier analysis in assessing cost efficiency within smallholder systems and emphasizes the importance of regional context in shaping cost structures. The case of Central Java, specifically Grobogan and Blora, demonstrates that uniformity in agroecological conditions does not necessarily result in homogeneity in cost efficiency. It highlights the influence of farmer behavior, input access, and operational scale. These findings align with Sahuri et al. (2023), who noted the heterogeneous nature of efficiency across different farmer typologies, even in similar biophysical environments. Moreover, the model serves as a methodological reference for future studies seeking to expand frontier cost analysis into broader value chain dimensions, such as transaction costs, institutional dynamics, and market access. Strengthening the theoretical and empirical foundation for efficiency assessment in this manner is crucial for designing more adaptive, inclusive, and region-specific agricultural development strategies. Building on the frontier estimates, farm-level cost efficiency scores were derived for all 200 respondents. Table 4 summarizes the distribution of these scores across the sample.

Table 4. Cost Efficiency Estimation of Soybean Farming in Central Java, Indonesia

Efficiency Range	Cost Efficiency (CE)		Efficiency Level	
	Freq	Percentage (%)	Statistical Descriptive	Freq
0.00 – 0.69	0	0.00	Average	0.8904
0.70 – 0,79	6	3.00	Minimum	0.7607
0.80 – 0.89	95	47.50	Maximum	0.9551
0.90 – 0.99	99	49.50	Standard deviation	0.0410
Total	200	100.00		

Source: Primary data processed, 2026

The mean cost efficiency score is 0.8904, indicating that farmers could reduce production costs by about 10.96% while maintaining the same output and input-price conditions. The distribution is relatively concentrated near the frontier, with 99 of 200 farmers scoring between 0.90 and 0.99, while only 6 farmers fall below 0.80. This pattern suggests that cost inefficiency is not widespread across the sample but concentrated among a limited number of farmers with weaker cost control. For these farmers, the relevant policy issue is not a broad input subsidy response, but more precise farm-level guidance on input dosage, labor use, and timing of expenditure during the planting seasons.

Table 4 also illustrates the total economic losses incurred by soybean farms in Central Java due to cost inefficiency. The difference between the observed variable cost and the cost frontier represents excess costs borne by these farms. Research by Ho et al. (2023) suggests that it is more cost-efficient to enhance productivity by optimizing the use of existing technologies rather than introducing new ones. Thus, farmers should focus on minimizing cost inefficiencies to improve production profits.

These results indicate that farms could achieve greater cost and efficiency by improving technical efficiency, particularly by reducing labor, land use, and fertilizers. If the sample farms in this study accurately represents the broader population of soybean farms in Central Java, the findings suggest potential improvements in cost and efficiency without significant policy intervention. For example, technical training programs designed to enhance farmers' technical efficiency could significantly boost performance in soybean farming. Furthermore, removing input subsidies could encourage more efficient resource use Siagian & Soetjipto (2020). In line with these findings, inefficiency models suggest that targeted field extension programs and production skills training could reduce inefficiencies among farmers (Thanh Nguyen et al., 2012). These findings suggest that the efficiency gap is relatively modest but still economically relevant.

The estimated coefficients show that output and labor wage are the main cost drivers, both significant at the one-percent level. Fertilizer price is positive but only weakly significant, whereas seed price is statistically insignificant. The coefficient of output is below one, suggesting that total cost rises less than proportionally with output. This points to cost economies in soybean farming rather than a purely linear cost response. Therefore, the efficiency issue should not be interpreted narrowly as excessive input use. It is more accurately understood as a problem of input allocation, labor management, and cost control under smallholder production conditions. Similar findings were reported by Jiang & Sharp (2014) in their study of cost efficiency in dairy farming in New Zealand, where decreasing returns to scale were observed. Furthermore, Jiang's research confirmed significant associations between inefficiency and farm characteristics, particularly capital intensity, livestock quality, and farm size.

These findings highlight the significant role of input costs, it aligns with studies on cost efficiency that suggest larger or better-resourced farms tend to operate more efficiently (Aigner et al., 1977). Furthermore, increasing income leads to reduced input allocations supporting the idea that higher-income farmers are more likely to invest in efficiency-enhancing technologies. In contrast, lower-income farmers often experience inefficiency due to limited access to resources (Aji et al., 2023).

To address the possibility that cost inefficiency is shaped by farm-level characteristics, a second-stage OLS regression was estimated using the predicted inefficiency score ($\hat{u}_i$)from the stochastic frontier model as the dependent variable. The explanatory variables include irrigation access, age, farming experience, education, and planting frequency. The purpose of this model is not to establish causal effects, but to identify farmer and management characteristics associated with deviations from the minimum-cost frontier. Table 5 presents the results of the second-stage OLS regression, estimating the determinants of predicted cost inefficiency across the 200 sampled farmers.

Table 5 Second-Stage OLS: Determinants of Cost Inefficiency

Variable	Coefficient	Std. Error	t-stat
Irrigation	−0.0323	0.0153	−2.11**
Age	−0.0002	0.0005	−0.38
Farming Experience	−0.0002	0.0004	−0.47
Education	−0.0013	0.0015	−0.87
Planting Frequency	−0.0312	0.0076	−4.12***
Constant	0.1676	0.0257	6.52
R^2	*0.1135*	F (5,194)	4.97
Adj. R^2	0.0907	Prob > F	0.0003

Dependent variable: predicted inefficiency score ($\hat{u}$). **p<0.05; ***p<0.01.

Source: Primary data processed, 2026

Two variables are associated with lower cost inefficiency. Planting frequency has the strongest and most precise coefficient. Farmers who plant soybeans more often within a year tend to show lower inefficiency scores. This pattern is consistent with a learning-by-doing mechanism: repeated planting cycles may help farmers become more familiar with input timing, labor needs, and field-level cost control. The result should not be read as evidence that planting frequency alone causes efficiency gains, but it does suggest that routine production experience matters in explaining why some farmers operate closer to the cost frontier.

Irrigation access is also negatively associated with cost inefficiency. Farmers with irrigation tend to face lower inefficiency, which is plausible because water availability makes crop management less uncertain. Under more stable water conditions, farmers may have less need for corrective spending during the season, especially on labor and crop maintenance. In contrast, rainfed plots are more exposed to timing risks, which can make input use less predictable and more costly.

Age, farming experience, and education are not statistically significant in this model. This does not mean that these characteristics are unimportant in all soybean farming contexts. A more cautious interpretation is that, in this sample, their effects are not strong enough to explain differences in cost inefficiency after accounting for planting frequency and irrigation. The explanatory power of the model is modest, so the second-stage results should be interpreted as indicative patterns rather than a complete explanation of inefficiency differences among farmers.

4. CONCLUSION

The results show that output and labor wage are the main drivers of production cost, both significant at the one-percent level. Fertilizer price has a positive but weakly significant effect, while seed price does not show a statistically significant effect. These findings indicate that cost variation among soybean farmers is mainly shaped by output scale and labor-related expenses, whereas seed price variation plays a limited role in explaining differences in total production cost.

The estimated mean cost efficiency score is 0.8904, suggesting that farmers could reduce production costs by approximately 10.96% while maintaining the same output and input-price conditions. The efficiency distribution is relatively concentrated near the frontier, indicating that severe cost inefficiency is not widespread across the sample. However, the remaining inefficiency gap remains relevant in a smallholder farming context, where even moderate excess costs can affect farm profitability.

The second-stage inefficiency analysis shows that planting frequency and irrigation access are significantly associated with lower cost inefficiency. Farmers who plant soybeans more frequently tend to operate closer to the minimum-cost frontier, suggesting the role of routine production experience and learning-by-doing in improving cost control. Irrigation access is also associated with lower inefficiency, indicating that reliable water availability helps farmers manage input timing and production activities more predictably. In contrast, age, farming experience, and education are not statistically significant in the second-stage model. This suggests that, in this sample, specific production routines and water access explain cost inefficiency more clearly than general farmer characteristics.

The policy implication is that improving soybean farming efficiency should not rely only on broad input subsidy schemes. More targeted support is needed, particularly in labor scheduling, fertilizer timing, planting-cycle management, and irrigation-based production planning. Extension programs should prioritize farmers with lower efficiency scores and those operating under rainfed conditions, since these groups are more likely to experience avoidable deviations from the minimum-cost frontier. Future studies could improve this analysis by using panel data, richer land-quality indicators, and a one-step inefficiency model to better capture the dynamic determinants of cost inefficiency.

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