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ARTICLE

Maintaining Business Ease Through Bank Loans and Digital Transformation on Oil Palm Productivity in Lampung Province

A Polynomial Approach

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Abstract: This study analyses the complementary effects of bank financing and digital transformation on palm oil productivity in the Lampung Province. This study used secondary panel data from 15 districts and cities in Lampung from 2014 to 2022. This study applies spatial efficiency analysis in the form of slack-based measurement and data envelopment analysis to measure the amount of productivity. Meanwhile, the effect of banking financing and digital transformation on productivity uses an advanced polynomial static panel regression, generalized least squares. The results show that banking credit in the agricultural sector has a significant positive effect, and digitalization has a U-shaped characteristic (Kuznet's U-shaped curve) that leads to a positive effect on palm oil productivity under certain conditions. Bank credit acts as a medium-term funding stimulus, so the scale of the palm oil business is relatively maintained. In line with this, it needs to be accompanied by technological capacity and support in the form of internalization, both structurally and functionally, so that the efficiency of palm oil production can be navigated properly. Therefore, the government and institutions must expand digital access across Lampung to surpass the critical threshold and improve farmers' digital skills. At the same time, basic access, such as subsidized fertilizers and the development of agricultural platforms, is essential given the substantial future potential of digitalization. Financial institutions must also evaluate and simplify credit access with sufficient guarantees and provide interest subsidies (through interbank and local government collaboration) to accommodate potential productivity gains. In terms of regional living standards, promoting job creation across sectors could be beneficial. Meanwhile, to mitigate the adverse effects of industrialization on palm oil productivity, a synergistic partnership system between farmers and industries with fair pricing is necessary to ensure a broader supply and sustained production growth.

Keywords: Bank Financing; Digital Transformation; Productivity; Efficiency; Palm Oil.

1. Introduction

The agricultural sector plays an important role in the economy of the Lampung Province. This sector plays a fundamental role as a provider of employment and driver of economic growth (Emalia, 2018). Based on BPS-Statistics Lampung Province (2023), the agricultural sector absorbed 1,914,133 jobs, equivalent to 43% of the total workforce, and contributed the largest increase in gross regional domestic product (GDP), which was 27.9% in 2022. This indicates that the agricultural sector is strategic, considering its legitimacy in achieving community welfare.

Most of the agricultural sector in Lampung is dominated by oil palm plantations. This is evidenced by the area covered by oil palm land, which reached 109,175 ha in 2021. The area of oil palm land occupies the second position as the largest land for plantation crops in Lampung, whereas the first position is held by the area of rubber land, which reaches 196,816 hectares. According to Bappeda Provinsi Lampung (2021), Lampung ranks 14th among oil palm-producing provinces in Indonesia. The total production in 2021 reached 206,609 tons, surpassing approximately 197,639 tons produced in 2020. Under these conditions, the oil palm has a high potential for productivity and supports welfare in Lampung.

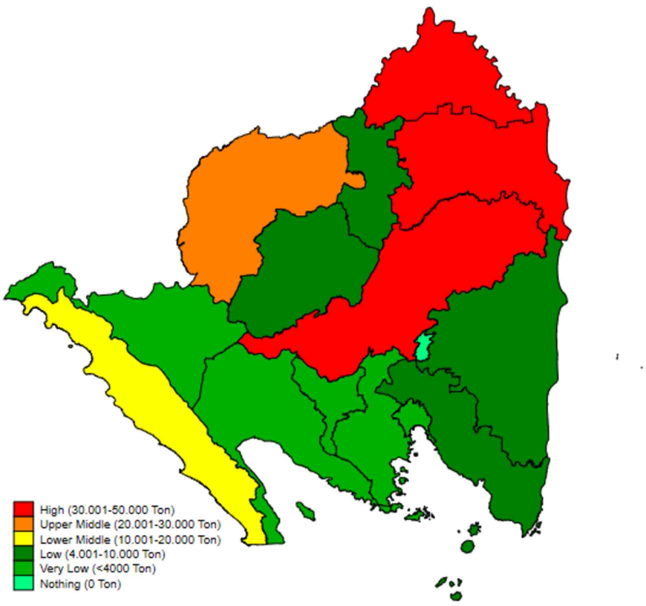


Figure 1. Palm Oil Production in 2022

Five districts are the center of palm oil production in the Lampung Province area, including Tulang Bawang Barat Regency, Lampung Tengah Regency, Mesuji Regency, Way Kanan Regency, and Pesisir Barat Regency. Other regions also have the potential to produce oil palms, although not to the same extent as the five related districts (BPS-Statistics Lampung Province, 2023). The high productivity of oil palm in Lampung has potential for use in regional development, including plantation expansion, down streaming, integrated business development, and cultivation technology research (Bappeda Provinsi Lampung, 2021). Of these four potentials, the downstream is most likely to be further developed (Matupalesa et al., 2019). Down streaming encourages industrial growth, which in turn creates added value in the processing process, allowing for increased value in palm oil. Downstream will not only create added value but also open new jobs; therefore, down streaming has an impact on labor absorption and improves community welfare (Azahari, 2018).

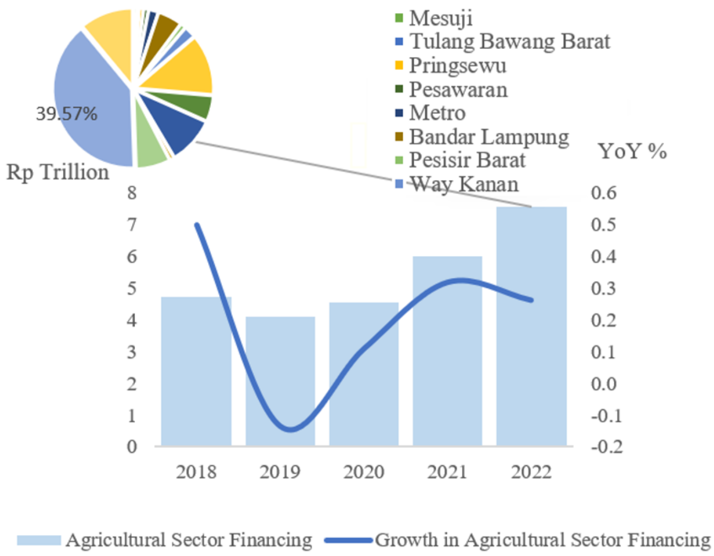


Figure 2. Development of Bank Financing in the Agriculture System

Source: Bank Indonesia (2022)

Based on Bank Indonesia (2022), the value of financing for the agricultural sector in Lampung is larger than that for financing in other sectors. This sector is ranked fourth based on the amount of financing accessed, with 11.5% of the total financing position disbursed. Meanwhile, the agricultural sector tends to increase its amount of financing from year to year. From 2017 to 2022, this sector increased, and the amount of financing decreased only in 2019. The total financing in 2022 reached 1.6 trillion, which is higher than the previous year, which only reached 1.4 trillion. This shows that Lampung has good prospects for the intermediation of regional agriculture.

Nowadays, digitalization has developed quite massively. Rapid digitalization needs to be navigated by investing in the real sector, one of which is banking financing. Banks can provide funding to assist economic actors in redesigning and automating their business processes to be more efficient through digitalization. This could include investments in supply chain management systems, automation of production processes, and system integration that allows smoother workflows. In addition, digitalization is often synonymous with processes that involve new innovations. Banking financing can help in financing innovative projects with the potential to improve production efficiency, such as the development of new products, more efficient production processes, and improvements in supply chain management. Therefore, proper and organized banking financing support can accelerate the digitalization process and achieve greater production efficiency, which in turn can improve competitiveness and profitability in an increasingly digitally connected market.

In general, the prospect of digitalization in Lampung has relatively good performance. This is reflected in the results of the digital competitiveness index calculation, which increased in 2022 compared to the previous period. The increase in the competitiveness index was supported by a strong human resources base, recovering economic activity, vibrant businesses, and the availability of infrastructure. This is also one of the efforts and synergies of the central and regional governments in supporting inclusiveness and accelerating equitable digitalization.

Table 1. Lampung Digitalization Component

	2021	2022	yoy
Digital Competitiveness Index			
Human Resources			
ICT Usage			
ICT Expenditure			
Economy			
Entrepreneurship			
Employment			
Infrastructure			
Montary			
Capacity			

Source: East Ventures (2021), Processed

Based on the current performance of digitalization and agricultural financing in Lampung, there is an urgent need for targeted policies to enhance palm oil productivity. Previous studies have highlighted the independent role of digital transformation and agricultural credit in boosting productivity. Several previous studies have examined the relationship between digital transformation and credit to productivity. The first finding states that digital transformation positively influences productivity (Aly, 2022; Gal et al., 2019; Myovella et al., 2020). Digital transformation allows people to explore opportunities to develop their businesses (Aly, 2022). Digital transformation increases the adoption of technology, which helps increase productivity (Gal et al., 2019). Digitalization contributes positively to the economic growth of a country (Myovella et al., 2020). The second finding states that credit can boost agricultural productivity (Kehinde & Ogundeji, 2022; Narayanan, 2016; Shuaibu & Nchake, 2021). Access to credit and services has a simultaneous effect on farmers' productivity, as evidenced by an increase in productivity in farmers who receive credit (Kehinde & Ogundeji, 2022). Access to credit obtained by farmers affects farming inputs and increases productivity (Shuaibu & Nchake, 2021). Credit levels are also observed in the credit market. Better credit market conditions create a better level of agricultural productivity (Narayanan, 2016).

However, existing studies predominantly assume linear relationships and often overlook the potential nonlinearities or threshold effects that may arise when digital transformation and credit interact. This study introduces a novel approach by employing a polynomial panel regression model to uncover possible U-shaped effects, particularly in the relationship between digitalization and productivity, a pattern referred to as the Kuznets U-shaped curve. By doing so, this research not only integrates the dual impact of credit and digitalization, but also addresses the underexplored dynamic interplay between them, offering fresh insights for policymakers aiming to maximize the returns of agricultural digitalization and financing in regional contexts. Based on this, this study focuses on the role of credit and digital transformation in productivity in Lampung. We hope that this study first examines the methodology related to digital transformation and productivity measurements. Second, it provides recommendations related to efforts to increase palm oil productivity in Lampung.

2. Methods

2.1. Data

This study used secondary panel data from 15 districts/cities in Lampung Province from 2014 to 2022. The year 2014 was selected as the starting point because it marks the post-implementation phase of major national infrastructure and digital acceleration programs, including the early expansion of Internet access and rural electrification, which are relevant to measuring the impact of digital transformation. Meanwhile, 2022 was chosen as the endpoint to ensure the availability of the most recent, complete, and consistent data across sources, before major structural changes following COVID-19 recovery programs could potentially alter the dynamics. These data were obtained through the publication of Regions in Figures of the Central Statistics Agency (DDA BPS), BPS Village Potential Data Collection (PODES BPS), Statistics on Investment Streams of the Investment Coordinating Board (BKPM), Bank Indonesia Regional Financial Statistics (SEKDA BI), PLN Electricity Statistics, and the Ministry of Finance's Regional Financial Information System (SIKD Kemenkeu) in real time. The detailed definitions and data sources used are as follows.

Table 2. Lampung Digitalization Component

No.	Indicator	Measurement	Sources
1	Palm Oil Production	Ton	DDA BPS
2	Gross Regional Domestic Product of the Agricultural Sector	Rp Billion	DDA BPS
3	Gross Fixed Capital Expenditure in the Agricultural Sector	Rp Million	BKPM
4	Agricultural Sector Labor	Person	DDA BPS
5	Oil Palm Land Area	Hectar	DDA BPS
6	Business Field Credit in the Agricultural Sector	Rp Million	SEKDA BI
7	MSME Loans in the Agriculture Sector	Rp Billion	SEKDA BI
8	Ratio of Internet Access Penetration (4G and 3G)	Persen	PODES, BPS
9	Regional expenditure (Fiscal Decentralization)	Rp Billion	Kemenkeu
10	Population	Person	DDA BPS
11	Regional Electricity Consumption	GWh	PLN

The above data were then processed to obtain the value of palm oil productivity and to test the consistency of the role of digital transformation and banking financing on palm oil productivity. In this study, the digital transformation variable was proxied by the ratio of Internet access penetration (3G/4G) across districts/cities. This choice assumes that Internet access serves as a fundamental enabler for broader digital adoption in agriculture, facilitating the flow of information, market access, and the utilization of digital services by farmers. The ratio of 3G/4G users reflects not only physical infrastructure readiness, but also the potential for farmers and institutions to engage in digital platforms, including e-commerce, mobile-based advisory systems, and online credit services (Munawaroh & Fajri, 2023).

2.2. Palm Oil Productivity Measurement

The measurement of palm oil productivity in this study used a parametric testing approach involving a linear program scheme in the form of Data Envelopment Analysis (DEA) and slack-based measurement (SBM). The primary goal of the analytical technique is to determine the efficiency value, which serves as a proxy for productivity. In general, if the measurement results are equal to one, it can be called Technically Efficient, and vice versa, if it is less than 1, it is Technically Inefficient, which is then referred to as less productive.

2.2.1. Data Envelopment Analysis

Based on Toma et al. (2015), the efficiency value using DEA can be calculated in the following stages:

$$
\begin{aligned}
&Max\ \theta(KabKo_0) = \Sigma_{k=1}^{s} v_k y_{k0} + \mu \\
&\text{s. t } \Sigma_{k=1}^{s} v_k y_{kj} - \Sigma_{i=1}^{m} u_i x_{ij} + \mu \leq 0;\ \text{when } j = 1, 2, \dots, n \\
&\Sigma_{i=1}^{m} u_i x_{i0} = 1, \\
&v_k \geq \varepsilon, k = 1, 2, \dots, s, \\
&u_i \geq \varepsilon, i = 1, 2, \dots, m \\
&\mu - free,
\end{aligned} \tag{1}
$$

Where the value *ϑ(KabKo0)* is an inefficiency measured in every district/city in Lampung, *ε* is an archimatic factor used to prevent non-negative equation and an absolute value equal to zero.

2.2.2. Slack Based Measurement

The value of efficiency using SBM refers to Fajri (2023), Fajri et al. (2023), and Fajri and Munawaroh (2023) It can be calculated through the following stages:

$$
\rho_{it} = min\left[\frac{1 - \frac{1}{N}\sum_{n=1}^{N}\frac{s_{nt}^{x}}{x_{nt}^{j}}}{1 - \frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{s_{mt}^{y}}{x_{mt}^{j}} + \sum_{i=1}^{I}\frac{s_{it}^{b}}{x_{it}^{j}}\right)}\right]
$$

$$
\begin{aligned}
&\text{s. t } \sum_{k=1}^{K} z_k s_{nt}^{m} + s_{nt}^{x} = x_{nt}^{j},\ \text{where } n = 1, 2, \dots, N \\
&\sum_{k=1}^{K} z_k s_{mt}^{k} - s_{mt}^{y} = y_{mt}^{j},\ \text{where } m = 1, 2, \dots, M \\
&\sum_{k=1}^{K} z_k s_{it}^{k} - s_{it}^{b} = b_{it}^{j},\ \text{where the value of } i = 1, 2, \dots, I \\
&\sum_{k=1}^{K} z_k = 1 \\
&z_k \geq 0, s_{nt}^{x} \geq 0, s_{mt}^{y} \geq 0,\ \text{and } s_{it}^{b} \geq 0
\end{aligned} \tag{2}
$$

The value of *K(k=1,2,...,K)* dicision, *N(n=1,2,...,N)* inputs, *M(m=1,2,...,M)* expected outputs, and *I(i=1,2,...,I)* another desirable output in district-j at year-t.

2.3. Empirical Model: The Role of Banking Financing and Digital Transformation on Palm Oil Productivity

Based on the background and literature review, an empirical model of the influence of banking financing and digital transformation was adapted using polynomial equations. The use of polynomial regression is motivated by the possibility of a nonlinear relationship, particularly a U-shaped or inverted U-shaped pattern between digital transformation and productivity, as indicated in previous studies, such as Myovella et al. (2020) and Gal et al. (2019). In the early stages, digitalization may be associated with inefficiencies due to adjustment costs, technological gaps, or limited farmer capacity. However, once a certain threshold for digital adoption is surpassed, its impact tends to become more positive and significant. A polynomial specification allows capturing these threshold effects more flexibly than a linear model, making it a suitable choice to test for the existence of a Kuznets-type digitalization curve in the context of palm oil productivity.

Furthermore, this study applies the generalized least squares (GLS) method to estimate the static panel regression model. GLS is chosen due to its robustness in handling panel data structures with heteroskedasticity and autocorrelation across entities (in this case, districts/cities) (Gujarati, 2021; Gujarati & Porter, 2015). Unlike

Ordinary Least Squares (OLS), which assumes homoscedastic and uncorrelated error terms, GLS efficiently adjusts for potential cross-sectional heterogeneity and serial correlation, thereby producing more reliable and efficient parameter estimates. This is particularly important, given the nature of regional-level data, where variance in scale, infrastructure quality, and institutional characteristics may differ significantly across districts.

While various panel data estimation techniques, such as the Fixed Effects Model (FEM) and the Generalized Method of Moments (GMM), exist, this study employs Generalized Least Squares (GLS) due to its suitability for estimating static relationships while addressing heteroskedasticity and serial correlation (Baltagi, 2005). Explanatory variables, such as credit access and Internet penetration, are treated as exogenous, minimizing concerns of endogeneity. The FEM is less preferred owing to its tendency to drop time-invariant variables, which are relevant in this study. Meanwhile, the GMM is designed for dynamic panels with large cross-sections and short periods, which do not align with this study's structure (small N, moderate T) and would require complex instrumentation that may not be feasible with limited observations.

Therefore, GLS provides a parsimonious, robust, and computationally efficient approach, allowing the model to account for heteroscedasticity and autocorrelation while retaining both time-varying and time-invariant explanatory variables. This approach ensures the consistency and efficiency of the estimates without overcomplicating the model, given the structure and size of the data.

Furthermore, the equation is estimated using the generalized least squares advanced static panel regression as follows:

$$\begin{aligned} Eff_{it} = {} & \alpha_0 + \alpha_1 lnKB_{it} + \alpha_2 lnKBUMKM_{it} + \alpha_3 id_{it}^2 + \alpha_4 id_{it} + \alpha_5 lnPDRBpercap_{it} \\ & + \alpha_6 infl_{it} + \alpha_7 lnBD_{it} + \alpha_8 lnindus_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

Where the value of *Eff* is the efficiency of palm oil (a proxy of productivity *lnKB* is a natural logarithm of banking credit, *lnKBUMKM* is a natural logarithm of banking MSME loans, id is the level of internetization, *lnPDRBpercap* is a natural logarithm of the gross domestic product per capita, *infl* is a inflation, *lnBD* is a natural logarithm of regional spending, *lnindus* is the natural logarithm of industrialization, and ε is another factor in the district/city -*i* and -*t* years.

Furthermore, to observe the effect of urban differentiation, COVID-19, and processing ownership status (downstreaming), a dummy was created, which was then applied as an interaction on the core components as follows:

$$\begin{aligned} Eff_{it} = {} & \alpha_0 + \alpha_1 lnKB_{it} + \beta_1 D_n \times lnKB_{it} + \alpha_2 lnKBUMKM_{it} + \beta_2 D_n \times lnKBUMKM_{it} \\ & + \alpha_3 id_{it}^2 + \alpha_4 id_{it} + \beta_3 D_n \times id_{it}^2 + \beta_4 D_n \times id_{it} + \alpha_5 lnPDRBpercap_{it} + \alpha_6 infl_{it} \\ & + \alpha_7 lnBD_{it} + \alpha_8 lnindus_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

D_n is an n-dummy, 1 is a COVID-19 dummy (1=during COVID 2019-2022 and 0=before), and 2 is a downstream dummy (1=regency/city that owns palm oil mills and 0=others).

After the estimation process is completed, the next stage is to calculate the optimal value of efficiency by involving the first derivative of the algebraic function for Equations (3) and (4). The process of calculating the derivative of Eq. (3) can be stated as follows:

$$\frac{dEff_{it}}{did_{it}} = Eff'_{it} = 2\alpha_3 id_{it} + \alpha_4 \tag{5}$$

The derivative of Equation (4) can be expressed as follows:

$$\frac{dEff_{it}}{did_{it}} = 2\alpha_3 id_{it} + 2\beta_3 id_{it} + \alpha_4 + \beta_4$$

$$\frac{dEff_{it}}{did_{it}} = 2(\alpha_3 + \beta_3)id_{it} + \alpha_4 + \beta_4 \tag{6}$$

Finally, to get the optimal interval of efficiency $\frac{dEff_{it}}{did_{it}}$. Thus, the optimal value can be expressed as

$$Eff_{it}^{p} = -\frac{\alpha_4^2 - 4\alpha_3\alpha_0}{4\alpha_3} \tag{7}$$

$$Eff_{it} = -\frac{(\alpha_4 + \beta_4)^2 - 4(\alpha_3 + \beta_3)\alpha_0}{4(\alpha_3 + \beta_3)} \tag{8}$$

The four estimation results are then compared to obtain information on the success of digitalization if supported by banking financing.

3. Results and Discussion

3.1. Descriptive Statistics and Correlation Coefficients

Based on the results of the descriptive statistical analysis, palm oil production efficiency in Lampung Province remains suboptimal, as indicated by an average efficiency score below one, suggesting that most districts have not yet operated at their production frontier. Although the share of banking credit disbursed to the agricultural sector is relatively substantial (56% for non-MSMEs and 43% for MSMEs), this financial support has not yet translated into full productive efficiency. This gap may reflect structural barriers such as limited absorptive capacity or ineffective credit allocation. In parallel, digital infrastructure, which is essential for technological transformation in agriculture, remains underdeveloped, with rural and urban digital service provision averaging only around 1%, a figure that underscores serious limitations in Internet penetration and functional connectivity. Despite a relatively high gross regional domestic product (GRDP) per capita of Rp12.08 million and stable macroeconomic conditions, such as low inflation (3.6%), local government expenditures averaging Rp1.36 trillion per year appear insufficient to accelerate industrialization, which remains modest at Rp4.02 trillion. These patterns suggest a disconnect between financial resources, digital readiness, and productive transformation, highlighting the need for better policy alignment across credit, technology, and infrastructure development to unlock higher agricultural productivity.

Furthermore, a correlation coefficient matrix is required to determine the potential relationship between the predictors and to avoid multicollinearity. Based on the results of the calculation, the highest correlation is supported by digitalization, while banking and MSME loans have a correlation value that almost resembles GDP per capita and industrialization. Regional spending has a relatively low correlation value and has the potential to have no effect on efficiency. In general, none of the predictors had an allegation of multicollinearity problems.

Based on the distribution of banking loans it shows that non-MSME and MSME banking loans tend to be uniform. Internetisation tends to disperse compared to other indicators. This suggests that the pattern of internetisation relationships will give rise to double information, which can be positive or negative, considering that the penetration is relatively longer. Therefore, in the estimation process, polynomial

Table 3. Statistics Descriptive

Variable	Obs	Mean	Min	Max
eff	135	.907	.567	1
kb	135	382362.42	4721.6	2859427
kb umkm	135	292815.96	27	1950519
id	135	.067	.008	.12
Pdrb pc	135	12088.313	1559.029	158309.98
inf	135	3.608	1.64	8.36
bd	135	1369.901	1.956	2700.059
indus	135	4029.724	156.43	18501.391

Source: Estimation result

calibration is required so that the information can be properly analyzed and not affect.exhibited.

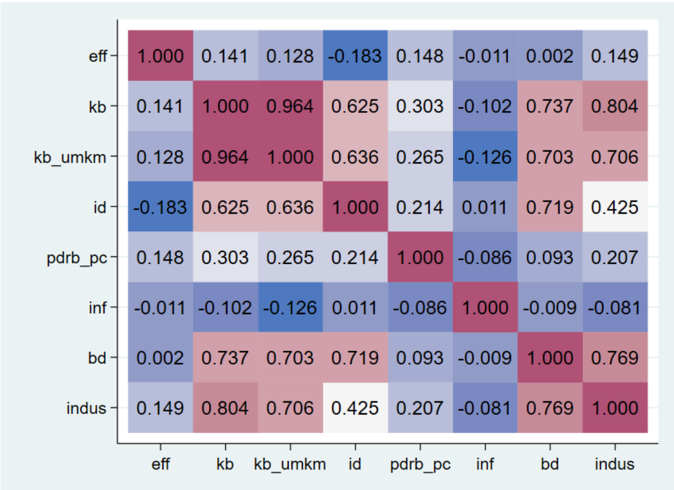


Figure 3. Heatmap Correlation

Source: Estimation result

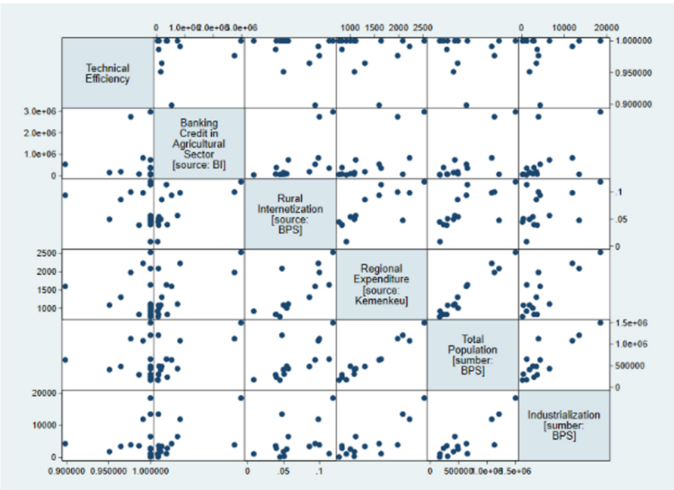


Figure 4. Correlation Matrix Scatter

Source: Estimation result

3.2. Results of Oil Palm Efficiency Estimation in Lampung Province

Figure 5 shows the results of mapping the spatial distribution of palm oil efficiency in the Lampung Province.

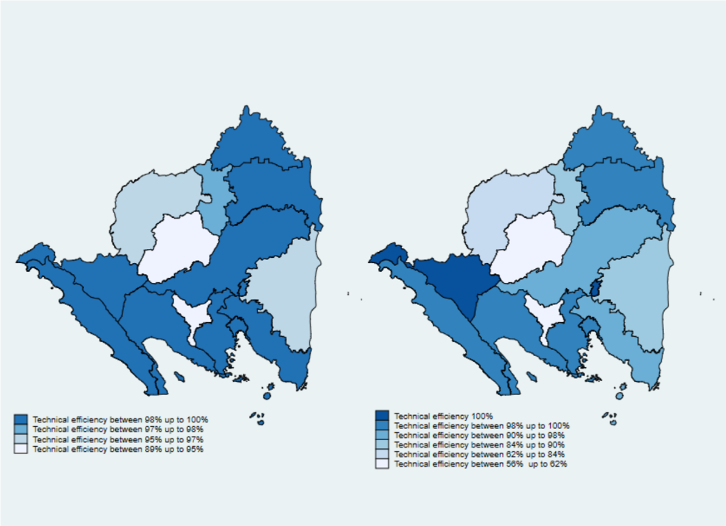


Figure 5. Efficiency Estimation Result in Spatial

Source: *Estimation result*

The findings show that there is a fundamental difference in efficiency calculations. Where in DEA the data density is smaller than SBM, for that reason, the SBM calculation is much more realistic and shows sharper information. For this reason, the overall results of the next estimate used are SBM.

Based on the findings, inefficient palm oil inputs account for approximately 9% of all production activities. This indicates that the synergy of production achievement still requires intensification, especially for the main inputs, namely investment (in this case, PMTB) and labor. Meanwhile, the magnitude of the efficiency value is supported by several regions that are considered successful in accommodating palm oil production. These districts/cities include Central Lampung, Pasawaran, Mesuji, Pringsewu, Bandar Lampung, and West Coast. Meanwhile, East Lampung, West Tulang Bawang, and Tanggamus tend to have quite small efficiency due to the shift in the orientation of farmers from oil palm to other crops.

	Efficiency
South Lampung Regency	0.98
Central Lampung Regency	1.00
North Lampung Regency	0.90
West Lampung Regency	0.86
Tulang Bawang Regency	0.99
Tanggamus Regency	0.76
East Lampung Regency	0.63
Way Kanan Regency	0.97
Pesawaran Regency	1.00
Mesuji Regency	1.00
Pringsewu Regency	1.00
West Tulang Bawang Regency	0.67
Bandar Lampung City	1.00
Metro City	0.85
West Coast Regency	1.00
Lampung	0.91

Source: *Estimation result*

Furthermore, the results of the efficiency estimation are presented in cross-tables using the available inputs. The results showed that there are quite massive temporal changes. Based on the results of residual mapping, the growth of inputs that are less efficient year-over-year (yoy) has decreased, particularly in investment, energy consumption, and land use. Meanwhile, the inefficient workforce experienced an increase yoy. However, concretely, an upward trend still occurs, especially in investment, because producers do not respond well to the surge in inflows, so the achievement of optimal output is not realized. On the other hand, the increase in inefficient labor indicates that less-skilled human resources are driving a decline in palm oil productivity in the short term.

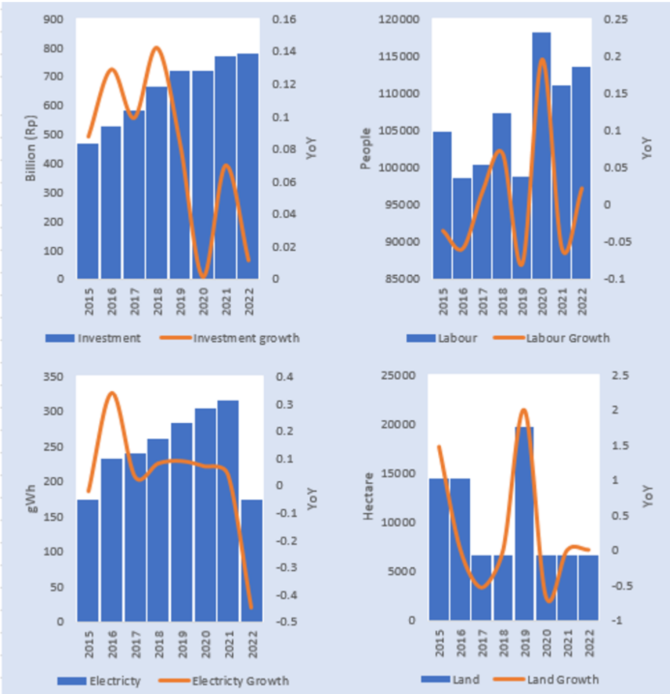


Figure 6. Inefficiency Result

Source: *Estimation result*

The average spatial distribution of each production input is shown in Figure 8. The results show that Central Lampung, Bandar Lampung, and South Lampung have the highest levels of investment inefficiency. This indicates that an increase in investment in the three regions has the potential to cause misallocation to encourage a residual increase. Meanwhile, Central Lampung, East Lampung, and Tanggamus are the areas with the highest level of labor inefficiency in Lampung. This is suspected to stem from uneven training and skills programs that encourage the expansion of less productive inputs during the production process. On the other hand, electricity consumption also has less productive value, among others, coming from Central Lampung, Bandar Lampung, and South Lampung, which are suspected to have an energy consumption distribution that tends to be less efficient. This is because of the high population density, which encourages disparities between individual and corporate consumers. Finally, land inefficiency also occurred massively for Mesuji, Tulang Bawang, and Central Lampung following the clearing of oil palm land into settlements and for the purpose of transitioning crops to other types.

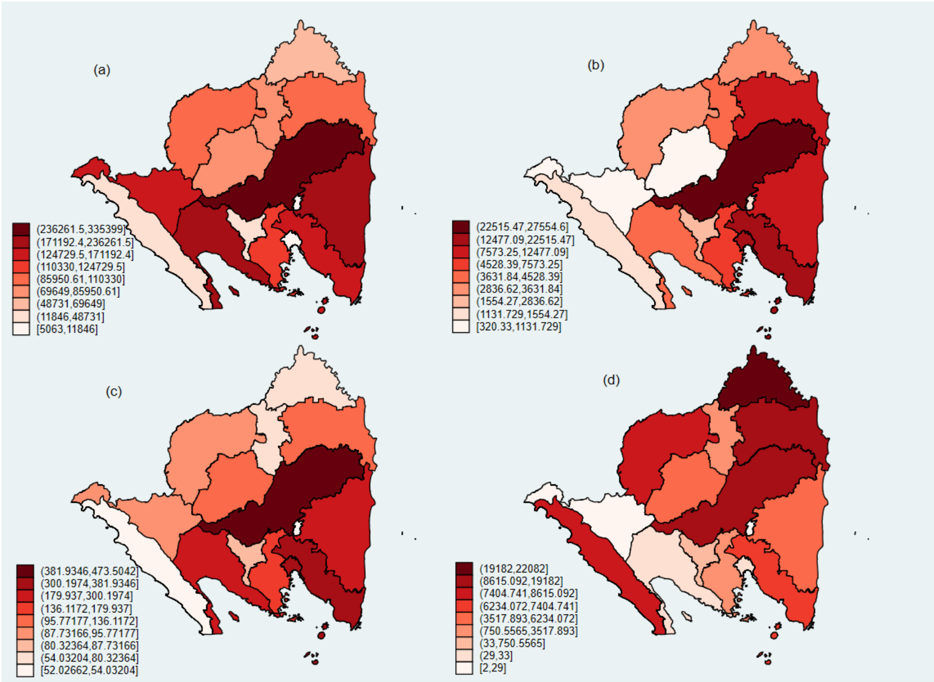


Figure 7. Inefficiency in Spatial Distribution

Where (a) Investment; (b) Labor; (c) Electricity Consumption; and (d) Land

3.3. Estimated Results of the Influence of Banking Financing and Digital Transformation on Palm Oil Efficiency

Based on Table 5, non-MSME loans, gross regional domestic income per capita, and regional spending have a significant positive effect on palm oil productivity. Meanwhile, digitalization has a two-way effect on palm oil productivity, initially having a negative impact and then, at a certain point, a positive one. Industrialization shows a different influence, namely a significant negative effect on palm oil productivity. Consistently, banking credit and digitalization, if not included in MSME loans, have a significantly lower influence on productivity. On the other hand, when MSME credit and digitalization are included and banking credit is not, it will have a lower significant influence on productivity. Then, if digitalization is not included but banking credit and MSME credit are included, it shows the lowest significant influence on productivity when compared to other equations. Finally, banking credit and MSME credit, if not included in digitalization, also have a significantly lower influence on productivity. Similarly, what happened after the COVID-19 pandemic, and when was the downstream oil palm implementation? This signifies that the consistency of its influence has been normalized, given that economic recovery has occurred.

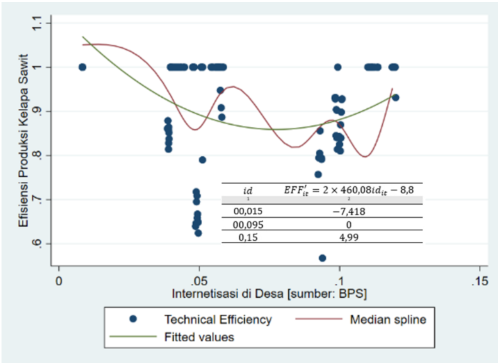
Table 5. Estimated Results Banking Credit and Digitalization on Efficiency

	(1) eff	(2) eff	(3) eff
ln *kb*	0,0545**	0,0566***	-0,0212
	(0,0214)	(0,0217)	(0,0273)
ln *kb* × $D^{covid19}$		-0,0218	
		(0,0448)	
ln *kb* × D^{hilir}			0,1462***
			(0,0524)
ln *kb umkm*	-0,0096	-0,0149	0,0035
	(0,0154)	(0,016)	(0,015)

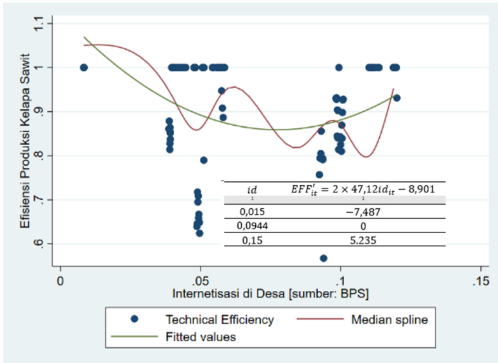
	(1) eff	(2) eff	(3) eff
ln *kb umkm* × $D^{covid19}$		0,0655	
		(0,0423)	
ln *kb umkm* × D^{hilir}			-0,0554
			(0,045)
id^2	46,08***	47,12***	121,2**
	(10,47)	(12,13)	(50,5)
id	-8,833***	-8,901***	-18,4**
	(1,497)	(1,734)	(8,183)
$id^2 \times D^{covid19}$		-16,51	
		(21,68)	
$id^2 \times D^{hilir}$			-78,8
			(50,19)
$id \times D^{covid19}$		1,292	
		(2,896)	
$id \times D^{hilir}$			7,917
			(80,097)
ln *pdrbk*	0,0618***	0,0609***	0,0868***
	(0,0146)	(0,0145)	(0,0161)
inf	0,0079	0,0057	0,0047
	(0,0058)	(0,0059)	(0,0054)
ln *bd*	0,0361**	0,0362**	0,039***
	(0,0166)	(0,0162)	(0,015)
ln *indus*	-0,0287**	-0,0274**	-0,0015
	(0,0116)	(0,0119)	(0,0171)
$D^{covid19}$		-0,5637*	
		(0,3215)	
D^{hilir}			-1,276***
			(0,2684)
cons	0,0735	0,1255	0,6368**
	(0,2065)	(0,2203)	(0,2809)
Observations	135	135	135
Quadratic Critical Values			
Digitalization (id_p)	0.09584***	0.09444***	0.07586***
Efficiency (EFF_p)	0.5767***	0.57965***	0.302185**
wald χ	59,79***	69,84***	108,16***

Source: *Estimation result*

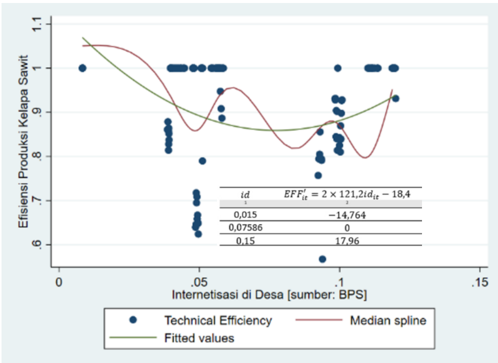
Based on the findings of the calculation of the quadratic panels, it is shown that in the normal case, when the level of digitization of districts/cities is 0.015%, there will be a potential increase of 1%, thus decreasing efficiency by 7.418%. Meanwhile, in districts/cities with a digitalization level of 0.095%, if there is an increase of 1%, the efficiency will not change, which tends to stagnate at the level of 57.67% (stationary). Then, if in districts/cities with a digitization level of 0.15, it will increase efficiency by 4.99 percent. Meanwhile, after COVID-19, the level of district/city digitization was 0.015%, then there was a potential increase of 1%, thus reducing efficiency by 9.0644%. Meanwhile, in districts/cities with a digitalization level of 0.0783%, if there is an increase of 1%, the efficiency will not change, which tends to be stagnant at the level of 56.11% (stationary). Then, in districts/cities with a digitalization level of 0.15, the efficiency level will increase by 10.246 percent. Finally, if the downstream scheme is carried out, there is a time when the district/city digitization rate is 0.015%, then there is an increase of 1%, which reduces the efficiency by 14.764%. Meanwhile, in districts/cities with a digitalization rate of 0.07586%, if there is an increase of 1%, the efficiency does not change and tends to stagnate at the level of 30.21% (stationary). Then, if in districts/cities with a digitization level of 0.15, it will increase the efficiency level by 17.96 percent.



(a)



(b)



(c)

Figure 7. Inefficiency in Spatial Distribution

3.4. Discussion

Based on the match between the estimated results and the qualifications, the research on the relationship between credit and productivity aligns with the findings of Bashir et al. (2010) and Narayanan (2016). Meanwhile, the same relationship, namely that between digitalization and productivity, was also found to be in accordance with Gal et al. (2019), Myovella et al. (2020), and Aly (2022). This indicates that banking financing and the level of digitalization still affect productivity.

In general, the results of the estimates indicate that following the COVID-19 pandemic and its downstream effects, there is a potential decline in palm oil productivity. This potential is possible due to the insufficient pace of capital, as well as changing business orientations, such as shifts in the structure of farmers' work. On the other hand, the downstream has the potential to reduce farmers' productivity because a holding appointed by the government takes over agricultural occupancy. This must then be used as a reference so that oil palm farmers can continue to benefit from their agricultural land.

Financing aspects from banks and financial institutions should obtain the same portion, namely, they can be used as a means of providing capital, using access to agricultural technology, land maintenance and management, and access to training. Based on the currently available data, farmers who can access financing account for no more than 12%, indicating that the financing potential in the agricultural sector, particularly in oil palm plantations, remains substantial. Capital fulfillment enables farmers to replace old plants with new, more productive ones. Even with sufficient modalities, palm oil farmers can purchase potentially superior seeds. Adequate access to financing also encourages farmers to invest in technology, such as the purchase of automated harvesting machines and effective irrigation modeling, as well as a more efficient fertilization process. Simultaneously, this provides direction for farmers to carry out good land maintenance through financing from banking and financial institutions. Finally, with sufficient funds, farmers can participate in various upskilling programs to increase their knowledge. These indicators can consistently increase palm oil productivity in the long term, thereby achieving a higher level of efficiency. More specifically, overall financing from banks and financial institutions can help reduce the capital gap, which has long been the primary obstacle for oil palm farmers in increasing productivity. Therefore, there is the potential to increase production and support the increase in income and welfare of oil palm farmers.

Digitalization is also a factor contributing to an increase in palm oil productivity, driven by financing incentives from banks and other financial institutions. With the penetration of the internet and mobile phones, it is possible for farmers to use monitoring plant conditions as well as being part of agricultural management references. In addition, a more potential marketing focus can be achieved through rapid digitalization. However, Indonesia has not experienced an equal distribution of digital penetration, especially in Lampung. Therefore, their utilization and use are still not well understood. On this basis, there needs to be navigation from the government and other institutions to encourage digital progress and penetration as the availability of facilities, so that the community, especially farmers, can use them optimally. Currently, Internet penetration among farmers is still less than the minimum target of 3.2%, which can have a negative impact on productivity. This negative influence occurs because farmers still understand the context and frame of mind from the Internet, so that job opportunities can be ignored (barriers to adaptation). Post-COVID-19, Internet penetration is quite massive, so that the increase can be one of the references to support better palm oil productivity. In addition, the downstream role is also quite relevant to the application of technology, considering that centralization is one of the references to increase productivity.

Furthermore, the locus of productivity increase is influenced by an increase in the per capita income of local communities and regional fiscal incentives. This is in line with research conducted by Adelekan and Omotayo (2017) and Wang et al. (2022) that indicates the higher per capita income increases allow farmers and companies to compete for mutual investment in these better agricultural technologies, including the use of automated machinery, efficient irrigation systems, and advanced land monitoring technologies. The local government's alignment with palm oil productivity can also support increasing efficiency. The government's focus on capital goods spending causes productivity qualifications to improve in line with the conditions of people in the regions. In addition, local governments also have the capacity to align and organize extension programs that provide information on best agricultural practices, new technologies, and efficient plantation management.

Finally, industrialization was found to have a negative effect on palm oil productivity. This is in line with research conducted by Davis and Hashimoto (2014) informs that Lampung oil palm farmers are not ready to accept industrialization because it can reduce productivity levels. This condition needs to be a reflection for local governments to strengthen accessibility and encourage work inclusivity, so that new supply chains can be adapted quickly, so that the potential to open up space for job opportunities is more optimal.

4. Conclusion

Based on the discussion results, it can be concluded that the research objectives have been successfully achieved, both in terms of empirical analysis and policy relevance. This study empirically shows that banking financing has a positive effect on palm oil productivity. Meanwhile, digitalization demonstrates a significant two-way relationship: it has a negative impact when penetration is below 9.5% but becomes positive once that threshold is surpassed. This finding confirms the argument that successful digitalization requires a critical minimum level to enhance production efficiency.

Methodologically, this study applies a polynomial approach in a static panel regression model (GLS) to capture the nonlinear (U-shaped) pattern of the impact of digitalization on palm oil productivity. The discovery of this U-shaped curve is novel, indicating that digital transformation does not automatically improve efficiency unless it surpasses the minimum level. In addition, this study emphasizes the importance of integrating banking financing with digitalization as an optimal strategy to enhance agricultural productivity.

Another contribution of this study lies in its policy relevance, which can serve as a basis for improving the effectiveness of regional fiscal policies and the development of financial inclusion in the agricultural sector. Factors, such as per capita income and regional government expenditure, have also been found to positively affect efficiency. Conversely, industrialization has a negative effect on productivity, suggesting the importance of institutional and social readiness among farmers in managing the transition to industrial activity.

Therefore, going forward, the government and institutions need to expand digital access across regions in Lampung, ensuring that penetration exceeds the threshold while also enhancing farmers' skills. Basic infrastructure, such as subsidized fertilizer provision and agricultural platform development, is also essential, considering the substantial potential of digitalization in the future. On the other hand, banks and financial institutions should conduct targeted evaluations and ease the provision of credit and financing with sufficient collateral, as well as offer interest subsidies (through interbank collaboration with local governments) to better accommodate the potential surge in farmers' productivity.

Improving the standard of living in rural areas can also be achieved by encouraging widespread job opportunities across sectors. Meanwhile, to avoid the adverse effects of industrialization on palm oil productivity, a synergistic partnership model between farmers and industry is necessary at affordable prices to ensure a broader industrial supply and well-supported production growth.

Nevertheless, this study had certain limitations. Ideally, digital transformation should be measured using more specific indicators such as the use of digital agricultural applications, e-commerce adoption, or the integration of precision farming systems. However, owing to the unavailability of longitudinal district-level data on these aspects, Internet access penetration was used as a practical and measurable proxy. Future studies are encouraged to refine this proxy by incorporating more granular digital behavior metrics as data becomes available. Subsequent research could also adopt dynamic modeling or multilevel quantitative approaches to explore the interplay between technology, productive capacity, and long-term policy intervention impacts in the agricultural sector.

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