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DOES THE USE OF MOBILE PHONES BY FARMERS HAVE AN IMPACT ON AGRICULTURAL PRODUCTIVITY IN EAST JAVA?

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ABSTRACT

This study examines the use of mobile phones on agricultural productivity in East Java Province and its comparison with peer provinces. This study uses a Propensity Score Matching (PSM) approach with a probit model to analyze the impact of using mobile phones for agricultural business activities on the amount of rice output in the form of rice. The data used in this study is IFLS wave 5 2014. The estimation results show that, in general, age, education, marital status, the natural logarithm of income, the number of paddy fields, and location affect the probability of using mobile phones for agricultural purposes. On the other hand, this study also found results that the probability of using a cell phone by individuals in East Java Province is influenced by their level of education. Individual education level in East Java Province positively relates to mobile phone use. It means that the level of education can increase the probability of using mobile phones for agricultural business purposes. Furthermore, the results of the impact of mobile phone use on the amount of rice output found that, on average, individuals who use mobile phones for farming purposes in East Java will get a higher amount of rice output by 841.3 kg compared to individuals who do not use mobile phones for business agriculture.

Keywords: *Propensity Score Matching; ICT; Productivity*

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ABSTRAK

Penelitian ini mengkaji penggunaan ponsel terhadap produktivitas pertanian di Provinsi Jawa Timur dan komparasinya dengan provinsi peer. Studi ini menggunakan pendekatan Propensity Score Matching (PSM) dengan model probit untuk menganalisis dampak penggunaan ponsel untuk keperluan aktifitas usaha pertanian terhadap jumlah output padi dalam bentuk beras. Data yang digunakan dalam studi ini adalah IFLS gelombang 5 tahun 2014. Hasil estimasi menunjukkan bahwa secara umum variabel usia, pendidikan, status pernikahan, logaritma natural pendappatan, jumlah plot sawah, dan lokasi mempengaruhi probabilitas penggunaan ponsel untuk keperluan usaha pertanian. Di sisi yang lain, studi ini juga ditemukan hasil bahwa probabilitas penggunaan ponsel oleh individu di Provinsi Jawa Timur dipengaruhi oleh tingkat pendidikan. Tingkat pendidikan individu di Provinsi Jawa Timur berhubungan positif terhadap penggunaan ponsel. Ini berarti tingkat pendidikan tersebut mampu meningkatkan probabilitas penggunaan ponsel untuk keperluan usaha pertanian. Lebih lanjut, hasil dari dampak penggunaan ponsel terhadap jumlah output beras ditemukan bahwa secara rata-rata individu yang menggunakan ponsel untuk keperluan usaha tani di Jawa Timur akan meningkatkan jumlah output beras lebih tinggi sebesar 841,3 kg dibandingkan individu yang tidak menggunakan ponsel untuk keperluan usaha pertanian.

Kata Kunci: *Propensity Score Matching; Teknologi informasi dan komunikasi; Produktivitas*

JEL**: C21; O13; O33**

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Introduction

The agricultural sector has an essential role in every country, including Indonesia. The agricultural sector is the primary sector in meeting human food needs (Khairad, 2020). According to Pebrianto (2018) the need for food for the Indonesian people is predicted to continue to increase. PERHEPI (Indonesian Agricultural Economic Association) in Pebrianto (2018) predicts an increase in food commodities, especially rice. PERHEPI stated that rice consumption is currently still at 97.6 kg per capita per year and is expected to increase to 99.08 kg in 2025 (about 1.5%). The agricultural sector also plays a vital role in supporting the economic life of the Indonesian people, as seen from the number of workers absorbed by the agricultural sector by 88.43 percent in 2021 (BPS, 2021). Therefore, everything related to development in the agricultural sector must continue to be improved so that the welfare of farmers also increases.

East Java is one of the provinces that has been nicknamed the national rice barn. East Java Province has relatively large data on rice production in Indonesia. In 2020, rice production in East Java reached 10,022,387 tons (BPS, 2020). This reasonably prominent production figure can be an opportunity to realize food security in East Java. Dahwilani (2020) states that one way to realize and maintain food security is by encouraging farmer productivity. For agricultural productivity to increase, it must support the agricultural sector, one of which is technology (William et al., 2021).

Information technology in the current era of globalization is crucial for society, including Information and Communication Technology (ICT) can help meet farmers' needs for information. Farmers need market information, new techniques and technologies, prices, weather forecasting, and much more that supports agricultural facilities and infrastructure (Sutisna, 2018). So that if farmers can use the technology well, it will increase productivity and provide good opportunities for agricultural development actors.

Simple technology such as mobile phones is one of the information and communication technology equipment that can support agricultural products. Farmers who own, use, and make good use of mobile phones will be able to access better information, for example, information on extension services, marketing information, and others that can increase their productivity (Issahaku et al., 2018). However, generally, farmers have not utilized information technology, in this case, digital technology via the internet. Only a few of them use their mobile phones to search for agricultural information. The rest use mobile phones as a means of regular communication and entertainment. Catur Yuantari et al. (2016) also stated that the level of knowledge of farmers about technology, one of which is in marketing agricultural products, is still not optimal. Simple technology, such as mobile phones, has not been used optimally for farming activities (Feryanto & Rosiana, 2021).

Currently, the level of technology literacy of farmers is still relatively low. The results of Crowde's research report in Indah (2021) stated that only 4.5 million farmers out of a total of 33.4 million farmers in 2020 have used their mobile phones and used the internet over the past year. Meanwhile, based on data from BPS (2018) in East Java, 862,397 farmers use the internet, and 5,427,710 farmers do not. It indicates that the number of farmers in East Java who have not used their mobile phones optimally, especially for agricultural purposes such as searching for information and communication on social media, is still significant. Meanwhile, if appropriately used, technology such as mobile phones will help increase productivity.

Several studies related to the impact of cell phone use have only been slightly analyzed due to the need for more required data. Several studies also only focus on the determinants of mobile phone use (Karim et al., 2020; Khan et al., 2022), technology adoption (Gupta et al., 2021; Zhang et al., 2021), and the use of mobile phones in accessing information agriculture (Khan et al., 2020). In addition, considering that there are a large number of farmers in the province of East Java who does not yet use cell phones for agricultural purposes, this study aims to analyze the impact of using cell phones on farmer productivity, especially in East Java and its comparison with Peer Provinces, namely West Java and Central Java. The selection of the peer province was based on the vast paddy fields on the island of Java. This study contributes to the literature by discussing what factors influence farmers' decisions to use cell phones as a medium for agricultural activities and how the impact of using cell phones for agricultural purposes has on farmer productivity as measured by the amount of rice harvest output in the form of rice.

This study is structured as follows. Part 1 consists of the background. Section 2 describes the literature review. Section 3 discusses the data and methodology and describes the empirical model used to estimate the effect of interest. Section 4 discusses the estimation results. Section 5 is conclusions and suggestions.

Literature Review

The production function shows the nature of the relationship between the production factors and the production level. The factors of production are also known as inputs, and the amount of production is always referred to as output. The production function is always expressed in the form of a formula, which is as follows:

$$Q = f(K, L, R, T) \tag{1}$$

Where K is the amount of capital stock, L is the amount of labor, including various types of labor and entrepreneurial skills, and R is natural wealth. T is the level of technology used. In contrast, Q is the number of products produced by various factors. Following Antle's (1983) approach, it is assumed that the Cobb-Douglas agricultural production function with a Hicks-neutral productivity level (A) depends on the ICT. These variables are captured by mobile phones and ICT tools that play an essential role in technology adoption to increase output. Thus, the agricultural production function takes the following functional form:

$$Q = AK^{\alpha} L^{\beta} R^{\delta} T \tag{2}$$

Farmers need much information on agricultural production to support their farming business. Farmers need a variety of information in every stage of the production process, from the land processing stage to the marketing process. In this regard, farmers can obtain this information from various sources by using and utilizing information and communication technology optimally. Farmers quickly access information on prices, products, and market share. It is evident from Akhmadi's (2018) study, which analyzes the role of information and communication technology, especially in marketing agricultural products. Using the explanatory review method, the results show that Information and Communication Technology positively influence the marketing of agricultural products.

Several previous studies have identified the determinants of using information and communication technology in the form of mobile phones by farmers. Several factors, including age, influence farmers' decisions to use mobile phones, length of education, income, marital status, home ownership status, and land area (Aminou et al., 2018; Folitse et al., 2019; Umaroh & Afifah, 2020; Feryanto & Rosiana, 2021; William et al., 2021). Folitse et al. (2019), in their study using logistic regression analysis it was found that the coefficient of the age variable had a negative and significant relationship with the use of mobile phones as a communication tool for agricultural information. It means that the probability that farmers who use mobile phones as a medium for communicating information about agriculture are younger than older farmers. It differs from Umaroh & Afifah's (2020) research, which shows that the age variable positively correlates with mobile phone use. Older farmers have a high probability of using mobile phones to communicate and exchange information with other farmers.

Other factors, such as education level and land area, also positively and significantly influence decisions to use mobile phones (Feryanto & Rosiana, 2021). The higher the education level, the higher the probability of farmers using mobile phones. Education provides insight to farmers to get more information to support their agricultural activities. Meanwhile, the more expansive agricultural land encourages farmers to use mobile phones for marketing activities. The more extensive land indicates that the agricultural products that will be obtained will also be significant. It encourages farmers to use and utilize mobile phones. The income variable also has a positive and significant influence on the use of mobile phones (Umaroh & Afifah, 2020). Farmers' income increases, so the probability of using mobile phones is also high because they can afford it.

Several previous studies examine the effect of mobile phones on agricultural productivity. Feryanto & Rosiana (2021) analyzed the impact of mobile phone use on farmers' welfare in Java and non-Java as measured by farm income. Using the Propensity Score Matching (PSM) method, the results show that the impact of the average income of farmers who use mobile phones is more significant, Rp—7,430,000 per year, compared to farmers who do not use mobile phones for marketing activities. Similarly, the study of Issahaku et al. (2018) found that mobile phones positively affect farmer productivity in Ghana. The Propensity Score Matching (PSM) method found that owning and using mobile phones can increase farmer productivity by 261.20 kg/ha per season.

Other studies, such as William et al. (2021), analyzed the use of mobile phones in increasing the productivity of banana farmers in Uganda. By using the interview method, the results found that by using and utilizing mobile phones, farmers will find it easier to communicate with other farmers when agriculture problems occur. In addition, mobile phones that utilize multimedia messaging services (MMS) applications can also help farmers take pictures as samples if there are problems and then share them in agricultural forums. Farmers can consult about their problems through virtual groups such as zoom. Some of these results can increase the productivity of banana farmers in Uganda. At the same time, Aminou et al. (2018) examine the effect of mobile phone ownership on farmer productivity in Benin. Using Benin's microdata, it found that mobile phone ownership can increase the productivity of corn farmers in Benin. The findings show that mobile phone ownership increases production by 0.26 and 0.06, respectively, in the two models. In this case, it will be easier to provide information related to agricultural techniques that can increase agricultural productivity through mobile extension workers.

Quandt et al. (2020) examined the impact of mobile phones on agricultural productivity in Tanzania. The results show that the use of mobile phones has a positive effect on corn farming activities. The study's results reported that many farmers who use and utilize mobile phones could increase agricultural profits, reduce costs, and invest time. Masuka et al. (2016) supported the study, which states that information and communication technology tools in the form of mobile phones can support better production and save time and costs for exchanging information, as can farmers in rural areas.

Several researchers have also found that ICT, which includes mobile phones, the internet, and other technological means, has a significant impact on increasing production yields, farmer incomes, and total factor productivity (Adenubi et al., 2021; Khan et al., 2022; Noubissi Domguia & Asongu, 2022). Noubissi Domguia & Asongu (2022) analyzes the impact of the internet and mobile phones on productivity as measured by production output in sub-Saharan Africa. The results show that breakthroughs in ICT facilities, as measured by the internet and cell phones, positively affect production results or an increase of 40%. These results are supported by Adenubi et al. (2021), who analyze the impact of mobile technology on agricultural productivity in sub-Saharan Africa. The results show that mobile phone technology positively impacts the growth of agricultural TFP in sub-Saharan Africa. Mobile technology has been found as a factor in agricultural productivity in SSA. Khan et al. (2022) evaluates the impact of mobile phone technology and the internet on farmers' income in Pakistan. They found an increase in farmers' income of about 41%.

Methodology

Data

The data used in this study is data from the Indonesia Family Life Survey (IFLS). The data used are cross-sectional data, namely wave 5 of 2014. IFLS data wave 5 is very relevant to be used in this study. The information needed for this study is the most comprehensive household data survey in Indonesia, one of which is the availability of information related to using mobile phones by farmers. The samples selected in this study are individuals who are heads of households in the selected provinces, which are 135 observations for the East Java sample, 241 observations for the Central Java sample, 149 observations for the West Java sample, and 1,339 observations for the Indonesian sample.

This study's primary independent variable (treatment) is using mobile phones for agricultural purposes. The variable was built from the IFLS questionnaire questions: "Do you or household members use mobile phones for agricultural business purposes?". Farmers will be given two answers "1" if "yes" using mobile phones for farming purposes and "0" if not. Furthermore, farmers who use mobile phones are included in the treatment group, and those who do not use them are included in the control group (comparison group). Table 1 shows that as many as 19.72% of farmers in Indonesia own and use cell phones for agricultural business purposes. Meanwhile, in East Java Province, 23.70% of farmers own and use mobile phones for agricultural business purposes. As many as 76.30% of farmers in East Java have not used mobile phones for agricultural business purposes.

Table 1: Use of Mobile Phones by Farmers for Agricultural Business Purposes

Provinces	Status of mobile phone usage by farmers for agribusiness	Frequency	Percentage
East Java	Yes (1)	32	23.70
	No (0)	103	76.30
West Java	Yes (1)	18	12.08
	No (0)	131	87.92
Central Java	Yes (1)	38	15.77
	No (0)	203	84.23
Indonesia	Yes (1)	264	19.72
	No (0)	1,075	80.28

Analysis Method

The analytical method used in this study is the Propensity Score Matching (PSM) method. According to Rosenbaum & Rubin (1983), PSM is an index of the probability of each person participating based on characteristics that can be estimated using the probit or logit model. The PSM method is a non-parametric approach to finding a comparison group from the selected non-intervention group. Therefore, the observed characteristics of the selected group will be the same as the group that was given the intervention (treatment group). Then, they will match the two groups based on their respective probabilities and propensity scores (Khandker et al., 2010).

The fundamental problem that is often encountered when using the PSM method is not being able to measure the potential outcomes of households using mobile phones (Y_{1i}) and the control group (Y_{0i}) at the same time (Feryanto & Rosiana, 2021). In this regard, only one can be observed, using an estimation model that allows seeing the average value of the impact of cell phone usage. This method is usually called the Average Treatment on Treated (ATT) approach. The PSM model with the ATT approach can estimate the average value of farmer households using mobile phones or not. The ATT model can be written as follows (Khandker et al., 2010):

$$ATT = E(Y_{i1} \mid D_i = 1) - E(Y_{i0} \mid D_i = 0) \tag{3}$$

Where ATT is the impact calculated from the outcome variable (rice harvest output) estimated from the results of farmer households using mobile phones, namely $E(Yi1 \mid Di = 1)$ minus households not using mobile phones, $E(Yi0 \mid Di = 0)$.

This study uses the probit model to estimate the propensity score. The specification of the probit model used in this study refers to the Sulistyaningrum & Kurniawan (2017) model, namely:

$$M = \alpha_0 + \sum \alpha_1 X + \mu_i \tag{4}$$

where:

$$\sum \alpha_1 X = \beta_{11} age + \beta_{12} educ + \beta_{13} dmarstat + \beta_{14} \ln income + \beta_{15} plot + \beta_{16} dhouse + \beta_{17} dregion + \varepsilon_i \tag{5}$$

In the above model, *M* is a dummy variable for mobile phones (treatment), with a value of 1 if farmers use mobile phones for agricultural business purposes and 0 if others. Variable *X* is a control variable in the form of characteristics consisting of age (age of head of household), *educ* (years of schooling of the head of household), *dmarstat* (dummy variable of the marital status of head of household, 1 if married, 0 if other), *lnincome* (natural logarithm the amount of income earned for 1 year by the head of the household), *plot* (number of rice fields owned), *dhouse* (dummy variable of type of house ownership by household, 1 if self-owned and 0 if other), *dregion* (location of residence, urban or rural, 1 if urban and 0 if rural).

The Propensity Score Matching (PSM) approach can reduce bias in decision-making due to the potential for heterogeneity and cofounding. The PSM method can overcome this problem, and there are several methods used, namely: (1) Nearest-neighbour Matching, including samples in the two groups that have the most similar Propensity Scores; (2) Caliper or Radius Matching, namely by determining the tolerance limit for the maximum difference in the Propensity Score. In this case, that can be matched only those with a Propensity Score per the limits; (3) Stratification Matching, a method that divides the common support area into several different strata or intervals. Then measure the impact for each group interval. The average of the scores across the impact intervals represents the original impact of the program, and (4) Kernel or Local Matching, which uses the weighted average value of the entire control group sample to create a suitable pair for each sample treatment group.

Results and Discussion

Table 2 presents the descriptive statistics for this study. Based on table 2, it can be seen that only 23.7 percent of individuals in East Java Province use mobile phones for agricultural business activities. However, this level is above the average level of West Java, Central Java, and Indonesia, which is only below 20 percent. In this case, there are relatively few individuals who use mobile phones and use them for agricultural business purposes. It is because individuals do not yet know the use of technology, especially mobile phones, for productive purposes and are only limited to regular communication and entertainment (Feryanto & Rosiana, 2021). In addition, the outcome variable, as measured by the output of rice harvest in the form of rice in East Java Province, is an average of 691.5 kg.

Table 2 also shows that the overall average age of individuals is 50 to 52 years. The average age of individuals in East Java Province is 50 years old. It means that the individual population in East Java Province in this study is quite old. Furthermore, the length of individual education in East Java Province has an average value of 5.64, which means that the individual's educational attainment is only up to 6 years on average. It proves that in this study, individual education level is still relatively low. The variables of marital status and home ownership have an average value close to 1, which means that individuals in this study are generally married, and home ownership is their own. On the other hand, the average individual income in East Java Province for a year in this case study is 14,200,000, with the average number of paddy fields owned in 2 plots. The location of individual residences in East Java Province has an average value of 0.267, which means that more respondents live in villages than in cities.

Table 2: Descriptive Statistics

	East Java		West Java		Central Java		Indonesia	
Variables	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**	**mean**	**sd**
Outcome								
Rice (kg)	691.5	762.3	655.59	286.6	548.6	759.9	811.0	1,407
Treatment								
dhandphone	0.237	0.427	0.120	0.380	0.158	0.365	0.197	0.398
Covariates								
age	50.42	13.00	49.64	13.46	51.59	13.49	49.68	13.55
educ	5.644	4.317	5.523	4.501	6.664	4.020	6.785	4.303
dmarstat	0.948	0.222	0.906	0.373	0.867	0.340	0.900	0.299
income	1.420e+07	1.584e+07	1.57e+07	1.673e+07	1.077e+07	1.358e+07	1.559e+07	3.564e+07
lnincome	15.93	1.144	15.69	1.250	15.60	1.229	15.93	1.147
plot	2.296	2.551	2.986	1.068	2.017	1.544	2.315	2.487
dhouse	0.941	0.237	0.919	0.177	0.959	0.200	0.942	0.234
location	0.267	0.444	0.248	0.496	0.0996	0.300	0.210	0.407
Number of Obs	135		149		241		1,339	

Estimating the Probability of Farmers Using Mobile Phones for Farming Activities

The table below presents the probit regression results related to the probability of individuals using mobile phones for farming activities. When viewed from the province of East Java, the variables that significantly influence the probability of using mobile phones for farming are the education variables measured by the length of the school and marital status. Higher education causes their curiosity is higher to learn new things about technology, especially by using and utilizing mobile phones for farming purposes. It follows the findings of Feryanto & Rosiana (2021), which state that there is a positive relationship between farmer education and the use of mobile phones. The longer the education takes, the higher the chance farmers can use mobile phones to get more information to support their agricultural activities. On the other hand, the marital status variable has a negative relationship with the probability of using mobile phones. Married farmers, in this estimate, are less likely to use mobile phones for agricultural purposes. This finding is slightly different from other studies, which show the opposite result (Feryanto & Rosiana, 2021).

Table 3: Determinant Probit Estimation of Using Mobile Phones for Farming Business Activities

Variables	(1)	(2)	(3)	(4)
	East Java	West Java	Central Java	Indonesia
Constant	-1.305	-6.547***	-0.466	-3.197***
	(2.176)	(2.294)	(1.736)	(0.680)
age	-0.0124	0.00264	**-0.0339*** **	**-0.00978*** **
	(0.0125)	(0.0123)	(0.00958)	(0.00337)
educ	**0.123*** **	0.0472	0.00125	**0.0493*** **
	(0.0377)	(0.0459)	(0.0296)	(0.0104)
marstat	**-1.045* **	*omitted*	*omitted*	**0.292* **
	(0.605)	-	-	(0.168)
lnincome	0.108	**0.298** **	0.0741	**0.148*** **
	(0.130)	(0.138)	(0.105)	(0.0395)
plot	0.0592	-0.0379	0.0423	**0.0288* **
	(0.0506)	(0.0465)	(0.0674)	(0.0158)
dhouse	-0.450	0.416	*omitted*	-0.231
	(0.522)	(0.565)	-	(0.161)
location	-0.293	-0.135	-0.476	**-0.210** **
	(0.313)	(0.382)	(0.421)	(0.106)
Observations	134	135	199	1,336

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Then viewed from the peer province, namely West Java, the income variable has a positive and significant relationship with the use of mobile phones. It means that the higher the income earned, the probability of using a mobile phone also increases, where with this income, individuals can buy it (Umaroh & Afifah, 2020). Then, when viewed from the Province of Central Java, the age variable negatively and significantly correlates with mobile phone use. It means that individuals use mobile phones for agricultural purposes tends to be greater in younger individuals.

When viewed in general, the variables that significantly influence the probability of using mobile phones for agricultural activities by individuals in Indonesia include age, education, marital status, income, number of rice fields, and location of residence. The age variable negatively affects mobile phone use; increasing age does not increase the chances of using mobile phones for agricultural activities. This finding is consistent with estimating samples from East Java and Central Java. The variables of education, marital status, and income in general in Indonesia are positively associated with cell phone use. It means that the higher the individual's education, income, and marital status, the more opportunities to use mobile phones for farming. This finding also consistently applies to East Java, West Java, and Central Java estimates.

On the other hand, the variable number of paddy fields also has a positive relationship with the use of mobile phones. In addition, the location of residence has a negative relationship with cell phone use. It means that individuals who live in cities do not increase their chances of using cell phones for agricultural purposes. It is pretty interesting that, based on current conditions, the area of rice fields in the city is lower than in the village. So that individuals who live in cities make sense if they do not use cell phones for agricultural activities but for other communication purposes. On the other hand, individuals who live in villages generally increase the opportunity to use mobile phones as a medium to support agricultural activities.

The Impact of Using Cell Phones on Farmers' Productivity (Amount of Rice Harvested Output in the Form of Rice)

Table 4 presents the results of the estimated Average Treatment Effect on the Treated Group (ATT), which can explain the impact of mobile phone use on the amount of rice output in East Java Province and other Peer Provinces. ATT PSM can correct the selection bias between observable and unobservable factors. The estimation results show that using mobile phones for agricultural business purposes in East Java Province has increased the amount of rice output in the form of rice. Individuals who use mobile phones for farming purposes have an average rice output of 841.30 kg. Meanwhile, individuals who do not use cell phones for agricultural purposes have an average rice output of 436.67 kg. Thus, there is a difference in the amount of rice output in the form of rice between individuals who use mobile phones and do not use phones for agricultural business purposes 404.63 kg. The results of the ATT estimation are also in line with the results of research by Umaroh & Afifah (2020), which shows that the use of mobile phones can increase the productivity of rice farmers. The use of mobile phones can increase productivity (the number of rice harvests in kg) by 40-41% greater than farmers who do not use mobile phones.

Table 4: The Impact of Mobile Phone Use on Total Rice Output in East Java Province and Peer Province: Average Treatment Effect on the Treated Group (ATT)

Province	Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
East Java	Rice	Unmatched	909.71875	628.843137	280.875613	153.326295	1.83
		ATT	841.296296	436.666667	404.62963	177.508686	2.28
West Java	Rice	Unmatched	1501.61111	568.290598	933.320513	290.09123	3.22
		ATT	1561.70588	816.941176	744.764706	716.399589	1.04
Central Java	Rice	Unmatched	656.052632	532.819876	123.232756	141.88124	0.87
		ATT	656.052632	436.421053	219.631579	207.027278	1.06
Indonesia	Rice	Unmatched	1252.81061	703.740672	549.069934	95.6149332	5.74
		ATT	1252.08462	807.726923	444.357692	155.377444	2.86

The estimation results in the peer province are also in line with the results in East Java Province. The use of mobile phones for agricultural business influences rice output in the peer provinces, namely West Java, Central Java, and Indonesia. When viewed from the difference between the amount of rice output of users and non-users of mobile phones for agricultural activities, the most significant difference is in the province of West Java. These findings follow the results of previous studies by Adenubi et al. (2021); Aminou et al. (2018); Feryanto & Rosiana (2021); Issahaku et al. (2018); Khan et al. (2022); Masuka et al. (2016); Noubissi Domguia & Asongu (2022); Quandt et al. (2020); and William et al. (2021) which shows that ICT facilities in the form of cell phones significantly affect agricultural productivity.

In testing the goodness of fit, this study uses the percentage of bias between the treatment and control groups (Rosenbaum & Rubin, 1985). Based on Appendix 2, there is a Mean Bias percentage between the observations of the treatment group and the control groups' observations. The mean bias value in East Java Province is 14.4; in West Java, 19.8; in Central Java, 15; and in Indonesia, the Mean Bias value of 4.9. From the test results, there is no standard for what percentage of bias is tolerated, and the standardized bias test also does not have a standard value for reducing bias that is used as a reference (Priyatna & Andini, 2020; Sulistyaningrum & Kurniawan, 2017). Thus, this study is still following the PSM estimation procedure.

Conclusion

This study analyzes the impact of mobile phone use on agricultural productivity as measured by the amount of rice output in East Java Province. Result of the probit model, the results obtained that the probability of using a mobile phone in East Java Province is influenced by the level of education and marital status. The higher the individual's education, the easier it is for the individual to learn and utilize technology. Based on the Propensity Score Matching (PSM) estimation, individuals' use of mobile phones as a necessity to support agricultural business activities in East Java has increased the amount of rice output in the form of rice. Individuals who use mobile phones for farming purposes have an average rice output of 841.30 kg, while those who do not use mobile phones for farming purposes have an average rice output of 436.67 kg. These results prove that using mobile phones for farming activities is necessary to increase farmers' productivity, especially those in rural areas.

The estimation results that have been obtained indicate that the need to expand the use of mobile phones for farming activities is essential in East Java Province. In this case, the Government, as a policymaker, can provide direct counseling to the public regarding using telecommunications for productive activities. In addition, the Government must also be proactive in helping agricultural problems related to information and communication technology. Thus, farmers in general and especially in East Java Province can use and utilize information and communication technology optimally, using mobile phones for productive activities such as agricultural activities, which will positively impact agricultural productivity.

This study has limitations; it cannot describe specifically what farmers do in using mobile phones to increase their productivity, for example, whether they are used for production, marketing, or other activities. Furthermore, it is impossible to calculate the productivity value in each plot owned by the farmer.

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Appendix 1. Processed results of PSM (Probit Model)

a. East Java

```
Probit regression                               Number of obs     =        134
                                                LR chi2(7)        =      28.69
                                                Prob > chi2       =     0.0002
Log likelihood = -59.315463                     Pseudo R2         =     0.1947
```

dhandphone	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.0124267	.0124534	-1.00	0.318	-.0368348	.0119814
educ	.1231672	.0377018	3.27	0.001	.0492729	.1970614
marstat	-1.044935	.6045677	-1.73	0.084	-2.229866	.139996
lnincome	.1079687	.1303635	0.83	0.408	-.147539	.3634765
plot	.0591698	.0505975	1.17	0.242	-.0399995	.1583391
dhouse	-.4503055	.5219111	-0.86	0.388	-1.473232	.5726215
location	-.2934161	.3129263	-0.94	0.348	-.9067402	.3199081
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

b. West Java

```
Probit regression                               Number of obs     =        135
                                                LR chi2(6)        =       9.62
                                                Prob > chi2       =     0.1414
Log likelihood = -48.199288                     Pseudo R2         =     0.0908
```

dhandphone	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.0026374	.0122531	0.22	0.830	-.0213784	.0266531
educ	.0471879	.0458624	1.03	0.304	-.0427007	.1370765
marstat	0	(omitted)				
lnincome	.2983329	.1378703	2.16	0.030	.028112	.5685538
plot	-.0378976	.0464673	-0.82	0.415	-.1289718	.0531766
dhouse	.415629	.5652777	0.74	0.462	-.692295	1.523553
location	-.1346645	.3821289	-0.35	0.725	-.8836233	.6142944
_cons	-6.547108	2.294055	-2.85	0.004	-11.04337	-2.050843

c. Central Java

```
Probit regression                               Number of obs     =        199
                                                LR chi2(5)        =      18.06
                                                Prob > chi2       =     0.0029
Log likelihood = -88.004721                     Pseudo R2         =     0.0930
```

dhandphone	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.0338955	.0095824	-3.54	0.000	-.0526767	-.0151143
educ	.0012473	.0295651	0.04	0.966	-.0566992	.0591939
marstat	0	(omitted)				
lnincome	.0741336	.1053807	0.70	0.482	-.1324087	.2806759
plot	.0422756	.0673697	0.63	0.530	-.0897665	.1743177
dhouse	0	(omitted)				
location	-.475584	.4214933	-1.13	0.259	-1.301696	.3505277
cons	-.465993	1.735882	-0.27	0.788	-3.86826	2.936274

d. Indonesia

```
Probit regression                               Number of obs     =      1,336
                                                LR chi2(7)        =     102.28
                                                Prob > chi2       =     0.0000
Log likelihood = -612.93709                     Pseudo R2         =     0.0770
```

dhandphone	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.009783	.0033656	-2.91	0.004	-.0163794	-.0031865
educ	.0493361	.0104301	4.73	0.000	.0288934	.0697787
marstat	.2917636	.1681693	1.73	0.083	-.0378422	.6213694
lnincome	.1478339	.0395397	3.74	0.000	.0703375	.2253304
plot	.0287581	.0157866	1.82	0.069	-.0021832	.0596993
dhouse	-.230731	.1610601	-1.43	0.152	-.546403	.084941
location	-.2102242	.1063549	-1.98	0.048	-.4186759	-.0017725
_cons	-3.196714	.6802431	-4.70	0.000	-4.529966	-1.863462

Appendix 2. Goodness of Fit Test

e. East Java

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
age	44.968	46.194	-10.1	-0.47	0.643	1.29
educ	8.3548	8.6129	-6.3	-0.23	0.816	0.76
marstat	.93548	.93548	0.0	0.00	1.000	.
lnincome	16.31	16.458	-12.4	-0.55	0.583	3.27*
plot	2.8387	3.0968	-10.2	-0.30	0.768	0.39*
dhouse	.87097	1	-47.0	-2.11	0.039	.
location	.25806	.19355	14.5	0.60	0.551	.

* if variance ratio outside [0.48; 2.07]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.030	2.37	0.883	14.4	10.2	40.0*	1.52	50

* if B>25%, R outside [0.5; 2]

a. West Java

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
age	47.176	49.059	-14.1	-0.44	0.665	1.13
educ	6.4706	6.8824	-10.7	-0.33	0.743	0.73
marstat	1	1	.	.	.	.
lnincome	16.311	16.287	2.0	0.08	0.940	1.18
plot	2.6471	1.5882	29.9	1.78	0.084	4.96*
dhouse	.94118	.82353	45.4	1.05	0.301	.
location	.17647	.23529	-13.6	-0.41	0.683	.

* if variance ratio outside [0.36; 2.76]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.112	5.28	0.508	19.3	13.9	71.5*	6.45*	25

* if B>25%, R outside [0.5; 2]

b. Central Java

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
age	43.474	43.158	2.6	0.12	0.903	1.04
educ	7.5789	7.1842	9.4	0.41	0.683	1.24
marstat	1	1	.	.	.	.
lnincome	15.961	15.563	34.1	1.23	0.221	0.54
plot	2.0263	1.8684	9.4	0.42	0.675	1.52
dhouse	1	1	.	.	.	.
location	.05263	0	19.8	1.43	0.156	.

* if variance ratio outside [0.52; 1.92]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.021	2.11	0.715	15.0	9.4	33.0*	0.96	0

* if B>25%, R outside [0.5; 2]

c. Indonesia

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	V(T)/V(C)
age	45.388	45.123	2.0	0.24	0.811	1.00
educ	8.4962	8.6885	-4.5	-0.50	0.616	1.04
marstat	.95385	.95385	0.0	-0.00	1.000	.
lnincome	16.326	16.241	7.4	0.91	0.362	1.59*
plot	2.4923	2.35	5.7	0.69	0.488	0.72*
dhouse	.91538	.88462	11.9	1.17	0.243	.
location	.18462	.19615	-2.9	-0.33	0.738	.

* if variance ratio outside [0.78; 1.28]

Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
0.004	2.96	0.889	4.9	4.5	15.1	1.03	50

* if B>25%, R outside [0.5; 2]