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Research Article

Does Government Agricultural Machinery Assistance Increase Paddy Yield? Impact Evaluation in West Java Province Using Propensity Score Matching

Kadir Ruslan*, Weni Lidya Sukma

Statistics Indonesia, Jakarta 10710, Indonesia

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**Corresponding author:*
E-mail:
kadirsst@bps.go.id

ABSTRACT

Amidst a decade of increasing government agricultural machinery assistance, paddy yield in East Java, a major paddy-producing region in Indonesia, has stagnated, threatening the region's food security. This study evaluates the impact of such assistance on paddy yield. Using Propensity Score Matching (PSM) and Endogenous Switching Regression (ESR) on 2018 and 2021 National Cro-cutting Survey data, we found that, on average, government agricultural machinery assistance significantly increased paddy yield by 0.66 to 0.68 tons per hectare. However, the impact was greater in 2018 (0.9 tons per hectare) than in 2021 (0.14 tons per hectare), with the latter not statistically significant, likely due to the pandemic and the broader adoption of mechanization. OLS regression analysis further suggests that yield gains only occur when assistance aligns with farmers' needs. Our findings underscore the importance of a farmer-centric approach and strengthening farmer institutions to effectively manage the machinery assistance. Expanding mechanization to farmers who have not yet adopted it is also recommended.

Keywords: *Agricultural machinery, Counterfactual analysis, East Java, Government assistance, Impact evaluation.*

Background

East Java is a key contributor to Indonesia's paddy production, accounting for 18% of the national output, with 9.71 million tons of unhasked paddy in 2023 (BPS, 2024). As one of the country's principal paddy granaries, the province's agriculture sector involves around 3.29 million individual farming operations, predominantly paddy farms (BPS, 2023). Paddy farming plays a crucial role in the socio-economic stability of the province, contributing significantly to its Gross Regional Domestic Product, economic growth (Choiroh, Diartho, & Komariyah, 2020; Dinesta, 2023; Oktavia, Hanani, & Suhartini, 2016), food inflation control (Nairobi & Caroline, 2021; Pangesti, Darsono, & Antriyandarti, 2023; Wulandari et al., 2020), rural employment (Oktavia et al., 2016), poverty alleviation (Ayu & Sukojo, 2023; Khafidzin & Istifadah, 2020; Rahmawati, Ichsan, Brintanti, & Jamil, 2023), and food security (Lisanty, Andajani, Pamudjiati, & Artini, 2021).

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However, East Java's paddy farming faces significant challenges, particularly the conversion of agricultural land for non-agricultural purposes driven by population growth, urbanization, and expanding non-agricultural economic activities (Aprianto, Hidayati, & Rahardjo, 2018; Prasada, Dhamira, & Masyhuri, 2019). Between 2018 and 2019, the province's paddy fields declined from 1.29 million hectares to 1.21 million hectares, representing an annual reduction of around 8,000 hectares (Kementerian Pertanian, 2020a). Land fragmentation is also increasing, with smallholder households rising from 4.93 million in 2013 to 5.45 million in 2023 (BPS, 2023). Concurrently, the farming population decreased from 6.18 million in 2013 to 5.68 million in 2023, and 45.57% of remaining farmers are aged 55 and above (BPS, 2023).

Despite these challenges, maintaining or increasing paddy production is essential for East Java's economy. Agricultural intensification, particularly through the adoption of modern mechanization, is a key strategy for enhancing yield and efficiency in paddy farming. Studies confirm that mechanization positively impacts paddy yield (Herdiansyah et al., 2023; Kadir & Prasetyo, 2022; Magezi, Nakano, & Sakurai, 2023; Verma, 2006).

However, the cost of adopting modern agricultural machinery remains prohibitive for many farmers, compounded by the need for maintenance and access to after-sales services (Aldillah, 2016). Government intervention is critical in facilitating mechanization through the distribution of machinery. In East Java, the government distributed 23,691 units of agricultural equipment between 2018 and 2022, with an additional 30,217 units distributed between 2015 and 2016 (Kementerian Pertanian, 2020b).

Despite this extensive distribution, paddy yield in East Java has stagnated at 5.6 million tons of dray unhasked paddy per hectare during the 2019-2022 period (BPS, 2023; Kementerian Pertanian, 2020a), raising concerns about the effectiveness of government assistance in enhancing yield. In this regard, this study aims to evaluate the impact of government-distributed agricultural machinery on paddy yields and quantify any resultant yield improvements in East Java Province.

Literature Review

Agricultural Mechanization and Government Assistance

Government assistance in agricultural mechanization aims to promote the use of tools and machines to enhance agricultural production (Rijk and UNESCAP, 2005). Mechanization, as defined by T Daum & Kirui (2021), involves replacing human labor with mechanical power in crop, livestock, fisheries, and forestry cultivation. In this study, agricultural mechanization specifically refers to adopting modern agricultural tools and machines, excluding the use of animals. For food crops, mechanization encompasses all stages of production, including land preparation, planting, harvesting, and post-harvest activities. The primary goals of mechanization are to increase land and labor yield, reduce harvest and post-harvest losses, and lower production costs (Daum, 2023; Rijk and UNESCAP, 2005; Verma, 2006).

According to the theory of induced innovation, mechanization is often driven by labor shortages and limited agricultural land (Hayami & Ruttan, 1985). This is highly relevant to East Java, where the number of farmers is declining, aging, and agricultural land is decreasing and becoming increasingly fragmented (BPS, 2023). Mechanization is also a key aspect of agricultural intensification, which involves increasing the use of inputs, such as labor and machinery, to boost agricultural yield in response to growing food demand (Boserup & Chambers, 2014; Weiner, Pingali, Bigot, & Binswanger, 1988).

Adopting mechanization is not a binary decision but a process that involves multiple stages, as outlined in the Stepwise Mechanization Process (SMP) framework (Brown, Nuberg, & Llewellyn, 2017; Brown, Paudel, & Krupnik, 2021). This process includes exposure to mechanization technology, evaluation of its benefits, adoption decisions, and continued use. Government intervention plays a crucial role in ensuring sustainable adoption. In Indonesia, technical guidelines for the distribution of agricultural machinery assistance exist to target those most in need (Kementerian Pertanian, 2021). Institutional cooperation, involving local governments and farmer groups,

is essential to the effective distribution and utilization of such assistance (Kementerian Pertanian, 2018).

Pre-harvest agricultural machinery assistance, such as tractors, transplanters, and water pumps, is expected to improve land yield by enhancing land preparation, mitigating risks such as drought or pests, and promoting uniform crop distribution (Peng, Zhao, & Liu, 2022). Mechanization can also reduce yield losses during harvesting and improve the overall quality of crops (Guru et al., 2018). Thomas Daum (2023) further argues that mechanization can improve fertilizer efficiency and encourage the adoption of other yield-enhancing technologies, such as high-quality seeds and pesticides.

Previous Studies and Limitations

In the Indonesian context, numerous studies have documented the positive impact of mechanization on yield. Kadir & Prasetyo (2022), using data from the 2018 Inter-Census Agricultural Survey, demonstrated that paddy farmers who adopted mechanization had higher crop yield. Similarly, Feryanto, Herawati, Rifin, & Tinaprilla (2022) found that mechanization significantly increased corn yield. Research by Fahmid, Wahyudi, Chaidirsyah, & Yofa (2021) also confirmed this finding, while Fahmid, Wahyudi, Makmun, et al. (2021) showed similar effects on paddy, based on interviews with farmers across eight provinces, including East Java.

In the context of East Java, several studies have shown the benefits of mechanization for paddy farming, such as Prayoga & Sutoyo (2017), Ahsani (2021), and Prayuginingsih, Fauzi, Badriyah, & Jannah (2021). However, these studies often focus on limited geographic areas and do not comprehensively analyse the province as a whole. Additionally, existing studies in the context of East Java Province failed to account for potential selection bias when evaluating the impact of government assistance. This study aims to address these practical gaps by applying counterfactual analysis to micro-level data from a survey representative of East Java, allowing for a more accurate and robust estimation of the impact of government agricultural machinery assistance on paddy yield.

Methods

Research Framework

The research framework is illustrated in Figure 1 based on the introduction and literature review. Government agricultural machinery assistance plays a crucial role in promoting agricultural mechanization in paddy farming. This occurs both directly, by benefiting farmers who receive the assistance (assisted users), and indirectly, by increasing public awareness of mechanization's benefits, thereby influencing non-assisted farmers (unassisted users). The broader adoption of mechanization enhances the quality of paddy cultivation, leading to increased yield and overall paddy production.

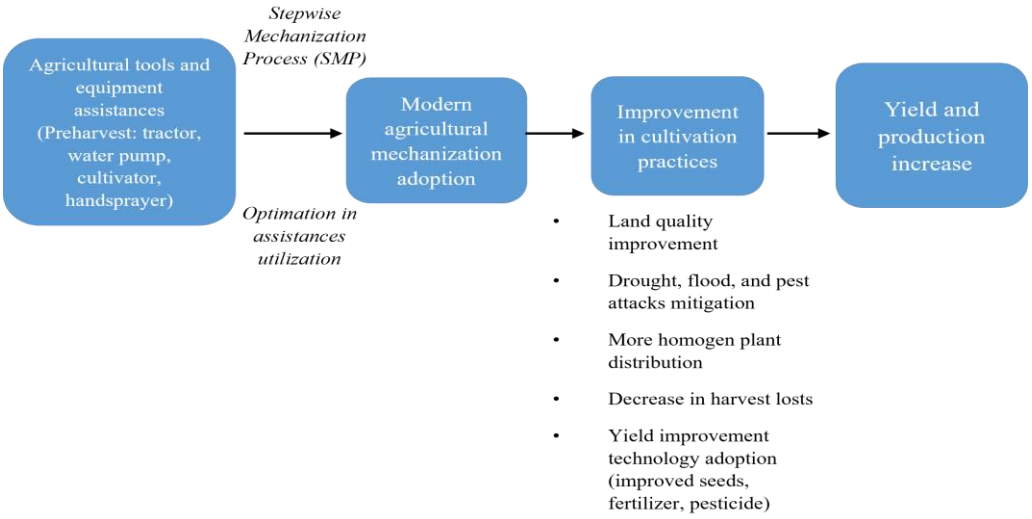

Figure 1. Research framework

Data and Variables

This study utilized microdata from the National Crop-cutting Survey, an annual household survey conducted by BPS across Indonesia. The survey is dedicated to estimating the average yield of food crops, such as paddy and secondary crops, by directly measuring harvested crops using the crop-cutting method. Alongside yield, the survey gathers information on cultivation characteristics such as land type, crop varieties, water availability, pest attack intensity, climate change impact, and access to government assistance (e.g., agricultural machinery, fertilizers, and seeds).

The survey is conducted in three periods: January-April (subround-1), May-August (subround-2), and September-December (subround-3). This study analyzes data from East Java Province for 2018 and 2021, with a total sample of 4,560 paddy plots that belonged to agricultural households (2,715 plots in 2018 and 1,845 plots in 2021).

Table 1. Definition and Statistical Description of Research Variables

No.	Research Variables	Description	Average	Standard Deviation
1.	Paddy yield	The paddy harvest results in the form of wet unhusked paddy on one hectare of land, expressed in tons/hectare.	6.6313	1.6718
2.	Government assistance for agricultural tools and machinery	It is a binary variable with categories of not receiving assistance at all (reference category = 0) and receiving assistance (= 1). Government assistance includes central and regional government assistance, while the scope of agricultural tools and machinery is water pumps, tractors, hand sprayers, paddy cultivators, threshing/harvesting machines, and other agricultural machinery. The reference time for assistance is not limited.	0.2421	0.4284
3.	Land type	Types of land used for paddy cultivation, both wet paddy fields and dry paddy fields, consisting of paddy fields other than irrigated paddy fields (non-irrigated paddy fields and dry land) (reference category = 0) and irrigated paddy fields (= 1).	0.6671	0.4713
4.	Planting system	The planting system consists of two categories, namely mixed (reference category = 0) and monoculture (= 1).	0.9252	0.2631
5.	Climate impact	This variable captures the impact of climate change in the form of floods and droughts based on farmer recognition during interviews. Consists of two categories, namely not experiencing the impact of climate change (reference category = 0) and experiencing the impact of climate change (= 1).	0.0708	0.2566
6.	Water Shortage	This variable captures the adequacy of water for paddy cultivation compared to the previous year based on farmer statements during interviews, which consist of no water shortage (reference category = 0) and experiencing water shortage (= 1).	0.0792	0.2700

No.	Research Variables	Description	Average	Standard Deviation
7.	Intensity of pest attacks	This variable captures the intensity of pest attacks on paddy cultivated by farmers compared to the previous year. Consists of three categories, namely decreasing (reference category = 1), the same (= 2), and increasing (= 3)	1.9397	0.5390
8.	Observation period	This variable captures the impact of variations in cultivation activities in each planting season which consists of three categories, namely the January-April planting period (reference category = 1), May-August (= 2), and September-December (= 3).	2.3643	0.7167
9.	Regency	It is a binary variable to capture the influence of unobserved regional characteristics, with categories of city (reference category = 0) and district (= 1).	0.8993	0.3009
10.	Year	It is a binary variable with categories 2018 (reference category=0) and 2021.	0.4043	0.4908

Empirical Method

To avoid bias in evaluating the impact of government agricultural machinery assistance on increasing paddy yield in East Java Province, we applied a counterfactual analysis using Propensity Score Matching (PSM). The impact of government agricultural machinery assistance on yield was measured through the Average Treatment Effects on the Treated (ATT) and Average Treatment Effects on the Untreated (ATU). ATT measures the average difference in yield in the recipient group with or without government assistance, while ATU measures the average difference in yield in the non-recipient group with or without government assistance. ATT and ATU can be expressed through the following equation:

$$ATT = E\{Y_1 - Y_0|P = 1\} = E(Y_1|P = 1) - E(Y_0|P = 1) \quad (1a)$$

$$ATU = E\{Y_1 - Y_0|P = 0\} = E(Y_1|P = 0) - E(Y_0|P = 0) \quad (1b)$$

where Y_1 is the yield of paddy for recipients of government agricultural machinery assistance and vice versa, Y_0 is the yield of paddy for non-recipients, and P is the status of receiving (*P=1*) or not receiving (*P=0*) government agricultural machinery assistance. The challenge in Equations (1a) and (1b) is that only the average paddy yield in the group of recipients of government agricultural machinery assistance, $E(Y_1|P = 1)$, was observed and the average yield of the group that did not receive government assistance $E(Y_0|P = 0)$, while the average yield of the government agricultural machinery assistance recipient group if they did not receive assistance $E(Y_1|P = 0)$ and the average yield of the non-assistance recipient group if they received assistance $E(Y_0|P = 1)$ were not observed. This is a consequence of evaluating the impact of government agricultural machinery assistance (treatment) on increasing yield (outcome) based on non-experimental observations (Konje et al., 2015).

This condition can bias estimates of the impact of government agricultural machinery assistance on paddy yield (Takahashi and Barrett, 2014) if yield comparisons are made solely between recipients and non-recipients. Recipient status is not random but influenced by factors like administrative requirements and farmer group membership. Assistance is typically distributed through farmer institutions, such as groups or associations (Kementerian Pertanian, 2021). Consequently, recipient status

results from a selection process, creating systematic differences between recipients and non-recipients.

PSM addresses bias in non-experimental observations and model specification errors (Khandker et al., 2009) by matching and balancing units in groups receiving and not receiving agricultural machinery assistance based on observed characteristics. This ensures both groups have the same likelihood of receiving assistance. This study uses Nearest-neighbor matching (*n = 5*) combined with Caliper matching (threshold = 0.01) to ensure differences in yield are solely due to the assistance, not observed characteristics (Sumartini and Nasrudin, 2024). The treatment group includes units receiving only agricultural machinery assistance, while the control group includes units receiving no government assistance.

Matching is conducted by estimating the propensity score, which is the probability of an observation unit getting government agricultural machinery assistance. The probability is estimated using the logit probability model in Equation (2), which is a function of some observed characteristics in Table 1, X (covariate).

$$p(X) = pr(P = 1)|X \quad (2)$$

Thus, Equations (1a) and (1b) can be written as follows:

$$ATT = E(Y_1|P = 1, p(X)) - E(Y_0|P = 1, p(X)) \quad (3a)$$

$$ATU = E(Y_1|P = 0, p(X)) - E(Y_0|P = 0, p(X)) \quad (3b)$$

PSM assumes conditional independence, which is conditional on the probability of receiving assistance and the covariates or observed characteristics that have been determined, yield without assistance and assistance status are statistically independent. PSM also assumes that there is a common support condition that requires a large overlap in covariates between the groups receiving assistance and not receiving assistance so that the observations being compared have a common probability of receiving and not receiving assistance, such that $0 < p(X) < 1$ (Takahashi & Barrett, 2014).

A regression model of paddy yield as a linear function of the status of government agricultural machinery assistance and paddy cultivation characteristics was also estimated to enrich the analysis.

$$W_i = \delta B_i + X_i'\theta + \varepsilon_i \quad (4)$$

where W_i is the natural logarithm of the yield of the paddy in the *i-th* observation unit and B_i is the status of government agricultural machinery assistance for *i-th* observation, which consists of three categories, namely not receiving any assistance at all, receiving agricultural machinery assistance and not utilizing it, and receiving agricultural machinery assistance and utilizing it. X_i' is a vector of observed agricultural cultivation characteristics in Table I. θ is a vector of parameters representing the direction and magnitude of the effect of each characteristic on paddy yield. ε_i is a random component. Thus, from the estimation of δ, it can be confirmed that government agricultural machinery assistance will only have an impact on increasing yield if utilized by farmers.

Result and Discussion

Paddy Plant Distribution by Government Agricultural Machinery Assistance

Our findings demonstrate that paddy yield is significantly higher in groups receiving government agricultural machinery assistance compared to those without. The kernel density distribution in Figure 2 shows a clear shift toward higher yield in the assisted group, suggesting that such assistance positively impacts paddy yields in East Java Province. This is consistent with previous studies indicating the positive effect of agricultural mechanization on crop yield (Diao, Silver, & Takeshima, 2016; Diao & Takeshima, 2020). However, further analysis, using PSM is needed for more robust conclusions (Rosenbaum & Rubin, 1983).

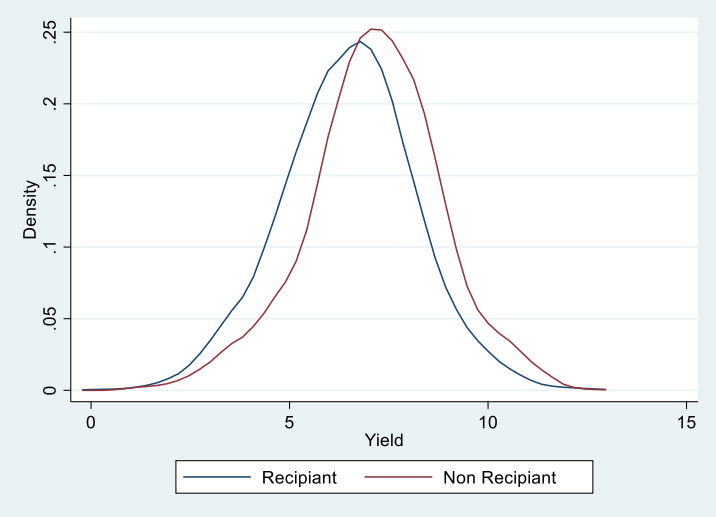

Figure 2. Distribution of paddy yield according to aid recipient status (pooled samples)

Impact of Government Agricultural Machinery Assistance on the Paddy Yield

The determinants influencing the likelihood of receiving government assistance are presented in Table 2. Compared to non-recipients, beneficiaries were more likely to have experienced increased yield, farmed in irrigated fields, and faced climate-related challenges, such as floods and droughts. These findings are aligned with research suggesting that mechanization tends to benefit farmers in areas with adequate irrigation and infrastructure (Takeshima, 2017). Conversely, some studies have noted that mechanization can have limited benefits in regions with poor water management or where farmers lack complementary inputs (P. Pingali, 2007).

Table 2. Results of logistic regression estimation of determinants of agricultural machinery aid recipient status

Dependent variable: aid status	Combined sample	2018	2021
Yield change compared to last year (increased)	0.320***	0.348***	0.204
	(0.0783)	(0.0965)	(0.147)
Land type (irrigated paddy fields)	0.757***	0.783***	0.691***
	(0.0937)	(0.109)	(0.188)
Planting system (monoculture)	-0.430***	-0.108	-0.434**
	(0.161)	(0.286)	(0.212)
Impact of climate change (affected)	0.554***	0.580***	0.541***
	(0.143)	(0.195)	(0.210)
Intensity of past attacks compared to last year			
- Just the same	-0.193**	-0.0911	-0.328**
	(0.0968)	(0.122)	(0.165)
- Increase	0.105	0.0403	0.165
	(0.138)	(0.189)	(0.206)
Water availability compared to last year (reduced)	0.303**	0.321*	0.290
	(0.145)	(0.180)	(0.257)
Harvest period			
- Subround 1	0.419***	0.582***	0.120
	(0.118)	(0.153)	(0.201)

Dependent variable: aid status	Combined sample	2018	2021
- Subround 2	0.387***	0.506***	0.192
	(0.119)	(0.152)	(0.201)
Region (district)	-0.483***	-0.770***	0.154
	(0.110)	(0.135)	(0.227)
Observation year (2021)	-0.648***	-	-
	(0.0779)		
Constants	-1,034***	-1,322***	-1,872***
	(0.238)	(0.363)	(0.382)
Number of observations	4,560	2,715	1,845
Pseudo R-squared	0.0215	0.0466	0.0221

Note: *** significant at α= 1%, ** significant at α= 5%, * significant at α= 10%, robust standard error against specification error is presented in periods. Figure 3 illustrates significant overlap in covariates between recipient and non-recipient groups, fulfilling the common support assumption necessary for valid PSM analysis (Heckman, Ichimura, & Todd, 1997). Figure 4 further confirms that the propensity scores between both groups are sufficiently similar, reinforcing the validity of comparing these groups. Post-matching balance tests indicate that covariate differences between the groups are minimal and statistically insignificant (Appendix).

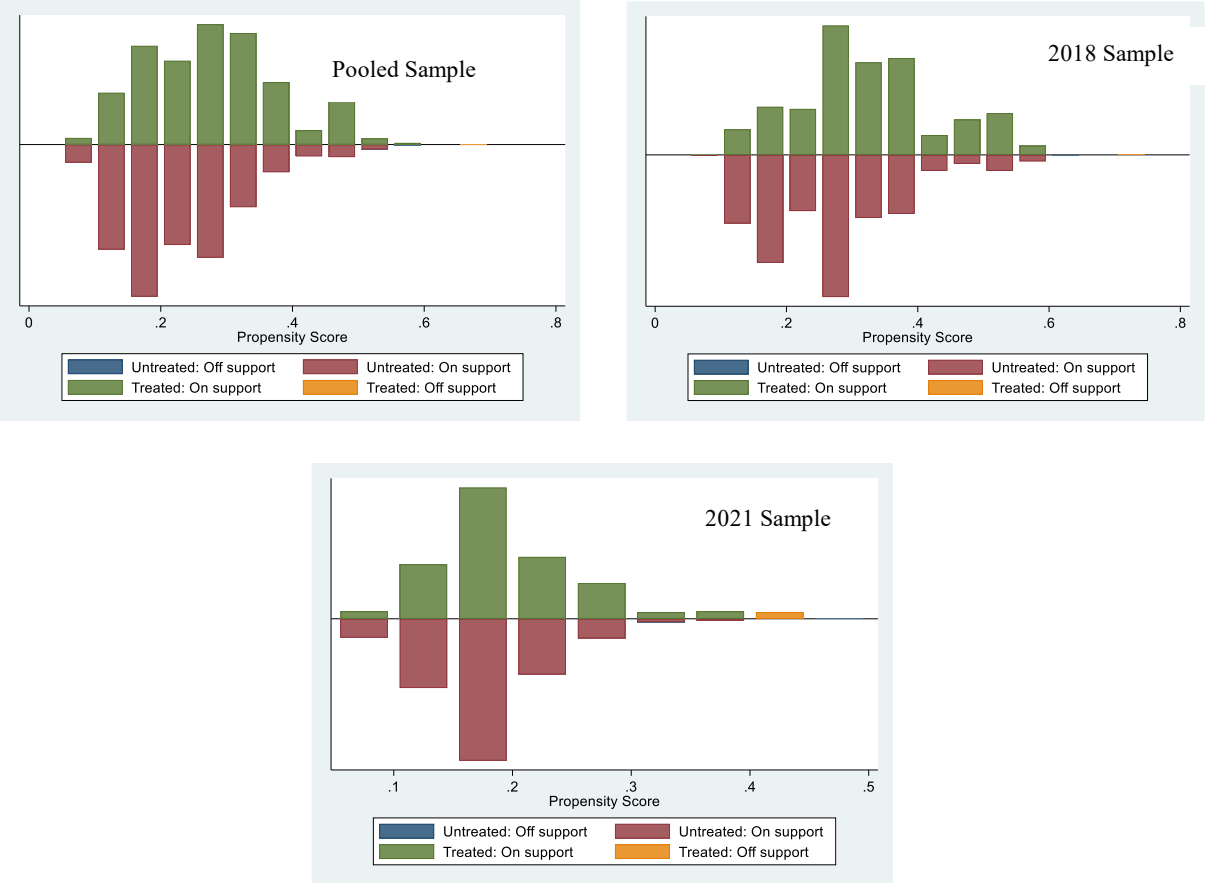

Figure 3. Common support propensity score estimation

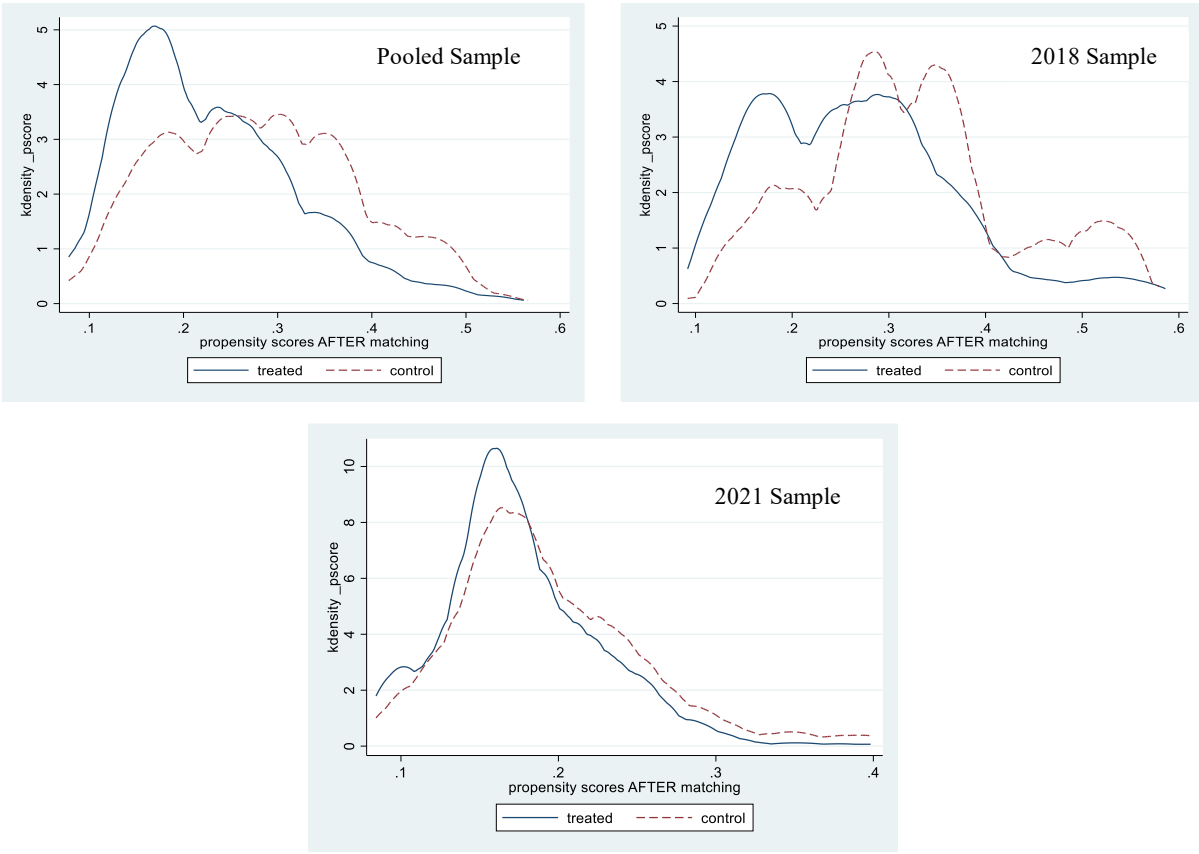

Figure 4. Distribution of estimated propensity scores after matching

The Average Treatment Effect on the Treated (ATT) and the Untreated (ATU) estimates, presented in Table 3, affirm the significant impact of machinery assistance on yield. For the combined 2018 and 2021 samples, average paddy yield in the assisted group was 7.14 tons per hectare, compared to 6.46 tons without assistance—yielding an ATT of 0.68 tons per hectare. Similar studies in Sub-Saharan Africa and South Asia have reported similar gains from mechanization (Thomas Daum & Birner, 2020; Mrema, Kienzle, & Mpagalile, 2018).

Table 3. ATT and ATU results using the PSM method (yield in wet unhusked paddy tons per hectare)

Sample group	Obtaining government agricultural machinery assistance	Not receiving government agricultural machinery assistance	ATT	ATU
2018				
Obtaining government agricultural machinery assistance	7,2479	6,3501	0.8978***	-
Not receiving government agricultural machinery assistance	7,4350	6,4387	-	0.9963***
2021				
Obtaining government agricultural machinery assistance	6.8825	6,7378	0.1447	-
Not receiving government agricultural machinery assistance	7,0738	6,5098	-	0.5640***

Sample group	Obtaining government agricultural machinery assistance	Not receiving government agricultural machinery assistance	ATT	ATU
Combined sample				
Obtaining government agricultural machinery assistance	7,1362	6,4551	0.6811***	-
Not receiving government agricultural machinery assistance	7,2728	6,4696	-	0.8033***

*** significant at α= 1%; number of observations 4,560

The ATU indicates that non-assisted groups would see an increase from 6.47 to 7.27 tons per hectare if they received assistance, with an estimated gain of 0.80 tons per hectare. These results corroborate evidence from other developing countries where mechanization has led to yield improvements when combined with complementary inputs like seeds and fertilizers (Houssou & Chapoto, 2015; Poole, 2017).

When analyzed separately by year, the data reveal that the yield gains were higher in 2018, with an ATT of 0.90 tons per hectare, compared to a mere 0.14 tons per hectare in 2021, which was statistically insignificant. This discrepancy may be due to the increased adoption of agricultural machinery between 2018 and 2021, as both government-assisted and non-assisted groups progressively adopted mechanization independently. Studies show that increased exposure to agricultural technologies often leads to higher adoption rates, even among non-recipients (P. L. Pingali, 1997). Additionally, the COVID-19 pandemic may have contributed to the reduced yield impact in 2021.

The accumulation of government agricultural machinery assistance from 2018 to 2021 likely had an indirect impact by increasing public awareness and knowledge of mechanization benefits. Such spillover effects have been documented in other studies, where government interventions foster broader adoption of technology, leading to sustained yield improvements (Sharma, Sultan, Ding, & Triggle, 2020).

The lower ATT and ATU estimates for 2021 compared to 2018 could also indicate that the optimization of the use of government agricultural machinery assistance was less effective in 2021. Several studies suggest that ineffective mechanization, particularly when not tailored to local needs, can lead to diminished yield benefits (Thomas Daum & Birner, 2020).

The distribution plot in Figure 5 suggests that the yield gains from government agricultural machinery assistance depend heavily on whether the machinery is effectively utilized. If the machinery is not used properly, there is little difference between recipients and non-recipients of assistance, echoing the findings of Prasetyo & Kadir (2024), who found that underutilized machinery does not significantly impact yields. However, when the assistance is optimized according to farmer needs, the yield increase is statistically significant, with a 10.15 percent $((e^{0.67} - 1) \times 100)$ gain for properly utilized machinery (Table 4).

This issue of suboptimal machinery utilization is consistent with other studies that highlight challenges in managing government-provided assistance, including mismatches between machinery types and farm sizes, inadequate training, and weak managerial support (Fahmid, Wahyudi, Chaidirsyah, et al., 2021; Syahyuti, Indraningsih, Swastika, Susilowati, & Suharyono, 2021).

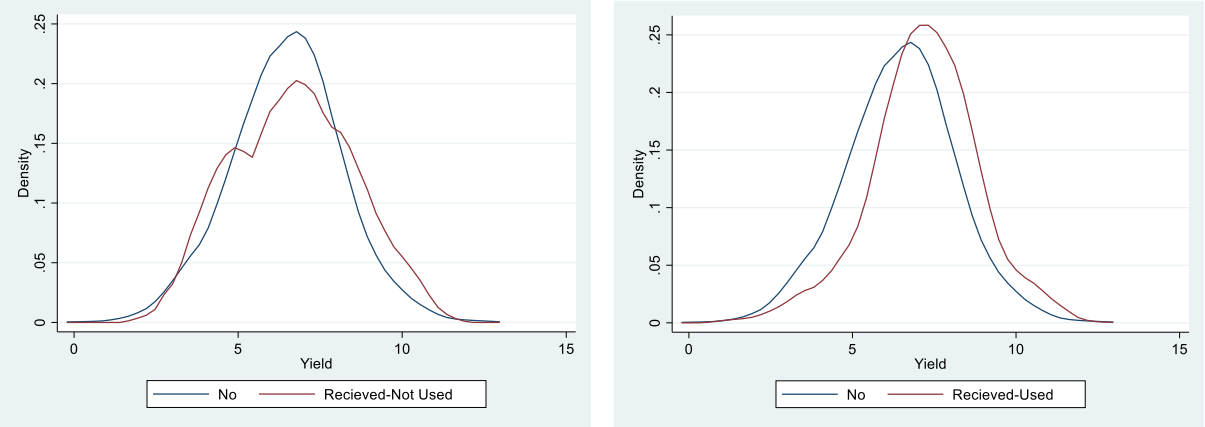

Figure 5. Distribution of paddy yield based on the utilization status of agricultural machinery assistance received (pooled samples)

Table 4. Results of OLS estimation of the impact of government agricultural machinery assistance

Dependent variable: natural logarithm of yield	Combined sample	2018	2021
Agricultural machinery assistance			
- Receive assistance and not be used	0.0133	0.0204	0.0131
	(0.0256)	(0.0375)	(0.0366)
- Receive help and be used	0.0967***	0.0973***	0.0720***
	(0.00931)	(0.0105)	(0.0184)
Yield change compared to last year (increased)	0.0963***	0.0933***	0.112***
	(0.00906)	(0.00987)	(0.0183)
Land type (irrigated paddy fields)	0.109***	0.114***	0.109***
	(0.0105)	(0.0120)	(0.0212)
Planting system (monoculture)	-0.0888***	0.0291	-0.127***
	(0.0181)	(0.0363)	(0.0232)
Impact of climate change (affected)	-0.0128	0.0131	-0.0363
	(0.0196)	(0.0260)	(0.0281)
Intensity of pest attacks compared to last year			
- Just the same	0.00561	0.0132	0.0136
	(0.0102)	(0.0127)	(0.0165)
- Increase	-0.110***	-0.0774***	-0.129***
	(0.0168)	(0.0236)	(0.0244)
Water availability compared to last year (reduced)	-0.122***	-0.135***	-0.103***
	(0.0186)	(0.0219)	(0.0333)
Harvest period			
- Subround 1	-0.0427***	-0.0537***	-0.0227
	(0.0130)	(0.0153)	(0.0235)
- Subround 2	-0.0350**	-0.0478***	-0.0161
	(0.0143)	(0.0154)	(0.0274)
Region (district)	-0.00329	-0.0858***	0.138***
	(0.0172)	(0.0135)	(0.0365)
Observation year (2021)	-0.0251***	-	-
	(0.00923)		

Dependent variable: natural logarithm of yield	Combined sample	2018	2021
Constants	1,869*** (0.0281)	1,827*** (0.0435)	1,727*** (0.0491)
Number of observations	4,560	2,715	1,845
R-squared	0.134	0.198	0.101

*** significant at α= 1%, ** significant at α= 5 %, * significant at α= 10 %; heteroskedasticity robust standard error is presented in less

While this study presents compelling evidence of the positive impact of government agricultural machinery assistance on paddy yield in East Java, several limitations suggest areas for improvement in future research. For instance, the relatively low Pseudo R-squared value in the PSM model indicates that the observed characteristics may not fully capture the factors influencing the likelihood of receiving assistance. Other socio-demographic factors could be incorporated into the model to improve explanatory power.

Conclusion

This study investigates the effect of government agricultural machinery assistance on paddy yield in East Java Province. Using counterfactual analysis on the 2018 and 2021 Crop-cutting the findings confirm a statistically significant increase in average paddy yield due to this assistance. To further enhance mechanization adoption, targeting farmers who have not yet adopted modern machinery is recommended. Moreover, ensuring the machinery aligns with farmers' needs and that its management by farmer groups is sustainable is crucial. Continuous support and monitoring from agricultural services are essential.

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Appendix

Results of the examination of the bias of the covariate differences between the recipient and non-recipient groups after matching was performed.