

TECHNICAL EFFICIENCY AND BANK CREDIT IN INDONESIAN RICE FARMING

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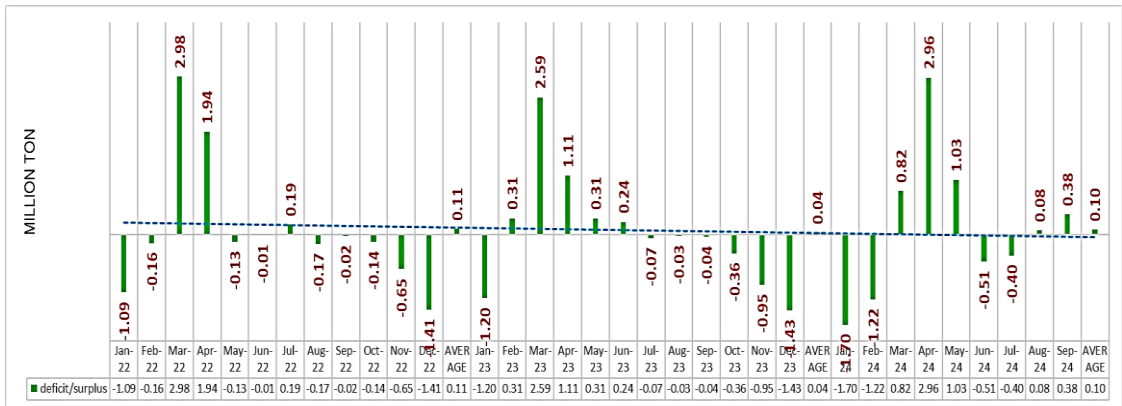
ABSTRACT

Rice farming in Indonesia faces high input costs and limited access to capital, increasing reliance on external financing. Despite the availability of bank credit, uptake among farmers remains low. This study assessed the impact of bank credit on the technical efficiency (TE) of rice farming, using 2024 survey data from 283 farmers across four provinces. Propensity Score Matching (PSM) and Stochastic Meta-Frontier (SC-SMF) models were employed to control for selection bias and technological differences. The Generalized Likelihood Ratio (GLR) test favored the *transcendental logarithmic* over the Cobb-Douglas production function, confirming heterogeneity in production technologies. Results showed that conventional models overestimated TE due to unobserved bias, while the SC-SMF model provided a more accurate benchmark. Using SC-SMF, credit users exhibited significantly higher TE (67.06%) than non-users (58.68%), indicating that credit access improved efficiency. However, both groups remained inefficient, with room for improvement of 32.94% and 41.32%, respectively. Findings suggest that expanding credit access can enhance productivity by optimizing input use.

Key words: formal credit, propensity score matching, stochastic meta-frontier, technical efficiency

INTRODUCTION

Rice is a strategic commodity in Indonesia, serving as the staple food for over 90% of the population, projected to exceed 280 million in 2024. Ensuring rice self-sufficiency is therefore central to national food security policy. Despite recent annual production surpluses, periodic monthly deficits continue to necessitate rice imports, highlighting ongoing challenges in achieving sustainable self-sufficiency. Fluctuations in deficits and surpluses were observed based on monthly rice consumption and production data from 2022 to 2024. However, on an annual average, surpluses of 0.11 million tons, 0.04 million tons, and 0.10 million tons were recorded in 2022, 2023, and 2024, respectively (Fig. 1).



inputs have driven up production costs, while labor shortages and generational renewal issues have further compounded the problem, with labor alone accounting for over 40% of total farming expenses (Suprehatin et al. 2024). Environmental challenges such as droughts, floods, shifting rainfall patterns, and pest outbreaks also continue to hinder productivity. These challenges emphasize the role of financial capital as a key enabling factor in achieving efficiency gains.

According to the Agricultural Household Model (Singh et al. 1986), farm households simultaneously make production, consumption, and labor allocation decisions subject to liquidity and credit constraints. Limited access to credit restricts their ability to purchase inputs or adopt new technologies, leading to suboptimal input combinations and lower productivity. Conversely, adequate access to credit relaxes these liquidity constraints, enabling farmers to move closer to the production frontier, thereby enhancing technical efficiency. This mechanism reflects the production approach to credit, where credit functions as a credit as funding or facilitating optimal use of production input that shifts the isocost line outward, allowing farmers to reach higher isoquants (Debertin 2012). Credit as a constraint-relaxing financial factor that eases liquidity limitations, shifts the isocost line outward, and expands the feasible input set.

Although the government has promoted agricultural credit programs such as KUR (Kredit Usaha Rakyat) and KPEN-RP, agricultural credit has remained below 8% of total national credit disbursement since 2000, despite exceeding IDR 400 trillion in nominal terms in 2022 (OJK 2025a). More broadly, credit access in Indonesia exhibits a dual structure in which informal sources, such as family networks, traders, and moneylenders, remain dominant, particularly in rural areas, while access to formal credit through commercial banks is still limited. Recent evidence shows that a significant proportion of borrowing still occurs outside the formal financial system: around 71% of borrowers rely on informal or semi-formal sources, with nearly 60% borrowing from family or friends, while only about 13% access credit through commercial banks. Similarly, informal and semi-formal providers account for roughly 60% of total loan access, highlighting the continued dominance of non-bank financing channels (OJK 2025b).

This study focuses on commercial bank credit because commercial banks are the primary providers of formal finance, the main channel for government lending programs, and operate under standardized regulatory and reporting frameworks that ensure data consistency. Moreover, commercial bank lending is central to monetary transmission and financial system stability, making it especially relevant for policy analysis. Other formal institutions, including rural banks, cooperatives, and microfinance institutions, play complementary roles but differ in scale, regulation, and clientele, and are therefore beyond the scope of this study. The imperfect credit market theory (Stiglitz and Weiss, 1981) suggests that asymmetric information leads to credit rationing, where even creditworthy farmers are excluded; this is reinforced by supply-side risks such as price volatility and climatic uncertainty, as well as demand-side constraints including low education, lack of collateral, and procedural complexity (Zeller 1994; Arshad et al. 2017a, b).

Empirical studies consistently show that access to credit improves farm performance by facilitating better input use, technology adoption, and risk management (Dong et al. 2010; Li et al. 2016; Amanullah et al. 2020). From the perspective of efficiency theory, technical efficiency (TE) represents the ability of a farm to produce the maximum possible output from a given set of inputs under existing technology (Farrell 1957; Battese and Coelli 1995). Credit enhances TE by enabling farmers to operate closer to the production frontier through optimal input allocation and adoption of improved technologies.

The Stochastic Frontier Approach (SFA) provides a framework to estimate TE by distinguishing between random shocks (e.g., weather) and inefficiency effects arising from managerial and financial constraints (Battese 1992). In this framework, credit acts as an efficiency-enhancing

variable that reduces the inefficiency component, enabling farmers to shift upward toward the production frontier. The theory of input complementarity also supports this relationship: access to capital increases the effective use of other inputs, particularly labor and fertilizers, leading to synergistic productivity gains (Feder et al. 1990; Carter and Olinto 2003).

Globally, evidence supports this linkage. Credit access has been shown to enhance farm productivity and efficiency in Pakistan (Chandio et al. 2017), Ghana (Abdallah 2016), Vietnam (Duy, 2015), and Bangladesh (Afrin et al. 2017). Studies in China (Dong and Featherstone 2006; Jia et al. 2010) and Latin America (Carter and Olinto 2003) highlight how credit constraints and informal lending limit production efficiency. Similarly, institutional economics posits that structural factors, such as property rights, extension systems, and social capital, mediate how credit affects farm outcomes (North 1990; Ostrom 2005).

Productivity in agricultural production can be measured using either partial or total factor approaches. Partial productivity refers to output per single input (e.g., yield per hectare or output per unit of labor), whereas total factor productivity (TFP) captures the efficiency with which all inputs are jointly transformed into output. TFP is commonly decomposed into several components, including technical efficiency (the extent to which producers operate close to the existing production frontier), technological change (shifts in the frontier due to innovation or improved production techniques), and, in some cases, scale efficiency. In this study, the focus is on technical efficiency, defined as farmers' ability to maximize output given a set of inputs and the prevailing technology. Accordingly, the analysis does not attempt to estimate technological change or other components of TFP, ensuring consistency with the stochastic frontier framework employed.

A clear distinction must be drawn between technical efficiency and technological change in the production process. Technical efficiency refers to the extent to which producers operate close to the existing production frontier, whereas technological change denotes an outward shift of the frontier resulting from innovation or improvements in production techniques. This study focuses exclusively on the technical efficiency channel. It hypothesizes that access to commercial bank credit relaxes liquidity constraints, enabling farmers to allocate inputs more efficiently and operate closer to the existing production frontier. While credit may, in principle, support technology adoption, this channel is not examined in the present study. Consistent with this focus, credit is incorporated as a determinant of the inefficiency term within a stochastic frontier framework, and no attempt is made to model shifts in the production frontier.

Building on this framework, the analysis examines whether access to commercial bank credit improves technical efficiency in Indonesian rice farming by enhancing farmers' ability to optimize input use within a given technological environment. Accordingly, the central research question is: Does access to commercial bank credit improve the technical efficiency of Indonesian rice farmers? The general objective of this study is to analyze the effect of access to commercial bank credit on the technical efficiency of Indonesian rice farmers. Accordingly, the specific objectives are to estimate the level of technical efficiency using a stochastic frontier approach and to examine the extent to which access to commercial bank credit influences farmers' technical efficiency by enabling more efficient input allocation within a given production technology. These objectives are strictly confined to technical efficiency and do not extend to technological change or technology adoption, ensuring full alignment between the conceptual framework, empirical specification, and research questions.

RESEARCH METHODOLOGY

Type and sources of data. The data utilized in this study were primary data, which were obtained from a survey conducted by the Micro Farming Study Team of the Department of Agribusiness, Faculty of Economics and Management, Bogor Agricultural University (IPB) in July to November 2024.

Data collection. The survey was conducted in four provinces (West Java, Central Java, East Java, and South Sulawesi) as the biggest rice production centers in Indonesia which contributes more than 50% of national rice availability. In each province, districts were selected purposively based on their status as major rice production centers in Indonesia, resulting in the selection of Karawang Regency, Grobogan Regency, Lamongan Regency, and Gowa Regency. Within each selected district, two sub-districts were purposively chosen using similar criteria as above. Subsequently, two villages in each sub-district were selected based on their designation as key rice production centers. The total number of respondents across the four provinces was 288 farmers, with 72 farmers from each province (Table 1).

The sampling frame consists of rice farming households engaged in on-farm production during the survey period. A stratified sampling approach was applied based on geographic regions and farm characteristics to ensure representativeness across major rice-producing areas. Farmers are classified into treatment and control groups based on access to commercial bank credit. The treatment group includes farmers who reported having access to or receiving credit from commercial banks during the production cycle, while the control group consists of farmers without access to commercial bank credit. This binary classification allows for the identification of the credit effect within the stochastic frontier framework.

Table 1. Number of farmer respondents by research location.

Province	District	Sub total (farmers)
West Java	Karawang	72
Center Java	Grobogan	72
East Java	Lamongan	72
South Sulawesi	Gowa	72
Total		288

The respondents in this study were rice farmers selected based on the following criteria: (1) rice farming constitutes the primary source of household income (>50%); (2) a minimum of four planting seasons of experience; (3) the most recent rice harvest occurred in 2024; (4) a monoculture cropping pattern; (5) irrigation-based water management; (6) non-organic cultivation techniques; and (7) total rice farming area of less than 10 hectares, (8) the last planting season is on 2024. To ensure data validity, observations identified as outliers were excluded from the data processing stage. The final sample consisted of 285 rice farmers, comprising 214 credit users and 71 non-credit users.

Based on the initial dataset of 285 farming households, a control group (non-credit users) with characteristics similar to the treatment group (credit users) was established using the PSMATCH2 command in STATA (15th version) (Leuven and Sianesi 2003). A probit binary choice model was employed to generate propensity scores (PS), followed by the application of the nearest neighbor matching method to identify a control group (non-credit users) that matched the treatment group (credit users). During this process, two farmers from the treatment group were excluded from the analysis because their PS values fell outside the common support range. Consequently, the final matched sample comprised 283 farmers, with 214 in the control group and 69 in the treatment group.

Analytical framework. Understanding the relationship between credit access and farm performance requires distinguishing between managerial efficiency and technological differences. Technical efficiency reflects the ability of a farmer to maximize output given available inputs and the existing production frontier. In contrast, technological change shifts the production frontier itself, representing innovations or improved production methods. In the context of smallholder rice farming in Indonesia, access to bank credit can relax liquidity constraints, enabling farmers to allocate inputs more effectively, purchase timely inputs, and operate closer to the prevailing production frontier. This study focuses

primarily on this efficiency channel, while acknowledging that credit may indirectly facilitate technology adoption.

The Stochastic Production Frontier (SPF) model provides a standard approach to estimating technical efficiency. By assuming a single production frontier for all farmers, SPF attributes deviations from the frontier to either random noise or inefficiency. However, smallholder farmers operate under heterogeneous technological environments due to variations in irrigation systems, mechanization levels, and agroecological conditions. In such cases, applying a single frontier risks confounding technological differences with inefficiency, as farmers using advanced technologies may appear more efficient while others are penalized simply for operating under less productive conditions.

To address technological heterogeneity, the Stochastic Meta-Frontier (SMF) framework is employed. The SMF distinguishes between group-specific frontiers, representing the technology available to each subset of farmers, and a common meta-frontier that envelops all group frontiers. This approach allows efficiency to be decomposed into two components: technical efficiency relative to the group frontier, capturing managerial performance, and the technology gap ratio, reflecting the distance between the group frontier and the meta-frontier. By combining SPF and SMF, it becomes possible to identify whether higher efficiency among credit users reflects true improvements in input allocation or merely differences in technological endowments.

Integrating credit into the meta-frontier framework highlights two mechanisms for improving farm performance. First, credit reduces inefficiency within a given technology group by enabling optimal input use, better timing of operations, and improved farm management practices. Second, credit may facilitate the adoption of improved technologies, reducing the technology gap between the group frontier and the meta-frontier. In this study, the primary focus is on the efficiency channel, ensuring that observed improvements among credit users represent real gains in technical efficiency rather than simply access to superior technologies.

Data analysis. This study evaluates the impact of bank credit on the technical efficiency (TE) of rice farming in Indonesia by comparing a treatment group (farmers who utilize bank credit) with a control group (farmers who do not utilize bank credit). Directly comparing TE values between these groups using the conventional Stochastic Production Frontier (SPF) method may produce biased estimates due to both observable and unobservable factors. To correct for selection bias arising from observed variables, the Propensity Score Matching (PSM) method is employed. The propensity scores are estimated using a logit model, which appropriately models the probability of credit adoption as a function of observable farm and household characteristics. One-to-one nearest-neighbor matching without replacement is applied to pair each credit-using farmer with the closest non-user in terms of propensity score. This approach ensures intuitive comparability between matched units while minimizing bias from dissimilar observations (Baglan et al. 2020a). Observations that do not satisfy the common support condition are excluded to maintain valid comparisons.

Bias arising from unobserved factors, such as managerial ability or risk preferences, is addressed using the Sample-Corrected Stochastic Production Frontier (SC-SPF) method, implemented in Limdep-11. Furthermore, when the production technologies employed by the two groups are heterogeneous, comparing TE values using separate frontiers may misrepresent efficiency differences. To account for technological heterogeneity, the Stochastic Meta-Frontier (SMF) approach is used, which constructs a common frontier enveloping all group-specific frontiers. When unobserved-variable bias is also present, the Sample-Corrected Stochastic Meta-Frontier (SC-SMF) model is employed, providing an efficiency benchmark that incorporates both selection bias and technological differences (Bravo-Ureta et al. 2020; Villano et al. 2015). This combined strategy ensures that the estimated effects of credit on TE are robust to both observed and unobserved confounding factors, as well as differences in production technologies across farmers.

Conventional-SPF Method (*Stochastic Production Function*)

Using the SPF model (Coelli et al. 1996), the technical efficiency (TE) value is estimated for each group (i.e., farmers using bank credit and those not using bank credit) and compared using an independent two-sample T-test. This SPF model (Coelli et al. 1996) can be estimated using the Corrected Ordinary Least Squares (COLS) method.

Model SPF (Coelli et al. 1998) :

$$y_i = \beta' x_i + (v_i - u_i)$$

Where ;

v_i = Error component (beyond managerial control)

u_i = Technical Inefficiency (IT) component

$u_i = |\sigma_u U_i| = \sigma_u |U_i|, \quad U_i \sim N(0,1)$

$y_i = \sigma_v V_i, \quad V_i \sim N(0,1)$

x_i = Production Input Vector

Model SPF (Coelli et al. 1996) :

$$y_i = \beta' x_i + (v_i - u_i)$$

Where ;

v_i = Error component (beyond managerial control)

u_i = Technical Inefficiency (IT) component \cong Technical Inefficiency (TE)

The technical efficiency (TE) of farming is influenced not only by access to bank credit but also by other variables (e.g., gender, age, education, experience, number of dependents, and farmer group membership), represented as vector z . When using a t-test (two independent samples), there is a potential for Bias in Observed Variables. This bias must be corrected using Propensity Score Matching (PSM).

The application of PSM begins by constructing a control group (farmers who do not use bank credit) with characteristics as similar as possible (in terms of vector z) to those in the treatment group (farmers who use bank credit) (Khandker et al. 2010; Sianesi 2001). Individuals in the control group served as comparable matches (in terms of vector z) for those in the treatment group if their propensity scores (PS) are closely aligned. The propensity score represented the probability of an individual using bank credit, estimated using a probit or logit model with predictors from vector z . The number of observations in each matched pair depended on the technique used to construct a comparable control group.

Several matching techniques are available for Propensity Score Matching (PSM), including nearest-neighbor, caliper, kernel, stratification, and radius matching. This study employed the one-to-one nearest-neighbor matching without replacement method, primarily due to its intuitive interpretation and direct comparability between treated and control observations. Each treated unit was paired with the control unit having the closest propensity score, minimizing the risk of matching with dissimilar units. Observations that do not satisfy the common support condition, i.e., those without an adequate match, were excluded to ensure valid comparisons and reduce extrapolation beyond the observed data.

While alternative methods, such as kernel or radius matching use weighted averages of multiple control units, they may include matches that are farther from the treated observation, potentially introducing bias if distant units are not truly comparable. Caliper matching can restrict matches within a specified distance to reduce bias but may result in fewer matches and reduced sample size, affecting efficiency. Stratification divides the sample into propensity score blocks, which smooths over local differences but may obscure fine-grained variation at the individual observation level. In contrast, nearest-neighbor matching strikes a practical balance: it minimizes bias by selecting the

closest match while retaining a sufficient number of observations for robust estimation. Although this method may have slightly higher variance compared with kernel or radius techniques, the clarity of interpretation and ease of implementation make it particularly suitable for assessing the impact of credit access on technical efficiency in the current study (Baglan et al. 2020b).

The comparison of the outcome variable, namely Technical Efficiency (TE), was conducted only between matched individuals. The output of the PSM procedure is a matched dataset for both groups, estimated using the PSMATCH2 Stata package. Based on this matched dataset, TE is estimated using LIMDEP-11 software through models such as Conventional-SPF, SC-SPF (Sample Correction – Stochastic Production Frontier), and SC-SMF (Sample Correction – Stochastic Meta Frontier Production Function). The impact of bank credit on TE can be directly measured through the Average Treatment Effect on the Treated (ATET) using the PSMATCH2 module in Stata 15.

$$ATET = E(Y_1|D = 1) - E(Y_0|D = 0)$$

Where :

- Y_1 and Y_0 represent the TE (outcome) values for the groups of farmers who use bank credit and those who do not use bank credit, respectively.
- D is a dummy variable, where $D=1$ if the farmer belongs to the group that uses bank credit, and $D=0$ otherwise;

If there is a potential bias due to Unobserved Variables, it can be corrected using the sample correction-stochastic production frontier (SC-SPF) method (Greene, 2010). The SC-SPF model is specified as follows.

$$d_i = 1[\alpha' z_i + w_i > 0], w_i \sim N[0,1] \Rightarrow \text{Logit Model}$$

$$y_i = \beta' x_i + \varepsilon_i; \varepsilon_i \sim N[0, \sigma_\varepsilon^2]$$

(y_i, x_i) It is only observed when $d_i=1$, with the following error structure:

$$\varepsilon_i = v_i - u_i$$

$$u_i = \sigma_u |U_i| \text{ with } U_i \sim N[0,1]$$

$$v_i = \sigma_v V_i \text{ with } V_i \sim N[0,1]$$

$$(w_i, v_i) \sim \text{normal bivariate } [(0,0), (1, \rho\sigma_v, \sigma_v^2)]$$

This condition allowed for the potential correlation between w_i and noise term v_i (i.e., $= \rho$). If the correlation coefficient (ρ) is ignored in the estimation of Technical Efficiency (TE), it may lead to bias due to unobserved variables. To address this issue, the sample correction-stochastic production frontier (SC-SPF) model must be applied to estimate TE using the matched dataset, which is obtained through LIMDEP-11.

Following this correction, a comparative analysis of the TE between the two groups was conducted using the Average Treatment Effect on the Treated (ATET). The final outcome ensures that the bias from both observed and unobserved variables in measuring the impact of bank credit access on rice farming TE is effectively corrected.

Stochastic Meta Frontier Production Function (SMF) approach

The comparison of technical efficiency (TE) scores between the two groups should be based on a common benchmark technology, following the Stochastic Meta-Frontier (SMF) Production Function Approach (Villano et al. 2015; Bravo-Ureta et al. 2020). The SMF procedure consists of the following steps.

1. The meta-frontier output obtained ($Y^* = e^{x_i\beta^*}$), through a two-step process:
 - First, we estimated the predicted output for each group (\hat{y}), using the Conventional-SPF or SC-SPF (Sample Correction – Stochastic Production Frontier) model.
 - Then, pool the predicted output values (\hat{y}) from both groups and estimate them using the SPF-Pooled model, yielding the meta-frontier function:

$$y^* = f(x_i, \beta^*) = e^{x_i\beta^*}$$

2. The Meta-Technology Gap Ratio (MTGR), which represents the ratio between the highest achievable output within a group and the maximum possible output under the meta-frontier, is calculated (Villano et al. 2015).

$$MTGR = \frac{e^{x_i\beta_j}}{e^{x_i\beta^*}}$$

where, $x_i\beta^*$ = Meta-frontier output

β^* = Vector of parameters SMF so that $x_i\beta^* \geq x_i\beta_j$

The TE score (with respect to the meta-frontier) is calculated as (Villano et al. 2015):

$$TE_M = TE_j \times MTGR_j$$

where TE_j = TE score obtained from the Conventional-SPF or SC-SPF model (whichever is the best-fitting model).

Generalized Log Likelihood Ratio Test (LR-Test)

To test whether the treatment and control groups rely on the same production technology, a generalized log-likelihood ratio test (LR test) was conducted based on the matched samples (Greene 2016; Chen et al. 2022).

Statistical Hypothesis:

H_0 : The production technology of both groups is the same.

H_1 : The production technologies of the two groups are different.

- Statistical tests:

$$LR_Stat = 2[\ln\{L(t)\} + \ln\{L(c)\} - \ln\{L(p)\}]$$

The log-likelihood value of the Cobb-Douglas model was obtained through Maximum Likelihood Estimation (MLE) based on sequential datasets: pooled group (p), treatment group (t), and control group (c).

where,

$\ln\{L(p)\}$ = Log-likelihood of the production function estimated through Maximum Likelihood

Estimation (MLE) for pooled data (restricted model).

$\ln\{L(t)\}$ = Log-likelihood for the treatment group (farmers using bank credit).

$\ln\{L(c)\}$ = log-likelihood for the control group (farmers not using bank credit).

- Testing:

If H_0 is true (fail to reject H_0), the LR statistic follows a chi-square distribution, with degrees of freedom equal to the difference between the restricted and unrestricted models (Greene 2016).

Estimation strategy of observed and unobserved bias correction. To formulate an estimation strategy for correcting observed and unobserved variable biases, the following steps should be undertaken.

1. Prepare the Matched Dataset using the PSM (Propensity Score Matching) technique based on Unmatched Data and Vector z (PSMATCH2 Stata Package).
2. We check for technology differences between the two groups using the Likelihood Ratio Test (LR Test) in Limdep-11 to determine whether the production functions differ.
3. The production function is estimated using three alternative models:
 - Conv-SPF (Conventional - Stochastic Production Frontier),
 - SC-SPF (Sample Correction – Stochastic Production Frontier),
 - SC-SMF (Sample Correction – Stochastic Meta Frontier Production Function), with the assistance of the Limdep-11 software.

Several previous studies, including those of Bravo-Ureta et al. (2012, 2020), Baglan et al. (2020a), and Chen et al. (2022), Lawin and Tamini (2018), and Villano et al. (2015) estimated bias correction using the following three-stage approach, which is also applied in this study:

- First, the PSM approach was used to correct the observed variable bias. If ρ the correlation between w_i and v_i is not significant and the two groups use the same production technology (single production function), then only observed variable bias needs correction. Technical Efficiency (TE) is estimated using Conventional - Stochastic Production Frontier in Limdep-11, and the impact of bank credit on TE is estimated using PSM (ATET - PSMATCH2).
- Second, the unobserved variable bias was corrected. The selectivity-corrected stochastic frontier production function (SC-SPF) model is applied to correct for unobserved variable bias. If ρ The correlation between w_i and v_i is significant, but the two groups still use the same production technology (single production function); then, both observed and unobserved variable biases must be corrected. TE is estimated using the sample correction-stochastic production frontier (SC-SPF) in Limdep-11, and the impact of bank credit on TE is estimated using PSM (ATET - PSMATCH2).
- Third, the meta-frontier production function (MFPPF) approach is applied. If the credit-user and non-credit-user groups are found to use different production technologies (Bravo-Ureta et al. 2020; Lawin and Tamini, 2018; Villano et al. 2015), the meta frontier production function (MFPPF) approach is applied. If ρ the correlation between w_i and v_i is significant and the two groups use different technologies (separate production functions), then both observed and unobserved variable biases must be corrected. TE is estimated using SC-SMF (Sample Correction – Stochastic Meta Frontier Production Function) in Limdep-11, and the impact of bank credit on TE is estimated using PSM (ATET - PSMATCH2). Table 2 presents the definitions of variables used in this study (PSM and SPF models).

Table 2. Definitions of research variables used in PSM and SPF models

Variables		Definition and Unit
Input and Output {y,x} :		
y	Output	Total Rice Production (GKP) per Planting Season (kilograms). Planting season in this research is the last planting season in 2024.
x	Input	(Vector of Classical Production Inputs)
X ₁	Land	Total Rice Planting Area (Owned and Non-Owned) (hectares)
X ₂	Seed	Total Rice Seed Input (kilograms per planting season)
X ₃	Fertilizer	Total Chemical Fertilizer Input (Urea, ZA, TSP19, NPK, KCL) (kilograms per planting season)
X ₄	Pesticides	Total Pesticide Input (Herbicides, Insecticides, Fungicides, Other Pesticides) (liters per planting season)
X ₅	Labor	Total Labor Input (Nursery, Land Preparation, Planting, Replanting, Weeding, Fertilization, Spraying, Harvesting) (HOK=working day per planting season)

Variables	Definition and Unit
Probit models {d,z} :	
d Credit	d = 1 ; if farmers access to commercial Bank Credit, and d=0, if farmers don't access to commercial Bank Credit.
z (vector from explanatory variables):	
Z ₁ Sex	Sex of farmer respondent (1 = Male, 0 = Female)
Z ₂ Age	Age of farmer respondent (years)
Z ₃ Education	Education of farmer respondent (years)
Z ₄ Training	Total Duration of Training (Rice Farming and/or AUTP) Received by Farmers (days per year)
Z ₅ Family_burden	Number of Household Dependents (persons)
Z ₆ Experience	Rice Farming Experience (years)
Z ₇ Cropping index	Rice Planting Frequency (times per year)
Z ₈ Farmer_group	Membership in Farmer Group (1 = Yes, 0 = No)
Z ₉ Farmer_cooperative	Membership in Cooperative (1 = Yes, 0 = No)
Z ₁₀ Plant_pests	Dummy for Pest and Disease Attack (OPT) (1 = If affected, 0 = If not)
Z ₁₁ Off-farm_Income	Net family income outside farming (trade, services, or employee in non-farm) (Rp/year)

RESULTS AND DISCUSSION

Respondents profile. Table 3 presents the descriptive statistics of the research variables based on matched samples. The table presents the output produced, inputs used, and characteristics of the farmers and their farming enterprises. The average rice productivity of credit-user farmers (69 individuals) was not significantly different from that of non-credit-user farmers, with 4.9 tons/ha for credit users and 5.2 tons/ha for non-credit-user farmers (214 individuals).

The average cultivated land area used for rice farming by credit-user farmers is 1.4 hectares, while that of non-credit-user farmers is 0.74 hectares. It can be concluded that the cultivated land area of credit-user farmers was larger and significantly different from that of non-credit-user farmers. This served as evidence of the allocation of credit received by farmers.

Similarly, pesticide usage during the research period, when pest infestations occurred, was higher among credit-user farmers (59.49 l/ha/season), indicating their ability to anticipate pest attacks, and this usage was significantly different from that of non-credit-user farmers (46.33 l/ha/season).

In contrast, credit-user farmers used seeds, fertilizers, and labor inputs more efficiently. Seed usage by credit-user farmers aligned more closely with the recommendations of agricultural extension officers (PPL), which is 25–30 kg/ha/season for irrigated land. Seed usage was significantly different, with credit-user farmers using seeds more efficiently (34.92 kg/ha/season) than non-credit-user farmers (45.10 kg/ha/season). Similarly, labor usage was more efficient among credit-user farmers (107.17 labor-days/ha/season) and significantly different from non-credit-user farmers (122.79 labor-days/ha/season).

Meanwhile, fertilizer usage by credit-user farmers was 529.12 kg/ha/season, and by non-credit-user farmers, it was 564.71 kg/ha/season, but this difference was not statistically significant. Thus, farming performance, as indicated by productivity, shows that credit-user farmers achieve their output by using inputs more optimally.

When examining the characteristics of the farmers and their farming enterprises in Table 3, it can be seen that gender, age, number of dependents, and farming experience did not differ significantly between credit-user and non-credit-user farmers. The majority of respondents (both credit users and

non-credit users) were male, aged 54 years, with 3–4 dependents, and had 27–30 years of farming experience. Almost all respondents were involved in farmer groups, and nearly all respondents experienced pest infestations during the research period.

Table 3. Descriptive statistics of research variables for production output, input, and the probit model based on matched samples.

Variables	Mean		Difference mean ^{a)}	
	Farmers who had access to credit	Farmers who did not have access to credit		
Output and input production {y, x}:				
y	Paddy production (kg) per hectare	4897.276 (283.981)	5185.795 (161.283)	-288.519
X ₁	Land (hectare)	1.439 (0.152)	0.746 (0.054)	0.693***
X ₂	Seed (kg) per hectare	34.921 (5.424)	45.100 (1.800)	-10.179**
X ₃	Fertilizer (kg) per hectare	528.126 (37.922)	564.714 (21.897)	-36.589
X ₄	Pesticides (liter) per hectare	59.490 (9.573)	46.326 (4.277)	13.164*
X ₅	Labor (HOK) per hectare	107.174 (7.299)	122.388 (4.266)	-15.214**
Socio-demographic {d, z}:				
Z ₁	Gender	0.884 (0.0389)	0.897 (0.020)	-0.013
Z ₂	Age	53.986 (1.296)	54.014 (0.779)	-0.029
Z ₃	Education	8.797 (0.3668)	8.089 (0.255)	0.708*
Z ₄	Training	3.449 (1.407)	1.486 (0.598)	1.963*
Z ₅	Family_burden	3.464 (0.159)	3.332 (0.100)	0.132
Z ₆	Experience	27.783 (1.647)	30.168 (1.040)	-2.386
Z ₇	Cropping index	2.0290 (0.0290)	2.313 (0.034)	-0.284***
Z ₈	Farmer_group	0.971 (0.020)	0.958 (0.014)	0.013
Z ₉	Farmer_cooperative	0.101 (0.037)	0.037 (0.013)	0.064**
Z ₁₀	Plant_pests	0.942 (0.028)	0.967 (0.012)	-0.025
Z ₁₁	Off-farm_income	18 800 000 (2985152)	12 100 000 (1107844)	6660393***
Observations		69	214	

Note: ^{a)} Mean difference using two-sample t-test between the group of farmers participating in bank credit and the group of farmers not participating in bank credit.

The parentheses indicate the standard errors.

*** Significant at 1 %, ** Significant at 5 %, * Significant at 10 % (one side test).

The characteristics that showed significant differences between the two groups were formal and non-formal education. Credit-user farmers have a higher level of formal education (8.8 years) than non-credit-user farmers (8.1 years). In terms of non-formal education or training experience, credit-user farmers participated in training sessions 3.4 times per year, whereas non-credit-user farmers participated 1.5 times per year. Membership in cooperatives also differed significantly, with a higher proportion of credit-user farmers involved in cooperatives. Off-farm income also showed a significant difference, with credit-user farmers earning higher off-farm income (IDR 18,800,000 per year) than non-credit-user farmers (IDR 12,100,000 per year). This served as evidence that farmers who have access to bank credit are those with higher off-farm income or those who are relatively wealthy. Off-farm income can act as a safety net in the case of credit default due to rice crop failure.

Another interesting finding is that the Planting Intensity Index (PII) or cropping index of credit-user farmers was significantly different from that of non-credit-user farmers. The IP of credit-user farmers was lower (two times per year) than that of non-credit-user farmers (2.3 times per year). This can be explained by the fact that credit-user farmers did not prioritize the frequency of planting per year but instead focused on expanding the cultivated land area and optimizing input usage.

Table 4 presents the results of the balance test for matching covariates obtained through propensity score matching (PSM) analysis, which was conducted using a probit approach and the nearest neighbor matching method. Based on the test results displayed in Table 4, no significant differences in means were found between the groups of farmers using commercial bank credit and non-credit-user farmers for all explanatory variables in the matched sample. These results provide empirical evidence that the matching quality achieved by the PSM method is excellent (Garcia-Iglesias 2022).

Table 4. Balance of matching covariates for farmer households for the matched sample

Matching covariates	Mean		% Bias	t-test	
	Farmers who access to credit (Treated)	Farmers who don't access to credit (Control)		<i>t</i> _{statistic}	P-value
Z ₁ Gender	0.884	0.913	-9.300	-0.560	0.576
Z ₂ Age	53.986	53.928	0.500	0.030	0.976
Z ₃ Education	8.797	8.797	0.000	0.000	1.000
Z ₄ Training	3.449	4.536	-10.500	-0.410	0.679
Z ₅ Family burden	3.464	3.362	7.300	0.470	0.643
Z ₆ Experience	27.783	26.478	9.000	0.510	0.610
Z ₇ Cropping Index	2.029	2.058	-7.200	-0.580	0.563
Z ₈ Farmer_group	0.971	0.942	15.700	0.830	0.407
Z ₉ Farmer_cooperative	0.102	0.130	-11.100	-0.530	0.598
Z ₁₀ Plant_pests	0.942	0.913	14.000	0.650	0.515
Z ₁₁ Off-farm income	19 000 000	17 000 000	9.100	0.550	0.584
Observations	69	214			

Note: *** Significant at 1 %, ** Significant at 5 %, * Significant at 10 %.

Selection of production function and technological differences. To determine the appropriate functional form for the stochastic frontier production function, both the Cobb–Douglas and the Translog specifications are estimated and compared using a generalized log-likelihood ratio (LR) test.

The Cobb–Douglas stochastic frontier model is specified as:

$$\ln Y_i = \beta_0 + \sum_{k=1}^K \beta_k \ln X_{ki} + (V_i - U_i)$$

where Y_i denotes output, X_{ki} represents input variables, V_i is the random error term, and U_i captures technical inefficiency.

The Translog stochastic frontier model is specified as:

$$\ln Y_i = \beta_0 + \sum_{k=1}^K \beta_k \ln X_{ki} + \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \beta_{kj} \ln X_{ki} \ln X_{ji} + (V_i - U_i)$$

where the additional interaction terms $\beta_{kj} \ln X_{ki} \ln X_{ji}$ allow for variable elasticities of substitution between inputs.

The selection of the optimal stochastic production frontier (SPF) function for the research sample data was conducted using the generalized log-likelihood ratio (LR) test based on an analysis of the matched sample. The test statistic is formulated as follows.

$$LR_Stat = 2[\ln\{L(t)\} + \ln\{L(c)\} - \ln\{L(p)\}].$$

The results of the test, presented in Table 5, indicate that the transcendental logarithmic model is the most appropriate stochastic frontier production function (SPF) approach for examining the impact of credit on the technical efficiency (TE) of rice farming in this study.

Table 5. Generalized likelihood ratio test of the hypothesis for choosing of SPF model based on matched sample

Null hypothesis	LR statistic	Critical value ^{a)}	Decision
The Correct Cobb-Douglas SPF Model.	35.0258063	24.9957901	Reject H_0 . The Appropriate Transcendental logarithmic SPF Model for This Research Sample Data

Note: ^{a)} Critical value based on chi-square table with 15 degrees of freedom at 5% significance level (Greene, 2016).

To ensure homogeneity of production technology between farmers who accessed credit (treatment group) and those who did not (control group), a generalized log-likelihood ratio (LR) test was conducted based on matched samples. The test statistic is defined as follows.

$$LR_Stat = 2[\ln\{L(t)\} + \ln\{L(c)\} - \ln\{L(p)\}].$$

The test results presented in Table 6 indicate that the null hypothesis is rejected, suggesting that credit and non-credit farmers utilize different production technologies. This finding underscores the necessity of estimating technical efficiency (TE) scores for both groups using the stochastic meta-

frontier production function (SMF) model. In this approach, the TE scores are estimated based on a higher common benchmark technology.

Table 6. Generalized likelihood ratio test of hypothesis based on matched sample

Null hypothesis	LR statistic	Critical value^{a)}	Decision
Both groups adhere to the same production technology.	44.0913479	31.4104329	Reject H_0 . The two groups adhere to different production technologies..

Note: ^{a)} Critical value based on chi-square table with 20 degrees of freedom at 5% significance level (Greene, 2016).

Estimation of parameter for Conventional-SPF Models, Selectivity-Corrected Stochastic Production Frontier (SC-SPF) Models, and Stochastic Meta-Frontier (SMF) models

The Conventional Stochastic Production Frontier (Conventional-SPF) model presents separate estimations for rice farmers who use credit and those who do not. The results reveal that the land variable has a positive and significant coefficient in both groups (+4.5 for credit-user farmers and +10.79 for non-credit-user farmers), meaning that an increase in cultivated area can significantly increase production. This occurs because the land managed is still on a small scale (1.4 ha for credit-user farmers and 0.7 ha for non-credit-user farmers). This condition is reasonable since it is difficult for farmers to purchase or rent fertile land suitable for rice cultivation due to its scarcity and high price.

The seed variable has a negative coefficient in both groups (credit-user farmers and non-credit-user farmers), indicating that seed use is already excessive. For non-credit-user farmers, this happens because the seed requirement per hectare is relatively low (25 kg/ha) and easily available, making its cost relatively cheap (1.9% of total cost). In addition, farmers often receive subsidies or assistance, which leads to uncontrolled use of seeds. There is also a perception that the more seeds are sown, the higher the yield, whereas seed use should actually be reduced. For credit-user farmers, the seed coefficient is negative but not significant, meaning that increasing or decreasing seed use does not affect production. This indicates that seed use among credit-user farmers is already optimal. This indicates that what is needed is not an increase in the quantity of seeds used, but an improvement in seed quality.

The fertilizer variable has a negative and significant coefficient in both groups (credit-user farmers and non-credit-user farmers), indicating that fertilizer use is already excessive. An increase in fertilizer use can actually reduce production significantly. This occurs because the amount of fertilizer applied has exceeded the recommended rate (377 kg/ha for credit-user farmers and 806 kg/ha for non-credit-user farmers, while the recommendation is 300 kg/ha). Over-fertilization may be driven by rice farmers' belief that more chemical fertilizer is needed on nutrient-depleted soils to boost production, particularly among farmers with credit access who have greater financial flexibility.

The pesticide variable has a negative and significant coefficient among non-credit-user farmers, indicating that pesticide use is already excessive. This happens because of the perception that spraying more pesticides will be more effective in killing pests and preventing crop failure. However, crop failure still occurs because the rice plants become poisoned, implying that farmers should start reducing pesticide use. For credit-user farmers, the pesticide coefficient is positive but not significant, meaning that increasing or decreasing pesticide use does not affect production. This suggests that pesticide use among credit-user farmers is already optimal.

The labor variable has a negative and significant coefficient in both groups (credit-user farmers and non-credit-user farmers), meaning that labor use is already excessive. This may occur due

to the low level of mechanization, causing farmers to rely heavily on manual labor, particularly family labor. Increased use of labor can, in fact, significantly decrease production.

Based on the above explanation, it can be concluded that production can be increased through land expansion or technological improvement. However, since these factors are relatively expensive, farmers with access to credit tend to allocate their funds toward purchasing other inputs (fertilizers, seeds, pesticides), which are already being used excessively. This serves as a warning for farmers to avoid credit misallocation. In this regard, the role of agricultural extension officers (PPL) is crucial in advising farmers on which inputs still need to be increased. In addition to PPL, the roles of farmer groups (POKTAN) and farmer group associations (GAPOKTAN) are also essential in facilitating access to land, mechanization, and seed technology to improve production.

Table 7. Parameter estimates for conventional-SPF separated models, SC-SPF models, and SC-SMF models based on matched sample.

Variables		Conventional-SPF		SC-SPF		SC-SMF
		Farmers with access to credit	Farmers without access to credit	Farmers with access to credit	Farmers without access to credit	
Constant		32.0749*** (7.97222)	39.2866*** (6.93405)	11.3573*** (0.38462)	28.4217*** (8.09064)	17.9241*** (4.55302)
LnX1	Land	4.50208** (1.78063)	10.7943*** (1.94241)	1.7851*** (0.08328)	6.7214*** (2.22876)	3.29739*** (.44536)
LnX2	Seed	-0.06833 (1.62439)	-6.3853*** (1.54687)	2.7909*** (0.04922)	-3.6783** (1.44165)	-1.17797*** (.30831)
LnX3	Fertilizer	-4.03314** (2.01875)	-2.35722** (1.18127)	1.2568*** (0.06557)	-1.1583 (1.85337)	-.47315 (.29520)
LnX4	Pesticides	0.13366 (.52069)	-1.3401*** (0.39991)	0.8451*** (0.02113)	-0.1491 (0.61385)	.00835 (.11746)
LnX5	Labor	-5.82276*** (1.37163)	-5.5666*** (1.52411)	-5.9946*** (0.07236)	-4.9234** (1.9708)	-3.17110*** (.43019)
LnX11	Land*	-0.10536 (0.12805)	0.72417*** (0.11551)	-0.0255*** (0.00353)	0.3153** (0.14197)	.04904 (.03655)
	Land					
LnX22	Seed *Seed	0.20193** (0.08488)	0.27691** (0.11805)	0.00578 (0.00407)	-0.0029 (0.14416)	-.02898 (.02638)
LnX33	Fertilizer*Fertilizer	-0.09253** (0.04659)	-0.02529 (0.07078)	-0.01697*** (0.00244)	-0.0581 (0.15591)	.06091*** (.01585)
LnX44	Pesticides*Pesticides	0.03484 (0.02567)	-0.00845*** (0.00301)	0.0059*** (0.00151)	-0.0055 (0.01276)	-.00267*** (.00085)
LnX55	Labor* Labor	0.18370 (0.27061)	0.07228 (0.19158)	0.7046*** (0.00679)	0.2011 (0.25101)	.24108*** (.04450)
LnX12	Land* Seed	0.04887	-0.84469***	0.2728***	-0.3732	-.08582**

Variables		Conventional-SPF		SC-SPF		SC-SMF
		Farmers with access to credit	Farmers without access to credit	Farmers with access to credit	Farmers without access to credit	
		(0.19842)	(0.24719)	(0.00489)	(0.24046)	(.04192)
LnX13	Land* Fertilizer	-0.53040 (0.34195)	-0.56958*** (0.20164)	0.0404*** (0.01085)	-0.28597 (0.2913)	-.12616** (.05158)
LnX14	Land* Pesticides	0.19451** (0.08687)	-0.26339*** (0.06574)	0.3476*** (0.00334)	0.0103 (0.10427)	.02132 (.02019)
LnX15	Land* Labor	-0.45475* (0.25313)	-0.79000*** (0.25804)	-0.8808*** (0.00874)	-0.7689*** (0.29335)	-.45561*** (.06545)
LnX23	Seed * Fertilizer	0.06623 (0.26199)	0.25852 (0.18489)	-0.4926*** (0.00812)	0.2836 (0.2127)	.00370 (.05037)
LnX24	Seed * Pesticides	0.05658 (0.06065)	0.05233 (0.05018)	0.0241*** (0.00261)	-0.0725 (0.07876)	.00123 (.01649)
LnX25	Seed * Labor	-0.30447 (0.22727)	0.66214*** (0.17474)	0.0945*** (0.00623)	0.5054** (0.2491)	.33633*** (.05008)
LnX34	Fertilizer* Pesticides	0.08524* (0.04952)	0.04133* (0.0217)	0.0016 (0.00275)	-0.0072 (0.0738)	-.06223*** (.01808)
LnX35	Fertilizer* Labor	1.03722** (0.44284)	0.42610* (0.23366)	0.0874*** (0.01383)	0.2424 (0.3162)	.00105 (.05946)
LnX45	Pesticides * Labor	-0.21740*** (0.06192)	0.19539** (0.08389)	-0.2097*** (0.00305)	0.1031 (0.13398)	.08762*** (.02428)
Log Likelihood		-6.96728	-121.96826	-66.8036	-202.67596	78.95562
	σ	0.53575	0.85545	0.61078	0.85767	.18306
	σ_u	0.53575	0.85545	0.61067	0.81711	.00000
	σ_v	0.00017	0.00015	0.01162	0.26062	.18306
	Rho(v, w)	-	-	-0.9991*** (0.0061)	0.11393 (0.8994)	-
Observations		69	214	69	214	283

Notes: Parentheses indicate standard errors.

*** Significant at 1%, ** significant at 5%, * significant at 10%.

Interaction terms in this model also highlight notable input dynamics. For instance, the *Land*Seed* and *Land*Fertilizer* interactions are negative and significant in the non-credit group, indicating diminishing marginal returns or input mismatches when land is used jointly with these inputs. The *Land*Labor* interaction is significantly negative in both groups, further reinforcing concerns around inefficient labor usage. These patterns, combined with the relatively higher log-likelihood for the non-credit group, suggest that the Conventional-SPF may capture some relationships but fails to fully account for unobserved heterogeneity between the groups.

Moving to the Stochastic Correction Stochastic Production Frontier (SC-SPF) model, the estimates are adjusted to account for unobserved variables that could bias technical efficiency (TE) estimation. After this correction, the key input variables (land, seed, fertilizer, and pesticides) for credit users become positive and highly significant, which contrasts with the negative or insignificant signs in the conventional model. This finding indicates that, once hidden biases are addressed, the use of credit is clearly associated with more productive use of inputs. For example, seed, which previously had no significant effect, now shows a strong positive impact (2.79) on output. Fertilizer and pesticides also switch to positive and significant, suggesting improved input effectiveness when unobserved factors are controlled.

Notably, the Rho value for credit users ($\rho = -0.9991^{***}$) is statistically significant, indicating strong correlation between inefficiency and the composite error term. This confirms the presence of substantial bias in the Conventional-SPF estimates and validates the superiority of the SC-SPF model for a more reliable efficiency analysis. However, labor input remains significantly negative even in the SC-SPF, underscoring persistent inefficiencies in how labor is deployed in rice production, possibly linked to high labor costs, aging workforce, or low mechanization.

The Stochastic Correction Stochastic Meta-Frontier (SC-SMF) model allows both groups to be compared under a common benchmark technology, providing a broader perspective on efficiency gaps. In this model, land continues to be a dominant positive factor (coefficient = 3.30), highlighting its consistent importance across technologies. However, seed and fertilizer inputs become negative and significant, implying that even with credit, these inputs are not always used optimally relative to the benchmark. Labor input also remains significantly negative, confirming a widespread inefficiency that transcends credit access and technological boundaries.

Interactions between inputs provide further insight. The *Seed*Fertilizer* interaction becomes insignificant, while the *Pesticides*Labor* interaction is positive and significant. This suggests potential synergies in using labor to apply pesticides more effectively. However, other interactions, such as *Land*Labor* and *Fertilizer*Pesticide*, remain negative, indicating persistent inefficiencies in combining these inputs. Importantly, squared terms like *Fertilizer²* and *Labor²* also show statistical significance, pointing to nonlinear effects and possible overuse beyond optimal levels.

The SC-SMF model's log-likelihood is the highest among the three, reinforcing its statistical superiority. This model confirms that both credit and non-credit users are operating below the potential frontier, but credit users are relatively closer to full efficiency. The ability of the SC-SMF model to compare farmers under a common technological framework reveals deeper inefficiencies masked by technology-specific frontiers and highlights the importance of improving input effectiveness, beyond merely increasing access.

In summary, the progression from Conventional-SPF to SC-SPF and finally to SC-SMF models reveals three critical findings. First, the conventional model underestimates the benefits of credit due to unobserved heterogeneity. Second, after correcting for these biases, credit usage is shown to significantly improve input effectiveness, especially in land, seed, and fertilizer utilization. Third, the meta-frontier model illustrates that, although credit helps close the efficiency gap, rice farmers in general, regardless of credit use, still operate below the optimal frontier, mainly due to labor inefficiencies and input mismanagement. These insights underscore the need for targeted credit policies, better input allocation, and technological upgrading to enhance rice farm productivity in Indonesia.

Impact of credit on technical efficiency in Indonesian rice farming. The results from Table 8 show significant differences in technical efficiency (TE) scores between rice farmers who access credit and those who do not, depending on the estimation model used. Under the Conventional Stochastic Production Frontier (Conventional-SPF) model, the mean TE scores for both credit users and non-users

are exceptionally high 99.903% and 99.914% respectively, with a negligible difference of -0.011%. (Table 8). Although the t-statistic (-4.060) is statistically significant, the extremely high TE values suggest a misleading impression that all farmers are operating near perfect efficiency. These results do not account for unobserved factors such as differences in farmer characteristics, local farming environments, or access to technology, rendering the Conventional-SPF model insufficient for drawing accurate conclusions about the role of credit.

Table 8. Predicted mean frontier TE score (%) calculated from the Conventional-SPF, SC-SPF and the SC-SMF models based on matched samples.

ATET	Conventional-SPF	SC-SPF	SC-SMF	Observation
Credit Users (Treated)	99.903	65.499	67.057	69
Non-Credit User (Control)	99.914	58.653	58.681	214
Difference	-0.011	6.846	8.375	
Standard error	0.003	3.798	3.980	
t-statistic^{a)}	-4.060	1.800	2.100	

Note: ^{a)} The t-statistic is used to test the null hypothesis that there is no difference between the mean of the outcome variables for the Credit and non-Credit groups. This is a test of the average treatment effect on the treated (ATET). The critical value based on the t-test table with 69 degrees of freedom at a 5% significance level one tail ≈ 1.67 , and for two tails ≈ 2 . Critical value based on T-test table with 69 degree of freedom at 1% significant level for one tail ≈ 2.38 , and for two tail ≈ 2.66 .

In contrast, when using the Stochastic Correction Stochastic Production Frontier (SC-SPF) model, which controls for unobserved heterogeneity, a more realistic picture emerges. The TE score for credit users drops to 65.499%, while that for non-credit users is 58.653%. This indicates a notable and economically meaningful difference of 6.846 percentage points, with a t-statistic of 1.80. Although this is only weakly significant at the 10% level, it highlights the positive influence of credit in improving farm performance. The results suggest that farmers who access credit are better able to allocate inputs more efficiently and adopt improved farming practices, likely because they can afford higher-quality seeds, fertilizers, or timely labor, thereby reducing production inefficiencies.

The most comprehensive model, the Stochastic Correction Stochastic Meta-Frontier (SC-SMF), takes the analysis one step further by comparing both groups against a common benchmark technology. This model shows that the TE of credit users is 67.057%, while non-credit users have a TE of 58.681%. The difference of 8.375 percentage points is statistically significant at the 5% level (t-statistic = 2.10), providing the strongest evidence that credit access enhances technical efficiency. This finding underscores that credit users are not only more efficient within their group but also operate closer to the ideal production frontier, benefiting from broader technological advantages or more optimal input combinations enabled by credit.

In summary, the progression from the Conventional-SPF to the SC-SPF and finally the SC-SMF model reveals that the true impact of credit on rice farming efficiency was previously underestimated. Once statistical biases and technology gaps are accounted for, credit emerges as a critical factor in boosting technical efficiency. These results advocate for targeted policies that improve smallholder farmers' access to credit, alongside efforts to strengthen financial literacy and simplify lending procedures. Expanding credit access would allow more farmers to adopt timely and efficient input use, thus contributing significantly to productivity growth and food security in Indonesia's rice sector.

CONCLUSIONS AND POLICY RECOMMENDATIONS

The PSM method produced high-quality matching, with no significant differences between credit users and non-users across explanatory variables. The Generalized Likelihood Ratio Test showed that the transcendental logarithmic model better fits the Stochastic Frontier Production Function (SPF) than the Cobb-Douglas, indicating different technologies between groups and justifying the use of the Stochastic Meta-Frontier Production Function (SMPF). The SC-SPF model revealed significant unobserved variable bias in the conventional SPF model, making SC-SPF a more accurate alternative. Further, the SC-SMPF model proved superior, offering a common and representative technology benchmark for both groups.

Credit access is found to significantly improve technical efficiency in rice farming, although the magnitude of its impact varies depending on the estimation approach used. More robust modeling indicates that farmers with access to credit consistently achieve higher efficiency levels than those without, despite overall efficiency remaining below optimal levels. These findings underscore the important role of credit access in enhancing farm performance and supporting improvements in agricultural productivity.

Improving the performance of Indonesia's rice farming sector requires not only expanding farmers' demand for credit but also addressing structural constraints on the supply side of formal agricultural lending. Access to commercial bank credit significantly enhances technical efficiency in rice farming. However, limited access is not solely attributable to farmer-level barriers; it also reflects risk perceptions, regulatory constraints, and low profitability associated with agricultural lending from the perspective of commercial banks. Therefore, policy interventions must simultaneously target both demand- and supply-side bottlenecks within the rural credit market.

On the demand side, simplifying administrative requirements and developing loan products tailored to agricultural production cycles remain essential. Flexible repayment schedules aligned with harvest periods and seasonal cash flows would reduce default risk and improve loan uptake among smallholders. Strengthening rural financial institutions and expanding branchless banking infrastructure would further enhance outreach in underserved areas.

On the supply side, commercial banks often perceive agricultural lending as high risk due to weather variability, price volatility, and limited collateral among smallholders. To mitigate these concerns, the feasibility of expanding credit guarantee schemes warrants careful evaluation. Partial credit guarantee mechanisms, whereby the government absorbs a predefined share of default risk, can incentivize banks to increase agricultural loan portfolios without fully socializing credit risk. The design of such schemes must ensure appropriate risk-sharing ratios to avoid moral hazard while maintaining fiscal sustainability.

The introduction or reinforcement of mandatory agricultural lending quotas is worth considering. The experience of the Philippines under the Agri-Agra Reform Credit Act provides a relevant case, where commercial banks are required to allocate a minimum percentage of their loanable funds to agriculture and agrarian reform beneficiaries. While such mandates can increase formal credit flows to agriculture, their effectiveness depends on enforcement capacity, penalty structures, and the availability of viable agricultural investment opportunities. In the Indonesian context, careful assessment is required to determine whether setting a required proportion of commercial bank lending to agriculture would improve credit access or instead lead to compliance substitution, such as indirect or low-risk agricultural investments that do not reach smallholders.

Risk mitigation mechanisms should complement these structural reforms. Expanding agricultural insurance programs can reduce exposure to weather-related shocks for both farmers and

lenders. Integrating insurance with credit contracts, through bundled loan-insurance products, may further reduce default risk. Additionally, the development of agricultural credit scoring systems incorporating agronomic, climatic, and behavioral data could improve risk assessment and reduce information asymmetry between farmers and banks. Digital financial platforms may enhance transparency, lower transaction costs, and facilitate monitoring.

Beyond financial instruments, improving technical efficiency also requires coordinated institutional support. Credit provision should be integrated with extension services, input access, and managerial training. Bundled service delivery through cooperatives or farmer organizations can reduce transaction costs and enhance monitoring while supporting technology adoption. Given the heterogeneity observed across production frontiers, differentiated credit products and technical assistance packages are necessary to address varying technological capacities among farmers.

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