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Rural ICT Penetration, Bank Credit, and Agricultural Sector Performance: A Panel ARDL Analysis in Eastern Indonesia

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Abstract

The relationship between ICT, the financial sector, and output growth has been extensively studied, however, macro-economic studies with an emphasis on the role of rural ICT on agricultural performance are few and yield mixed findings. Additionally, past research has not given sufficient attention to how bank credit affects agricultural performance. This paper highlighted the dynamic effect of rural ICT penetration and bank credit on agricultural performance in Eastern Indonesia. We used secondary data taken from the Central Bureau of Statistics and the Financial Services Authority. The panel data covered 16 provinces of eastern Indonesia from the first semester of 2010 to the second semester of 2022 (2010S1–2022S2). Using the panel autoregressive distributed lag (ARDL) approach, the results showed that in the long run, rural ICT penetration and bank credit played a significant role in boosting agricultural performance. However, in the short run, the impact of rural ICT penetration and bank credit on agricultural performance was statistically insignificant. Finally, we recommended several important policies that can practically impact and contribute to improving agricultural performance.

Keywords

Agriculture, Rural ICT, bank credit, ARDL, Eastern Indonesia.

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Introduction

As an agricultural country, the Indonesian government has long paid significant attention to the development of the agricultural sector. This is illustrated by Indonesia's achievement of receiving an award from the International Rice Research Institute (IRRI) in recognition of a food-agriculture system resiliency and self-sufficiency in rice during 2019-2021 through the application of innovative rice technology. The agricultural sector has contributed greatly to the national economy—especially through creating employment and providing food for food security-making it an instrument of poverty alleviation and a source of livelihood for the population. However, as Indonesia's economic structure changes, the performance of the agricultural sector continues to face serious problems related to its declining contribution to GDP compared to the industrial and service sectors. The Central Bureau of Statistics reports that in 2010 the contribution of the agricultural sector to Indonesia's GDP was 13.93%, decreasing to 12.40% in 2022. In eastern Indonesia, the contribution of the agricultural sector to the GDP was 17.62% in 2010 and 16.36% in 2022.

Improving the performance of the agricultural sector requires the support of technological advancements, including information and communications technology (ICT) (Dzanku et al., 2021; Nakasone et al., 2014; Olmstead and Rhode, 2014). Currently, ICT is experiencing rapid development in various fields. This is indicated by the emergence of a global digital era with deep internet penetration that supports the use of smartphones, computers, laptops, tablets, and other digital technology devices. Indonesia has great potential for the development of its digital economy and is expected to become one of the countries with the largest digital economy achievements in the world (Kemenkoinfo, 2019). The use of ICT in all economic sectors will provide benefits for accelerating economic growth through reduced transaction costs or efficiency, ease of information, expanding markets, and improving productivity (Farooqi et al., 2020; Kpodar and Andrianaivo, 2011; Toader et al., 2018). The role of ICT penetration on the agricultural sector performance through mobile phone and internet access is expected to include access to real-time weather updates, market trends, and competitive price information to determine sustainable production. These things increase the productivity and growth of agricultural output in the long run (Dzanku et al., 2021; Nakasone et al., 2014). In addition, the use of the Internet can create more efficient and direct marketing channels, expand and enlarge market access, reduce transaction costs, facilitate access to financial institutions, and reduce monopoly power of merchants (Aker and Ksoll, 2016; Dzanku et al., 2021; Fafchamps and Minten, 2012; Goyal, 2010).

The nexus of ICT and agricultural performance has been investigated by several researchers. However, the previous empirical studies offered mixed results and lacked consensus. Several empirical studies find strong evidence to support the significant role of ICT in agricultural development performance and conclude that ICT plays a significant role in boosting agricultural production (Hopestone, 2014; Kaila and Tarp, 2019, Lio and Liu, 2006; Nakasone, et al., 2014; Nguyen, et al., 2023; Oyelalmi et al., 2022; Suroso et al., 2022). However, several other studies find that the role of ICT does not provide major benefits to agricultural performance, such as study of Evans (2018), which revealed a negative relationship between internet access and the development of the agricultural sector. Fafchamps and Minten (2012) found that commercial market applications of mobile phone technology and weather information had little or statistically insignificant effects on prices or farming practices. Similarly, Aker and Ksoll (2016) concluded that using ICT via mobile phones does not increase crop sales or farmer-level prices received.

Most of the farming methods in Indonesia still rely on traditional methods with low productivity. A reform effort to switch from traditional rural farming methods to more modern methods requires consistent levels of funding (Ellinger and Penson, 2014; Miller and Jones, 2010; Olmstead and Rhode, 2014). However, one of the crucial problems in agricultural development is the lack of budget to carry out production activities (Ellinger and Penson, 2014). To compensate for the lack of financing, farmers generally apply for loans at the nearest financial institutions, both formal and informal. The role of bank credit in the growth of the real economy including the agricultural sector can be reviewed from the theory and previous empirical studies. The finance-growth theory suggests that the size of the financial sector affects the real sector of the economy directly. This theory is based on banks' ability to connect people with extra money to people who need it through financial intermediation (Mishkin, 2013). Schumpeter in 1911 was the first to hypothesize that the financial sector is very important in determining the growth of the real economy. Other scholars noted that the financial system boosts growth via capital accumulation and innovation (Levine, 1997) while King & Levine (1993) found “innovation” as the primary link between finance and output growth.

The importance of bank credit to the real economy can also be seen from several previous studies which find the significant role of commercial banks in the progress of the private sector and increasing economic growth (Vaithilingam et al., 2003; Ajibola, 2015; Morina and Özen, 2020). Meanwhile, research by Gani and Bahari (2020) found mixed findings where bank loans only contributed significantly in the long term and were not effective in influencing the real economy in the short term. Special empirical emphasis on the relationship between bank credit or bank loans and agricultural performance reveals that the provision of affordable credit enhances organized production activities in rural areas and leads to increased output and employment opportunities (Saleem and Jan, 2018; Sethi and Acharya, 2018). Furthermore, the previous research reveals that the use of agricultural credit to fund agricultural production activities has a positive and significant impact on the agricultural performance (Ngong et al., 2022; Peng, et al., 2021; (Rehman et al., 2017); Kumar et al., 2017). In contrast, Chuke and Anyalechi (2018) found that the use of bank credit in the agricultural sector only played a small role in improving the agricultural development progress in rural areas.

The main purpose of this study is to investigate the dynamic effect of rural ICT penetration and bank credit on agricultural performance. This research is unique in two ways. Firstly, the agricultural sector in Eastern Indonesia plays a more substantial role in GDP (Gross Domestic Product) than in Western Indonesia. However, to the best of our knowledge, there has been no previous research that has examined the impact of rural ICT and bank credit on agricultural performance in Eastern Indonesia using a dynamic econometric model. Secondly, while there have been some qualitative studies on the impact of rural ICT on agricultural performance in Indonesia, our study is unique in that it employs the Panel ARDL model to examine this impact. This research is expected to make a significant contribution to the advancement of science and provide practical policy direction that can help enhance agricultural performance and improve the welfare of farmers, particularly in Eastern Indonesia.

The topic of this paper is an interesting issue that revolves around macroeconomic analysis with the following research questions. Firstly, does rural ICT penetration influence agricultural performance in Eastern Indonesia, both in the short and long term? Secondly, does bank credit affect agricultural performance in Eastern Indonesia, both in the short and long run? The specific objectives of this research are to investigate the influence of rural ICT penetration on agricultural performance, both in the short and long term and to investigate the effect of bank credit on agricultural performance in Eastern Indonesia, both in the short and long term. The remaining sections of this paper include materials and methods, results and discussion, and conclusions.

Materials and methods

This study utilized secondary data from the Central Bureau of Statistics and the Financial Services Authority. The panel data covered 16 provinces in Eastern Indonesia, ranging from the first semester of 2010 to the second semester of 2022 (2010S1-2022S2). The 16 provinces consist of East Nusa Tenggara, West Nusa Tenggara, West Kalimantan, East Kalimantan, South Kalimantan, Central Kalimantan, South Sulawesi, North Sulawesi, Southeast Sulawesi, Central Sulawesi, Gorontalo, Maluku, North Maluku, Papua, and West Papua. Stata version 17 software was used for data processing and analysis.

The dependent variable of this study is agricultural sector performance (lnAGR). The independent variables of this study are bank credit (lnCR) and rural ICT penetration. Rural ICT penetration is represented by the rural internet (INT) and rural mobile phone (MP) penetration rates. Education (lnEdu) is treated as a control variable. In the domain of ICT penetration measurement, there are various indicators that can be utilized. However, in the case of rural areas, this study exclusively focuses on two ICT measures, namely mobile phone and internet penetration. This approach is motivated by the fact that the vast majority of village residents in Indonesia rely heavily on mobile phones and the Internet as their primary means of communication and information exchange. On the other hand, other ICT tools such as fixed-line telephones and radios have seen a significant decline in usage and have been abandoned by the village population (BPS, 2022). Furthermore, the majority of ICT models implemented by local governments in rural development projects in Indonesia rely heavily on internet and mobile phone connectivity (Amin, 2018). Although television can also be considered an ICT measure, it is less mobile than mobile phones and may not be as effective in the context of agricultural development. Additionaly, computer usage in rural areas is restricted to specific tasks (BPS, 2022). Therefore, it is crucial for policymakers to consider the limitations of each ICT medium and design models that align with the specific needs of their target communities. Education is regarded as a control variable due to its critical role in realizing the potential of technology, securing bank loans, and enhancing agricultural productivity in Eastern Indonesia. Table 1 presents the names, symbols, measurements, units, and expected signs of the variables.

Panel unit root test

We need to conduct a panel unit root test before applying the panel autoregressive distributed lag

Variable name	Symbol	Measurement	Unit	Expected sign
Agricultural sector performance	lnAGR	Value-added of the agricultural sector	IDR billion	+
Rural internet penetration	INT	Rural internet users	%	+
Rural mobile phone penetration	MP	Rural mobile phone users	%	+
Bank credit	lnCR	Agriculture credit	IDR billion	+
Education	lnEDU	Mean years of schooling	Year	+

Source: Authors identification, 2023

Table 1: Operational variables.

(ARDL). The presence of non-stationary data or unit roots may cause spurious regression parameters. One characteristic of stationary data is that the data trend should be closer to its mean value or it has a consistent mean and variation over time (Asteriou and Hall, 2016; Hansen, 2017). The first purpose of the panel unit root test is to check whether the data is stationary or non-stationary. The second purpose is to determine the degree of integration. The data used can be identified as stationary in integration order at level I (0), first-difference I (1), or mixture I(0) and I(1). Application of the panel unit root test has advantages compared to standard time series data due to the larger number of observations and heterogeneity across provinces. Thus, it allows us to minimize bias and potentially yield more precise parameters (Hansen, 2022). Levin et al. (2002) state that the use of panel unit root tests is more efficient than time series unit roots.

Researchers employ different approaches to determine the panel unit roots. In this study, we followed the panel unit root test method suggested by Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS). In their study, Levin et al. (2002) devised a method based on Quah's generalization procedure that allows heterogeneity of individual deterministic effects (constant and/or linear time trends) and heterogeneous autocorrelation error structures, assuming the parameter is AR(1) homogeneous. Another assumption is that N and T tend to infinity, but T increases faster; thus, $N/T \rightarrow 0$. IPS is a good fit for our varied panel data because it can manage individual-specific effects and distinct residual serial correlations. Although this method is superior to LLC, it requires a large amount of time series (T).

Panel cointegration test

The cointegration test is a widely utilized procedure in dynamic econometric models that aims to determine the presence of a long-term relationship between variables. This study adopted the panel cointegration test developed by Pedroni (1999, 2004), which includes eleven statistical indicators that can aid in establishing the existence of a long-term relationship between variables. These statistical indicators are divided into two groups, namely within dimensions and between dimensions. The within-dimension group includes the ADF-statistic parametric panel, PP-statistic non-parametric panel, rho panel, and v-statistic panel, while the between-dimensions group includes the ADF-statistic group, PP-statistic group, and rho-statistic panel group, as noted by Neal (2014) and Asteriou and Hall (2016). By employing these statistical indicators, we can ensure that our panel autoregressive distributed lag (ARDL) model meets the necessary criteria and provides insightful results. The utilization of these indicators is crucial in achieving the desired outcome of the study, which is to determine the existence of a long-term relationship between the variables under investigation. As such, the panel cointegration test's utilization is paramount in ensuring the study's accuracy and reliability, making it a valuable tool in the field of econometrics.

Model specification

This study employed the panel ARDL (autoregressive distributed lag) to investigate the effect of rural ICT penetration and bank credit on agricultural performance in eastern Indonesia. Using panel ARDL provides many advantages, enabling us to estimate short-term and long-term coefficients dynamically which includes three types of estimators: pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE). The application of the panel ARDL or the PMG estimator allows us to estimate short-term and long-term relationships including the speed of adjustment coefficient or the speed of the long-term equilibrium by allowing for heterogeneity of the short-term coefficient and error variance across provinces (Pesaran, et al, 1999). However, the coefficients of the long-run equilibrium relationships between variables are similar (homogeneous) across provinces. In contrast to PMG, the MG estimator produces a regression coefficient of short-term and long-term relationships that are heterogeneous for each province. Finally, the DFE estimator assumes that the short-term adjustment speed coefficient and the long-term coefficient must be identical for all cross-sections (Asteriou and Hall, 2016).

The formation of the basic model is as follows:

$$\begin{aligned} lnAGR_{it} &= \beta_0 + \beta_1 INT_{it} + \beta_2 MP_{it} + \\ &+ \beta_3 lnCR_{it} + \beta_4 lnEDU_{it} + v_{it} \end{aligned} \tag{1}$$

where *AGR* is the agricultural sector's performance, *INT* is the rural internet penetration rate, *MP* is the rural mobile phone penetration rate, *CR* is bank credit and *EDU* is education. The rural ICT penetration is represented by the *INT* and *MP* variables for province *i* at time *t*. l*nAGR, lnCR*, and l*nEDU* variables are the respective natural logarithms of *AGR, CR*, and *EDU*. *lnEDU* is treated as a control variable.

The MG model used to evaluate the long-run relationship between variables is as follows:

$$lnAGR_{it} = \theta + \beta_{0i} lnAGR_{i,t-1} + \beta_{1i} INT_{i,t-1} + \\ + \beta_{2i} MP_{i,t-1} + \beta_{3i} lnCR_{i,t-1} + \beta_{4i} lnEDU_{i,t-1} + \varepsilon_{it} \quad (2)$$

Equation (2) explains that the estimation of the MG model assumes that both the short-term and long-term coefficients are heterogeneous across provinces. Therefore, selecting the optimum time lag using the Akaike Information Criterion (AIC) requires a larger number of periods (T) than the number of cross-sections (N).

The long-run relationship model using the PMG and DFE estimators can be written as follows:

$$lnAGR_{it} = \alpha_i + \sum_{j=1}^{o} \lambda_{ij} lnAGR_{i,t-j} + \sum_{j=0}^{p} \delta_{1ij} INT_{i,t-j} + \\ + \sum_{j=0}^{q} \delta_{2ij} MP_{i,t-j} + \sum_{j=0}^{r} \delta_{3ij} lnCR_{i,t-j} + \\ + \sum_{j=0}^{s} \delta_{44ij} lnEDU_{i,t-j} + \varepsilon_{it} \quad (3)$$

where, i represents the province (1, 2, 3…..16), *t* is the period of 2010S1–2022S2 and *o, p, q, r*, and *s* are the optimum time lags. αi is the provinces specific effect, and εit refers to the error terms. The model includes an error-correction term that denotes a short-run relationship, which can be written as follows:

$$\Delta lnAGR_{it} = \alpha_i + \phi_i (lnAGR_{i,t-1} - \lambda_1 INT_{i,t-1} - \\ - \lambda_2 MP_{i,t-1} - \lambda_3 lnCR_{i,t-1} - \lambda_4 lnEDU_{i,t-1}) + \\ + \sum_{j=1}^{o} \lambda_{ij} \Delta lnAGR_{i,t-j} + \sum_{j=1}^{p} \lambda_{1ij} INT_{i,t-j} + \sum_{j=1}^{q} \lambda_{2ij} MP_{i,t-j} + \\ + \sum_{j=1}^{r} \lambda_{3ij} lnCR_{i,t-j} + \sum_{j=1}^{s} \lambda_{4ij} lnEDU_{i,t-j} + \varepsilon_{it} \quad (4)$$

The speed of dynamic change to long-term equilibrium for *lnAGR* due to changes in *INT*, *MP, lnCR*, and *lnEDU* is measured by ϕ_i, while λ_i indicates the long-run parameters. ϕ_i represents the existence of a long-run relationship. The presence of a cointegration relationship among *lnAGR, INT, MP, lnCR*, and *lnEDU* is revealed by a significant and negative ϕi coefficient. All ECM dynamics (ε) follow an independent and identical distribution assumption. The model can estimate coefficients for both stationary and non-stationary regressors and provide a reliable parameter estimation. Pesaran et al. (1999) revealed that the MG and PMG estimators are suitable for panel data analyses with large cross-sections (*N*) and time series (*T*). However, if homogeneity exists, the MG estimator is inefficient. When homogeneity exists, the PMG estimator based on the maximum likelihood is more efficient (Asteriou and Hall, 2016).

The optimal lag length and Hausman test

We applied the Hausman test to select the best estimator among MG, PMG, and DFE. When comparing the MG and PMG estimators, if the p-value of the Hausman test is greater than 0.05 (insignificant), then we conclude that the PMG estimator is more efficient and preferable under the null hypothesis (Asteriou and Hall, 2016). Furthermore, PMG is more efficient and preferred if the difference in estimation results between PMG and DFE is not significant or the null hypothesis is not rejected.

Results and discussion

Table 2 provides a comprehensive overview of the panel data, presenting statistics such as the mean, standard deviation, minimum and maximum values, and the number of observations for each variable. To improve clarity, all data was transformed into natural logarithms (ln), except for variables measured in percentage units (MP and INT). This approach ensures that the statistical information is more easily interpreted and understood.

By converting the data to natural logarithms, it is possible to compare the relative magnitudes of the variables more effectively. Furthermore,

Variable	N	Mean	Std. dev	Min	Max
lnAGR	416	2.014	0.652	0.661	3.593
INT	416	77.140	16.895	15.230	96.960
MP	416	35.025	23.755	2.580	93.300
lnCR	416	6.467	1.791	1.609	9.610
lnEDU	416	1.872	0.149	1.470	2.195

Source: Authors computation, 2023

Table 2: Descriptive statistics.

this technique has the added benefit of reducing the impact of outliers, which can distort the results of statistical analyses.

The data presented in Table 2 depicts the findings of a study that analyzed a set of variables. The study included a total of 416 observations (N) and aimed to identify the characteristics of the variables under consideration. The results of the statistical analysis indicated that *INT* exhibited the highest mean value, minimum value, and maximum value when compared to the other variables. To assess the degree of variation between the actual data and their mean values, the standard deviation was employed. The standard deviation of *MP* was found to be the highest at 23.775. Conversely, *lnEDU* exhibited the lowest standard deviation at 0.149 and also the lowest mean value at 1.872. The findings imply that *INT* was the most significant variable in this study, and the degree of variation in *MP* was markedly higher than that in *lnEDU*.

Table 3 shows a correlation matrix, which is a useful tool for predicting the direction and strength of correlation between variables and identifying multicollinearity issues. However, it has its limitations as it cannot establish cause-and-effect relationships between variables. Hence, it is essential to use inferential statistical techniques such as econometric models to evaluate the causality of these variables. By using such methods, we can gain a better understanding of the underlying relationships between variables, which helps us make informed decisions based on the results.

Table 3 presents the correlation matrix using Pearson's correlation coefficient for each combination of variables. All pairs of variables were positively correlated. The variables *lnAGR* and *lnCR* had the highest degree of correlation compared to other pairs of variables, indicating that *lnCR* (i.e., bank credit) as an independent variable was moderately and positively associated with the dependent variable *lnAGR* (agricultural performance). Moreover, the pairwise independent variables (*MP, INT, lnCR,* and *lnEDU*) had correlation coefficients of less than 0.70, which suggests that the relationships between independent variables do not present a multicollinearity issue. To ensure the accuracy of the data, it is necessary to conduct a test to examine the stability of the variables of interest. To accomplish this, a panel unit root test is employed to avoid the issue of spurious regression. This test was conducted utilizing two distinct approaches: the Levin, Lin, and Chu (LLC) method and the Im, Pesaran, and Shin (IPS) approach. The results of the test are presented in Table 4.

In Table 4, we can see the results of the panel unit root test using both the LLC and IPS approaches. The LLC statistical test indicated that variables l*nAGR, MP, INT*, and *lnCR* were significant at that level, while *lnEDU* did not reject the null hypothesis. However, all variables were significant at the first difference, indicating that they were

	lnAGR	*MP*	*INT*	*lnCR*	*lnEDU*
lnAGR	1.000				
MP	0.351	1.000			
INT	0.319	0.661	1.000		
lnCR	0.754	0.549	0.533	1.000	
lnEDU	0.325	0.407	0.499	0.421	1.000

Source: Authors computation, 2023

Table 3: Correlation matrix.

Variable	Levin, Lin, and Chu (LLC)		Im, Pesaran, Shin (IPS)	
	Level	First-difference	Level	First-difference
lnAGR	−4.535***	−34.886***	−0.336	−28.563***
MP	−9.914***	−2.557***	−10.557***	−1.195
INT	7.784***	−3.291***	10.493***	−0.869
lnCR	−1.724**	−9.324***	1.917	−9.063***
lnEDU	−0.194	−3.039***	6.358***	−2.581***

Note: *** and ** indicate the significance levels of 1% and 5%, respectively
Source: Authors computation, 2023

Table 4: Panel unit root test results.

stationary at the integration order of I(1). The IPS approach suggested a different outcome where *MP* and *INT* were stationary at the level, but not in the first difference. On the other hand, *lnAGR, lnCR*, and *lnEDU* did not reject the null hypothesis in the first difference. Therefore, we can conclude that all variables were stationary at the mixed integration order or combination I(0) and I(1), which confirms that the panel ARDL is suitable for analysis in this study. Subsequently, we conducted the Pedroni cointegration test to determine the presence of a long-term relationship between the variables. The results in Table 5 present valuable insights into their relationship.

The statistical analysis presented in Table 5 confirmed a strong long-term association between variables since 9 out of 11 indicators rejected the null hypothesis. We determined the optimal lag (*o, p, q, r, s*) through ARDL panel estimation to enable the estimation of short-term and long-term regression parameter estimates. The AIC indicator confirmed that the optimal lag for ARDL is (1, 1, 1, 1, 1), which was a crucial aspect of this process. We have obtained the outcome of the estimation of short-term and long-term relationships of the ARDL model in Table 6, which will be instrumental in our future analyses.

Table 6 summarises the results of the panel ARDL estimation which included PMG, MG, and DFE models. The Hausman test was adopted to select the best model and the results showed that PMG was superior to MG and DFE, showed

Indicator	Statistic	Prob.	Weighted statistic	Prob.
Within-dimension:				
Panel v-statistic	−1.083	0.861	−1.062	0.856
Panel rho-statistic	−8.886	0.000***	−7.483	0.000***
Panel PP-statistic	−26.652	0.000***	−24.056	0.000***
Panel ADF	−10.102	0.000***	−9.659	0.000***
Between-dimensions:				
Group rho-statistic	−4.948	0.000***		
Group PP-statistic	−28.837	0.000***		
Group ADF-statistic	−7.858	0.000***		

Note: *** indicates the significance level of 1%.
Source: Authors computation, 2023

Table 5: Panel cointegration test results.

Variable	PMG coefficient	t-stat	MG coefficient	t-stat	DFE coefficient	t-stat
Short-run						
ECT	−0.7400	−5.04***	−1.2929	−10.68***	−0.5346	−11.67***
ΔMP	−0.3564	−1.30	−0.5389	−4.38***	−0.2857	0.106
ΔINT	0.1024	0.594	0.1949	1.16	0.2946	2.07**
ΔlnCR	−0.0158	−1.11	0.1674	−1.69*	−0.0072	−0.52
ΔlnEDU	−0.0004	−0.00	0.135	0.6	−0.0188	−0.11
C	0.5233	3.88***	1.0324	0.055*	0.8196	5.62***
Long-run						
MP	0.5988	11.83***	0.7079	4.88***	0.4458	4.82***
INT	0.2114	11.60***	0.1686	2.68***	0.3456	6.97***
lnCR	0.0348	5.55***	0.0352	3.00***	0.0116	0.95
lnEDU	0.3235	5.22***	0.1757	0.47	−0.0229	−0.15
Hausman test: MG or PMG[1]		0.470	PMG or DFE[2]			0.011
P-value		0.977				0.991

Note: Dependent variable: lnAGR. The lag structure is ARDL (1, 1, 1, 1, 1)
[1] PMG is an efficient estimation than MG under the null hypothesis
[2] PMG is an efficient estimation than DFE under the null hypothesis
*** and ** indicate the significance level of 1% and 5%, respectively.
Source: Authors computation, 2023

Table 6: Short-run and long-run estimation results.

by the probability value (p-value) of the Hausman test was insignificant in both cases, supporting the appropriateness of the PMG estimator. In terms of PMG estimation results, we found no empirical evidence to support a short-term relationship; all the coefficients of the variables were statistically insignificant at all confidence levels. As expected, Table 6 demonstrated a valid and significant ECT, satisfying the requirements for long-term consistency and efficiency among the variables of interest. The ECT specification evaluates how long it takes to correct a short-term imbalance to achieve a long-term equilibrium among the variables of interest. The coefficient of ECT of −0.7400 showed that the deviation of variables from the short-run disequilibrium to the long-run equilibrium was significantly adjusted and corrected by 0.74% half-yearly in the provinces of eastern Indonesia.

Table 6 also presents the results of the long-term relationship of the PMG model which were inconsistent with the MG and DFE models. The results of PMG model estimation, in the long run, revealed that all of the independent (MP, INT, lnCR) and control variables (lnEDU) had a positive and significant impact on the performance of the agricultural sector in eastern Indonesia at the 1% significance level. The rural ICT penetration, as proxied by the rural mobile phone (MP) and rural internet (INT) penetration, played a significant role in boosting the agricultural sector's performance with coefficients of 0.5988 and 0.2114, respectively. This suggests that in the long run, a 1% increase in the rural mobile phone and rural internet penetration would lead to an increase of 0.60% and 0.21%, respectively, in the agricultural sector performance of the 16 provinces of eastern Indonesia. This finding is consistent with the findings reported by Nguyen et al. (2023), Kaila and Tarp (2019), Suroso et al. (2022), Lio and Liu (2006), Oyelalmi et al. (2022), Nakasone et al. (2014), and Hopestone (2014). However, it contradicted the findings of Evans (2018), Akinlo et al. (2021), Fafchamps and Minten (2012).

Bank credit also exerted a statistically significant and positive effect on the performance of the agricultural sector in eastern Indonesia. The PMG results demonstrated that a 1% increase in the percentage of bank credit values will improve agricultural performance by 0.03% and this improvement was significant at the 1% level of significance. The present study is based on empirical evidence that suggests a positive correlation between the expansion of farmers' access to bank credit and the long-term development of the agricultural sector in Eastern Indonesia. This finding concurs with the research conducted by Rehman et al. (2017), Ngong et al. (2022), and Kumar et al. (2017). However, Nwude and Anyalechi (2018) presented contradictory results, indicating that the use of bank credit in the agricultural sector has a limited impact on the developmental progress of the agricultural sector in rural areas.

After conducting a thorough analysis of the PMG estimation results, we found conclusive empirical evidence that confirms the existence of a long-term relationship between the use of information and communication technology (ICT) and bank credit in the rural agricultural sector. However, our findings did not support the existence of short-term impacts, implying that the use of ICT and bank credit may not provide immediate benefits to the rural agricultural sector. Nonetheless, our analysis suggests that the adoption of these tools can positively contribute to agricultural productivity in the long term, ultimately leading to benefits for farmers. Our findings are in line with the predictions of the Solow growth model or neo-classical theory, which suggests that increasing savings as a source of capital accumulation can result in higher output per capita in the long term. Additionally, our analysis indicates that the adoption of technology, including ICT, can make a significant and permanent contribution in the long run (Mankiw, 2017). To achieve successful agricultural development in Eastern Indonesia through the implementation of ICT and banking credit, it is crucial to provide adequate infrastructure, knowledge, and education for rural communities. Therefore, it is essential to garner support from the government, private sector, and investors. We can ensure that the agricultural sector in the region benefits from the adoption of these technologies, leading to long-term growth and progress.

Conclusion

This research paper focused on the impact of rural ICT penetration and bank credit on agriculture performance in eastern Indonesia. The study used panel data from 16 provinces in eastern Indonesia, covering the period from the first semester of 2010 to the second semester of 2022 (2010S1–2022S2). The panel ARDL approach was used to analyze the data. The empirical findings of this study suggested that rural ICT penetration played a crucial role in agricultural performance. The analysis demonstrateed that rural mobile phone and internet usage had significant coefficients of 0.5988 and 0.2114, respectively. The results are consistent with previous research. Moreover, the study revealed that bank credit had a positive and statistically significant effect on the performance of the agricultural sector in eastern Indonesia. The study found that a 1% increase in the percentage of bank credit values improved agricultural performance by 0.03%, and this improvement was significant at the 1% level of significance. The evidence suggests that expanding farmers' access to bank credit is crucial for the long-term development of the agricultural sector in eastern Indonesia. However, our findings did not support the existence of short-term impacts, implying that the use of ICT and bank credit may not provide immediate benefits to the rural agricultural sector.

Our study has identified several key policies that can significantly impact agricultural development and improve the welfare of farmers in rural areas. Firstly, the government should prioritize providing adequate internet infrastructure that covers all rural areas in Eastern Indonesia. This will greatly enhance the performance of the agricultural sector by improving connectivity and facilitating the economic activity, distribution, and marketing of products. In turn, this is expected to reduce the development gap between rural and urban areas, including between the eastern and western regions of Indonesia. Secondly, it is essential to provide farmers with easy access to financial services, such as bank credits. Inclusive banking credit is crucial for financing agricultural activities, which can stimulate farmers' productivity and income. The government should intervene by reducing interest rates, which are a significant capital cost and business burden for farmers. Thirdly, educating rural communities on the adoption and use of ICT can significantly increase agricultural productivity, financial management, and agricultural production. Therefore, the government should focus on providing education and knowledge related to the use of ICT for these purposes.

Based on our study, we recommend several important policies that can practically impact and contribute to improving agricultural development and the level of welfare of farmers in rural areas as follows: First, the government should emphasize providing adequate internet infrastructure that reaches all rural areas in eastern Indonesia because this will make a major contribution to improving the performance of the agricultural sector. The availability of adequate infrastructure in the eastern region of Indonesia will increase connectivity and improve the flow of economic activity, distribution, and marketing of products. It is expected to reduce the development gap between rural and urban areas, including between the eastern and western regions of Indonesia. Second, provide adequate and easy access for farmers to obtain financial services such as bank credit. Providing inclusive banking credit is an essential factor for financing agricultural activities, which can stimulate farmers' productivity and income. The government must intervene by reducing interest rates which are the capital costs and business burdens of farmers. Third, providing education and knowledge related to the adoption and use of ICT to increase agricultural productivity, financial management, and agricultural production for rural communities.

Recommendations for further research can be made based on these limitations. This study has some limitations related to its research methods and scope. Firstly, it only considers two measures of ICT penetration, rural mobile phone, and internet penetration, and excludes other measures such as fixed-line telephone, computers, radio, and television. Secondly, this study only uses panel data from the provinces in the eastern region of Indonesia, and future research should cover all provinces in the country. Lastly, the control variable in this research is limited to educational factors, even though agricultural development is also linked to production efficiency, competitive market prices, ease of marketing, and farmers' income.

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