Is the bank credit able to accelerate economic transformation? A multivariate modeling of key sectors in Indonesia

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Abstract

This study assess how credit provision to MSMEs by sector impacts sectoral economic growth (manufacturing, retail and wholesale trades, transportation, accommodation and food beverage providing, company services, and others services) in 34 provinces in Indonesia, using control variables (population, workforce, and digitalization), as well as dummy variables before and during the COVID-19 pandemic and the economic recovery period. The results of a multivariate regression analysis indicate that credit provision to MSMEs in a sector has a unique effect on other sectors. Interestingly, digitalization has a dominant impact on the Indonesian economy. Priority policies aimed at transforming the national and regional economies can be effectively implemented by providing capital stimulus in the form of business credit to MSMEs, particularly in Indonesia's leading sectors, and by optimizing the development of ICT facilities and infrastructure.

Keywords: digitalization; MSME credit; economic transformation; multivariate regression

JEL Classification: C22; I18; R11

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1. Introduction

The COVID-19 pandemic has altered economic patterns on both global and national scales. BPS (2020) reported that the national economy experienced a contraction starting in the second quarter of 2020, amounting to -5.32 percent (year-on-year) as the pandemic began in Indonesia. This contraction was the worst in the last ten years. The economic downturn continued until the first quarter of 2021, exactly one year after the pandemic hit Indonesia. The initial sign of economic recovery was marked by accelerated economic growth of 7.07 percent (year-on-year) in the second quarter of 2021. In the early stages of the pandemic, almost all economic sectors experienced contraction, particularly leading sectors such as the manufacturing industry (-6.19 percent) and mining (-2.72 percent).

Sectors closely related to tourism experienced even deeper contractions, such as transportation and warehousing (-30.84 percent), accommodation and food services (-22.02 percent), other services (-12.60 percent), business services (-12.09 percent), and trade (-7.57 percent). Meanwhile, agriculture, as a leading sector, still grew positively amid the pandemic storm, although it experienced a slowdown. At the regional level, average provincial economies in 2020 also contracted, especially in Sumatra, Java, Bali, and Kalimantan. As of 2021, Bali's economy was still contracting due to the long-term impact on tourism activities.

Besides disrupting economic activities in both government institutions and the private sector, the COVID-19 pandemic also affected the social structure. This was marked by an increase in the number of unemployed people as of August 2020, reaching 9.77 million people, as well as a rise in the number of part-time workers and those still seeking other jobs. As a result, employment in the agriculture and trade sectors increased compared to August 2019, by 2.23 percent and 0.46 percent, respectively. Meanwhile, the manufacturing sector saw the most significant decline among all sectors, decreasing by 1.3 percent.

This aligns with the substantial increase in informal sector workers, around 60.47 percent, higher than in August 2019 (55.88 percent) and August 2018 (56.98 percent) (BPS, 2020). This labor structure shift also corresponded with the phenomenon of rising MSMEs (Micro, Small, and Medium Enterprises) utilizing digital platforms during the pandemic as an alternative to layoffs, especially in the manufacturing sector, or due to restrictions in sectors like trade, hospitality, and restaurants that typically involve large gatherings. Tokopedia, one of Indonesia's largest marketplaces (Burhan, 2022), showed an increase in the number of MSMEs transacting on its platform. In February 2020, transactions increased by 5.8%, then by 37.5% in April 2020, and by 63.8% in the May–June 2020 quarter. The number of businesses transacting on the marketplace even grew by 81.1 % in July–August 2020 (Lidwina, 2021).

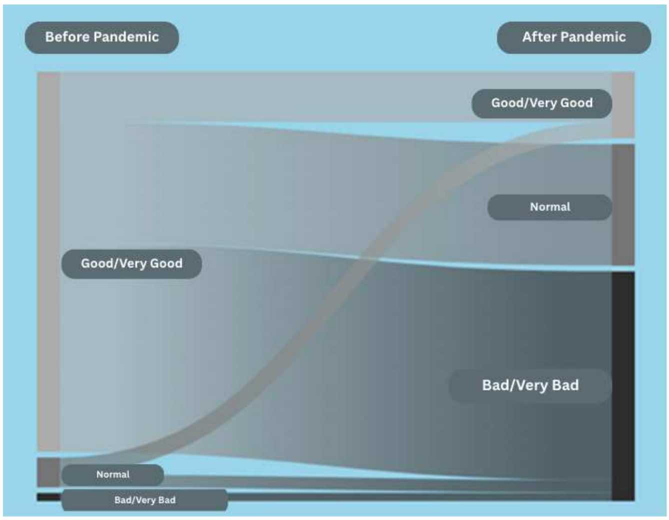
This phenomenon illustrates how the pandemic opened new opportunities to leverage the internet and information technology to survive amid limited mobility and interaction. This technological adoption in economic activities aligns with modern production theory by Pindyck & Rubinfeld (2008), which posits technology as a production input. The use of the internet in daily life and economic activities reflects the digital transformation process, including purchasing daily necessities online, marketing home industry products and others via digital means, and conducting transactions.

Through digital wallets or cashless systems, people can access financial, educational, and healthcare services online without physical interaction, a trend that became commonplace during the pandemic. Sugiarto (2021) noted that the use of online applications (for learning, working, and health consultations) rose by 443%, and online retail by up to 400%. Zhang et al. (2022) also observed in their research that demand for the digital industry during the COVID-19 era exceeded available supply. These facts further underscore that the pandemic created greater room for digital adoption in economic transformation.

The increase in MSMEs coincides with the momentum of a more inclusive digital transformation, yet MSMEs still faced challenges during the pandemic. Research conducted by Katadata Insight Center (2021) in the Greater Jakarta area found that 56.8% of MSMEs were in poor condition, while only 14.1% remained in good condition. The transition of MSME business conditions from before to during the pandemic is illustrated in Figure 1.

The majority of MSMEs experienced a downturn during the pandemic. This aligns with a Bank Indonesia survey, which showed that only 12.5% of MSMEs in Indonesia were immune to the COVID-19 pandemic (Victoria, 2021). As part of economic recovery efforts, the government has implemented various policies reaching the district/city level, such as providing social assistance to the public, credit restructuring policies, and interest subsidies, stimulus for the private sector and MSMEs, expansion of vaccine coverage, budget reallocations for COVID-19 response in the health sector, and other efforts. The government's attention to MSMEs has been substantial, as reflected in the allocation of Rp 186.81 trillion for MSME and corporate support under the 2021 National Economic Recovery (PEN) program. This support includes MSME interest subsidies of Rp 31.95 trillion, productive assistance for micro enterprises of Rp 17.34 trillion, and guarantee service fee subsidies of Rp 8.51 trillion (Victoria, 2021).

Figure 1. Transition of MSME Business Conditions Before and During the Pandemic



Source: Katadata Insight Centre, 2021.

These policies are aligned with production theory, which focuses on input-output systems, where input elements include labor, capital, raw materials, energy sources, land, information, managerial/entrepreneurial skills, and technological advancement (Gaspersz, 1996). The significant economic contraction in the affected sectors presents an interesting gap for further study. Government policies involving MSME credit provision and ongoing support for digitalization, especially during the pandemic, need further observation to assess whether they can trigger economic recovery across sectors. The findings of this research may contribute to strengthening planning in the face of a potential recession, considering the uncertainty brought about by climate change and global economic shifts that affect both national and regional economies.

Previous studies have analyzed the aggregate impact of digitalization and credit on economic growth, while this study examines the sectoral effects of digitalization and credit using multivariate statistical methods. This allows us to determine how credit provided to MSMEs affects economic recovery on a sectoral basis. Credit provision, as a form of capital input, combined with digitalization, which enhances literacy and expands business networks, is expected to improve the quality of MSMEs in carrying out production activities and help them overcome the pressures of the pandemic.

Production activity is defined as the act of generating output by using specific production techniques to process inputs in a particular way (Sukirno, 2002). The theory of production factors includes input elements such as labor, capital, raw materials, energy sources, land, information, managerial/entrepreneurial skills, and technological advancement (Gaspersz, 1996). Modern production theory also adds technology as one of the input elements (Pindyck and Rubinfeld, 2008).

According to Rosyidi (2005:54), production is any effort that creates or increases the utility of goods. To carry out the production process, individuals naturally require labor, raw materials, various forms of capital, and skills or expertise. All these components are referred to as production factors. The Cobb-Douglas function is one of the most commonly used production functions because, according to Soekartawi (2003), it is easily transformed into a linear form. In general, the equation for the Cobb-Douglas production function is:

$$Q=AKa\ L\beta \tag{1}$$

Description :
Q = Output
K = Capital Input
L = Labour Input
A = efficiency parameter/technology coefficient
a = elasticity of capital input
β = elasticity of labour input

By applying a logarithmic transformation, the equation can be converted into a linear form, namely :

$$LnQ=LnA+aLnK+\beta LnL+\varepsilon \tag{2}$$

Research by the Financial Services Authority (OJK) in 2015, before the pandemic. Using fixed-effect panel data regression analysis, the study found that credit distribution in the agriculture, fisheries, trade, manufacturing, construction, and mining/quarrying sectors had an impact on the economy of each province in Indonesia. However, the effects varied across regions. That study was limited to examining the overall impact of credit distribution on the economy and did not disaggregate the effects into the respective sectors.

Ikhsan and Amri (2023) conducted research on the effects of aggregate bank credit on sectoral economic output (specifically in the manufacturing, construction, transportation, trade, and agriculture sectors), with the COVID-19 pandemic as a moderating variable in Indonesia. Their study differs from the one conducted by OJK (2015). Using a log-linear regression method, Ikhsan and Amri found that aggregate bank credit has a positive impact on increasing economic output in the manufacturing, construction, and transportation sectors. In contrast, it has no significant effect on the agriculture and trade sectors.

Osman and Shafenti (2020) found that the credit by sector has positive and significant impacts on GDP growth, both partially and simultaneously, based on the fixed effect method using panel data in Indonesia. Okwuosa and Ifeosame (2024) found that sectoral credit in the manufacturing and mining industries in Nigeria, as analyzed using Autoregressive Distributed Lag (ARDL), along with its associated long-run bond test and the Granger causality test, indicates causality to economic development. These studies analysed the impact of sectoral credit separately for each sector.

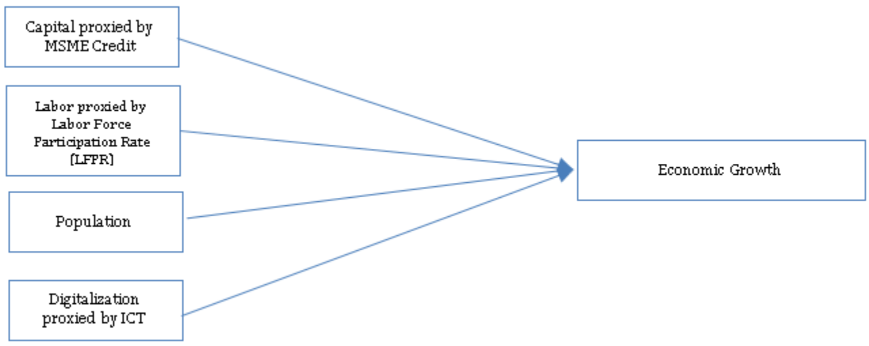
Majeed and Iftikhar (2020) have built a model of banking sectoral credit and economic growth for Pakistan using series data from 1982 to 2017. They found that the manufacturing sector is highly dependent on bank credit, while transport and communication and construction sectors are positively influenced by credit provided to these sectors. Meanwhile, credit to wholesale and retail trade has shown a negative and significant impact on its sector's growth.

According to the research by Mahmud et al. (2022), which examines the association between trade credit and firm profitability using 1002 firm-year observations, a negative relationship between trade credit and firm performance was found. In other research by Pham dan Huynh (2020), using 227 Vietnamese publicly listed manufacturing firms for the period 2005–2017, the results showed a robust, statistically significant inverted U-shaped relationship between trade credit investment and profitability.

Initially, trade credit investment increases manufacturing firms' revenues. However, the working capital would be tied to the trade credit investment, thus increasing the cost of equity, and the more the firms invest in the trade credit, the higher the administrative costs increase.

Based on the Cobb-Douglas production factor theory, the conceptual framework of this study is illustrated in Figure 2. It represents how capital, labor, population, and technology accelerate economic growth. We use MSME credit as an approximation of capital, labor force participation rate (LFPR) as a labor proxy, and ICT as a digitalization or technology proxy.

Figure 2. The Analytical Framework



Source: Processed by Authors.

From this conceptual framework, the hypotheses used are as follows:

Table 1. Research Hypothesis

Hypothesis	Statement
H1	MSME credit has a positive effect on the economy
H2	The labor force participation rate (LFPR) has a positive effect on the economy.
H3	Population has a positive effect on the economy.
H4	The ICT Development Index (IDI) has a positive effect on the economy

Source: Processed by Author

According to Table 1, four hypotheses will be assessed in this article. We consider separately that MSME credit, labor force participation rate (LFPR), population, and ICT Development Index (IDI) have a positive effect on the economy.

2. Methodology

This study is quantitative research consisting of data description and explanatory analysis. The data set is described in Table 2, compiled from Bank Indonesia (2022), and Statistics Indonesia-BPS (2020, 2021, 2022). The data description is conducted to illustrate the GDP at constant prices (ADHK) of the main sectors in 34 provinces in Indonesia for the period 2019–2021 and their determinants. The explanatory analysis aims to determine the effect of main sector credit, labor force participation rate (LFPR), population, and the ICT development index (IP-TIK) on the GDP at constant prices of the respective sectors. The research variables used are as follows:

Table 2. Research Variables

Panel Data Model Selection Test	Variable	Unit	Source
Dependent Variable	GDP at constant prices – Manufacturing Industry	Million Rupiah	BPS - Statistics
Dependent Variable	GDP at constant price - Trade	Million Rupiah	BPS - Statistics
Dependent Variable	GDP at constant price - Transportation	Million Rupiah	BPS - Statistics
Dependent Variable	GDP at constant price – Accommodation and Food Services	Million Rupiah	BPS - Statistics
Dependent Variable	GDP at constant price – Business Services	Million Rupiah	BPS - Statistics
Dependent Variable	GDP at constant prices – Other services	Million Rupiah	BPS - Statistics
Independent Variable	Credit – Manufacturing Industry	Million Rupiah	Bank Indonesia
Independent Variable	Credit - Trade	Million Rupiah	Bank Indonesia
Independent Variable	Credit - Transportation	Million Rupiah	Bank Indonesia
Independent Variable	Credit – Accommodation and Food Services	Million Rupiah	Bank Indonesia
Independent Variable	Credit – Business Services	Million Rupiah	Bank Indonesia
Independent Variable	Credit – Other Services	Million Rupiah	Bank Indonesia
Independent Variable	Labor Force Participation Rate (LFPR)	Percentage	BPS - Statistics
Independent Variable	Population	Person	BPS - Statistics
Independent Variable	ICT Development Index (IP-TIK)	Point	BPS - Statistics

Source: Processed by Author

Based on table 2, one of the aspects that must be examined in multivariate regression is the multivariate normal distribution. Variables $X_1, X_2, \ldots, X_p$ are said to follow a multivariate normal distribution with parameters μ and Σ if they have the following probability density function (Johnson & Wichern, 2007).

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{p/2}|\boldsymbol{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})}, -\infty < x_j < \infty \tag{3}$$

The examination of multivariate normal distribution can be carried out by creating a Q-Q plot of the d_i. It is said to follow a multivariate normal distribution if more than 50% of the data have $d_i^2 \le \chi^2_{p;0,5}$.

An observation with p variables, namely the vector Y1, Y2, …, $Y_{p,}$ is said to be independent if the correlation matrix (**ρ**)between variables is equal to the identity matrix (I) (Morrison, 2005). To determine whether the variables are independent, Bartlett's Test is used, with the null hypothesis (H_0) being **ρ = I** (the quality characteristics are mutually independent) and the alternative hypothesis (H_1) being **ρ ≠ I** (the quality characteristics are mutually dependent).

The results can be presented in the form of tables or figures, along with an analytical explanation highlighting key points based on the theoretical framework that has been established. Therefore, references to tables should be indicated as:

$$\chi^2 = -\left\{n - 1 - \frac{2p+5}{6}\right\} \ln|\mathbf{R}| \tag{4}$$

A multivariate regression model is a regression model with more than one correlated response variable and one or more predictor variables (Johnson & Wichern, 2007). Suppose there are q response variables, namely $Y_1, Y_2, \ldots, Y_q$, and p predictor variables, namely $X_1, X_2, \ldots, X_p$, then the linear multivariate model for the q-th response is:

$$Y_1=\beta_{01}+\beta_{11} X_1+\cdots+\beta\_p1 X\_p+\varepsilon\_1$$
$$Y_2=\beta_{02}+\beta_{12} X_1+\cdots+\beta_{p2} X_p+\varepsilon_2$$
$$Y_q=\beta_{0q}+\beta_{1q} X_1+\cdots+\beta_{pq} X_p+\varepsilon_q \tag{5}$$

The multivariate regression model consisting of q linear models simultaneously can be represented in matrix form as shown in the following equation:

$$Y_{(nxq)}=X_{nx(p+1)}\ \beta_{(p+1)xq}+\varepsilon_{(nxq)} \tag{6}$$

With the assumption:

$$E(\varepsilon_{(i)})=0$$
$$Cov(\varepsilon_{(i)},\varepsilon_{(i)})=\sigma_{ii}I \tag{7}$$

This test is conducted to determine whether the parameters are not equal to zero overall. The hypotheses used are as follows:

$$H_0:\beta_{11}=\beta_{12}=\cdots=\beta_{p1}=\cdots=\beta_{pq}=0$$

$$\text{With } \mathbf{B} = \begin{pmatrix} \beta_0^T \\ \mathbf{B_1} \end{pmatrix} = \begin{pmatrix} \beta_{01} & \cdots & \beta_{0q} \\ \vdots & \ddots & \vdots \\ \beta_{p1} & \cdots & \beta_{pq} \end{pmatrix} \tag{8}$$

The test statistic used is Wilk's Lambda

$$\Lambda = \frac{|\mathbf{E}|}{|\mathbf{E+H}|} = \frac{|\mathbf{Y^TY} - \hat{\mathbf{B}}^\mathbf{T}\mathbf{X^TY}|}{|\mathbf{Y^TY} - n\bar{y}\,\bar{y}^T|} \tag{9}$$

Where y is the mean vector of matrix **Y**

H_0 is rejected $\Lambda_{count} \leq \Lambda_{\alpha,q,p,n-p-1}$. The value $\Lambda_{\alpha,q,p,n-p-1}$ It is the critical table value for Wilk's Lambda, where *p* is the number of predictor variables and *q* is the number of response variables.

Partial testing is conducted to examine the significant effect of each predictor variable on the response variable individually. The hypotheses used are as follows:
H_0:β_{jk}=0 (the regression parameter of predictor *j* has no significant effect on response variable *k*)
H_1:$\beta_{jk}\neq0$ (the regression parameter of predictor *j* has a significant effect on response variable *k*)

The test statistic used is as follows:

$$\Lambda = \frac{|\mathbf{E}|}{|\mathbf{E+H}|} = \frac{|\mathbf{Y^TY} - \hat{\boldsymbol{\beta}}^\mathbf{T}\mathbf{X^TY}}{|\mathbf{Y^TY} - \hat{\boldsymbol{\beta}}_j^T X_j^T Y} \tag{10}$$

If $\Lambda_{calculated} \leq \Lambda_{\alpha,q,p,n-p-1}$ then Ho is rejected, meaning the predictor variable p has a significant partial effect on the response variable *q*. The basic assumptions used in multivariate regression modeling are that the residuals follow a multivariate normal distribution, have a homogeneous variance–covariance matrix, and are independent.

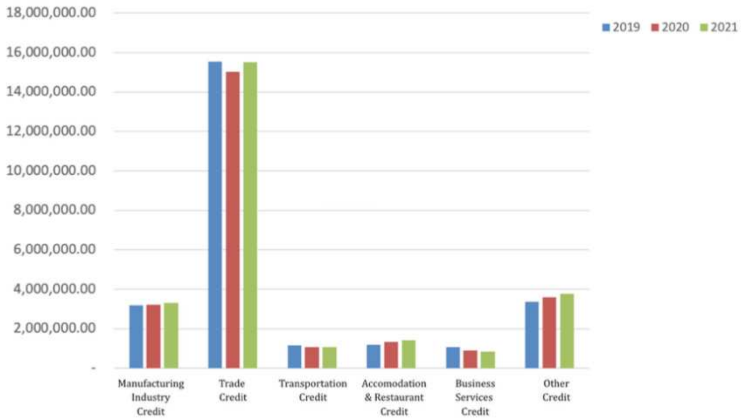
However, some literature suggests that when using panel data, these basic assumptions may not need to be considered in the study. Panel data analysis does not require all the classical assumption tests typically used in linear regression. Panel regression models do not require equations to be free from autocorrelation. This is because there is serial correlation among residuals due to the data being ordered in a time series.

3. Results and Discussion

An overview of the Gross Value Added of MSME credit, and the Gross Value Added at constant prices (ADHK) of the main sectors is as follows.

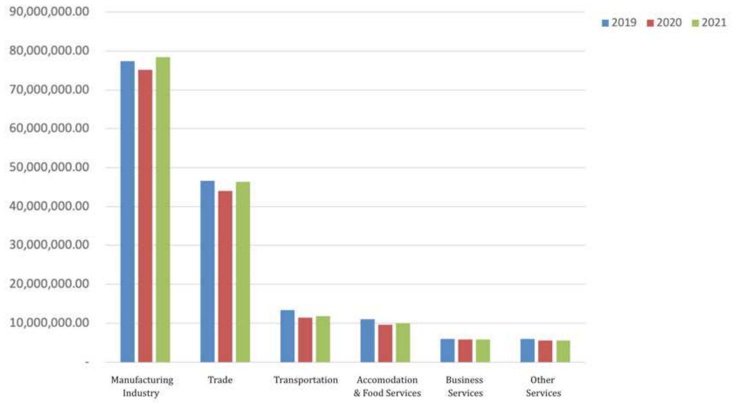
Based on Figure 3, the trade sector had the highest MSME financing from 2019 to 2021, while the sector with the lowest MSME credit value was the business services sector. During the economic recovery period in 2021, there was an increase in credit financing for MSMEs in the manufacturing industry, accommodation and food services, and other services sectors.

Figure 3. Position of MSME Credit Value in 7 Main Sectors



Source: Processed by Author

Figure 4. Overview of GDP at Constant Prices in the 7 Main Sectors



Source: Processed by Author

Figure 4 shows that the manufacturing industry had the highest GDP at constant prices throughout the observation period, although its value added declined during the pandemic. Subsequently, the value added began to increase again in 2021 in line with the economic recovery period.

Data quality testing is carried out to determine whether the data used can be analyzed multivariate or not. The data quality tests conducted include the dependency assumption test and the multivariate normality test. The method used for the dependency test is Bartlett's Sphericity, and the technique for assessing multivariate normality is the proportion of Mahalanobis distances (dj^2) > 50%.

The dependency assumption test is conducted to determine whether the response variables are correlated multivariate or not. The results of the multivariate dependency assumption analysis using the Bartlett's Sphericity method are as follows.

Table 3. Results of the Multivariate Dependency Test

χ^2	P-*value*	Decision
416.756	0.000	H_0 Rejected

Source: Processed by Author

Based on Table 3, the p-value is less than the 5% significance level, leading to the decision to reject H_0. This means that the response variables used in this study, GDP (Constant Prices) for manufacturing industry, trade, transportation, accommodation and food services, business services, and other services, are correlated or multivariate dependent.

The testing of the multivariate normality assumption is carried out to determine whether the response variables follow a multivariate normal distribution or not. The results of the multivariate normality assumption analysis using the Mahalanobis distance proportion method are as follows.

Table 4. Results of the Multivariate Normality Test

Criteria	Proportion
di^2	0.520

Source: Processed by Author

From Table 4 above, it can be observed that the Mahalanobis distance values less than the χ^2 table value have a proportion of 0.520 or 52%. This indicates that more than 50% of the di^2 values are below the table value. Therefore, it can be concluded that the response variables, namely Gross Regional Domestic Product at constant prices (ADHK) based on the business fields of manufacturing, trade, transportation, accommodation and food service, business services, and other services, follow a multivariate normal distribution. Based on the results of the data quality testing, it was found that the response variables are multivariate dependent and follow a multivariate normal distribution.

This satisfies the data assumptions required for multivariate regression analysis. Subsequently, modeling was carried out using multivariate regression. The modeling was carried out using the multivariate regression method, in which the predictor variables consist of credit extended to MSMEs based on the business fields of manufacturing, trade, transportation, accommodation and food service, business services, and other services; the labor force participation rate (LFPR); population; and the ICT development index.

These predictors were regressed against the response variables, which comprise the constant Gross Regional Domestic Product (GRDP) of manufacturing, trade, transportation, accommodation and food service, business services, and other services. The analysis was conducted across three time periods, namely 2019 (before the COVID-19 pandemic), 2020 (during the COVID-19 pandemic), and 2021 (the period of economic recovery), with the time variable included in the model as a dummy variable (X0). Before conducting the modeling, the best predictor variables were selected from the ten variables considered.

The selection of predictor variables was based on the smallest Mean Squared Error (MSE) while also considering the significance of the variables. Based on this evaluation, the best model was obtained, consisting of the response variables and the predictor variables: credit extended to MSMEs in the business fields of manufacturing, trade, transportation, accommodation and food service, business services, and other services; the labor force participation rate (LFPR); population; the ICT development index; as well as the year variable, which serves as a comparator between the pre-pandemic period, the COVID-19 pandemic period, and the economic recovery period. The MSE obtained from the estimation of the model with the selected predictor variables is presented in Table 5.

After selecting the best predictor variables, the next step was to conduct significance testing of the parameters, both jointly and individually. The results of these tests are presented as follows (Table 5). The joint significance test was conducted to determine whether the predictor variables have a simultaneous significant effect on the response variables.

Table 5. MSE Values

Criteria	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
MSE	0.116	0.022	0.045	0.065	0.404	0.043

Source: Processed by Author

The test statistic used was Wilks' Lambda. The results of the joint parameter significance test are presented in Table 6 below. The table below shows that the p-value is less than 5%, leading to the rejection of H0. This indicates that at least one predictor variable has a significant effect on the response variables.

Table 6. Results of the Joint Significance Test

Test Statistic	P-*value*	Decision
Wilk's Lambda	0.002	H_0 Rejected

Source: Processed by Author

The partial significance test (Table 6) was conducted to determine whether each predictor variable has a significant effect on the response variables. The test statistic used was Wilks' Lambda. The results of the partial parameter significance test are presented as follows.

Table 7. Results of the Partial Significance Test

Variable	P-*value*	Decision
Log (Trade Credit)	0.000	H_0 Rejected
Log (Transportation Credit)	0.000	H_0 Rejected
Log (Accommodation and Restaurant Credit)	0.002	H_0 Rejected
Log (Business Services Credit)	0.003	H_0 Rejected
Log (Other Services Credit)	0.023	H_0 Rejected
Log (Labor Force Participation Rate / LFPR)	0.000	H_0 Rejected
Log (Population)	0.000	H_0 Rejected
Log (ICT Development Index)	0.000	H_0 Rejected
Year	0.002	H_0 Rejected

Source: Processed by Author

According to Table 7, we can analyze that credit provided by banks to MSMEs in the main sectors has a significant effect on the constant GRDP of those sectors. This finding is consistent with the government's objective that extending credit to key sectors can stimulate economic recovery within those sectors. In addition, the labor force participation rate (LFPR), population, and the ICT development index (IP-TIK) were also found to be significant with the constant GRDP of the main sectors. This result aligns with the theory of production factors, which posits that capital in the form of credit, labor, population, and technological progress can shape or accelerate economic growth.

The next step was to estimate the parameters used for the constant in the established model. The following are the estimation results obtained from the nine significant predictor variables. From the parameter estimation results, it can be observed that each response variable demonstrates varying levels of significance with its corresponding predictor variables. These parameter estimates are utilized for the model interpretation presented in the subsequent subsection. After calculating the parameter estimates, the next step was to identify the strength of the relationship between the response variables and the significant predictor variables by using eta square lambda (η_Λ²). The results of the eta square lambda calculation are presented as follows.

$$\eta_{\Lambda}^{2} = 1 - \Lambda. \tag{11}$$

$$\eta_{\Lambda}^{2} = 1 - 0.161 = 0.839 \tag{12}$$

Based on equations 11 and 12, the eta square lambda value was obtained at 0.839. This indicates that the significant predictor variables can explain the variability of the response model by 83.9 percent. In comparison, the remaining 16.1 percent is explained by other predictor variables outside the model that are presumed to influence the constant GRDP of the leading business sectors in Indonesia.

After conducting the modeling and obtaining the best-fitting model (Table 8), the next step was to evaluate the model based on the assumptions that must be satisfied. These assumptions include: the residuals have to have a homogeneous variance-covariance matrix (identical residuals assumption), the residuals have to be mutually independent (independent residuals assumption), and the residuals have to follow a normal distribution (multivariate normal residuals assumption). The results of the analysis for each assumption are presented as follows.

Based on the model evaluation results in Table 9, it was found that the residual variance-covariance matrix of the data did not satisfy the independence assumption. After applying data transformation and using the Cochrane-Orcutt method, the independent residual assumption still could not be fulfilled. Subsequently, a check for multicollinearity was conducted by examining the Variance Inflation Factor (VIF) values for each predictor variable in relation to the response variables. The results showed no evidence of multicollinearity, as all predictor variables had VIF values of less than 10.

The impact of time in this study was not sufficiently significant; it exhibited a relatively strong correlation both multivariately and univariately. Therefore, this study disregards the assumption of residual independence. After evaluating the established model, the next step was to interpret the model based on the parameter estimations that had been carried out.

The best-fitting model obtained in this study, along with its interpretation, is presented as follows. The best model obtained in this study is the model relating the manufacturing industry, trade, transportation, accommodation and food service, business services, and other services with their respective predictor variables, as shown in Table 8.

Log (GRDP at Constant Prices - Manufacturing Industry) = 1.563 - 1.180 log(Trade Credit) + 0.657 log(Transportation Credit) + 0.555 log(Business Services dit) + 0.37 log(Other Services Credit) + 1.348 log(Population) +2.182 log Development Index (13)

Based on the GRDP at constant prices model for the manufacturing industry in equation (13), it can be observed that trade credit has a negative impact on the manufacturing industry. Research by Mahmud et al. (2022) confirms a negative association between trade credit and firm profitability, particularly among micro-scale enterprises. The result of research by Pham dan Huynh (2020) also showed the inverted U-shape that explained the adverse effect of trade credit on the performance of the manufacturing industry because of the increase in the cost of equity. In contrast, transportation credit, business services credit, other services credit, population, and the ICT development index exert positive effects. Positive effect of sectoral credit in this model is in line with previous literature (OJK, 2015; Ikhsan and Amri, 2023).

Table 8. Parameter Estimation

Dependent Variable	Parameter (*in log*)	Coefficient
Log (ADHK Manufacturing Industry)	Intercept	1.563
Log (ADHK Manufacturing Industry)	Trade Credit	-1.180
Log (ADHK Manufacturing Industry)	Transportation Credit	0.657
Log (ADHK Manufacturing Industry)	Business Services Credit	0.555
Log (ADHK Manufacturing Industry)	Other Services Credit	0.237
Log (ADHK Manufacturing Industry)	Population	1.348
Log (ADHK Trade)	ICT Development Index	2.182
Log (ADHK Trade)	Intercept	3.359
Log (ADHK Trade)	Trade Credit	0.480
Log (ADHK Trade)	Transportation Credit	0.293
Log (ADHK Trade)	LFPR	-2.559
Log (ADHK Trade)	Population	0.552
Log (ADHK Trade)	ICT Development Index	2.125
Log (ADHK Trade)	Year = 2019 (base 2021)	0.116
Log (ADHK Transportation)	Intercept	-1.351
Log (ADHK Transportation)	Trade Credit	0.590
Dependent Variable	Parameter (*in log*)	Coefficient
Log (ADHK Transportation)	Transportation Credit	0.289
Log (ADHK Transportation)	Population	0.422
Log (ADHK Transportation)	LFPR	3.135
Log (ADHK Transportation)	Tahun=2019 (base 2021)	0.203
Log (ADHK Accommodation and Food Service)	Intercept	-12.885
Log (ADHK Accommodation and Food Service)	Trade Credit	-0.703
Log (ADHK Accommodation and Food Service)	Transportation Credit	0.361
Log (ADHK Accommodation and Food Service)	LFPR	3.891
Log (ADHK Accommodation and Food Service)	Population	1.342
Log (ADHK Accommodation and Food Service)	ICT Development Index	7.013
Log (ADHK Accommodation and Food Service)	Tahun=2019 (base 2021)	0.368
Log (ADHK Accommodation and Food Service)	Tahun=2020 (base 2021)	0.133
Log (ADHK Business Services)	Intercept	-11.967
Log (ADHK Business Services)	ICT Development Index	3.796
Log (ADHK Other Services)	Intercept	-2.691
Log (ADHK Other Services)	Trade Credit	1.084
Log (ADHK Other Services)	Population	0.371
Log (ADHK Other Services)	ICT Development Index	3.210
Log (ADHK Other Services)	Tahun=2019 (base 2021)	0.164

Source: Processed by Author

In the recovery of the manufacturing sector, the credit variable specific to this sector was not found to have a significant influence; somewhat, it was affected by credit from other sectors. This indicates that credit from different sectors can contribute to the performance of the manufacturing industry. Furthermore, the increase in Indonesia's population supports the recovery of the manufacturing sector. In the context of an increasingly digital era, ICT development has a substantial positive impact on the GRDP of the manufacturing industry. The time effect was found to be insignificant in the manufacturing industry, suggesting that the pre-pandemic, pandemic, and recovery periods did not have a significant impact on this sector.

Log (GRDP at Constant Prices – Transportation) = –1.351 + 0.590 log(Trade Credit) + 0.289 log(Transportation Credit) + 0.442 log(Population) + 3.135 log(ICT Development Index) + 0.203 (t = 1) (14)

Table 9. Model Evaluation Results

Evaluation	Method	Test Statistic	Conclusion
Residual Variance-Covariance Matrix (Identical)	Box's M	p-*value* = 1.000	The residual variance-covariance matrix is already homogeneous (identical).
Residual Variance-Covariance Matrix (Independent)	Bartlett Spericity	p-*value* = 0.000	The residual variance-covariance matrix is dependent.
Residual Variance-Covariance Matrix (Multivariate Normal)	Mahalanobis Distance Proportion	di = 51.3514%	The residual variance-covariance matrix is normally distributed since more than 50% of the values fall below the threshold.

Source: Processed by Author

Based on the GRDP at constant prices model for the transportation sector in equation (14), it can be observed that trade credit, transportation credit, population, and the ICT development index exert positive effects. The positive impact of sectoral credit in this model aligns with previous literature (OJK, 2015; Ikhsan and Amri, 2023), which demonstrates how sectoral credit accelerates economic growth. In the recovery of the transportation sector, transportation credit consistently provides a positive impact on transportation GRDP.

In addition, trade credit also exerts a positive influence, indicating that credit from other sectors can contribute to the performance of the transportation sector. Furthermore, the increase in Indonesia's population supports the recovery of the transportation sector. In the context of an increasingly digital era, ICT development has a substantial positive impact on transportation GRDP. The time effect was found to be significant in the transportation sector, particularly when comparing 2019 with 2021. This suggests that there is a substantial difference between the pre-pandemic and recovery periods.

Log (GRDP at Constant Prices – Accommodation and Food Service) = –12.885 – 0.703 log(Trade Credit) + 0.361 log(Transportation Credit) + 3.891 log(Labor Force Participation Rate) + 1.342 log(Population) + 7.013 log(ICT Development Index) + 0.368 (t = 1) + 0.133 (t = 2) (15)

Based on the GRDP at constant prices model for the accommodation and food service sector in equation (15), it can be observed that trade credit exerts an adverse effect, which is confirmed by Mahmud et. al. (2022), who found that the association between trade credit and firm profitability is negative. In contrast, transportation credit, the labor force participation rate (LFPR), population, and the ICT development index exert positive effects. In the recovery of this sector, credit specifically for accommodation and food services does not exert a significant influence; instead, it is affected by credit from other sectors. This indicates that credit from different sectors can contribute to the performance of the accommodation and food service sector. Furthermore, the increase in Indonesia's population supports the recovery of this sector. In the context of an increasingly digital era, ICT development has a substantial positive impact on the GRDP of the accommodation and food service sector. The time effect was found to be significant in this sector, particularly when comparing 2021 with 2019 and 2020. This suggests that the pre-pandemic and pandemic periods are significantly different from the recovery period.

Log (GRDP at Constant Prices – Business Services) = –11.967 + 3.796 log(ICT Development Index) (16)

Based on the GRDP at constant prices model for the business services sector in equation (16), it can be observed that the sector is influenced solely by the ICT development index. This indicates that digitalization positively affects the GRDP of business services. One percent increase in the ICT development index leads to an estimated growth of 3.796 in business services GRDP, assuming other factors remain constant. The time effect was found to be insignificant in the business services sector, suggesting that there was no difference in the recovery of business services between the pre-pandemic, pandemic, and recovery periods.

Log (GRDP at Constant Prices – Other Services) = –2.691 + 1.084 log(Trade Credit) + 0.371 log(Population) + 3.210 log(ICT Development Index) + 0.164 (t = 1) (17)

Based on the GRDP at constant prices model for the other services sector in equation (17), it can be observed that trade credit, population, and the ICT development index exert positive effects. In the recovery of this sector, credit allocated explicitly to other services does not significantly affect the GRDP of the sector; rather, it is influenced by credit from different sectors. This suggests that credit from other sectors can positively impact the performance of the services sector.

Furthermore, the increase in Indonesia's population supports the recovery of this sector. In the context of an increasingly digital era, ICT development has a substantial positive impact on the GRDP of the other services sector. The time effect was found to be significant in this sector, particularly when comparing 2021 with 2019.

This suggests that there is a substantial difference between the pre-pandemic and recovery periods. The positive effect of population on accelerating the manufacturing, transportation, accommodation, and food service industries, as well as other service industries, aligns with modern production theory (Pindyck and Rubinfeld, 2008), which incorporates technology as a key input element of production. The positive effect of ICT on industry growth in all models has confirmed Myovella et al. (2020) on the impact of digitalization on economic growth in 41 Sub-Saharan African countries.

4. Conclusion

Based on the modeling conducted in this study, the first conclusion is that bank credit provided to MSMEs in specific sectors not only stimulates value added within those sectors but also exerts spillover effects on the value added of other sectors. This is evidenced by the models, which show that credit from different sectors has a significant influence. In addition, several models demonstrate that population and labor force variables have important effects. The role of digitalization in the modern era also exerts a substantial impact on economic recovery, particularly in manufacturing, trade, transportation, accommodation and food service, business services, and other services sectors. The modeling results align with the production factors model, wherein capital or credit, population, labor, and digitalization play critical roles in influencing economic growth.

The second finding is the presence of time effects in the models for the trade, transportation, accommodation and food service, and other services sectors. This indicates that the provision of credit in 2021 contributed to the recovery of these sectors. Concerning this, as economic activities within society become more widespread, it is necessary for the government to implement policies that stimulate Indonesia's key sectors to foster economic growth, both at the national and regional levels. Based on the analysis in this study, several recommendations can be made for the government at both the regional and national levels, as well as for the public, particularly researchers.

There is a need for government regulation and innovation in banking products, particularly financing services for MSMEs in the trade and transportation sectors. Bank credit in these two sectors not only generates economic impacts within the sectors themselves but also produces spillover effects on other sectors. In addition, the accommodation and food service sector is also strongly influenced by MSME credit provided in the trade and transportation sectors. Labor has a positive effect on the economic recovery of several sectors. Labor-related issues continue to be a significant concern, particularly as many workers were laid off during the COVID-19 pandemic. In times of crisis as well as during economic recovery, labor in the trade sector and the accommodation and food service sector need to be given special attention, as it plays a crucial role in driving the economy in both phases.

The government should not only focus on creating job vacancies but also continue to provide training for job seekers in entrepreneurship to encourage the growth of MSMEs. The ICT development index exerts a powerful effect on economic growth. This is evidenced across all models, where the ICT development index variable is significant with a high intercept. In the present era, digitalization continues to expand and can be leveraged to support economic recovery by facilitating economic activities.

The government may collaborate with relevant institutions to optimize the development of adequate digital infrastructure to reduce technological disparities across Indonesia. Special attention should be directed to provinces or regions with low ICT development index scores so that they can build digital competitiveness in the future. In addition to providing recommendations for Indonesia's economic recovery, this study also offers suggestions for future research.

This study did not incorporate spatial effects; therefore, further research is needed to examine the potential presence of spatial effects in the provision of credit to MSMEs in key sectors. From the established models, it was found that some predictor variables had an adverse impact. This requires further investigation through both qualitative and quantitative methods. An essential finding of this study is that MSME credit provided in a given business sector not only affects that sector but also has spillover effects on other sectors.

Future research could adopt an Input-Output table approach to examine the impact of financial services on all economic sectors and institutions during times of crisis. Additionally, the use of the Inter-Regional Input-Output (IRIO) table is recommended for future research to analyze spatial spillover effects across provinces and to assess intersectoral linkages.

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