ASSESSING THE ROLE OF AGRICULTURAL PEOPLE'S BUSINESS CREDIT (KUR) IN ENHANCING PRODUCTIVITY IN INDONESIA'S RICE FARMING: EVIDENCE FROM THE ACF APPROACH

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Abstract

Background: Indonesia continues to face persistent rice productivity challenges that differ across regions. Conventional econometric approaches often fail to properly address endogeneity and simultaneity issues, leading to biased assessments of policy effectiveness. To overcome these limitations, this study applies the Ackerberg–Caves–Frazer (ACF) method to panel data from 32 provinces (2016–2023) to obtain reliable estimates of Total Factor Productivity (TFP) and quantify the true contribution of the Agricultural People's Business Credit (KUR) toward efficiency improvement and technology adoption.
Purpose: The main objective is to generate consistent input elasticity estimates and accurately measure TFP in Indonesia's rice sector, enabling a more credible assessment of how KUR influences production performance and efficiency across provinces.
Design/methodology/approach: Using a quantitative two-stage ACF–TFP estimation framework, the analysis shows that KUR significantly enhances rice productivity, primarily through TFP gains rather than increases in input quantities. Regional disparities are substantial, with western provinces demonstrating higher efficiency than eastern provinces. Input elasticities are relatively small, indicating diminishing factor responsiveness. The Wald Test rejects the hypothesis of Constant Returns to Scale ($\sum\beta=1$), confirming scale inefficiencies, particularly in low-TFP regions. These findings underscore that productivity gains are driven by efficiency rather than quantity.
Findings/Results: (1) TFP varies widely across provinces, (2) Efficiency levels are consistently higher in the western region, (3) Low or negative TFP values indicate suboptimal use of KUR and other inputs, and (4) Scale inefficiencies persist, reflecting structural and managerial constraints in rice farming systems.
Conclusion: Policy design should move from uniform, input-driven support toward a targeted productivity-based approach. Integrating KUR financing with technical assistance and region-specific strategies, such as technological upgrading, efficiency improvement, and scale consolidation, can help reduce interregional TFP gaps and strengthen the sustainability of rice farming.
Originality/value (State of the art): This study offers a methodological advancement by applying the ACF approach, commonly used in industrial economics, to agricultural productivity evaluation. The model effectively mitigates endogeneity bias and provides a more accurate measurement of TFP, offering new insights into how financing instruments influence efficiency in Indonesia's rice sector

Keywords: financing efficiency, ackerberg-caves-frazer, people's business credit, productivity, rice farming

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INTRODUCTION

Global food security remains an urgent concern as the world continues to face structural challenges in food production, distribution, and access. The 2024 FAO and Global Network Against Food Crises report indicates that 281.6 million people in 59 countries are experiencing acute food insecurity, while around 735 million individuals remain chronically undernourished. These alarming figures not only underline the fragility of global food systems but also reinforce the importance of improving agricultural productivity, expanding access to technology, and stabilizing food prices as key pillars of resilience (GNAFC, 2024). Historically, the Malthusian theory (Malthus, 1798) predicted that unchecked population growth would outpace food production, causing recurring food shortages unless productivity increased through technological advancement. This warning remains relevant for developing economies where agricultural systems often face structural constraints such as decreasing land availability, low input efficiency, and limited access to credit. Rice plays a central role in global food security. Asia accounts for 84% of world rice production, with Indonesia ranking fourth globally (Figure 1), contributing approximately 5% of total global output. As both a top producer and the third-largest consumer of rice, Indonesia's role is critical regionally and globally (USDA Gov, 2025).

As shown in Figure 1, China and India dominate rice production compared to other countries, with production levels of 144.62 and 137.83 million tons, respectively. Bangladesh and Indonesia follow with significantly lower production levels, while the remaining countries produce below 30 million tons. However, despite this strategic role, Indonesia has experienced declining harvested area and stagnating output in recent years, driven by resource constraints and climate variability (Heriqbaldi et al. 2015). As both a major producer and the world's third-largest consumer, these trends raise concerns about sustainability and self-sufficiency (FAO, 2024; IDN Times, 2025). Indonesia's declining productivity threatens its self-sufficiency and global food security contribution. Data from Statistics Indonesia (BPS Indonesia, 2024) show that the harvested area has declined, and production has become relatively stagnant due to land conversion, climate variability, pest outbreaks, and limitations in financing. The stagnation raises important policy questions: (1) Can Indonesia sustain its rice self-sufficiency? and (2) How can productivity be enhanced when land expansion is no longer viable?

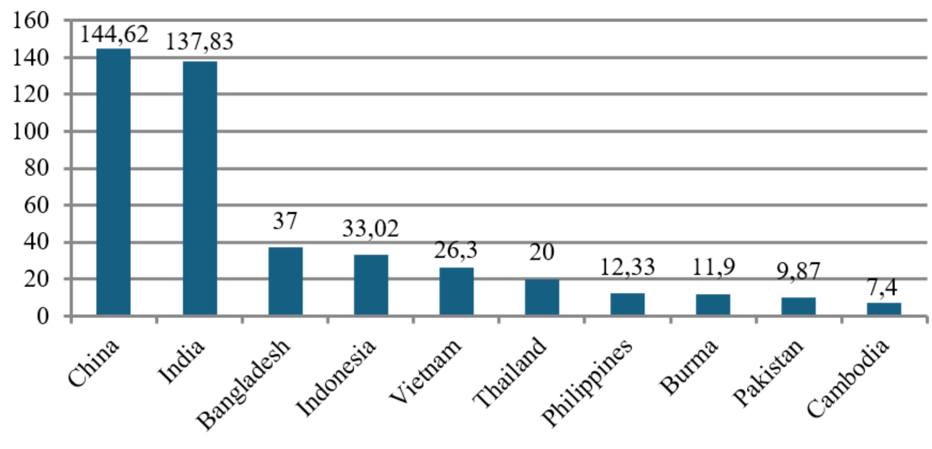

Figure 1. Top 10 Rice-Producing Countries in the World, 2023/2024 (Million Tons) (USDA, 2024)

Figure 2 shows that both harvested area and rice production in Indonesia tend to decline over the period 2018–2024. Harvested area decreased from about 11.38 million hectares in 2018 to around 10.05 million hectares in 2024, while rice production fell from approximately 59.2 million tons to about 53.1 million tons (BPS Indonesia, 2024). From a production economics perspective, reduced input availability without innovation or technology substitution will logically decrease output (Gujarati, 2003). This is especially problematic for smallholder farmers, who make up the majority of Indonesia's agricultural workforce. According to the 2023 Agricultural Census, 62% of Indonesian farmers are small-scale, cultivating less than 0.5 hectares of land. These farmers often face limited access to capital, technology, and managerial capability, resulting in low productivity and greater vulnerability to shocks. Among these constraints, limited access to formal agricultural financing remains a critical barrier. Credit enables farmers to invest in improved seeds, fertilizers, machinery, land preparation, and post-harvest equipment, while also facilitating technology adoption and other productivity-enhancing innovations. One of the central constraints is limited access to formal agricultural financing.

Credit plays a proven role in enabling farmers to invest in improved seeds, fertilizers, machinery, land preparation, and post-harvest equipment. In this context, access to agricultural financing becomes crucial. Access to financing also facilitates technology adoption, mechanization, and productivity-enhancing innovations that are otherwise unattainable for capital-constrained farmers (Haryanto et al. 2023; Naqvi & Ashfaq, 2014; Rehman et al. 2017). Recognizing these challenges, the Indonesian government introduced the Agricultural KUR (People's Business Credit) in 2016, which aims to reduce financing barriers, increase agricultural investment, and support national food security. In Indonesia, the People's Business Credit (KUR) program aims to expand farmers' access to formal financing. This study therefore examines the role of KUR in influencing rice productivity. While farmers' managerial capability may affect production decisions, the current dataset does not allow direct measurement of this factor. Accordingly, the estimated effect of KUR should be interpreted with this limitation in mind. By 2023, KUR disbursement had reached IDR 80 trillion, equivalent to 80% of Indonesia's food security budget. This positions KUR as one of the most significant financing interventions in Indonesia's agricultural sector (Kementerian Keuangan, 2023). Yet despite its magnitude, empirical evaluations of Agricultural KUR remain limited.

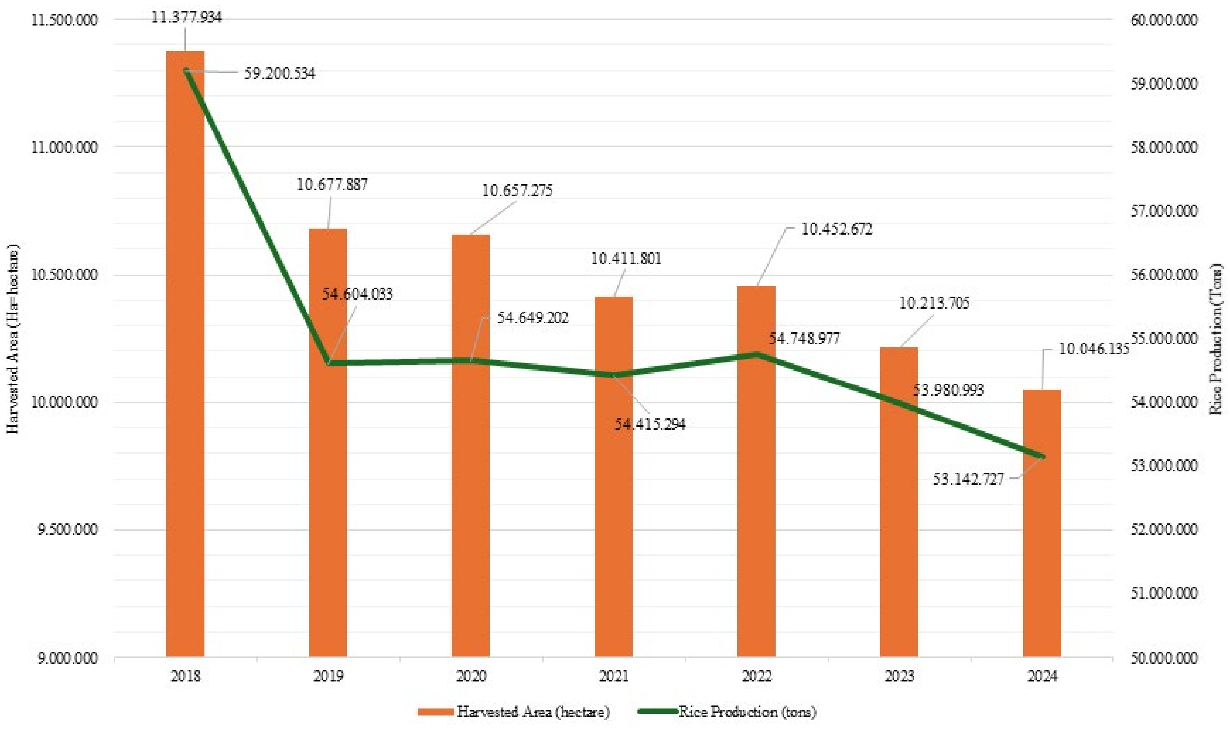

Figure 2. Harvested Area (ha) and Rice Production (tons), 2018–2024 (Statistics Indonesia (BPS), 2024)

Existing studies tend to focus on distribution metrics, such as loan size, beneficiary counts, and repayment performance, rather than quantifying their direct impact on productivity. Many studies indicate positive effects of credit on productivity (Rehman et al. 2017), but they suffer from several limitations: (1) Small, localized samples, often based on a few districts or provinces. (2) Heavy reliance on primary data reduces generalizability. (3) Limited methods, such as FE or SFA, cannot fully address endogeneity, simultaneity, or unobserved productivity shocks.

Bahta, Jordaan, and Sabastain highlighted the role of human capital and management in technical efficiency but focused only on selected African regions (Bahta et al. 2020). In Indonesia, studies have shown that formal credit, including KUR, tends to improve productivity (Haryanto et al. 2023), yet findings were geographically restricted (e.g., 10 maize-producing or 15 rice-producing provinces) and relied heavily on primary data. Other research (Anzory, 2018; Harianto, 2024) indicated that KUR funds are often diverted to consumption, suggesting inefficiencies in program implementation. In the Indonesian context, some studies even suggest that a portion of KUR funds may be diverted to consumption purposes, indicating imperfect program targeting and monitoring. This raises concerns about the effectiveness of credit in stimulating actual agricultural investment. Furthermore, most Indonesian studies have employed conventional econometric models such as Fixed Effects (FE) or Stochastic Frontier Analysis (SFA) (Amaluddin et al. 2024; Anzory, 2018; Bosawer et al. 2024; Stenny et al. 2024). While these models are widely used, they may not adequately address simultaneity bias arising from endogenous input choices. In rice farming, farmers adjust input use, such as labor, fertilizer, and capital, based on expected productivity, which is itself influenced by unobserved shocks, including weather variability, pest incidence, and price uncertainty. When such productivity shocks are time-varying and correlated with input decisions, conventional FE or SFA estimates may yield biased productivity measures. To overcome methodological limitations, this research applies the Ackerberg–Caves–Frazer (ACF) approach, an advanced production function estimation method that improves identification by addressing simultaneity between input choices and unobserved productivity shocks.

The two-stage ACF framework explicitly corrects for the simultaneity by using intermediate inputs as proxy variables for unobserved productivity, thereby allowing for more consistent estimation of total factor productivity (TFP). By explicitly modeling the productivity process rather than treating it as a residual term, the ACF framework provides a structurally grounded identification strategy. Unlike the standard Fixed Effects model, ACF allows a more accurate estimation of total factor productivity (TFP) by addressing simultaneity bias and better capturing heterogeneity in input use efficiency. In this framework, productivity is decomposed into observable input effects and an unobserved productivity component (Manjón & Mañez, 2016). Farmers' managerial capability, which is difficult to measure directly using available survey data, may be partially embedded in this unobserved productivity term. Therefore, although managerial capability is not explicitly included as a separate variable, its influence may be indirectly reflected in the estimated TFP. However, since the unobserved productivity term also captures other time-varying shocks, the specific contribution of managerial capability cannot be separately identified.

Indonesia's agricultural landscape is geographically diverse, with substantial differences between western and eastern regions in terms of infrastructure, land quality, rainfall patterns, capital availability, and input prices. While western provinces generally have better access to irrigation, input markets, and financial services, many eastern provinces face high logistical costs, weaker institutions, and low mechanization rates. As a result, identical credit injections may generate different productivity outcomes depending on regional efficiency conditions. Therefore, this study analyzes the impact of Agricultural KUR on rice productivity across 32 provinces during 2016–2023, focusing not only on output levels but also on efficiency differences between western and eastern regions.

This study therefore, contributes to the literature in three major ways: (1) Nationwide coverage across 32 provinces from 2016 to 2023, providing a more representative assessment of KUR's impact; (2) Application of the ACF method, enabling robust productivity measurement and addressing endogeneity concerns; (3) Comparison of efficiency gaps between western and eastern Indonesia, offering insights into regional disparities and policy implications.

By integrating economic theory, national data, and advanced econometric methods, this research provides a more comprehensive understanding of how agricultural credit affects rice productivity at the macro level.

The findings are expected to support evidence-based policymaking, strengthen program targeting, and enhance the design of credit mechanisms to maximize their contribution to Indonesia's food security objectives.

Despite the substantial financing provided through KUR, national evidence indicates that productivity improvements have not been proportional to credit expansion. While credit disbursement grew sharply from 2016 to 2023, rice productivity remained relatively stagnant, suggesting that financial inputs are not automatically transformed into efficiency gains. This mismatch highlights the possibility of structural bottlenecks, such as insufficient extension services, low mechanization capacity, and inadequate market access, limiting the effectiveness of credit utilization. Moreover, productivity disparities between western and eastern Indonesia suggest that the impact of credit may vary across regions, requiring a more nuanced analysis beyond aggregate output. Therefore, assessing the role of KUR through the lens of Total Factor Productivity (TFP), rather than merely production levels, becomes essential to capture true efficiency improvements. Without evidence-based evaluation, credit distribution risks become a quantity-based rather than performance-based policy. Understanding whether KUR truly enhances efficiency is crucial for designing targeted interventions and avoiding resource misallocation.

This study tests the null hypothesis (H_0) that KUR financing does not significantly affect rice productivity nor contribute to TFP growth. The alternative hypothesis (H_1) posits that KUR financing significantly enhances rice productivity, primarily through improvements in Total Factor Productivity. Existing studies on KUR and agricultural productivity primarily focus on output or income effects using conventional estimation methods, without distinguishing whether productivity gains stem from increased input use or improvements in Total Factor Productivity (TFP). In addition, limited attention has been paid to regional disparities and scale inefficiencies. This study addresses these gaps by applying a two stage ACF–TFP framework to account for input endogeneity and to decompose productivity growth into efficiency-driven and input-driven components. By doing so, it offers a more rigorous empirical assessment of KUR's role in enhancing rice productivity and highlights the importance of regionally differentiated, productivity-based policy design.

METHODS

This study employs a quantitative research design with a causal explanatory approach to analyze the effect of Agricultural People's Business Credit (KUR) on rice productivity in Indonesia. The quantitative approach is appropriate as it enables objective testing of causal relationships through statistical and econometric analysis based on numerical data (Creswell, 2003). The object of this study is the rice farming sector at the provincial level, focusing on the relationship between KUR distribution and productivity performance. The data used are annual secondary data for the period 2016–2023, obtained from official sources, the Ministry of Agriculture. The unit of analysis consists of 32 provinces. Although Indonesia had 34 provinces before 2022, two provinces, Riau Islands and Jakarta, were excluded as outliers due to their disproportionately small KUR realization compared to rice production levels, which could bias the estimation results. The use of provincial-level data is based on both methodological and policy considerations. From a methodological perspective, aggregation at the provincial level minimizes data gaps and extreme variability that often occur at the district level, thereby improving the stability of econometric estimates. From a policy perspective, most agricultural credit and productivity programs are implemented within a regional framework, making the provincial level relevant for analysis.

This study employs a documentation technique to collect secondary data. The data were obtained from official publications and statistical databases provided by the Ministry of Trade of the Republic of Indonesia. These sources include reports and datasets related to trade activities that are relevant to the variables analyzed in this research. The input variables include the amount of Agricultural People's Business Credit (KUR) disbursed, harvested rice area, agricultural labor in the food crop subsector (both landowning farmers and farm workers), subsidized fertilizer distribution (Urea, SP36, ZA, NPK and Organic), the number of two and four-wheel tractors, and the number of water small reservoirs (embung) as irrigation infrastructure. The expected coefficient signs are positive. Similarly, KUR reflects access to financing for inputs, technology, or infrastructure improvements, where greater capital access is expected to enhance productivity (Lingala et al. 2024; Mtenga et al. 2024; Stenny et al. 2024).

Fertilizer intensity ($PC1_{it}$) is derived from Principal Component Analysis (PCA) of five major fertilizers

(Urea, NPK, SP36, ZA, and organic). In this study, let x_{ij} denote the amount of fertilizer type j (j = 1, 2, …, 5) used by observation unit i (i = 1, 2, …, n). Through principal component analysis (PCA), these five variables are transformed into a new variable called PC1, which represents the largest variance of overall fertilizer use. Thus, PC1 is not merely an average, but rather a linear combination of the five types of fertilizer with specific weights (determined by PCA), referred to as fertilizer intensity (Annu et al. 2016; Yang et al. 2016). Tractorit represents agricultural mechanization, expected to positively affect production by improving land preparation efficiency (Gao et al. 2022; Liu et al. 2024). Small Reservoirs it reflects irrigation, with an expected positive sign as they reduce drought risk (Gao et al. 2022; Rahman & Connor, 2024). Finally, the error term (ε_{it}) accounts for unobserved factors such as extreme weather, pests, government policies, or price fluctuations.

Data were processed and analyzed using panel data econometric techniques and the Ackerberg Caves Frazer (ACF) production function approach, which allows for a consistent estimation of productivity while controlling for potential endogeneity in input selection. The expected coefficient signs are positive, as access to credit, labor, fertilizer, and mechanization are generally associated with higher productivity, while the error term (εit) captures unobserved shocks such as weather variability, pest attacks, or price fluctuations. Existing empirical evaluations also suffer from methodological limitations. Most studies rely on cross-sectional primary data with small sample sizes or use econometric approaches that assume exogenous input choices. In real-world agricultural practices, farmers adjust input usage after observing productivity shocks, resulting in simultaneity bias. The Ackerberg Caves Frazer (ACF) method addresses this issue by incorporating investment or intermediate inputs as proxy variables, allowing unobserved productivity shocks to be controlled. This methodological advantage makes ACF particularly suitable for measuring the true contribution of credit to productivity (Manjón & Mañez, 2016).

Previous studies have investigated the determinants of agricultural productivity using production function approaches. Boyke emphasizes the role of key production inputs, such as labor, capital, and technology, in determining farm output and finds that differences in input allocation and efficiency contribute to productivity variation among farmers. Similarly, Faradilla reports that land, labor, and capital significantly affect agricultural output and highlights the existence of productivity heterogeneity across farming units, which may stem from differences in technology adoption, human capital, and access to production inputs. However, conventional production function estimations often face methodological challenges, particularly simultaneity bias and unobserved productivity shocks that may lead to inconsistent parameter estimates. Consequently, more advanced econometric approaches, such as the Olley-Pakes, Levinsohn-Petrin, and Ackerberg Caves Frazer (ACF) methods, are required to address endogeneity problems and produce more reliable estimates of input elasticities and total factor productivity (Faradilla & Hakim, 2025; Purnomo & Risdianto, 2025). By rewriting the formula, this study not only clarifies the mathematical representation but also introduces methodological improvements that differentiate it from previous works. The refined model integrates context-specific variables, adjusts for endogeneity issues using a more appropriate estimation technique, and restructures the equation to align with actual conditions in Indonesian rice farming. These methodological enhancements contribute to novelty by providing a more realistic and policy-relevant analytical framework.

Access to agricultural financing is expected to improve farmers' ability to adopt better technology and production inputs, which in turn may increase productivity. Therefore, this study formulates the following hypotheses:

H_0: KUR financing does not significantly affect rice productivity through Total Factor Productivity (TFP) growth.

H_1: KUR financing significantly improves rice productivity, primarily through increases in Total Factor Productivity (TFP).

Therefore, the hypotheses formulated in this study are empirically tested using the econometric model described in the methodology section to assess the impact of KUR financing on rice productivity through Total Factor Productivity (TFP).

The conceptual framework systematically illustrates the causal pathways through which the allocation of People's Business Credit (KUR), land area, labor input, fertilizer use intensity, and mechanization affect rice productivity, highlighting both their individual and interactive effects. By clarifying these relationships, it establishes a structured and coherent basis for conducting panel data analysis in a holistic, rigorous, and comprehensive manner.

The framework in Figure 3 illustrates the pathway through which population growth influences food security through agricultural production, particularly rice productivity. Population growth increases food demand, making food availability a critical policy concern. Enhancing agricultural productivity is therefore essential to ensure a stable food supply. Farmers rely on various sources of financing to support agricultural production, including both formal and informal funding. In Indonesia, the People's Business Credit (KUR) program represents a key formal financing mechanism aimed at expanding farmers' access to capital. Access to credit enables farmers to obtain production inputs and invest in farming activities. Through improved financial access, farmers can strengthen key production factors, including labor, technology, and capital. These factors encompass agricultural labor, farmers, land, seeds, fertilizers, agricultural machinery, and irrigation, all of which contribute directly to rice productivity. However, the effectiveness of these inputs depends not only on their availability but also on farmers' managerial capability. Managerial capability influences how farmers allocate resources, adopt technologies, and make production decisions. Farmers with stronger managerial skills are more likely to utilize credit and production inputs efficiently, thereby achieving higher productivity. Ultimately, improved rice productivity contributes to greater food availability and supports broader food security objectives.

Ackerberg Caves Frazer (ACF) Method

This method uses intermediate input consumption, such as fertilizer, as a proxy for unobserved productivity shocks. ACF has the advantage of accommodating labor input decisions that are not necessarily simultaneous with fixed capital choices, resulting in more consistent estimates of production elasticities and reducing simultaneity bias (Ackerberg et al. 2007; Manjón & Mañez, 2016). The ACF method uses intermediate input consumption, particularly fertilizer intensity (PC1), as a proxy for unobserved productivity shocks that are observed by farmers but not by researchers. Compared with traditional approaches such as Olley Pakes (OP) and Levinsohn Petrin (LP), ACF improves identification by allowing labor input decisions to be determined separately from fixed capital decisions. Although heterogeneity in farmers' human capital, institutional performance, and governance quality may also influence productivity outcomes, the provincial panel structure and the inclusion of regional fixed effects partially capture time-invariant structural differences. Within the ACF framework, part of this heterogeneity may also be reflected in the unobserved productivity component. However, due to data limitations, these factors cannot be separately identified in the estimation. This distinction leads to more consistent estimates of input elasticities and reduces simultaneity bias. The estimation of Total Factor Productivity (TFP) using the Ackerberg, Caves, and Frazer (ACF) method is carried out in two stages. First stage, a flexible input, PC1 (fertilizer intensity), is employed as a proxy for the productivity shock (ωit), which is known to farmers but unobserved by researchers. In the first stage, the baseline production function is specified as:

$$\text{Ln\_Rice Production}_{it} = \beta_0 + \beta_k \text{ln\_Land Area}_{it} + \beta_l \text{ln\_labor}_{it} + \omega_{it} + \varepsilon_{it}$$

Where ω_{it} represents unobserved productivity. If ω_{it} is omitted, the estimated coefficients of land and labor (β_k and β_l) may become biased. To address this issue, fertilizer intensity (PC1) is assumed to be monotonically related to productivity, allowing inversion and recovery of ω_{it}. Substituting this proxy into the production function provides:

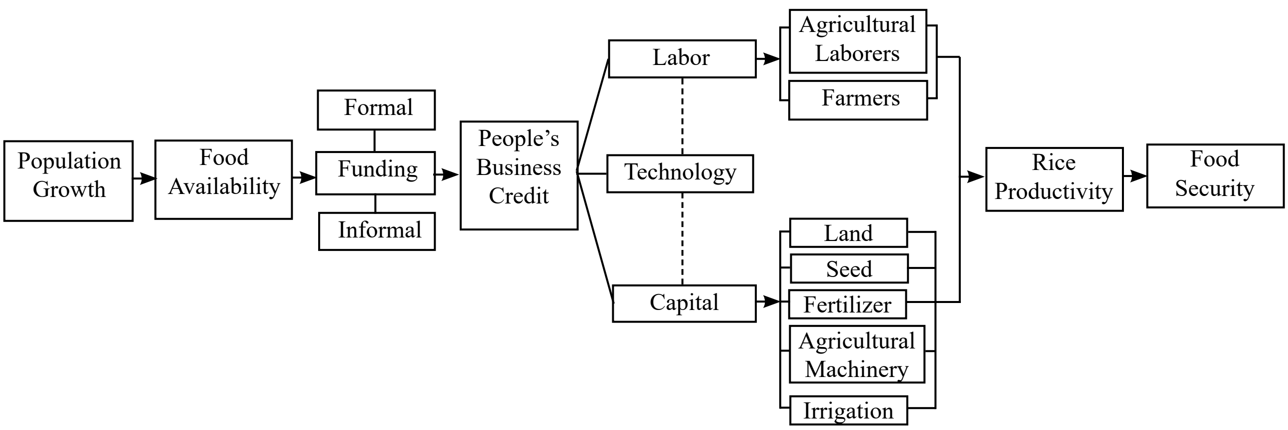

Figure 3. Conceptual framework of KUR financing and rice productivity through agricultural inputs

$$Ln\_Rice\ production_{it} = \beta_l ln\_labor_{it} + ø_t(PC1_{it}, ln\_Land\ Area_{it}) + \varepsilon_{it}$$

$$ø_t(.) = \beta_0 + \beta_k ln\_Land\ Area_{it} + h_t(PC1_{it}, ln\_Land\ Area_{it})$$

where $ø_t(.)$ is flexibly estimated using a semiparametric procedure, allowing separation of labor's contribution from the unobserved productivity component. In the second stage, after obtaining $ø_{t-1}$, all input coefficients (land, labor, KUR, tractor, and small reservoir) are reestimated using the Generalized Method of Moments (GMM). The ACF framework addresses simultaneity bias in production function estimation by modeling unobserved productivity as a control function of intermediate inputs. However, the structural parameters are ultimately identified through moment conditions that require valid instruments. In this context, the Generalized Method of Moments (GMM), as discussed by Manjón and Máñez (2016), is employed to exploit orthogonality conditions between lagged inputs and the error term. The use of GMM is particularly appropriate in agricultural productivity analysis, where input choices such as labor, fertilizer, and credit are potentially endogenous, and productivity exhibits dynamic persistence across periods. Therefore, GMM is not an alternative to ACF, but rather the estimation procedure embedded within the ACF framework. ACF assumes productivity follows a first-order Markov process, ensuring that current productivity depends on its past value (Manjón & Mañez, 2016). From this stage, all β coefficients are obtained and used to compute TFP. Once all coefficients are recovered, TFP is calculated as:

$$\begin{aligned}\widehat{\omega}_{it} = {} & \ln_{Rice}\ Production_{it} - \hat{\beta}_{Land\ Area}\,.\ \ln_{Land}\ Area_{it} \\ & - \hat{\beta}_{Labor}\,.\ ln\_Labor_{it} - \hat{\beta}_{KUR}\,.\ ln\_KUR_{it} \\ & - \hat{\beta}_{Tractor}\,.\ ln\_Tractor_{it} \\ & - \hat{\beta}_{Small\ Reservoirs}\,.\ ln\_Small\ Reservoirs_{it}\end{aligned}$$

Where: Rice $Production_{it}$ (Total rice output in province i, year t); Land $Area_{it}$ (Harvested paddy field area in province i at year t); $Labor_{it}$ (Number of workers in the agricultural sector in province i at year t); KUR_{it} (Agricultural KUR disbursement in province i at year t); $PC1_{it}$ (Fertilizer intensity (principal component score) in province i at year t); $Tractor_{it}$ (Number of two-wheel/four-wheel tractor units in province i at year t); Small $reservoirs_{it}$ (Number of small reservoirs (embung) in province i at year t); ε_{it} (Error term in province i at year t)

Additionally, the Wald test (constant returns to scale) is conducted. Following the estimation of the production function, a Wald Test was conducted to formally assess the Returns to Scale (RTS) of rice farming in Indonesia. The null hypothesis (H_0) posited Constant Returns to Scale (CRS), meaning the sum of all input elasticities equals one ($\sum\beta_i = 1$). Failure to reject H_0 suggests efficient scaling, whereas rejection indicates either increasing or decreasing returns to scale.

Understanding RTS is essential for identifying structural and managerial constraints in Indonesian rice farming systems. Previous studies on agricultural productivity have primarily focused on identifying the role of production inputs and farmers' characteristics in influencing output levels. For example, Ayuka (2025) finds that labor, fertilizer, and plant population significantly affect clove productivity in East Java, while Muliyadi (2025) highlights the importance of institutional support and information access in improving farmers' adaptive capacity (Ayuka et al. 2025; Muliyadi et al. 2025). However, most existing studies rely on conventional production function approaches, which may suffer from simultaneity bias due to unobserved productivity shocks. Therefore, this study employs the Ackerberg, Caves, and Frazer (ACF) method to obtain more consistent estimates of production function parameters.

RESULTS

The descriptive statistics provide an overview of the key variables used in this study, including the distribution, central tendency, and variation across observations. Table 1 presents the descriptive statistics of 256 provincial observations, showing large variation across all key variables. Rice production averages 1.92 million tons but ranges widely from 22 thousand to over 13 million tons, reflecting substantial regional disparities in agricultural capacity and land area. Labor involvement in rice farming and KUR allocation also vary considerably, with credit disbursement highly concentrated in a few provinces. PC1 (Fertilizer Intensity) indicates notable differences in fertilizer use, while mechanization and irrigation infrastructure show similarly uneven distributions, evidenced by large gaps in tractor ownership and the number of reservoirs. Overall, the descriptive results highlight strong spatial heterogeneity, underscoring the importance of panel data analysis to identify the drivers of rice production across Indonesian provinces.

Following the descriptive overview, the distribution of each variable is further illustrated through graphical visualizations to provide a clearer understanding of the data patterns. The boxplot visualizations reveal consistent patterns of spatial disparities across key agricultural variables. Rice production in Figure 4 shows relatively stable variation within provinces over time, with only a few provinces, mainly major rice-producing regions such as West Java, Central Java, and East Java, appearing as high outliers, indicating their dominant contribution to national output. Land area in Figure 5 and agricultural labor in Figure 6 display low dispersion and stable medians throughout the period, suggesting limited expansion potential and relatively static labor absorption across most provinces. Figure 8 describes Fertilizer intensity (PC1), which also appears homogeneous for the majority of provinces, with declining outlier values over time, indicating reduced or stabilized fertilizer use in previously high-intensity regions. In contrast, KUR disbursement in Figure 7 exhibits more dynamic heterogeneity, with shifting dispersion and concentrated outliers, reflecting uneven credit allocation across provinces despite increasing medians. Mechanization (tractor availability in Figure 9) and water reservoir construction (embung) in Figure 10 display sharp declines in median and variability after 2016–2018, suggesting reductions in reported machinery stock and lower infrastructure development intensity, except in a few provinces that remain outliers. Overall, these patterns underscore strong regional imbalances and highlight the importance of efficiency-focused policies rather than uniform input expansion.

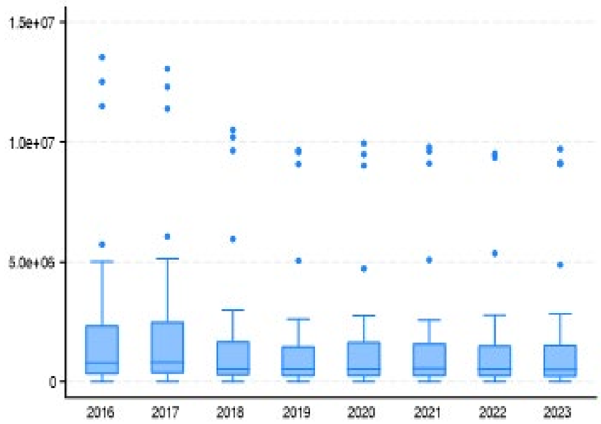

Figure 4. Distribution of rice production by year (2016–2023)

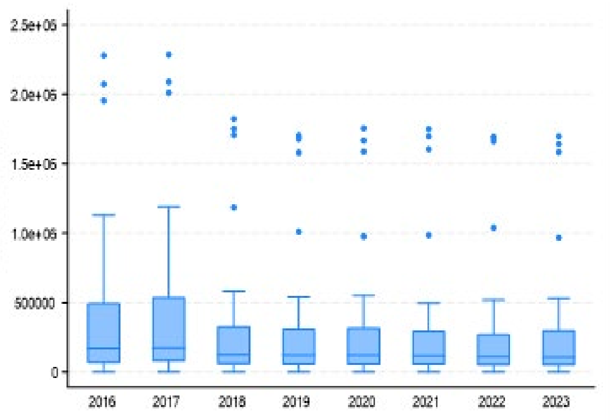

Figure 5. Distribution of harvested area by year (2016–2023)

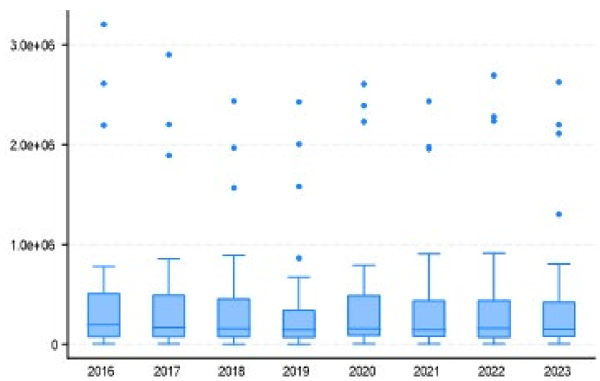

Figure 6. Distribution of labor by year (2016-2023)

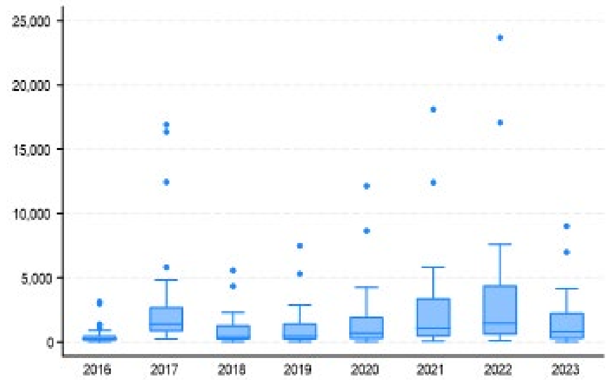

Figure 7. Distribution of KUR disbursement by year (2016-2023)

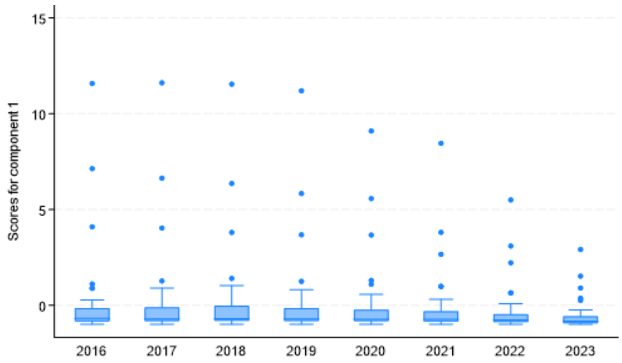

Figure 8. Distribution of PC1 (Fertilizer intensity) by Year (2016-2023)

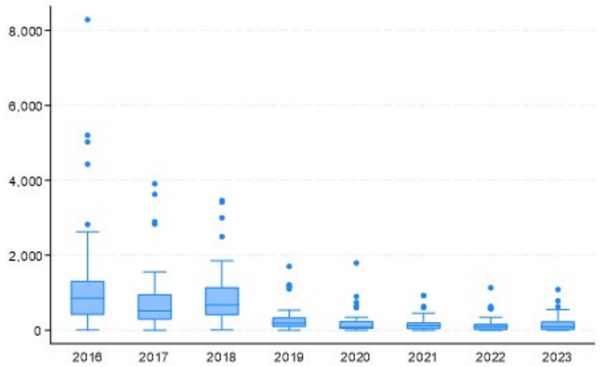

Figure 9. Distribution of tractor by year (2016-2023)

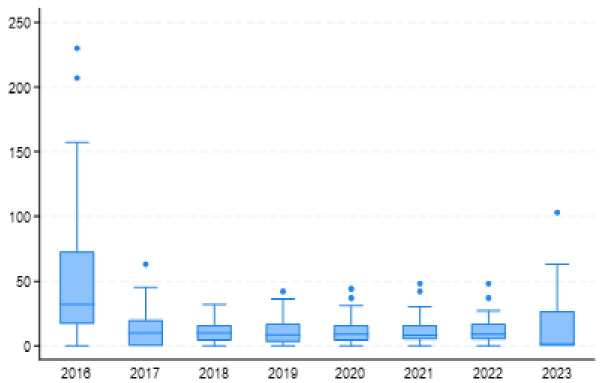

Figure 10. Distribution of small reservoir by year (2016-2023)

Based on the ACF estimation procedure, rice TFP is calculated by controlling for flexible inputs and state production factors. The estimation results in Table 2 show that land area, labor, and KUR have a positive and significant effect on rice production. The Wald test (Chi2 = 11.55; p = 0.0007) indicates increasing returns to scale, while the Sargan-Hansen test could not be performed because the model is exactly identified. This confirms that these three inputs drive output growth, in line with the Cobb-Douglas production function, with KUR financing playing an important role in supporting farming activities. In contrast, fertilizer intensity (PC1), number of tractors, and small reservoirs are not significant. The negative coefficients on fertilizer and tractors can be explained by excessive fertilizer use leading to diminishing returns, ineffective distribution and utilization of mechanization, and high operational costs. Simultaneity also plays a role, as less productive farmers tend to use more inputs, making them appear negatively correlated with output. Inefficiency, misallocation, and mismatch with land conditions further contribute to these results (Gao et al. 2022; Heriqbaldi et al. 2015; Linnenluecke et al. 2017; Manjón & Mañez, 2016; Ndlovu et al. 2014).

Figure 11 illustrates the distribution of Total Factor Productivity (TFP) estimated using the ACF method across provinces in Indonesia. The results reveal significant interregional disparities: provinces in the western regions (Java, Sumatra, and Bali) tend to exhibit more stable median TFP, whereas eastern provinces (Papua, West Papua, Maluku, and East Nusa Tenggara) consistently record lower TFP, in line with constraints in infrastructure, input access, and agricultural distribution (Harianto, 2024). Beyond interprovincial differences, the figure also highlights intraprovincial inequality. For instance, Bangka Belitung, Jambi, and North Sumatra show wide TFP dispersion, suggesting the coexistence of highly efficient and inefficient farmer groups. In contrast, Papua, West Papua, and East Nusa Tenggara display narrower spreads, reflecting homogeneity of efficiency at relatively low levels. These patterns suggest that productivity policies should target both low-TFP regions and provinces with large efficiency gaps. The boxplots also support the ACF results, showing that input heterogeneity persists and that additional inputs do not uniformly translate into higher output across regions.

Table 3 presents the average TFP by province for 2022–2023, revealing wide regional disparities. Provinces with negative TFP indicate that increases in inputs did not translate into higher output, reflecting inefficiencies in technical aspects, management, or external constraints. Such outcomes may also be associated with underlying regional heterogeneity in biophysical conditions, infrastructure, governance quality, and institutional arrangements, which structurally shape production environments across provinces. The existence of this heterogeneity is acknowledged as a fundamental characteristic of Indonesia. While the ACF (Ackerberg Caves Frazer) approach addresses endogeneity arising from unobserved productivity shocks through a proxy variable strategy, the standard ACF specification does not explicitly control for time-invariant regional heterogeneity. Therefore, the estimated input elasticities should be interpreted as capturing the average production relationship across regions rather than region-specific structural effects. To the extent that regional characteristics are relatively persistent over time, their influence may be partially absorbed into the productivity term.

Bangka Belitung and Bali recorded the highest positive TFP, suggesting relatively efficient input utilization, while eastern provinces such as Papua, West Papua, Maluku, and East Nusa Tenggara posted negative TFP, the lowest nationally. These findings imply that productivity policies should prioritize provinces with the weakest TFP. In this context, access to financing through KUR becomes a key instrument to improve productivity, although its effectiveness ultimately depends on how credit is utilized at the farmer-level. In Eastern Indonesia, however, farmer-level utilization is shaped by structural constraints such as limited infrastructure, higher transportation costs, and greater climatic risks. Therefore, policy adjustments, including longer repayment periods, credit guarantees, and integration with agricultural insurance schemes, are necessary to enhance credit effectiveness under these regional conditions. The initial TFP estimates then serve as the basis for regression analysis, treating TFP as the dependent variable, to identify factors driving productivity dynamics in agriculture and to evaluate the role of KUR and other supporting variables in enhancing efficiency (Manjón & Mañez, 2016).

Table 4 presents the regression results of rice TFP using the ACF method. Model (1) includes only KUR, while Model (2) adds controls such as tractors, small water reservoirs, and fertilizer intensity (PC1). The results show that KUR, mechanization, and infrastructure contribute positively to productivity, whereas the negative coefficient of PC1 indicates that certain factors actually reduce efficiency. The negative coefficient on PC1 does not necessarily imply that fertilizer use universally reduces productivity. Instead, it suggests that under certain production conditions, additional fertilizer application may exhibit diminishing or even negative marginal returns. This may occur when fertilizer is applied beyond the optimal agronomic threshold, when soil quality constraints limit nutrient absorption, or when complementary inputs such as irrigation and technology are insufficient. It is important to distinguish between productivity and technical efficiency. In the context of the ACF production function, the coefficient captures output elasticity rather than technical efficiency. Therefore, a negative coefficient reflects a declining marginal contribution of fertilizer to output, rather than an immediate indication of inefficiency in a strict technical efficiency sense (Annu et al. 2016; Yang et al. 2016). Land and labor variables are excluded since they have already been accounted for in the initial TFP estimation. This regression focuses more on policy, infrastructure, and technology factors. KUR not only serves as additional capital but also improves input-use efficiency, thereby driving TFP growth. However, the effectiveness of KUR in eastern Indonesia remains low, as it is often used for consumption purposes (Anzory, 2018; Harianto, 2024; Stenny et al. 2024).

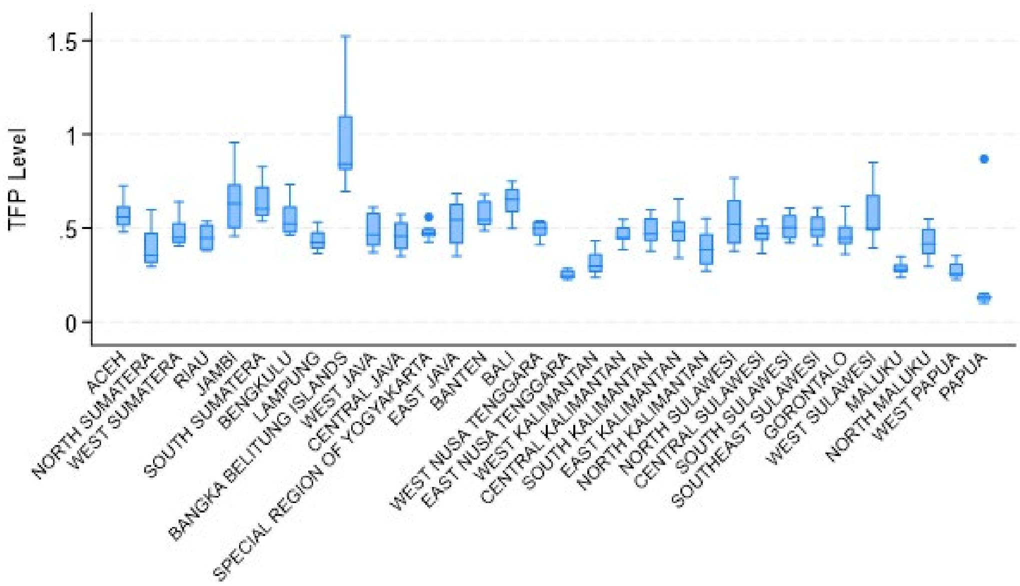

Figure 11. Distribution of Estimated Total Factor Productivity (TFP) Across Provinces

Table 1. Summary statistics of variables used in the empirical analysis

Variable	Obs	Unit	Mean	Std. Dev.	Min	Max
Rice Production	256	Ton	1,921,910	2,976,662	22,566	13,543,321
Harvested Area	256	Hectare	369,722	519,865	840	2,285,232
Labor	256	Person	448,966	645,728	1,295	3,202,972
KUR	256	IDR Trillion	1,888	3,151	11	23,693
PC1 (Fertilizer intensity)	256	-	0.06	2.13	-0.97	11.61
Tractor	256	Unit	581	956	0	8,291
Small Reservoir	256	Unit	18	28	0	230

Source: Ministry of Agriculture, Publications Report (2016–2023)

Table 2. Estimation Results of the ACF Production Function Model

Input	Model
	ACF
Harvested Area	0.552***
	(0.202)
labor	0.568**
	(0.173)
KUR	0.105***
	(0.0305)
PC1	-0.0580
	(0.0718)
Tractor	-0.00217
	(0.0207)
Small Reservoir	0.0122
	(0.0226)
Observations	236

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Wald test of constant returns to scale: Chi2 = 11.55 ($p = 0.0007$).

Table 3. TFP Results Across Provinces in Year 2022–2023

Province	Year 2022	Year 2023	Mean
Bangka Belitung Islands	0.415	0.382	0.398
Bali	0.333	0.418	0.376
South Sumatra	0.201	0.316	0.259
Banten	0.172	0.284	0.228
Aceh	0.116	0.073	0.095
West Nusa Tenggara	-0.010	0.146	0.068
South Sulawesi	-0.021	0.034	0.006
Bengkulu	-0.089	-0.003	-0.046
West Sumatra	-0.102	-0.013	-0.058
Central Kalimantan	-0.066	-0.058	-0.062
Southeast Sulawesi	-0.143	-0.020	-0.081
North Sulawesi	-0.155	-0.017	-0.086
South Kalimantan	-0.218	0.013	-0.102
Special Region of Yogyakarta	-0.159	-0.050	-0.105
Central Sulawesi	-0.244	0.024	-0.110
Jambi	-0.141	-0.096	-0.118
West Java	-0.182	-0.069	-0.125
West Sulawesi	-0.235	-0.049	-0.142
East Kalimantan	-0.017	-0.309	-0.163

Table 3. TFP Results Across Provinces in Year 2022–2023 (Continue)

Province	Year 2022	Year 2023	Mean
Gorontalo	-0.352	0.023	-0.165
Lampung	-0.232	-0.143	-0.187
Central Java	-0.277	-0.220	-0.248
Riau	-0.266	-0.314	-0.290
East Java	-0.347	-0.265	-0.306
North Sumatra	-0.451	-0.393	-0.422
North Maluku	-0.430	-0.460	-0.445
West Kalimantan	-0.543	-0.651	-0.597
East Nusa Tenggara	-0.691	-0.591	-0.641
Maluku	-0.713	-0.792	-0.752
North Kalimantan	-0.756	-0.793	-0.775
Papua	-1.686	0.056	-0.815
West Papua	-0.916	-0.988	-0.952

Table 4. Regression Results on the Impact of KUR Financing on Rice TFP

	Model	Model
	(1)	(2)
KUR	0.0412**	0.0359*
	(0.0174)	(0.0198)
tractor		0.0545***
		(0.0176)
Small reservoir		0.0545**
		(0.0262)
PC1		-0.0274*
		(0.0152)
Constant	-0.321***	-0.701***
	(0.118)	(0.158)
Observations	256	256
R^2	0.022	0.111

Note: Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results of this study show that Agricultural KUR has a significant effect on TFP, indicating improvements in production efficiency. This finding aligns with Rehman et al. (2017), who argue that agricultural credit enhances productivity through increased investment in technology. However, the results differ from Anzory (2018), who reported that KUR did not effectively increase productivity because part of the funds was diverted for consumption. This discrepancy can be explained by differences in data coverage and analytical methods. The present study employs the ACF approach, which addresses simultaneity bias and produces more accurate TFP estimates compared to conventional models such as Fixed Effects.

The differences in TFP between the western and eastern regions of Indonesia are also consistent with Bahta, Jordaan, and Sebastian (2020), who highlight that institutional factors influence efficiency levels. These regional disparities may also reflect differences in human capital quality, institutional effectiveness, and governance capacity, which condition the productivity impact of credit. However, this study finds a sharper TFP gap, likely due to disparities in access to credit, technology adoption, and infrastructure availability. Thus, the contribution of KUR to productivity is not evenly distributed across regions, indicating the need for more targeted and region-specific policy interventions. Therefore, KUR policies should be directed toward productive financing, accompanied by improvements in infrastructure, input and technology access, and local institutions to enhance productivity.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study investigates the contribution of the Agricultural People's Business Credit (KUR) program to rice farming productivity in Indonesia. The results reject the null hypothesis (H_0) and confirm that Agricultural KUR significantly improves rice productivity, primarily through increases in Total Factor Productivity (TFP). This finding indicates that productivity gains are driven not only by the quantity of inputs but also by improvements in production efficiency. Using the Ackerberg Caves Frazer (ACF) production function estimator, the study addresses simultaneity bias and provides more consistent estimates of input elasticities. The results show that KUR financing contributes positively to productivity, although its overall impact remains relatively modest. Substantial regional heterogeneity is observed: regions with higher TFP demonstrate more efficient input utilization and stronger technology adoption supported by KUR, while several regions, particularly in Eastern Indonesia, exhibit low or negative TFP, indicating suboptimal use of credit and production inputs. These findings suggest that expanding credit alone is insufficient to drive sustained productivity growth. Policies that integrate agricultural credit with improvements in rural infrastructure, technology adoption, and institutional capacity are essential to enhance the effectiveness of KUR and reduce regional productivity disparities.

Recommendations

Based on these findings, agricultural credit policy should move beyond the uniform expansion of credit access and instead focus on improving productivity outcomes. The results suggest the need for a shift from an input-based uniform policy toward a productivity-based targeted policy that considers regional differences in efficiency and structural constraints. Mapping provincial Total Factor Productivity (TFP) levels would enable policymakers to design differentiated interventions aligned with the specific drivers of productivity in each region. Such an approach allows policy interventions to address the specific productivity constraints faced by farmers in different regional contexts. Policy design should therefore address the underlying sources of productivity constraints. First, in regions where input elasticities indicate limited marginal returns to conventional inputs, policies should prioritize technological upgrading through improved seed varieties, mechanization, irrigation development, and digital farming support. Second, where low or negative TFP reflects inefficient input allocation, interventions should focus on improving technical efficiency through strengthened agricultural extension services, farmer training, and better input management. Third, in regions characterized by small and fragmented landholdings, policies should encourage scale enhancing mechanisms such as cooperative based production, land consolidation, or cluster based agricultural development. Integrating KUR financing with these targeted interventions would allow credit to function not only as liquidity support but also as an instrument for structural productivity improvement. Future research should also evaluate the long term effectiveness of KUR through cost benefit analysis comparing fiscal subsidies with productivity and income gains.

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REFERENCES

Ackerberg, D., Lanier Benkard, C., Berry, S., & Pakes, A. (2007). Econometric tools for analyzing market outcomes. Handbook of Econometrics, 6, 4171–4276. https://doi.org/10.1016/S1573-4412(07)06063-1

Amaluddin, A., Indiastuti, R., Effendi, N., & Cupian, C. (2024). Rural ICT penetration, bank credit, and agricultural sector performance: A panel ARDL analysis in Eastern Indonesia. Agris On-Line Papers in Economics and Informatics, 16(1), 3–14. https://doi.org/10.7160/AOL.2024.160101

Annu, A., Sisodia, B. V. S., & Rai, V. N. (2016). An application of principal component analysis for pre-harvest forecast model for rice crop based on biometrical characters. Journal of Applied and Natural Science, 8(3), 1164–1167. https://doi.org/10.31018/jans.v8i3.935

Anzory, A. (2018). Analisis pendapatan petani melalui program Kredit Usaha Rakyat. Jurnal Ilmiah Mahasiswa FEB, 6(2), 1–13.

Ayuka, I. R., Fariyanti, A., & Etriya, E. (2025). The effect of production inputs on productivity and production risk of cloves in East Java Province. Jurnal Manajemen & Agribisnis, 22(1), 39–50. http://dx.doi.org/10.17358/jma.22.1.39

Bahta, Y. T., Jordaan, H., & Sabastain, G. (2020). Agricultural management practices and factors affecting technical efficiency in Zimbabwe maize farming. Agriculture, 10(3), Artikel 78. https://doi.org/10.3390/agriculture10030078

Bosawer, A. L., Tinaprila, N., & Feryanto, F. (2024). Faktor-faktor yang memengaruhi penyaluran Kredit Usaha Rakyat (KUR) sektor agribisnis Bank Papua. Jurnal Ekonomi Pertanian dan Agribisnis, 8(1), 257–270. https://doi.org/10.21776/ub.jepa.2024.008.01.21

BPS Indonesia. (2024). Luas panen, produksi, dan produktivitas padi menurut provinsi - Tabel statistik. Badan Pusat Statistik Indonesia. https://www.bps.go.id/id/statistics-table/2/MTQ5OCMy/luas-panen--produksi--dan-produktivitas-padi-menurut-provinsi.html

Creswell, J. W. (2003). Research design: Qualitative, quantitative, and mixed methods approaches (2nd ed.). Sage Publications.

FAO. (2024). The state of food and agriculture 2024: Value-driven transformation of agrifood systems. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/cd2616en

Faradilla, C., & Hakim, L. (2025). Assessment of food insecurity among marginal farming households in North Aceh Regency. Jurnal Manajemen & Agribisnis, 22(3), 355–370. http://dx.doi.org/10.17358/jma.22.3.355

Gao, X., Ji, L., Chandio, A. A., Gul, A., Twumasi, M. A., & Ahmad, F. (2022). Towards sustainable agriculture in China: Assessing the robust role of green public investment. Sustainability, 14(6), 1–18. https://doi.org/10.3390/su14063613

GNAFC. (2024). Global Report on Food Crises 2024. Global Network Against Food Crises.

Gujarati, D. N. (2003). Basic econometrics (4th ed.). McGraw-Hill.

Harianto, F. (2024). Pengaruh KUR terhadap pendapatan petani. Jurnal Pertanian, Peternakan, Perikanan, 2(1). https://doi.org/10.3766/hibrida.v1i2.3753

Haryanto, T., Wardana, W. W., Jamil, I. R., Brintanti, A. R. D., & Ibrahim, K. H. (2023). Impact of credit access on farm performance: Does source of credit matter? Heliyon, 9(9), e19720. https://doi.org/10.1016/j.heliyon.2023.e19720

Heriqbaldi, U., Purwono, R., Haryanto, T., & Primanthi, M. R. (2015). An analysis of technical efficiency of rice production in Indonesia. Asian Social Science, 11(3), 91–102. https://doi.org/10.5539/ass.v11n3p91

IDN Times. (2025). 10 negara konsumen beras terbesar di dunia, ada Indonesia. https://www.idntimes.com/business/economy/negara-konsumen-beras-terbesar-di-dunia-q9t03-00-qftxr-k0y5sx

Kementerian Keuangan. (2023). Informasi APBN 2023: Peningkatan produktivitas untuk transformasi ekonomi yang inklusif dan berkelanjutan. Media Kementerian Keuangan. https://media.kemenkeu.go.id/getmedia/6439fa59-b28e-412d-adf5-e02fdd9e7f68/Informasi-APBN-TA-2023.pdf

Lingala, S., Freymond, M., Tshering, P. P., Kumari, P., Kraemer, K., & Beesabathuni, K. (2024). The egg hub model: A sustainable and replicable approach to address food security and improve livelihoods. Current Developments in Nutrition, 8(8), 103795. https://doi.org/10.1016/j.cdnut.2024.103795

Linnenluecke, M. K., Verreynne, M. L., de Villiers Scheepers, M. J., & Venter, C. (2017). A review of collaborative planning approaches for transformative change towards a sustainable future. Journal of Cleaner Production, 142, 3212–3224. https://doi.org/10.1016/j.jclepro.2016.10.148

Liu, T., Li, X., Li, X., Wang, Z., Yin, H., Ma, Y., Luo, Y., Liu, R., Li, Z., Deng, P., Peng, Z., Yang, Z., Sun, Y., Ma, J., & Chen, Z. (2024). Utilizing machine learning to optimize agricultural inputs for improved rice production benefits. IScience, 27(12), 111407. https://doi.org/10.1016/j.isci.2024.111407

Malthus, T. R. (1798). An essay on the principle of population. J. Johnson.

Manjón, M., & Mañez, J. (2016). Production function estimation in Stata using the Ackerberg-Caves-Frazer method. Stata Journal, 16(4), 900–916. https://doi.org/10.1177/1536867x1601600406

Mtenga, R. P., Funga, A., & Kadigi, M. (2024). Participation in village savings and lending associations and rice profitability in Tanzania: Application of propensity score matching and endogenous switching regression. Sustainable Futures, 7, 100169. https://doi.org/10.1016/j.sftr.2024.100169

Muliyadi, K. A., Wahyuningtyas, A. S. H., & Sujarwo. (2025). Adaptation strategies and constraints to climate change among clove farmers in East Kolaka. Jurnal Manajemen & Agribisnis, 22(3), 317–330. http://dx.doi.org/10.17358/jma.22.3.317

Naqvi, S. A. A., & Ashfaq, M. (2014). Estimation of technical efficiency and it's determinants in the hybrid maize production in district chiniot: A Cobb-Douglas model approach. Pakistan Journal of Agricultural Sciences, 51(1), 181–185.

Ndlovu, P. V., Mazvimavi, K., An, H., & Murendo, C. (2014). Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. Agricultural Systems, 124, 21–31. https://doi.org/10.1016/j.agsy.2013.10.004

Purnomo, B. R., & Risdianto, A. M. (2025). Risk analysis of farmers and rice milling businesses: A study on the rice supply chain in Yogyakarta. Jurnal Manajemen & Agribisnis, 22(2), 133–145. http://dx.doi.org/10.17358/jma.22.2.133

Rahman, M. M., & Connor, J. D. (2024). Does supplemental irrigation enhance smallholder monsoon season rice yield? Evidence from Bangladesh. Irrigation and Drainage, 73(2), 601–612. https://doi.org/10.1002/ird.2909

Rehman, A., Chandio, A. A., Hussain, I., & Jingdong, L. (2017). Is credit the devil in the agriculture? The role of credit in Pakistan's agricultural sector. Journal of Finance and Data Science, 3(1–4), 38–44. https://doi.org/10.1016/j.jfds.2017.07.001

Stenny, R., Ayal, E., Girsang, W., & Siwalette, J. D. (2024). Pengaruh Kredit Usaha Rakyat (KUR) terhadap produktifitas dan pendapatan padi sawah. Jurnal Penelitian Ekonomi dan Akuntansi, 4(6), 1910–1924.

USDA Gov. (2025). Global production rice. USDA Foreign Agricultural Service. https://www.fas.go.v/data/production/commodity/0422110

USDA. (2024). Top 10 rice production countries 2023/2024. United States Department of Agriculture. https://www.fas.usda.gov/data/production/commodity/0422110

Yang, J., Gong, W., Shi, S., Du, L., Sun, J., & Song, S. L. (2016). Estimation of nitrogen content based on fluorescence spectrum and principal component analysis in paddy rice. Plant, Soil and Environment, 62(4), 178–183. https://doi.org/10.17221/802/2015-PSE