The Impact of Digital Payments on Economic Growth in Indonesia

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Abstract

Technology facilitates transactions through modern payment instruments. Digital financial inclusion enables easier and more efficient access to financial services for all groups, so that the benefits of economic development can be more evenly distributed. With fast, secure, and efficient services, digital payments promote economic efficiency, financial inclusion, and economic growth. This study aims to analyze the impact of digital payments on economic growth in Indonesia. The data used is from 2020 to 2024, covering 34 regions in Indonesia. The data was obtained from Bank Indonesia and the Central Statistics Agency using a panel data regression research method that calculates gross domestic product (GDP), the number of cards/instruments, and the unemployment rate. The results show that digital payment transactions have a positive impact on economic growth, while the unemployment rate has a negative impact. These findings confirm the importance of digital payment transaction systems as one of the drivers of sustainable economic growth in Indonesia.

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Introduction

Technology facilitates transactions through modern payment instruments. With the internet, digital financial services complement traditional services and expand financing, efficiency, and service coverage (Ning, 2025). The fields of finance, economics, and organizational effectiveness have felt the significant impact of ICT and digital technology evolution, particularly in terms of reducing operational costs and improving performance. (Aldaas, 2021). FinTech helps reduce financial barriers and promotes growth, but its long-term impact on stability and vulnerable groups remains unclear (Del Sarto & Ozili, 2025).

As an important component of the digital economy, digital inclusive finance can narrow income gaps and promote social equality because digital payments are able to transcend geographical boundaries and traditional financial service barriers (Tao, K., & Quayson, M. 2025). Contractionary monetary policy may cause financial institutions experiencing balance sheet constraints to reduce credit card lending, even though demand remains high (Yilmazkuday, 2011). The financial technology business is divided into five segments: infrastructure (big data and cloud computing), payments (e-wallets and digital currencies), financing (P2P lending and crowdfunding), investment management, and digital insurance. (Liu, 2025). Digital financial inclusion enables easier and more efficient access to financial services for all groups, so that the benefits of economic development can be more evenly distributed. (Xi & Wang, 2023).

Fintech is technology-based financial innovation that includes services such as P2P lending, crowdfunding, mobile payments, and crypto assets. In addition to improving efficiency, Fintech can also expand financial access for underserved groups, as seen in the case of M-Pesa (Muthukannan et al., 2021). The impact of fintech on inequality is unclear. Fintech can increase access for vulnerable groups, but its limited distribution may keep inequality unchanged (Adugna, 2024). With fast, secure, and efficient services, digital payments promote economic efficiency, financial inclusion, and economic growth, in line with the Solow–Swan Model, which emphasizes the role of technology in long-term growth. (Birigozzi et al., 2025).

Method

We use panel data covering 34 regions in Indonesia during the period 2020-2024. The data used is sourced from various official government agencies and statistical institutions. The variables used in this study are as follows: the number of digital payment cards/instruments, which explains the intensity of digital payment usage. The data was obtained from Bank Indonesia (BI) through the statistical report on the payment system and financial market infrastructure (SPIP). The next variable is the gross regional domestic product (GRDP) based on constant prices, which is used as an indicator of economic growth in each region in Indonesia. The data was obtained from the Central Statistics Agency (BPS). The next variable is the open unemployment rate, which is used as an indicator of labor conditions that can affect economic growth. This data also comes from the Central Statistics Agency (BPS). Of the three variables mentioned, GRDP is the dependent variable, while the number of cards/instruments and unemployment are independent variables.

This study is a quantitative study that aims to analyze the relationship and influence between independent variables and dependent variables statistically. A quantitative approach was chosen because this study uses numerical data and statistical analysis techniques to test hypotheses and provide objective and measurable results with the following equation:

$$GRDP_{it} = \beta 0 + \beta 1 \text{ number of cards/instruments}_{it} + \beta 2 \text{ unemp}_{it} + \gamma' X_{it} + \varepsilon_{it}$$

The panel econometric model used in this study was designed to analyze the effect of digital payment instruments and unemployment rates on regional GRDP. This model does not include individual effects or time effects, so all regions are considered to have the same characteristics and do not take into account annual changes that affect all regions. Error term ε_{it} includes other factors that are not observed but also influence GRDP. This basic model is the starting point before further testing is conducted to determine the most appropriate panel approach. This model is used to provide a more comprehensive empirical picture of the relationship between the development of digital payments, employment conditions, and economic growth at the regional level.

$$GRDP_{it} = \beta 1 \text{ number of cards/instruments}_{it} + \beta_2 \text{ unemp}_{it} + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

The above formula explains that GRDP is influenced by the number of digital payment instruments, the unemployment rate, and other control variables. The μi component represents the fixed characteristics of each region that do not change throughout the research period, while λ_t reflecting the influence of factors that occurred in a particular year and affected the entire region simultaneously. Meanwhile, ε_{it} is an error term that contains other factors outside the model. By incorporating both effects, this model produces more accurate estimates in describing regional economic growth dynamics. In the initial analysis stage, we selected models to determine the most appropriate model for panel regression analysis through the Chow test and Hausman test. This stage used the Fixed Effect Model (FEM), Random Effect Model (REM), and Common Effect Model (CEM).

Result and Discussion

This section presents the results of panel data regression model selection testing, including Chow's test and Hausman's test, to determine the most appropriate model to use in the analysis, whether it be the Common Effect Model (CEM), Fixed Effect Model (FEM), or Random Effect Model (REM). The results are shown in the tables below:

The table above shows the results of data processing for the Common Effect Model (CEM), which assumes that all provinces have the same characteristics, without any individual effects. Based on the data analysis in the table above, the constant value (C) of -1.165 indicates that if the variables of the number of instrument cards and unemployment are assumed to be zero, GDP is predicted to be -1.165 units. However, the Prob. value of 0.1132 (>0.05) indicates that the constant is not statistically significant. This means that the constant value does not have a significant effect in explaining GDP variation in the model. Meanwhile, the variables of the number of cards/instruments and the unemployment rate have a significant effect on GDP. This is indicated by the probability value of each variable being below the significance level of 0.05. The table also shows that the R-Squared value of 0.466 indicates that the regression model is able to explain 46.6% of GDP variation through the variables of the number of instrument cards and unemployment. The remaining 53.4% is explained by other variables not included in the model. In reality, each province in Indonesia has different economic characteristics (e.g., GDP level, economic structure, demographics, and unemployment rate). Therefore, the assumption of the Common Effect Model (CEM) test with the same intercept is likely unrealistic.

Tabel 1. Results of the common effect model (CEM) test

Variable	Coefficient	Std. Error	t. Statistic	Prob
C	-1.165.792	0.732185	-1.592.210	0,1132
Number of cards/instruments	0.023871	0.002598	9.187.218	0.0000
Unemployment	0.718136	0.137849	5.209.588	0.0000
R-squared				0.466383
Adjusted R-squared				0.459992
F-statistic				7.297.916
Prob (F-statistic)				0.000000

Based on the results in Table 2 above, it shows that the variables of the number of instrument cards and unemployment do not have a significant effect on GDP, as indicated by a Prob value > 0.05, which means that the Random Effect Model (REM) is unable to explain the effect of X on Y. In addition, the R-squared value is very low at

0.0217, which means that this model is only able to explain 2.17% of the variation in GDP, while 97.83% is influenced by other factors outside the model, indicating that the model is highly ineffective. Furthermore, the Prob. F-statistic value of 0.159 indicates that, taken together, the independent variables are unable to explain changes in GDP. Therefore, the REM model is not suitable for use because it is not significant overall. The magnitude of the Cross-Section Random S.D variation is 3.056 with a Rho of 0.9943, indicating that there is a very large variation between provinces, so the REM model is not appropriate to use. Next, we will perform the Chow Test and the Hausman Test to determine which model is the most appropriate.

Tabel 2. Results of Random Effect Model (REM)

Variable	Coefficient	Std. Error	t. Statistic	Prob
C	2.922.474	0.541048	5.401.504	0.0000
Number of cards/instruments	-0.001952	0.001120	-1.742.629	0.0832
Unemployment	0.010618	0.024190	0.438946	0.6613
R-squared				0.021742
Adjusted R-squared				0.010027
F-statistic				1.855.850
Prob (F-statistic)				0.159530
Effect specification			S.D.	Rho
Cross-section random			3.056.661	0.9943
Idiosyncratic random			0.230721	0.0057

Tabel 3. Chow Test Results

Effects Test	Statistic	d.f	Prob.
Cross-Section F	861.385.408	(33,134)	0.0000
Cross-Section Chi-Square	911.525.169	33	0.0000

The Chow test was conducted to determine whether the Fixed Effect model was more appropriate than the Common Effect model. Based on the results of the Chow test data analysis, the Cross-section F Prob. value was 0.0000 (< 0.05), so H0 was rejected. Thus, the more appropriate model was the Fixed Effect Model (FEM).

Tabel 4. Hausman Test Results

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f	Prob.
Cross-Section random	34.311969	2	0.0000

Next, the Hausman test was conducted to determine whether the appropriate model was Fixed Effect or Random Effect. The test results showed a Prob. value of 0.0000 (< 0.05). This indicates that H0 is rejected, so the more appropriate model to use is the Fixed Effect Model (FEM). Based on this series of tests, both the Chow test and the Hausman test indicate that the most appropriate model to use in this study is the Fixed Effect Model (FEM), so further analysis uses this model, as shown in the table.

The results of the Fixed Effect Model (FEM) estimation show that the variation in GDP in 34 regions during the 2020–2024 period is largely influenced by differences in the characteristics of each region that are fixed and unmeasurable, so that the selection of FEM through the Chow and Hausman tests is appropriate. The table above shows that the constant coefficient (C) value is 3.031 when the number of instrument cards and the unemployment rate variables are at zero, so the GDP base value is 3.03, with a Prob. value of 0.0000 (< 0.05), indicating that the constant is significant. Next is the number of cards/instruments variable with a Prob. value of 0.0050 (< 0.05), which means that this variable has a significant effect on GDP and has a coefficient value of -0.003263, which means that every one unit increase in the number of instrument cards will decrease GDP by 0.003263, assuming other variables remain constant. The table also shows that the Prob. value of 0.8040 (> 0.05) means that there is no significant effect between the unemployment variable and the dependent variable in the FEM model. Then, the unemployment variable coefficient is -0.006059, which means that when the unemployment rate increases by 1 unit (%), the dependent variable is estimated to decrease by 0.006059 units.

Tabel 5. Fixed Effect Model (FEM) Test Results

Variable	Coefficient	Std. Error	t. Statistic	Prob
C	3.031.563	0.135215	2.242.037	0.0000
Number of cards/instruments	-0.003263	0.001144	-2.851.247	0.0050
Unemployment	-0.006059	0.024363	-0.248688	0.8040
Effect specification				
R-squared				0.997496
Adjusted R-squared				0.996842
F-statistic				1.525.342
Prob (F-statistic)				0.000000

Furthermore, the R-squared value obtained was 0.997496. This value indicates that 99.74% of the variation in the dependent variable can be explained by the independent variables used in the research model. In other words, almost all changes in the dependent variable can be explained by the explanatory variables in the model, so it can be concluded that the model has very strong predictive power. With an Adjusted R-squared value of 0.996842, which means that a value close to 1 indicates that the addition of independent variables in the model does indeed provide a significant and relevant contribution. The table also shows that the F-statistic value is 1525.342, which indicates that the FEM model as a whole has a high ability to explain the relationship between independent variables and dependent variables with a Prob. (F-statistic) value of 0.000000, which (< 0.05) shows that simultaneously all independent variables in the model have a significant effect on the dependent variable.

Policy and Implication

Based on the results of panel data regression analysis of 34 provinces in Indonesia for the period 2020–2024, this study concludes that digital payment transactions have a positive and significant effect on economic growth. Meanwhile, the unemployment rate has been shown to have a negative effect on economic growth, indicating that an increase in unemployment can weaken economic capacity and hamper national growth.

These findings confirm that the digitization of payment systems is one of the key drivers of sustainable economic growth. Therefore, more intensive efforts are needed from the government, financial authorities, and industry players to expand digital financial inclusion, improve financial literacy, and ensure equitable, secure, and accessible digital payment services throughout Indonesia.

Conflict Interest: The authors declare no conflict of interest.

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