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THE EFFECTS OF IMPROVED CASSAVA VARIETY ADOPTION ON FARMERS' TECHNICAL EFFICIENCY IN INDONESIA

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ABSTRACT
The adoption of technological innovations, such as an improved variety, has been widely promoted worldwide to improve agricultural productivity. This study aimed to examine factors affecting farmers' decision to adopt a new improved cassava varieties (NICV), and to estimate the effects of NICV adoption on farmers' technical efficiency. This research used cross-sectional data from 300 cassava farmers in East Java, Indonesia. Furthermore, the data were analyzed by probit regression to examine factors affecting farmers' decision to adopt NICV. Propensity score matching (PSM) procedures and stochastic frontier analysis were applied to evaluate the impact of NICV adoption on farmers' technical efficiency. The results indicated that adoption was highly influenced by cooperative membership, access to credit, internet access, certified land, and off-farm work. The stochastic frontier analysis, by controlling the matched sample using PSM procedures, demonstrated that NICV adoption positively and significantly impacted farmers' technical efficiency. Those who adopted NICV showed a higher technical efficiency level than those who did not. This finding implies that improved varieties could be further promoted to increase productivity. The research suggests that there is a need to improve NICV adoption to increase the levels of technical efficiency and productivity.

Contribution/Originality: This study provides two contributions to the literature. First, it essentially contributes empirical estimations of the impacts of NICV adoption on technical efficiency in Indonesia. Second, it comprehensively estimates the technical efficiency of cassava farmers in Indonesia, the world's third-largest cassava exporter.

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1. INTRODUCTION
Cassava is one of the key commodities contributing to food security, as it can be both a staple food resource and a raw material of the food industry (Muhaimin, Toiba, Retnoningsih, & Yapanto, 2020). FAO (2018) reported that Indonesia is the world's third-largest cassava exporter; the country was the second-largest cassava-producing

country in ASEAN after Thailand from 2015 to 2018. However, smallholder farmers in Indonesia are in poverty due to low agricultural productivity. According to Susilo, Saleha, Darmansyah, Oktawati, and Maryanto (2021), more than 60% of poor people live in rural areas and engage with agricultural sectors. On the other hand, the lack of technological innovation complicates Indonesian farmers dealing with agricultural problems, such as environmental threats (i.e., temperature change, drought, and flood). This condition becomes the most damaging factor in the agricultural sector and frequently influences agricultural production. A study by Dar and Dar (2021) found that annual agricultural production has declined because of increasing drought intensity. Furthermore, Ju, van der Velde, Lin, Xiong, and Li (2013) claim that water scarcity, increasing frequency and severity of pest and disease outbreaks, and soil degradation induced by environmental changes have contributed to lower agricultural yields.

Increasing farm productivity is one way to alleviate poverty in developing countries. Afolami, Obayelu, and Vaughan (2015) believe that one essential factor in reducing long-term rural poverty is adopting agricultural technology innovations, such as enhanced varieties that can reduce farmers' poverty by providing higher agricultural productivity and income. Agricultural productivity can be escalated by the adoption of improved varieties in three ways. First, improved varieties are more tolerant to climate changes, such as temperature fluctuation and drought (Lunduka, Mateva, Magorokosho, & Manjeru, 2019). Second, improved varieties are more resistant to pests and diseases (Hong-Xing et al., 2017; Nyangena & Juma, 2014). Third, improved varieties produce higher crop yields (Kumar et al., 2020; Nabasirye, Kiiza, & Omiat, 2012). Besides rice and maize, the Indonesian government has also developedanew improved cassava varieties (NICV) to maintain national and global food security. Cassava farmers in Indonesia may have benefitted from NICV because these varieties are resistant to pests and plant diseases, require shorter planting times, and taste better (Ariani, Estiasih, & Martati, 2017). This innovation provides benefits for smallholder farmers and enhances national economic growth (Abate, Dessie, & Mekie, 2019).

Previous studies have documented how NICV have been applied internationally to alleviate farmers' poverty. For example, Afolami et al. (2015) estimated the welfare impacts of adopting an improved variety in Nigeria and showed that adoption raised farmers' annual income and purchasing power. Amao and Awoyemi (2008) measured the correlation between adopting an improved variety and farmers' poverty level. The results showed that farmers who did not adopt the variety had a higher poverty level than those who did. Several studies have also shown that an improved variety produces better yields (Afolami et al., 2015), helps improve food security (Abdoulaye, Wossen, & Awotide, 2018; Donkor, Onakuse, Bogue, & de Los Rios Carmenado, 2017; Simon, Olufemi, Oluwasegun, & Adetola, 2019), and enhances asset ownership (Awotide, Alene, Abdoulaye, & Manyong, 2015). In addition, one direct indicator by which to understand agricultural productivity is to examine the correlation of technical efficiency levels with farmers' poverty levels. Ma, Renwick, Yuan, and Ratna (2018) assert that increasing farmers' technical efficiency can be a key strategy to alleviate poverty in rural areas of developing countries because it can improve agricultural production. However, smallholder farmers usually face several barriers to achieving technical efficiency, such as lack of input availability (i.e., seeds, fertilizers, and labor), waste of input usage due to environmental threats, and unavailability of technology innovation.

Existing studies have documented some insights regarding factors associated with farmers' technical efficiency. Among others, they capture the effect of cooperative membership (Ma et al., 2018), cultivation technology adoption Abdulai, Zakariah, and Donkoh (2018), and agricultural information (Mwalupaso, Wang, Rahman, Alavo, & Tian, 2019). For instance, Ma et al. (2018) estimated the impacts of cooperative membership on apple farmers' technical efficiency in China. They concluded that cooperative membership provides a higher technical efficiency level by promoting efficient usage of agriculture inputs. Abdulai et al. (2018) explored the effects of adopting cultivation technology on rice farmers' technical efficiency. They revealed that farmers who adopted cultivation technologies had 10% higher technical efficiency levels than farmers who did not. Meanwhile, Mwalupaso et al. (2019) assessed the correlation between agricultural information and technical efficiency. They discovered that agricultural information gained by using mobile phones significantly affected farmers' technical efficiency and reduced their poverty levels.

However, empirical evidence on the effect of NICV adoption on farmers' technical efficiency in Indonesia is very scanty in the literature. To fill this gap, this study investigated the impacts of NICV adoption on the technical efficiency of smallholder cassava farmers. The research will answer two questions to address the gap; first, what are the factors associated with farmers' decision to adopt NICV?; and second, what are the impacts of NICV adoption on farmers' technical efficiency levels?

2. MATERIALS AND METHODS

2.1. Research Data

The research sites were decided by multistage sampling. First, we purposively determined East Java province as the location (Figure 1). Second, three regencies were chosen by considering the volume of cassava production; these were Malang, Blitar, and Trenggalek. Third, we randomly chose three subdistricts for inclusion in the current study: Arjowilangun and Sukowilangun in Malang Regency, Sumberagung and Balerejo in Blitar, and Gading and Durenan in Trenggalek Regency. The respondents of this study were cassava farmers who had adopted NICV and those who had not. The sample was determined using a simple random sampling method. First, we established a list of farmers who planted cassava to build the sampling framework. Then, we randomly selected 300 farmers, 50 from each district. The research survey employed a structured questionnaire developed by considering a literature review and information from relevant institutions, such as government agencies and farmer groups. After creating the questionnaire, this research conducted a pilot test to check farmers' understanding.

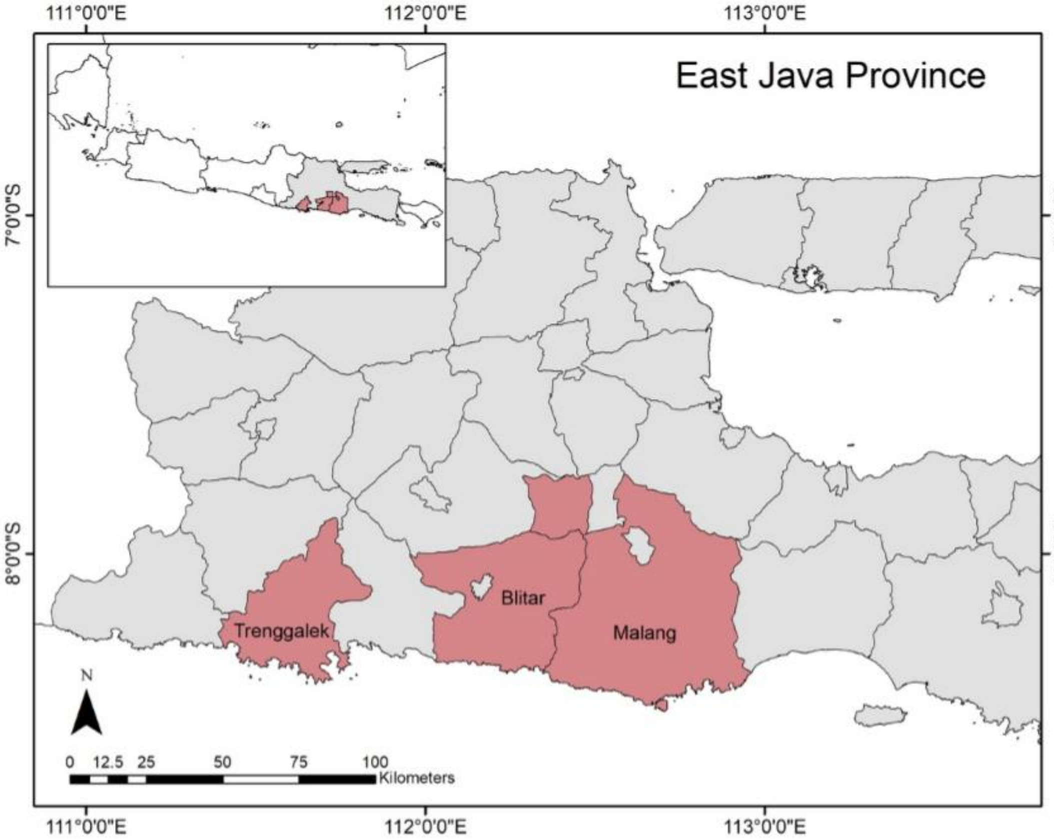

Figure-1. Research sites in East Java, Indonesia.

2.2. Estimation Strategy

Two common strategies for estimation of technical efficiency have been widely applied, stochastic frontier and data envelopment analysis. The former is more appropriate in the agricultural sector than the latter, because agricultural production is vulnerable to external factors such as environmental conditions and unpredictable weather. Data envelopment analysis assigns inefficiency to variances from the production frontier, assumes no stochastic errors, and is vulnerable to outlying (Ma et al., 2018). In contrast, the stochastic frontier approach allocates inefficiency to both random and inefficient terms. To estimate cassava farmers' technical efficiency, this study assumed that the respondents adopted and did not adopt the improved cassava variety. Hence, the stochastic frontier model of this study is formulated in Equation 1:

$$C = f(Z_i, A_i)\varepsilon_i \text{ with } \varepsilon_i = \omega_i - u_i \quad (1)$$

where C is the cassava production of i^{th} farmers, Z_i is inputs of cassava farmers (i.e., seeds, fertilizers, and labor). A_i represents the adoption variable measured by a dummy (1 if farmers adopt NICV, 0 otherwise). ε_i represents the error of the model and is structured by a symmetric stochastic that can be written as $\omega_i \sim N(0, \sigma_\omega^2)$ and can summarize the noise of statistic. Meanwhile, half-normal stochastic can be written as $u_i \sim N(0, \sigma_u^2)$ and captures for efficient production.

Moreover, to estimate the production frontier, this study employed a Cobb–Douglas estimation, as in Equation 2:

$$ln(Y_i) = a_0 + \sum_{j=1}^{5} \beta_j \, lnZ_i + \delta_i A_i + \epsilon_i \quad (2)$$

ln denotes natural logarithm, Y_i cassava production of the i^{th} farmers (kg per hectare), and Z_i an input of cassava production vectors divided into five items: hired labor, family labor, seed, organic fertilizers, and chemical fertilizers. a_0 is a constant, β_j and δ_i are the estimated parameters, and ϵ_i denotes uncorrelated random errors with the distribution of $N(0, \sigma_\epsilon^2)$.

Furthermore, this study employed PSM to estimate the impacts of NICV adoption. The PSM method is commonly used to estimate the impacts of evaluating a program by comparing the outcome variables of matching respondents in treatment and control groups. The treatment group of this study was farmers who had adopted NICV while the control group was those who had not. PSM utilizes the propensity score, or farmers' probability to adopt NICV, as a reference to build comparable respondents. Following Rahman, Toiba, & Huang (2021), who employed the propensity score, this study employed a probit regression model as in Equation 3. The propensity score is formulated in Equation 4.

$$D_i^* = z_i\beta + e_i \; ; \; D_i^* = 1 \text{ if } D_i^* > 0 \text{ and 0 otherwise} \quad (3)$$

$$S(z_i) = Prob(D_i = 1|Z_i) \quad (4)$$

in Equation 3, D_i^* represents NICV adoption (1 if adopted, 0 otherwise). Meanwhile, β is a coefficient and z_i is an independent variable (vector), including farmers' sociodemographic characteristics; e_i is the error term. In Equation 4, $S(z_i)$ represents the propensity score of each respondent.

After estimation of propensity score matching, the matching group was formulated using matching techniques. Several matching techniques are provided in the literature, such as nearest-neighbor matching, Caliper matching, stratification matching, and kernel-based matching. Following research by Qu et al. (2020), this study employed the nearest-neighbor method to formulate a matching or comparable group between adopter and non-adopter. After matching the group, this research compared the technical efficiency of the adopter and non-adopter groups.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

This sub-chapter starts by describing the statistical variables of the study (Table 1). The treatment variable was the NICV. This variable was measured by a dummy (1 if farmers adopted NICV, 0 otherwise). The descriptive statistics denoted that 37.0% of respondents adopted the NICV, while 63.0% did not. The control variables of this research included the dummy of land ownership, with an average value of 0.330. This finding implies that that farmers own 33% of the cultivated land.

Table-1. Descriptive statistic of research variables.

Variables	Description	Mean	Std.
Adoption	1 if farmers adopt the NICV, 0 otherwise	0.370	0.484
Certified land	1 if farmers' land is certified, 0 otherwise	0.330	0.471
Age	Age of household head (years)	55.167	10.411
Education	Duration of household heads' education (years)	7.307	3.077
Experience	Household head's length of farming experience (years)	26.867	13.693
Off-farm work	1 if farmers participate in off-farm work, 0 otherwise	0.271	0.446
Farmer groups	1 if farmers participate in farmer group, 0 otherwise	0.953	0.211
Cooperative	1 if farmers participate in off-farm work, 0 otherwise	0.353	0.479
Access to credit	1 if farmers have a cooperative membership, 0 otherwise	0.360	0.481
Internet access	1 if farmers access the internet, 0 otherwise	0.243	0.430
Malang	1 if farms are located in Malang Regency, 0 otherwise	0.333	0.472
Blitar	1 if farms are located in Blitar Regency, 0 otherwise	0.333	0.472
Trenggalek	1 if farms are located in Trenggalek Regency, 0 otherwise	0.333	0.472
Inputs and outputs			
Hired labor	Number of hired labor (days/ha)	158.083	72.729
Family labor	Number of family members (days/ha)	42.510	29.367
Seed	Number of seeds used (unit/ha)	13245.520	2704.407
Organic fertilizers	Number of organic fertilizers used (kg/ha)	496.937	955.943
Chemical fertilizers	Number of chemical fertilizers used (kg/ha)	445.192	442.286
Production	Total of cassava production (kg/ha)	4454.043	8177.255

The average farmers' age was 55 years, with a seven-year education. This value implies that farmers' education was in elementary school. In addition, their experience of farming cassava was 27–28 years. Then, 27.1% of respondents had other off-farm occupations, such as agricultural product sellingor enterprise-related roles. The majority of respondents (95.3%) participated in farmers' groups, 35.3% participated in a cooperative and 36.0% had access to credit. On the other hand, only 24.3% of respondents accessed the internet. Lastly, the dummy of location represented 33.3% of 100 respondents in each regency. The input variables for technical efficiency estimation consisted of five items: (1) hired labor with an average value of 158.08 days/ha; (2) farmers' average family labor of 42.52 days/ha; (3) seed, with average use of 13,245.52 units/ha; (4) organic and chemical fertilizers, with average use of 496.93 and 445.19 kg, respectively; and (5) average cassava production of 4,454.043 kg/ha.

3.2. Mean Differences of Research Variables

The mean differences of this study are summarized in Table 2. The survey showed that 111 farmers had adopted the NICV while 189 farmers did not. The mean test of variables was employed to estimate the propensity score in an unmatched sample, and showed that adopter and non-adopter groups had significant differences in land ownership, cooperative membership, access to credit, and internet access. In the matched sample, only two variables were significantly different – cooperative membership and access to credit.

In the unmatched sample, farmers who adopted the NICV tended to have certified land while those who did not adopt the NICV did not have certified land. However, adopter and non-adopter farmers in the matched sample did not show a significant difference in regard to certified land. Furthermore, adopter farmers were more likely to become cooperative members and have access to credit in unmatched and matched samples. Lastly, in the unmatched samples, adopter farmers were more likely to access the internet. However, in matched samples, adopter and non-adopter farmers did not show significant differences.

Table-2. Mean differences in sociodemographic characteristics.

Variable	Unmatched			Matched		
	Adopter (111)	Non-adopter (189)	Diff.	Adopter (111)	Non-adopter (142)	Diff.
Certified land	0.378	0.302	0.077*	0.378	0.331	0.047
Age	55.441	55.005	0.436	55.441	56.035	0.594
Education	7.523	7.180	0.343	7.523	7.338	0.184
Experience	26.694	26.968	0.275	26.694	27.035	-0.342
Off-farm work	0.307	0.250	0.057	0.307	0.331	-0.024
Farmers' group	0.955	0.952	0.003	0.955	0.937	0.018
Cooperative	0.604	0.206	0.397***	0.604	0.261	0.343***
Access to credit	0.640	0.196	0.444***	0.640	0.261	0.427***
Internet access	0.297	0.212	0.086**	0.297	0.261	0.037
Malang	0.306	0.349	-0.043	0.306	0.444	0.137
Blitar	0.360	0.317	0.043	0.360	0.254	0.107
Trenggalek	0.333	0.333	0.000	0.333	0.303	0.031

Note: *, **, *** denote significance at 10, 5, and 1%, respectively.

Table-3. Mean differences in farmers' inputs and outputs.

Variables	Unmatched			Matched		
	Adopter (111)	Non-adopter (189)	Diff.	Adopter (111)	Non-adopter (142)	Diff.
Hired labor (ln)	4.981	5.003	0.021	4.981	5.010	0.029
Family labor (ln)	3.553	3.541	0.012	3.553	3.484	0.069
Seed (ln)	9.475	9.480	-0.005	9.475	9.496	0.208*
Organic fertilizers (ln)	5.378	5.129	0.248**	5.378	4.943	0.435***
Chemical fertilizers (ln)	5.886	5.787	0.100*	5.886	5.730	0.156**
Production (ln)	8.126	7.846	0.279	8.126	7.905	0.221**

Note: *, **, *** denote significance at 10, 5, and 1%, respectively.

The mean differences between adopter and non-adopter farmers in using inputs are presented in Table 3. The unmatched sample showed that the use of organic and chemical fertilizers was significantly different. Farmers who adopted the NICV used higher levels of organic fertilizers and chemical fertilizers than those who did not adopt. After controlling for farmers' characteristics, the matched sample showed three significantly different variables: seeds, organic fertilizers, and chemical fertilizers. Adopting farmers tended to use more seed by a factor of 0.208, organic fertilizers by 0.434, and chemical fertilizers by 0.156. Lastly, we concluded that production in the unmatched sample was insignificantly different, but it was insignificantly different in the matched sample. Farmers who adopted the NICV had significantly higher cassava production (by 5%) than farmers who did not adopt it.

3.3. Factor Affecting Cassava Adoption and Propensity Score Estimation

This study employed the probit model to estimate the propensity score of respondents and to determine factors affecting farmers' decision to adopt the NICV. This section begins by discussing factors affecting farmers' decision to adopt the NICV. Table 4 shows that land certification, off-farm job, cooperative membership, access to credit, internet access, and dummy location of Malang significantly affected farmers' likelihood of adopting the NICV. On the other hand, age, education, experience, farmer group, and the dummy location of Blitar and Trenggalek did not significantly affect adoption. Probit estimation results indicated that land status positively and greatly influenced farmers' decision to adopt the NICV (by 5%). This finding revealed that farmers with land ownership were likely to adopt the NICV. Nurwahyuni, Arianti, and Hindarwati (2021) and Ramirez (2013) state that land status correlates with farmers' decision to adopt technology because they have control over their land. Having off-farm work significantly triggered farmers' decision to adopt the NICV (by 10%). It is predicted that off-farm work provides farmers with available cash to buy agricultural inputs, such as improved varieties. This finding agrees with a study by Ma et al. (2018), who investigated factors affecting technology adoption in China. They employed endogenous switching regression analysis and found that having an off-farm job positively influenced farmers to adopt agricultural technology.

Cooperative membership positively affected farmers' likelihood to adopt the NICV (by 1%). Ma and Abdulai (2017) argue that a cooperative is an important institutional arrangement to overcoming constraints preventing smallholder farmers from taking advantage of agricultural production. Moreover, belonging to a cooperative can strengthen farmers' capacity to achieve a better quality of agricultural inputs. In Indonesia, cooperatives function by distributing improved varieties, including the improved cassava variety, from the government. Zhang et al. (2017) claim that cooperatives might encourage farmers to adopt technology in agricultural production, thereby improving crop productivity. This study discovered that access to credit positively and significantly affected NICV adoption (by 1%). Those farmers with access to credit were more likely to adopt the NICV. Access to credit refers to financial support assisting farmers to purchase good-quality agricultural inputs, such as improved cassava varieties. This finding is consistent with a previous study by Simtowe and Zeller (2006), who concluded that access to credit significantly and positively influenced farmers to adopt improved varieties. The variable of internet access had a positive effect on farmers' decision to adopt the NICV. This finding implies that farmers who have access to the internet were more likely to adopt the NICV than those who did not. Internet connectivity provides widespread farming information. Farmers with better internet connections were more likely to join an organization and implement more farm innovations. Salazar, Jaime, Figueroa, and Fuentes (2018) discovered that internet connection increased the scope and intensity of farm innovation adoption. Among the three regencies in this study, the farming location in Malang regency was the one including farmers most significantly motivated to adopt the NICV. This finding revealed that the improved cassava variety was mostly distributed in Malang regency. As a result, farmers in this area had a greater opportunity to adopt it.

Table-4. Factors affecting farmers' decision to adopt the NICV.

Adopter	Coef.	Std. Err.	*z*	*P*>|*z*|
Certified land	0.480	0.246	1.960	0.050**
Age	0.005	0.011	0.410	0.682
Education	0.007	0.029	0.240	0.809
Experience	-0.001	0.009	-0.100	0.917
Off-farm work	0.382	0.219	1.750	0.081*
Farmer group	-0.214	0.404	-0.530	0.597
Cooperative	0.821	0.189	4.340	0.000***
Access to credit	1.405	0.214	6.570	0.000***
Internet access	0.593	0.219	2.710	0.007***
Malang	0.761	0.324	2.350	0.019**
Blitar	0.464	0.291	1.600	0.110
Trenggalek	-0.115	0.207	-0.550	0.580
_cons	-2.133	0.733	-2.910	0.004
log likelihood	-142.982			
LR chi²(11)	108.480			
Prob > chi²	0.000			
Pseudo-R^2	0.275			

Note: *, **, *** denote significance at 10, 5, and 1%, respectively.

Furthermore, probit regression estimated the propensity score of each respondent. Based on the estimation of probit regression, the common support regions ranged between 0.094 to 0.974 of propensity score. Figure 2 summarizes the propensity score of adopter farmers (treated) and non-adopter farmers (untreated). The adopters' and non-adopters' propensity scores are shown in the upper and lower halves of the graph, respectively. This study revealed 111 adopter farmers and 142 non-adopter farmers in the common support regions.

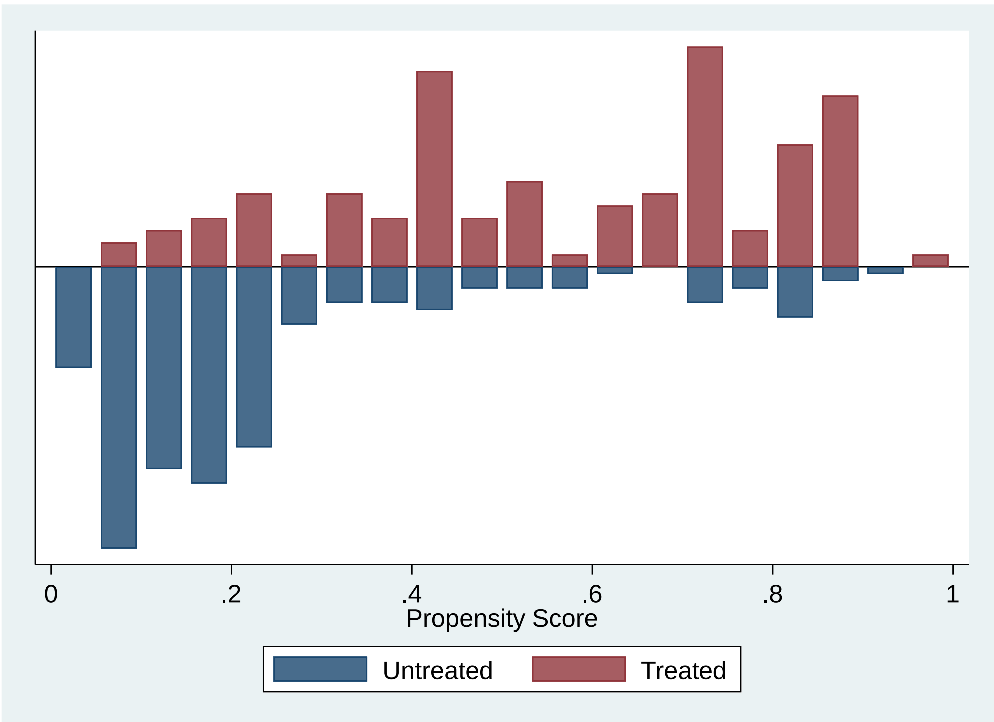

Figure-2. Propensity score distribution for adopting and non-adopting farmers.

3.4. Stochastic Frontier Estimation

The stochastic frontier estimation using unmatched respondents is presented in Table 5, while the use of matched respondents is presented in Table 6. This study applied a Cobb–Douglas stochastic frontier with a single output – cassava production (in kg/ha) – and five inputs, including hired labor, family labor, seed, organic fertilizers, and chemical fertilizers. We estimated the pooled, adopter, and non-adopter models in each unmatched and matched sample. The estimation resulted indicated a significant effect of all input variables on the pooled model in unmatched and matched samples. In addition, the adoption variable indicated a positive and significant effect on cassava production. The findings suggest that adopting a cassava variety is associated with higher output.

Furthermore, all estimations of the stochastic frontier model in Table 5 and Table 6 suggest that hired labor positively and significantly affected cassava production for both adopter and non-adopter farmers. This finding suggests that cassava farming needs professional labor because it enables farmers to achieve enhanced quality and output. This finding supports a previous study by Ma et al. (2018), who estimated the technical efficiency level of apple farming in China and discovered that hired labor enabled farmers to employ better technology innovation and, as a result, farming output increased. Although family labor negatively impacted cassava production in the pooled model, this variable was not significant in separate models (adopter and non-adopter models). This finding implies that family labor did not have such a key role as hired labor. Finally, the seed variable positively and significantly affected cassava production in all estimation models. Increasing cassava seed quantity could improve production. This study advises that farmers improve their seed quality to achieve maximum output. This finding agrees with Missiame, Nyikal, and Irungu (2021), who employed the stochastic frontier method and found a positive and significant impact of seed on cassava production in Ghana.

Table-5. Parameter estimates for SPF models: unmatched samples.

Variables	Pooled (Model 1)		Adopter (Model 2)		Non Adopter (Model 3)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hired labor (ln)	0.599***	0.118	0.645***	0.238	0.786***	0.121
Family labor (ln)	-0.125**	0.062	-0.163	0.114	-0.056	0.063
Seed (ln)	1.959***	0.258	2.190***	0.553	3.352***	0.349
Organic fertilizers (ln)	-0.083**	0.034	-0.134**	0.068	-0.106***	0.038
Chemichal fertilizers (ln)	0.130*	0.071	0.251*	0.134	0.056	0.076
Adoption (dummy)	0.310***	0.079				
Constant	-13.599**	2.492	-16.014***	5.365	-27.063***	3.437
Mu	-1.224	151.765	-1.626	198.161	-529.302	1995.408
Usigma	-5.775	160.403	-5.312	161.075	5.306	3.764
Vsigma	-0.840***	0.082	-0.474***	0.134	-1.954***	0.208
Sample	300		111		189	

Note: *, **, *** denote significance at 10, 5, and 1%, respectively.

Furthermore, organic fertilizers had a negative and significant impact on cassava output. This finding implies that that farmers necessarily reduce organic fertilizer use to improve production. In contrast, although the adopter model showed that chemical fertilizers had a positive and significant effect on cassava production, it was not significant in the adopter model. This finding implies that chemical fertilizers are more efficient than organic. The combination of organic and chemical fertilizers reduces the effectiveness of the former because this combination boosts plant nutrients faster than the latter.

3.5. The Effect of NICV Adoption on Technical Efficiency

The scores of technical efficiency for all SPF models in Table 5 and Table 6 are shown in Table 7. The average technical efficiency score of cassava farmers in the unmatched sample is 0.754 for the pooled model and 0.818 for the individual model. Furthermore, the matched sample indicated an average technical efficiency score of 0.821 for the pooled model and 0.826 for the individual model. This finding suggests that farmers who adopted the NICV had a higher technical efficiency score than those who did not – 0.242 in the unmatched samples and 0.254 in the matched.

Table-6. Parameter estimates for the SPF models: matched samples.

Variable	Pooled (Model 1)		Adopter (Model 2)		Non-adopter (Model 3)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hired labor (ln)	0.494***	0.140	0.645***	0.238	0.591***	0.157
Family labor (ln)	-0.149**	0.070	-0.163	0.114	-0.089	0.075
Seed (ln)	1.869***	0.281	2.190***	0.553	3.233***	0.387
Organic fertilizers (ln)	-0.081**	0.039	-0.134**	0.068	-0.121**	0.049
Chemichal fertilizers (ln)	0.161**	0.080	0.251*	0.134	0.114	0.090
Adoption (dummy)	0.294***	0.089				
Constant	-12.314***	2.723	-16.013***	5.363	-25.084***	3.852
Mu	-0.989	74.563	-1.620	130.289	-586.751	1004.540
Usigma	-5.621	98.348	-5.002	105.437	5.510	1.717
Vsigma	-0.744***	0.089	-0.474***	0.134	-1.913***	0.248
Sample	253		111		142	

Note: *, **, *** denote significance at 10, 5, and 1%, respectively.

Moreover, the individual model showed that the mean difference in technical efficiency score between adopters and non-adopters was significantly and positively different. Farmers who adopted the NICV showed a higher technical efficiency score than those who did not – 0.283 in the unmatched samples and 0.303 in the matched. Ma et al. (2018) proposed that the pooled model cannot be used to compare technical efficiency scores of different groups because they use different technology innovations. Therefore, the sample must be separated into different groups – for instance, adopter and non-adopter groups. Thus, the technical efficiency of the individual stochastic model can be compared. On the other hand, a good comparison is derived from two groups with similar characteristics. In this study, a good comparison was shown in the matched sample and, as a result, the best comparison in Table 7 indicates the individual mode of matched samples.

The matched sample with a separated model indicated that adopter farmers had a higher technical efficiency score than non-adopters (by 0.303). This finding answers the main objective about the impacts of improved cassava varieiesy on technical efficiency, by showing the positive impacts of NICV adoption on technical efficiency. The NICV is a technological innovation aimed to improve cassava productivity in four ways. First, the variety improves tolerance to climate phenomena, such as drought, rain intensity, and temperature changes. Second, the improved variety was developed to resist pests, such as red spiders and mites, and plant diseases, such as rotten tubers, that are a fundamental problem in Indonesian cassava farming. Third, improved cassava can be planted at maximal intensity (i.e., 15,000 plants/ha).

Table-7. The effect of NICV adoption on technical efficiency.

SPF models	Combined	Adopters	Non-adopters	Diff.
Unmatched sample				
Pooled	0.754	0.906	0.664	0.242***
Separated	0.818	0.996	0.713	0.283***
Matched sample				
Pooled	0.821	0.959	0.714	0.245***
Separated	0.826	0.996	0.692	0.303***

Note: *** denotes significance at 1%.

Generally, the findings of this study agree with those of a previous study by Rahman, Matin, and Hasan (2018), who compared the technical efficiency score of improved and traditional varieties. Their findings concluded that the improved variety produced a higher technical efficiency score than the conventional. Meanwhile, Abdul-Rahaman, Issahaku, and Zereyesus (2021) investigated the impacts of an improved rice variety in Ghana and discovered that farmers who adopted the improved variety were 24% more technically efficient than farmers who did not adopt it. A study by Ghimire, Wen-Chi, and Shrestha (2015) showed that improved varieties enable farmers to enhance farming inputs, such as labor and managerial time. As a result, they can improve the efficiency of farming operations. The findings of the present research support previous literature that found positive impacts of improved varieties on household income (Wordofa et al., 2021), poverty reduction (Manda et al., 2019; Wossen et al., 2019; Wu, Ding, Pandey, & Tao, 2010), and food security (Jaleta, Kassie, & Marenya, 2015; Shiferaw, Kassie, Jaleta, & Yirga, 2014).

4. CONCLUSION

This study assessed the impact of adoption of a new improved cassava variety (NICV) on the technical efficiency of smallholder farmers in East Java, Indonesia, by examining cross-sectional data from 300 cassava farmers. The study employed probit regression to estimate factors associated with farmers' decision to adopt the NICV. Furthermore, we estimated the farming technical efficiency score using stochastic frontier analysis. Lastly, propensity score matching was applied to evaluate the effects of NICV adoption on farmers' technical efficiency. This study provides valuable information about the NICV and the effects of specialized efficiency farming in Indonesia. The study reveals that farmers' decision to adopt the NICV was positively associated with certified land, off-farm work, cooperative membership, access to credit, internet access, and the geographical status of Malang Regency. Furthermore, the inclusion of skilled labor, seed, and chemical fertilizers enabled farmers to increase production. However, family labor and organic fertilizers harmed cassava production. The exciting finding of this study was that NICV adoption positively and significantly affected farmers' technical efficiency.

We suggest that cassava farmers should adopt the NICV continuously to improve productivity and thus support food demands in Indonesia. Policy measures encouraging cassava farmers to adopt the NICV are critical to Indonesia's agricultural growth. The government and extension agents, in particular, can offer training to farmers to improve their knowledge of NICV adoption. Furthermore, in considering the research findings we suggest the improvement of agricultural institutions, such as agricultural cooperatives and financial institutions, to support farmers' needs in farming activities, especially in adopting the NICV.

Lastly, the limitation of this research is that it employed only a desirable output (i.e., cassava production) to estimate farming technical efficiency. This study did not include an undesirable output (i.e., emission) to estimate farming efficiency and environmental efficiency; this could become a consideration for future research. Hence, estimating the relation between NICV adoption and environmental efficiency using an undesirable output could support the findings of this study.

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