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Economic Complexity as a Driver of Economic Growth in Indonesia: A Multidimensional Analysis of Trade, Technology, and Research

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Abstract

This study investigates how economic complexity influences Indonesia's economic growth through three interrelated dimensions: research, technology, and trade. Using annual time-series data from 2000 to 2021, several econometric techniques including Ordinary Least Squares (OLS), Robust Least Squares (RLS), Fully Modified OLS (FMOLS), Canonical Cointegrating Regression (CCR), Dynamic OLS (DOLS), and Quantile Regression (QR) are applied to capture both short-run and long-run dynamics. The results reveal that the contribution of economic complexity to growth is heterogeneous and stage dependent. Research and trade-based complexities emerge as the primary long-run drivers of growth, enhancing productivity, export diversification, and structural transformation. In contrast, technology-based complexity exerts a negative effect in both the short and long run, reflecting Indonesia's limited absorptive capacity, skill mismatches, and institutional constraints. Quantile regression results further show that research-based complexity supports growth during low-performance phases, whereas trade-based complexity becomes more influential at higher stages of development. These findings highlight the need for phase-specific development strategies that strengthen research and innovation in early stages, improve technological absorption during industrial transitions, and promote export sophistication and value-chain integration to achieve resilient, knowledge-driven, and sustainable economic growth.

1. Introduction

Economic growth is one of the key indicators of a nation's development success [1, 2]. However, the quality and sustainability of growth depend not merely on macroeconomic expansion but on the structure of production that supports it. This concept aligns with the idea of economic complexity, which explains how a nation's collective knowledge determines its capacity to produce and export diverse, high-value-added goods [3]. The Economic Complexity Index (ECI) quantifies this capacity by assessing the diversity and sophistication of a country's export basket, specifically its ability to produce products that few other countries can make. Economies with high ECI values are typically more innovative, competitive, and resilient to global shocks [4]. Conversely, countries with low ECI values tend to experience structural stagnation or fall into the middle-income trap, as they fail to shift toward higher-value production [5].

From a theoretical standpoint, the concept of economic complexity builds on the endogenous growth theory developed by Romer [6] and Lucas [7], which places

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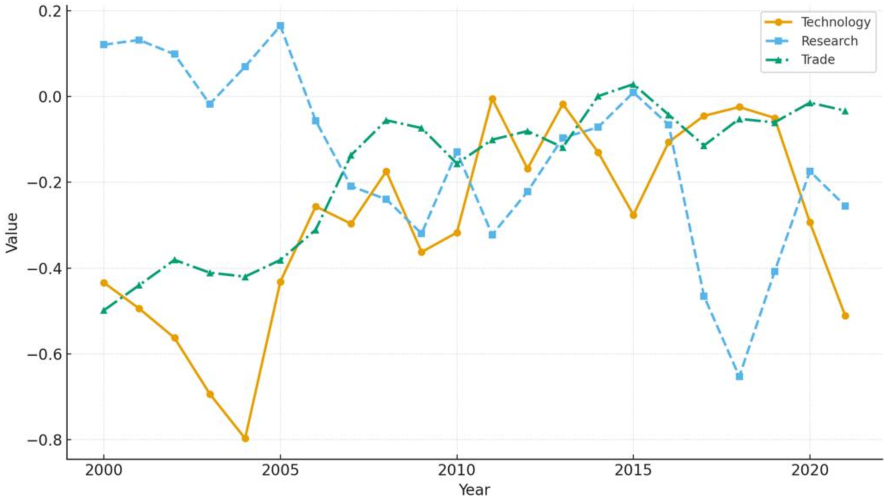


Figure 1. Indonesia's economic complexity index 2000-2021.
Source: OEC [8], processed data.

knowledge, innovation, and human capital at the core of long-term growth. Unlike the neoclassical Solow model, which treats technology as exogenous, the endogenous approach conceptualizes innovation as a product of deliberate investment in knowledge creation. Economic complexity extends this framework by viewing production as a network of interrelated capabilities, where the accumulation and recombination of knowledge determine a country's potential to move up the technological ladder [4]. The ECI is therefore more dynamic than traditional measures such as GDP or the Human Development Index (HDI), as it captures not only the outcomes of economic performance but also the capabilities underlying those outcomes [9].

The ECI's advantage lies in its multidimensional nature: it reflects both diversity, the number of distinct products a country can export, and ubiquity, the rarity of those products across nations [10]. Countries that export diverse yet rare products tend to possess higher productive knowledge and advanced technological capacities [11]. This makes the ECI a preferable measure compared to other indicators like total factor productivity or industrial concentration indexes, which fail to capture the embedded knowledge within production networks. Moreover, empirical evidence from cross-country studies demonstrates that increasing economic complexity consistently predicts higher long-term growth [4, 12].

In the context of developing economies, economic complexity provides a useful diagnostic for identifying structural weaknesses. Indonesia's relatively stable economic growth over the past two decades, averaging around 5 percent per year, has not been matched by corresponding improvements in productivity or industrial diversification [13]. The nation's export structure remains dominated by primary commodities such as coal, palm oil, and mineral-based products, which leaves the economy vulnerable to external price shocks and limits its progression toward knowledge-intensive industries [14, 15].

The Figure 1 disaggregates the national ECI into three main dimensions: Technology, Research, and Trade to capture the underlying dynamics of structural transformation. The trade dimension shows a gradual upward trend until 2015, followed by relative stabilization, indicating steady but limited progress in export diversification. However, the technology and research dimensions display sharp fluctuations and downward cycles, suggesting a fragile link between innovation capacity and export sophistication [16]. This pattern supports the ECI report's conclusion that economies dependent on primary resources tend to experience a plateau in complexity once technological upgrading and research intensity remain insufficient [11].

Indonesia's dependence on medium- and low-technology exports, such as processed natural resources and basic manufactures, further constrains its transition toward a knowledge-based economy [14, 15]. The decline in technology and research indices between 2017 and 2021 indicates widening gaps between digital adoption and the creation of frontier innovations. OECD [17] and IMF [18] both affirm that Indonesia's economic trajectory remains vulnerable to global commodity cycles and constrained by an underdeveloped innovation ecosystem. Yudhoyono et al. [19] likewise reveal a persistent disconnect between national research output and industrial needs, underscoring the need for stronger innovation linkages.

Empirical studies on Indonesia's economic complexity remain limited in both conceptual and methodological

Table 1. Variable descriptions and data sources.

Variable Symbol	Variable Full Name	Unit of Measurement	Source
GDP	Gross Domestic Product	Constant 2015 USD (log-transformed)	WDI [21]
ECI_Research	Economic Complexity of Research	Score (-2.5 to +2.5)	OEC [8]
ECI_Tech	Economic Complexity of Technology	Score (-2.5 to +2.5)	OEC [8]
ECI_Trade	Economic Complexity of Trade	Score (-2.5 to +2.5)	OEC [8]
GLB	Globalization Index	Score (1-100)	KOF Index [20]
GFCF	Gross Fixed Capital Formation	Constant 2015 USD (log-transformed)	WDI [21]
LF	Labor Force	Total person (log-transformed)	WDI [21]

Note: OEC = Observatory of Economic Complexity; WDI = World Development Indicators; KOF = *Konjunkturforschungsstelle*.

coverage. Earlier research, such as Andriansyah et al. [22] and Permana et al. [15], examined export diversification and industrial upgrading but did not account for how innovation and technological capacity interact with growth. More recent works, including Fadhlani et al. [23] on export diversification, Putri [24] on provincial green complexity, and Idroes & Wiranatakusuma [10] on business confidence and complexity provide valuable insights but remain fragmented. These studies typically isolate one dimension of complexity (trade, technology, or research) and use conventional econometric methods that overlook long-run interactions. Consequently, the literature has yet to provide an integrated framework capturing how the interdependence of these dimensions drives Indonesia's economic performance.

This study aims to fill that gap by comprehensively examining how economic complexity influences Indonesia's economic growth through three interrelated dimensions: trade, technology, and research. Trade-based complexity (ECI_Trade) reflects export diversification and value-added intensity; technology-based complexity (ECI_Tech) measures innovation capacity and absorptive ability; and research-based complexity (ECI_Research) captures knowledge creation through R&D expenditure, patents, and scientific output. Using annual data from 2000 to 2021, the study employs a sequential econometric design, combining Ordinary Least Squares (OLS), Robust Least Squares (RLS), Fully Modified OLS (FMOLS), Dynamic OLS (DOLS), and Canonical Cointegrating Regression (CCR) to identify both short- and long-run relationships while correcting for endogeneity and autocorrelation. Quantile Regression (QR) is further applied to detect heterogeneous effects of complexity across different growth regimes.

Theoretically, this research extends the endogenous growth and structural transformation frameworks by embedding economic complexity as a mechanism that links knowledge accumulation with productive diversification. Empirically, it introduces a unified analytical model for Indonesia, integrating trade, technology, and research into a single system to explain disparities in structural upgrading and productivity. By doing so, the study contributes new evidence and practical insights for policymakers seeking to strengthen innovation capacity, enhance technological readiness, and guide Indonesia's transition toward a resilient, knowledge-based economy.

2. Materials and Methods

2.1. Data

This study employs annual time-series data covering the period 2000 to 2021 to examine the relationship between economic complexity and economic growth in Indonesia. The dataset integrates macroeconomic indicators from multiple international sources, as summarized in Table 1. The primary data sources include the World Development Indicators (WDI) for macroeconomic aggregates [21], the Observatory of Economic Complexity (OEC) for economic complexity indices [8], and the KOF Globalization Index for global integration measures [20].

The dependent variable, Gross Domestic Product (GDP), is expressed in constant 2015 U.S. dollars and transformed into natural logarithms to stabilize variance and allow elasticity-based interpretation. The core explanatory variables consist of three distinct dimensions of the Economic Complexity Index (ECI) namely, research-based (ECI_Research), technology-based (ECI_Tech), and trade-based (ECI_Trade) each representing a different channel through which productive knowledge and capability accumulation influence long-run growth. These indices are standardized on a scale from –2.5 to +2.5, where higher values denote greater complexity. To control for key macroeconomic determinants of output, three additional variables are included: the Globalization Index (GLB), which ranges from 1 to 100 and captures economic, social, and political openness; Gross Fixed Capital Formation (GFCF), expressed in constant 2015 USD and log-transformed as a proxy for physical capital accumulation; and the Labor Force (LF), measured in total persons and also log-transformed to represent human resource input.

All variables are selected based on their theoretical relevance to the endogenous growth and structural transformation frameworks, ensuring alignment with

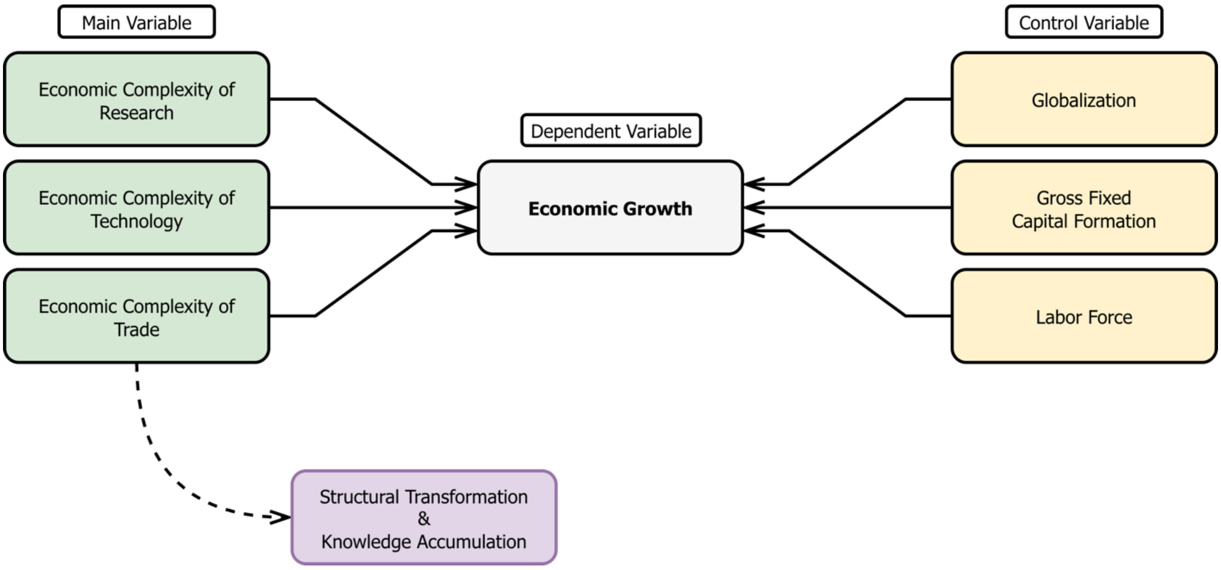


Figure 2. Conceptual framework.

prior empirical studies on economic complexity and economic performance. In the endogenous growth framework, economic progress is driven by the accumulation of knowledge, innovation, and human capital, which collectively enhance productivity and output growth. The structural transformation framework complements this view by emphasizing the reallocation of productive resources from low-productivity sectors to high-productivity ones, reflecting the dynamic evolution of industrial capabilities. Within these theoretical bases, economic complexity acts as a unifying mechanism that captures how the diversity and sophistication of a country's productive structure influence its long-term growth trajectory. Research-based complexity (ECI_Research) reflects the capacity for innovation, R&D intensity, and knowledge creation. Technology-based complexity (ECI_Tech) represents technological capability, adoption, and absorptive capacity that drive productivity improvements. Trade-based complexity (ECI_Trade) captures the diversity and sophistication of exports as indicators of industrial competitiveness and participation in global value chains. Meanwhile, GFCF, LF and GLB function as key control variables that influence the transmission of complexity effects through investment, human capital, and openness.

The conceptual framework of this study integrates the dimensions of economic complexity into the endogenous growth and structural transformation paradigms illustrated in Figure 2. Economic complexity is conceptualized as both a driver and a reflection of structural upgrading, where productive knowledge embedded in research, technology, and trade enhances the economy's capacity for innovation and diversification. The conceptual framework explains that economic complexity, represented by three dimensions ECI_Research, ECI_Tech, and ECI_Trade drives economic growth both directly and indirectly. These dimensions reflect a country's ability to innovate, adopt technology, and diversify trade, which together enhance productivity and competitiveness. The framework also introduces Structural Transformation and Knowledge Accumulation as the mediating channel through which complexity fosters long-term growth. Furthermore, GFCF, LF, and GLB act as control variables that strengthen the effect of complexity through investment, human capital, and openness. Overall, the model highlights that higher economic complexity leads to sustained economic growth through innovation and structural upgrading.

2.2. Methods

The methodology employed in this study follows a sequential approach to comprehensively explain the dynamic relationship between economic complexity and Indonesia's economic growth, covering both short-run and long-run dynamics. It begins with a basic log-linear model estimated using Ordinary Least Squares (OLS) and Robust Least Squares (RLS) for baseline analysis, followed by stationarity and cointegration tests, and then long-term estimations using Fully-Modified Ordinary Least Squares (FMOLS), Canonical Cointegrating Regression (CCR) and Dynamic Ordinary Least Squares (DOLS) approaches. Finally, Quantile Regression (QR) is applied to capture heterogeneity across growth levels.

Initially, the study employed Ordinary OLS and RLS estimations to establish the baseline relationships and assess the consistency of coefficient signs. These methods provide initial insights. The empirical model in this study was estimated using FMOLS, CCR and DOLS approaches. These three methods have the main advantage of producing efficient and bias-free long-term estimates of autocorrelation and endogeneity problems that often arise in cointegrated time series models. This approach allows researchers to accurately capture the long-term influence of three dimensions of economic complexity, namely research-based complexity, technology-based complexity, and trade-based complexity on Indonesia's economic growth.

Through this approach, the research aims to gain an in-depth empirical understanding of the extent to which economic complexity in the dimensions of research, technology, and trade contributes to Indonesia's economic growth, as well as to formulate relevant policy implications in strengthening the structural capacity and competitiveness of the national economy.

2.3. Basic Log-linear Model

All variables are transformed into a natural logarithmic form to stabilize the variance of the data and to allow interpretation of the coefficients as elasticities. Mathematically, the study specifies three core models as shown in Equations 1-3, which form the analytical foundation of the research:

Model 1 Research-based Economic Complexity:

$$\begin{aligned} ln(GDP_t) &= \alpha_0 + \beta_1 ECI\_Research_t + \beta_2 GLB_t \\ &+\beta_3 lnGFCF_t + \beta_4 lnLF_t + \varepsilon_t \end{aligned} \tag{1}$$

Model 2 Technology-based Economic Complexity:

$$\begin{aligned} ln(GDP_t) &= \alpha_0 + \beta_1 ECI\_Tech_t + \beta_2 GLB_t \\ &+\beta_3 lnGFCF_t + \beta_4 lnLF_t + \varepsilon_t \end{aligned} \tag{2}$$

Model 3 Trade-based Economic Complexity:

$$\begin{aligned} ln(GDP_t) &= \alpha_0 + \beta_1 ECI\_Trade_t + \beta_2 GLB_t \\ &+\beta_3 lnGFCF_t + \beta_4 lnLF_t + \varepsilon_t \end{aligned} \tag{3}$$

All variables are expressed in their natural logarithms, allowing the coefficients to be directly interpreted as elasticities. The estimation of Equations 1–3 enables identification of the long-term effects of economic complexity across different dimensions on Indonesia’s economic growth.

To ensure the robustness of the time-series properties of the data, a stationarity test was conducted using the Phillips–Perron (PP) approach. The PP test evaluates the null hypothesis that a variable contains a unit root, as shown in Equation 4.

$$\Delta z_t = \gamma\, z_{t-1} + \nu_t \tag{4}$$

Where z_t represents the series being tested, Δ denotes the first-difference operator, γ is the parameter to be estimated, and ν_t is the white-noise error term. If the variable is non-stationary at level but becomes stationary after first differencing, it is classified as $I(1)$.

Once all variables were confirmed to be integrated of the same order, the Johansen cointegration test was applied to examine the existence of potential cointegrating relationships among them. The Johansen test is derived from the following Vector Error Correction Model (VECM) representation shown in Equation 5.

$$\Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \cdots + \Gamma_{p-1} \Delta Z_{t-p+1} + \Pi Z_{t-1} + u_t \tag{5}$$

Where Z_t is a vector of endogenous variables, Γ_1 captures the short-run dynamics, Π represents the long-run cointegrating relationships, and u_t denotes the deterministic term. The Johansen test provides two statistics: the Trace Statistic in Equation 6a and the Maximum Eigenvalue Statistic in Equation 6b, respectively.

$$\textit{Trace Statistic} \quad = -T \textstyle\sum_{i=r+1}^{k} \; ln(1 - \hat{\lambda}_i) \tag{6a}$$

$$\textit{Max-Eigen Statistic} \quad = -T ln\,(1 - \hat{\lambda}_{r+1}) \tag{6b}$$

Cointegration is said to exist when the calculated test statistics exceed the corresponding critical values at the 5% significance level.

2.4. Long-Term Estimation Model (FMOLS, CCR & DOLS)

Once the long-term relationship between variables is confirmed, the next step is to perform long-term estimation using three main approaches: Fully-Modified Ordinary Least Squares (FMOLS), Canonical Cointegrating Regression (CCR) and Dynamic Ordinary Least Squares (DOLS) [25–28].

2.4.1. Fully-Modified Ordinary Least Squares (FMOLS)

The FMOLS method, developed by Phillips [29], improves upon conventional OLS to estimate long-term relationships (cointegration) between non-stationary variables that are integrated of order one, $I(1)$ [29–31]. FMOLS corrects autocorrelation and endogeneity through adjustments to the long-run covariance of residuals, producing unbiased and efficient estimators. This approach does not require a complex pre-testing stage to determine the number of cointegrating vectors and can be applied in VAR and simultaneous equation systems that include both stationary and non-stationary variables [29, 30]. However, FMOLS still assumes a valid cointegration relationship and may face limitations when applied to models with a large number of variables.

The FMOLS estimator, developed by Phillips [29], corrects for endogeneity and serial correlation by adjusting the long-run covariance of the residuals, as shown in Equation 7.

$$\widehat{\beta}^{FMOLS} = (\sum X_t^* X_t^{*\top})^{-1}(\sum X_t^* y_t^*) \tag{7}$$

with X_t^* and y_t^* has been corrected against long-run covariance using the Newey–West kernel.

2.4.2. Canonical Cointegrating Regression (CCR)

The CCR estimator, developed by Park [32], uses canonical transformations to remove the correlation between residuals and regressors [33, 34], as shown in Equation 8.

$$\widehat{\beta}^{CCR} = (\sum \tilde{X}_t \tilde{X}_t^{\top})^{-1}(\sum \tilde{X}_t \tilde{y}_t) \tag{8}$$

where $\tilde{X}_t$ and $\tilde{y}_t$ is a transformed form that is free of autocorrelation.

2.4.3. Dynamic Ordinary Least Squares (DOLS)

The DOLS estimator, proposed by Stock & Watson [35], corrects estimation bias in OLS when dealing with non-stationary variables integrated of order one [36, 37]. It does so by introducing leads and lags of first-differenced regressors, which account for short-term dynamics and remove endogeneity,introduces leads and lags of the first-differenced independent variables to eliminate endogeneity, as expressed in Equation 9.

$$y_t = \alpha + \beta^{\top} X_t + \sum_{j=-q}^{q} \delta_j \Delta X_{t-j} + \varepsilon_t \tag{9}$$

The β coefficient describes the long-term relationship between economic complexity and GDP after accounting for short-term dynamics. Hence, the long-run DOLS form of the model can be written compactly as shown in Equation 10.

$$ln(GDP_t) = \alpha_0 + \beta_1 ECI_t + \beta_2 GLB_t + \beta_3 lnGFCF_t + \beta_4 lnLF_t + \sum_{j=-q}^{q} \delta_j \Delta X_{t-j} + \varepsilon_t \tag{10}$$

This approach allows for more consistent and efficient long-term parameter estimation than conventional OLS [35, 38]. DOLS is widely used in macroeconomic and energy studies due to its ease of implementation without complex data transformation [39]. The accuracy of the DOLS results is highly dependent on the number of lags and leads selected, and still requires a cointegration relationship between variables [38, 39].

These three methods were used simultaneously to assess the consistency of the estimated results and verify the stability of the long-term coefficients between models.

2.5. Quantile Regression (QR) Model

After confirming the long-term equilibrium relationship and estimating the long-run parameters, the study further applies Quantile Regression (QR) to analyze the heterogeneity of economic complexity effects across different growth phases [36, 40–42]. This approach identifies how the impact of economic complexity varies at different points of the GDP distribution (e.g., lower, median, and upper quantiles), as expressed in Equation 11. Thus, QR provides a richer understanding of the asymmetric effects of complexity throughout Indonesia's economic cycle.

$$Q_\tau(\,ln(GDP_t) \mid X_t\,) = \alpha_\tau + \beta_{1\tau} ECI_t + \beta_{2\tau} GLB_t + \beta_{3\tau} lnGFCF_t + \beta_{4\tau} lnLF_t + \varepsilon_{\tau t} \tag{11}$$

The parameter vector $\beta_\tau$is obtained by minimizing the check-loss function in Equation 12.

$$\rho_\tau(u) = u[\tau - 1(u < 0)] \tag{12}$$

This estimation approach allows the analysis of asymmetric effects of economic complexity across different growth regimes, providing deeper insights into how research-, technology-, and trade-based complexity drive Indonesia's economic performance.

2.6. Workflow of the Study

To provide a clearer understanding of the methodological design, a flow analysis is presented to help readers follow the research process more easily [43–45]. The analytical workflow of this study is summarized in Figure 3, which illustrates the sequential application of various econometric techniques. The workflow encompasses all stages of the empirical process, from data preparation and diagnostic testing to long-term estimation and heterogeneity analysis, thereby ensuring the robustness and validity of the results. Following a structured and systematic approach, each stage builds upon the preceding one, beginning with the verification of data properties and concluding with robustness and heterogeneity assessments. This integrated framework enables a comprehensive evaluation of how different dimensions of economic complexity influence Indonesia's economic growth over time, providing a solid empirical foundation for the discussion of results in the following section.

3. Results and Discussion

3.1. Descriptive Statistics

Table 2 shows descriptive statistics of the variables used in the study, including GDP, ECI_Research, ECI_Tech, ECI_Trade, GLB, GFCF and LF. The convergence between the mean and median values across variables indicates

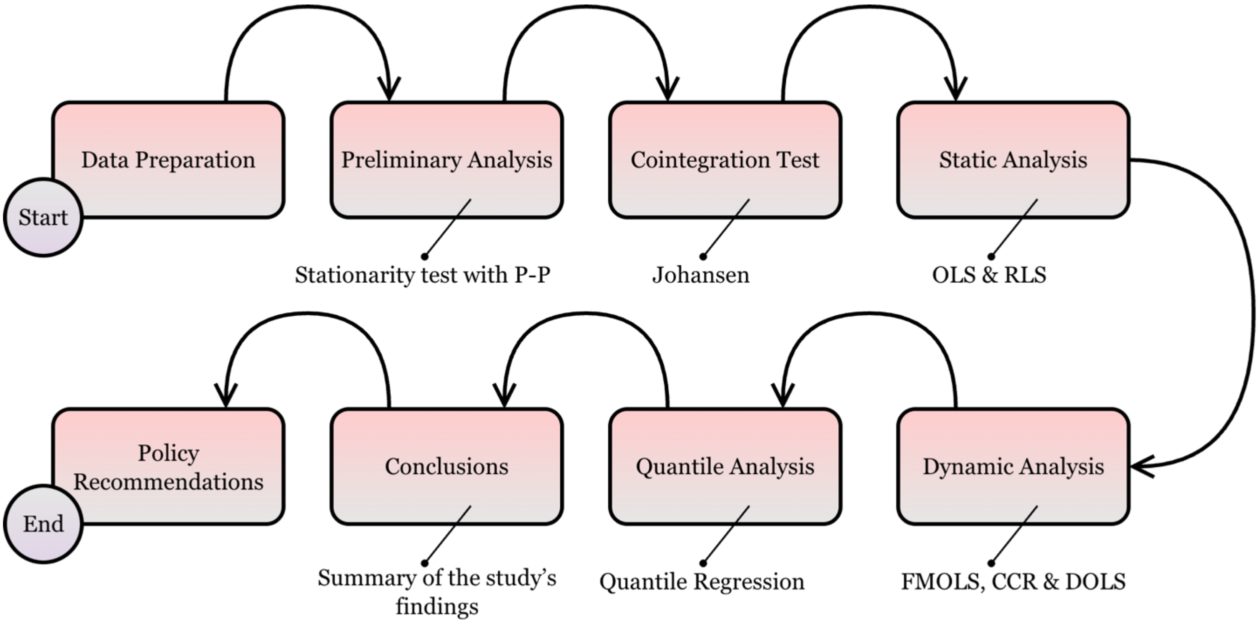


Figure 3. Analytical workflow of the study on economic complexity and Indonesia's economic growth.

Table 2. Descriptive statistics.

Variable	Mean	Median	Max.	Min.	Std. Dev.
GDP	27.229	27.242	27.695	26.702	0.3268
ECI_Research	-0.1412	-0.1125	0.1652	-0.6531	0.2074
ECI_Tech	-0.2930	-0.2845	-0.0045	-0.7976	0.2214
ECI_Trade	-0.3274	-0.3045	0.0203	-0.6409	0.1773
GLB	60.887	61.364	62.981	56.675	1.6077
GFCF	26.044	26.096	26.579	25.357	0.4068
LF	18.579	18.589	18.729	18.427	0.1027

that the data are symmetrically distributed, with no extreme outliers. The standard deviation of GDP, at 0.3268, reflects moderate variability that implies steady yet dynamic growth movements. Among the complexity indicators, ECI_Research has a standard deviation of 0.2074, denoting consistent development in research and human capital formation. ECI_Tech displays a slightly higher variability at 0.2214, suggesting that technological progress in Indonesia fluctuates more substantially, likely due to differences in innovation adoption and industrial upgrading capacity. Meanwhile, ECI_Trade records the lowest variability at 0.1773, reflecting gradual but stable integration into global trade structures and export diversification. Thereafter, GLB has the highest standard deviation at 1.6077. It highlights more pronounced changes in Indonesia's international exposure. This volatility may reflect external shocks and shifts in trade and capital flows that accompany global integration. Conversely, GFCF exhibits low variability at 0.4068, emphasizing the consistency of physical investment in supporting productive capacity. LF shows the smallest standard deviation at 0.1027, indicating strong demographic and employment stability, an essential foundation for sustained economic growth.

3.2. Stationarity Test

Table 3 presents the results of the Phillips-Perron (PP) stationarity test for all variables. The results show that only GDP and ECI_Trade are stationary at level I(0). When trend and intercept are included, GDP remains stationary at the 1% significance level, indicating strong stability over time, whereas ECI_Research becomes stationary at the 5% level under the model without deterministic components. Following this, all variables are stationary at first difference I(1). Specifically, GDP, ECI (research-based, technology-based, and trade-based), GLB, GFCF, and LF are found to be stationary at the 1% significance level. The presence of first-order integration fulfills the statistical condition for cointegration analysis, validating the use of long-run estimators such as FMOLS, CCR and DOLS to explore equilibrium relationships among growth, complexity, and globalization. These findings demonstrate that economies undergoing structural diversification tend to exhibit integrated but cointegrated processes over time.

3.3. Cointegration Test

The Johansen cointegration test results presented in Table 4 confirm the existence of long-run equilibrium

Table 3. Phillips–Perron (P–P) test results.

Variable	Intercept		Trend & Intercept		None	
	t-stat.	**Prob.**	**t-stat.**	**Prob.**	**t-stat.**	**Prob.**
Level						
GDP	-1.0214	0.7427	-4.1374*	0.0081	8.3991	0.9999
ECI_Research	-2.0221	0.2770	-2.4970	0.3290	-1.3581	0.1607
ECI_Tech	-1.7029	0.4263	-1.5543	0.8028	-0.9166	0.3166
ECI_Trade	-0.4436	0.8959	-2.3221	0.4175	-2.4845**	0.0134
GLB	-1.5583	0.4995	-2.0623	0.5590	-0.3844	0.7929
GFCF	-1.6645	0.4456	-1.6796	0.7521	-5.4172	0.9999
LF	-0.7531	0.8268	-2.6088	0.2776	-7.6034	0.9999
First Difference						
GDP	-14.1177*	0.0001	-15.6295*	0.0000	-9.2195*	0.0000
ECI_Research	-9.1932*	0.0000	-9.1528*	0.0000	-9.2195*	0.0000
ECI_Tech	-9.1662*	0.0000	-9.1866*	0.0000	-9.2195*	0.0000
ECI_Trade	-9.8567*	0.0000	-9.8036*	0.0000	-9.2195*	0.0000
GLB	-9.1847*	0.0000	-9.1461*	0.0000	-9.2195*	0.0000
GFCF	-12.8108*	0.0001	-14.2798*	0.0000	-9.2195*	0.0000
LF	-11.1776*	0.0001	-11.1483*	0.0000	-9.2195*	0.0000

Note: * and ** indicate significance at the 1% and 5% levels, respectively.

Table 4. Johansen cointegration test results.

Hypothesized	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.**
Model 1							
None	0.5482	134.1479*	69.8189	0.0000	66.7335*	33.8769	0.0000
At most 1	0.3177	67.4144*	47.8561	0.0003	32.1069*	27.5843	0.0122
At most 2	0.2242	35.3075*	29.7971	0.0105	21.3191*	21.1316	0.0471
At most 3	0.1167	13.9885	15.4947	0.0833	10.4228	14.2646	0.1856
At most 4	0.0416	3.5656	3.8415	0.0590	3.5656	3.8415	0.0590
Model 2							
None	0.6071	151.1077*	69.8189	0.0000	78.4706*	33.8769	0.0000
At most 1	0.4168	72.6371*	47.8561	0.0001	45.2899*	27.5843	0.0001
At most 2	0.1919	27.3472	29.7971	0.0934	17.8962	21.1316	0.1338
At most 3	0.0644	9.4510	15.4947	0.3253	5.5937	14.2646	0.6657
At most 4	0.0449	3.8573	3.8415	0.0495	3.8573*	3.8415	0.0495
Model 3							
None	0.5046	103.2211*	69.8189	0.0000	58.9938*	33.8769	0.0000
At most 1	0.2504	44.2273	47.8561	0.1053	24.2146	27.5843	0.1274
At most 2	0.1605	20.0127	29.7971	0.4220	14.6937	21.1316	0.3109
At most 3	0.0401	5.3190	15.4947	0.7741	3.4356	14.2646	0.9136
At most 4	0.0222	1.8834	3.8415	0.1699	1.8834	3.8415	0.1699

Note: * indicates significance at the 5% level where the test statistic exceeds the 5% critical value.

relationships among the analyzed variables. In Model 1, both the trace and maximum eigenvalue statistics indicate three significant cointegrating vectors at the 5% significance level. Model 2 identifies two cointegrating relationships based on the trace test and three based on the maximum eigenvalue test. Conversely, in Model 3, both the trace and maximum eigenvalue statistics suggest one significant cointegrating vector.

3.4. OLS and RLS Estimations

The results of the OLS and RLS estimations, as reported in Table 5, provide the first empirical evidence of the short-run relationship between economic growth and the three dimensions of economic complexity: research, technology, and trade. The RLS estimators (m-e, s-e, and mm-e) were applied to address potential heteroskedasticity and outlier effects, ensuring the robustness of the estimated coefficients. Across all specifications, the results remain stable and consistent, confirming the reliability of the identified relationships.

It is worth noting that this multidimensional approach remains relatively new in the economic complexity literature. To date, only Stojkoski et al. [46] have introduced a framework that simultaneously integrates trade-, technology-, and research-based complexities within a cross-country setting. However, no prior study has yet applied this multidimensional structure within a single-country context such as Indonesia, nor explored its short-run dynamics. Hence, this section not only presents the empirical estimation results but also offers early

Table 5. OLS and RLS results.

Variable	OLS		RLS					
			M-estimation		*S-estimation*		*MM-estimation*	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Model 1								
ECI_Research	0.0238***	0.0582	0.0242***	0.0645	0.0134***	0.0774	0.0243***	0.0660
GLB	-0.0135*	0.0000	-0.013*	0.0000	-0.0060*	0.0000	-0.0130*	0.0000
GFCF	0.5946*	0.0000	0.5756*	0.0000	0.5663*	0.0000	0.5736*	0.0000
LF	1.0309*	0.0000	1.1069*	0.0000	1.0584*	0.0000	1.1150*	0.0000
C	-6.5838*	0.0007	-7.5302*	0.0001	-6.8187*	0.0000	-7.6300*	0.0001
Model 2								
ECI_ Tech	-0.0382*	0.0025	-0.0409*	0.0025	-0.0391*	0.0001	-0.0432*	0.0018
GLB	-0.0102*	0.0001	-0.0097*	0.0001	-0.0091*	0.0000	-0.0093*	0.0003
GFCF	0.6115*	0.0000	0.5945*	0.0000	0.2401*	0.0000	0.5826*	0.0000
LF	0.9442*	0.0000	1.0153*	0.0000	2.4894*	0.0000	1.0652*	0.0000
C	-5.6273*	0.0003	-6.5391*	0.0003	-24.7368*	0.0000	-7.1789*	0.0001
Model 3								
ECI_ Trade	0.1022*	0.0004	0.1005*	0.0007	0.2525*	0.0000	0.0975*	0.0058
GLB	-0.0145*	0.0000	-0.0143*	0.0000	-0.0063*	0.0000	-0.0137*	0.0000
GFCF	0.5657*	0.0000	0.5642*	0.0000	0.5144*	0.0000	0.5626*	0.0000
LF	0.9583*	0.0000	0.9671*	0.0000	0.8280*	0.0000	0.9756*	0.0000
C	-4.3948**	0.0144	-4.5308**	0.0157	-1.0825	0.1526	-4.6811**	0.0361

Note: * , ** and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

insights into how each dimension of complexity distinctly contributes to Indonesia's short-run growth dynamics.

The empirical findings indicate that each dimension of economic complexity affects Indonesia's GDP differently in the short run. The research-based complexity (ECI_Research) model yields a positive and statistically significant coefficient across both OLS and RLS estimations, indicating that a one-score increase in research-based complexity raises GDP by approximately 1.3–2.4%. This implies that greater research intensity and scientific capability are associated with higher short-term productivity and faster diffusion of innovation outcomes. The result reflects that, even within a limited time horizon, the translation of research knowledge into applied innovation, through mechanisms such as university–industry collaborations, applied R&D projects, and government-led innovation programs, can generate immediate productivity spillovers. Seminal works such as Griliches [47], Coe & Helpman [48], and Verspagen [49] provide the conceptual foundations for understanding this mechanism, showing that R&D and innovation can yield measurable short-run productivity improvements through knowledge spillovers, technology diffusion, and learning-by-doing even before long-run structural transformation occurs. Although most contemporary research tends to emphasize the long-term effects of innovation, these classical frameworks remain central to explaining the near-term productivity responses observed in emerging economies. In Indonesia's context, the growing orientation toward applied research and collaborative innovation has accelerated the conversion of scientific outputs into productive capacity, reaffirming that research-based knowledge enhances short-run productivity through innovation diffusion, absorptive learning, and applied knowledge transfer, even as its broader structural impacts require more time to unfold.

In contrast, the technology-based complexity (ECI_Tech) model produces a negative and statistically significant coefficient across OLS and RLS estimations, where a one-score increase in technological complexity is associated with approximately a 4% decline in GDP. This short-run inverse relationship implies that while technological sophistication offers substantial long-run potential, it can initially generate structural frictions and adjustment costs. As emphasized by Stojkoski et al. [46], technological and trade complexities may act as substitutes during early stages of development, leading to temporary inefficiencies as resources shift from labor-intensive toward technology-intensive sectors. Consistent with Ferrarini & Scaramozzino [50], rising complexity can temporarily lower aggregate productivity due to the learning and coordination costs required to absorb new technologies. In Indonesia's context, where industrial upgrading and R&D capacity remain uneven across sectors, these transitional costs likely dominate, reflecting that technology adoption still outpaces the country's absorptive capability, hence dampening short-run growth despite higher sophistication in technological structures.

Meanwhile, the trade-based complexity (ECI_Trade) model reveals a statistically significant relationship with GDP across all estimations, where a one-score rise in trade complexity contributes to approximately 10–

Table 6. Dynamic estimation results: FMOLS, CCR, and DOLS.

Variable	*FMOLS*			*CCR*			*DOLS*		
	Coeff.	**t-stat.**	**Prob.**	**Coeff.**	**t-stat.**	**Prob.**	**Coeff.**	**t-stat.**	**Prob.**
Model 1									
ECI_Research	0.0417**	2.1392	0.0354	0.0407**	2.1433	0.0350	0.0418***	1.6880	0.0960
GLB	-0.0136*	-3.8803	0.0002	-0.0137*	-3.9692	0.0002	-0.0132*	-2.9927	0.0039
GFCF	0.5612*	8.2578	0.0000	0.5633*	8.6014	0.0000	0.5664*	6.3896	0.0000
LF	1.1931*	4.8015	0.0000	1.1860*	4.9096	0.0000	1.1650*	3.6030	0.0006
C	-8.7172*	-2.9102	0.0046	-8.6343*	-2.9530	0.0041	-8.3542*	-2.1395	0.0360
R-squared	0.9972			0.9972			0.9979		
Adjusted R-squared	0.9971			0.9971			0.9974		
Model 2									
ECI_Tech	-0.0624*	-2.8077	0.0062	-0.064*	-2.8178	0.0061	-0.0726**	-2.2162	0.0300
GLB	-0.0092**	-2.2054	0.0302	-0.0091**	-2.2206	0.0291	-0.0085	-1.5857	0.1175
GFCF	0.6234*	8.7957	0.0000	0.6237*	9.1524	0.0000	0.6379*	7.1643	0.0000
LF	0.9156*	3.5885	0.0006	0.9181*	3.7185	0.0004	0.8660*	2.6815	0.0092
C	-5.4767	-1.8097	0.0740	-5.5318***	-1.8804	0.0636	-4.9769	-1.2899	0.2014
R-squared	0.9974			0.9973			0.9979		
Adjusted R-squared	0.9972			0.9972			0.9974		
Model 3									
ECI_Trade	0.0916**	2.1118	0.0378	0.0923**	2.0828	0.0404	0.0882***	1.7054	0.0927
GLB	-0.0160*	-4.8359	0.0000	-0.0159*	-4.8803	0.0000	-0.0167*	-4.0113	0.0002
GFCF	0.5970*	9.1828	0.0000	0.5955*	9.5108	0.0000	0.6263*	7.7739	0.0000
LF	0.8658*	3.7667	0.0003	0.8696*	3.9008	0.0002	0.7670*	2.7227	0.0082
C	-3.3999	-1.2139	0.2283	-3.4351	-1.2583	0.2119	-2.2862	-0.6708	0.5046
R-squared	0.9976			0.9976			0.9981		
Adjusted R-squared	0.9975			0.9975			0.9976		

Note: * , ** and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

25% higher output. This finding suggests that diversification and export sophistication act as immediate sources of productivity gains through learning-by-exporting and sectoral spillovers. The result is consistent with Hidalgo [11], who demonstrates through the trade-based complexity framework that countries with more diversified and knowledge-intensive exports experience faster growth due to the accumulation of productive knowledge embedded in their export structures. Supporting evidence from Doğan et al. [51] similarly confirms that complex and diversified export portfolios stimulate short-term output expansion, while Zhu & Li [52] find that higher export complexity enhances short-run productivity through knowledge diffusion and efficiency gains. Relatedly, Li et al. [53] emphasize that the positive contribution of complexity becomes more pronounced when supported by digital governance and institutional readiness, which facilitate innovation diffusion across sectors. Collectively, these studies reinforce that Indonesia's short-run gains from trade-driven complexity stem from its ability to diversify and upgrade export structures. The empirical evidence suggests that Indonesia's immediate growth response to rising trade complexity is driven by the expansion of downstream processing and semi-manufacturing industries such as palm oil derivatives, mineral refining, and automotive components, which generate productivity spillovers and foster technology absorption even before deeper industrial capabilities are fully established. This phase of diversification delivers measurable short-run growth benefits, although the transition toward a more advanced production structure remains gradual.

Regarding the control variables, both GFCF and LF exhibit positive and statistically significant effects on GDP in the short run. A 1% increase in GFCF raises GDP by about 0.24–0.61%, while LF increases GDP by 0.83–2.5%. These findings suggest that Indonesia's short-term growth is largely input-driven, relying on capital accumulation and labor absorption to sustain output expansion. This pattern reflects the logic of the Cobb–Douglas production framework, where capital accumulation and labor utilization jointly drive short-run output growth through efficient factor allocation. Empirical evidence from Sarsar & Echaoui [54] supports this relationship, showing that investment efficiency and workforce participation are key accelerators of short-run output growth, particularly in developing economies. Conversely, GLB displays a negative and significant effect, where a 1% increase in globalization reduces GDP by about 0.6–1.4%. This suggests that, in the short run, external openness may expose domestic industries to import competition and macroeconomic shocks. Similar evidence has been discussed by Latif et al. [55] and Xu et al. [56], who noted that globalization can exert adverse short-term effects in developing and Asian economies due to weak institutional capacity, limited competitiveness, and

Table 7. Quantile regression results.

Variable	Low			Medium			High		
	Q (0.10)	Q (0.20)	Q (0.30)	Q (0.40)	Q (0.50)	Q (0.60)	Q (0.70)	Q (0.80)	Q (0.90)
Model 1									
ECI_Research	0.0538**	0.0567***	0.0738**	0.0324	0.0158	-0.0057	0.0186	0.0186	0.0110
	[0.0273]	[0.0855]	[0.0121]	[0.1035]	[0.1989]	[0.6746]	[0.2019]	[0.1688]	[0.3661]
GLB	-0.0080*	-0.0080*	-0.0072*	-0.0064*	-0.0061*	-0.0163*	-0.0169*	-0.0166*	-0.0260*
	[0.0001]	[0.0018]	[0.0008]	[0.0014]	[0.0037]	[0.0000]	[0.0000]	[0.0000]	[0.0048]
GFCF	0.4179*	0.4256*	0.4941*	0.5209*	0.5289*	0.63708	0.6199*	0.6141*	0.7720*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LF	1.6760*	1.6492*	1.4024*	1.2521*	1.2044*	0.8339*	0.9785*	0.9971*	0.3972***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0715]
Model 2									
ECI_Tech	-0.0246***	-0.0358**	-0.0411*	-0.0688*	-0.0448**	-0.0440	-0.0437***	-0.0503**	-0.0538**
	[0.0690]	[0.0413]	[0.0054]	[0.0023]	[0.0398]	[0.1108]	[0.0877]	[0.0427]	[0.0326]
GLB	-0.0077*	-0.0134	-0.0133	-0.0039	-0.0051***	-0.0130*	-0.0132*	-0.0110*	-0.0074
	[0.0001]	[0.1089]	[0.1006]	[0.1148]	[0.0681]	[0.0078]	[0.0031]	[0.0063]	[0.1231]
GFCF	0.3575*	0.6241**	0.6388*	0.5632*	0.5157*	0.6243*	0.6748*	0.7330*	0.7424*
	[0.0000]	[0.0168]	[0.0093]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LF	1.8636*	0.9951	0.9443	1.0894*	1.2871*	0.9431*	0.7370*	0.4645**	0.3669**
	[0.0000]	[0.2252]	[0.2264]	[0.0000]	[0.0000]	[0.0000]	[0.0002]	[0.0279]	[0.0161]
Model 3									
ECI_Trade	0.0329	0.1095	0.1464*	0.0026	0.1918*	0.1374**	0.1053***	0.1198**	0.1059*
	[0.3061]	[0.1781]	[0.0000]	[0.9637]	[0.0015]	[0.0244]	[0.0818]	[0.0201]	[0.0097]
GLB	-0.0092*	-0.0126	-0.0173*	-0.0068**	-0.0077*	-0.0185*	-0.0182*	-0.0144*	-0.0136*
	[0.0000]	[0.1086]	[0.0000]	[0.0222]	[0.0099]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
GFCF	0.3005*	0.4458**	0.6439*	0.4720*	0.4721*	0.5914*	0.6915*	0.6234*	0.6195*
	[0.0000]	[0.0420]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
LF	2.0192*	1.4169***	0.7082***	1.4016*	1.1169*	0.8180*	0.4745**	0.6594*	0.6943*
	[0.0000]	[0.0800]	[0.0837]	[0.0000]	[0.0000]	[0.0000]	[0.0103]	[0.0001]	[0.0000]

Note: * , ** and *** indicate significance at the 1%, 5%, and 10% levels, respectively.

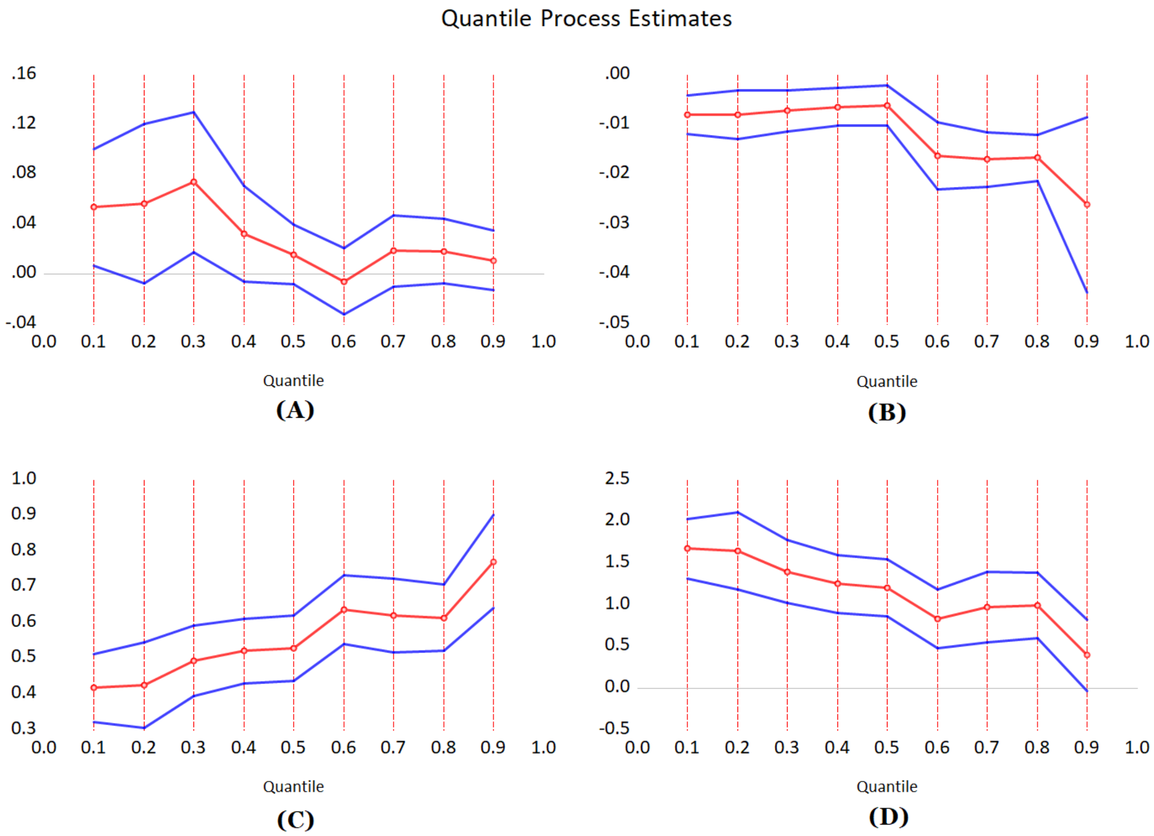
structural dependence on imports. These findings indicate that when the pace of globalization outstrips domestic readiness, short-run integration into global markets may temporarily suppress output before potential long-run benefits can materialize.

Overall, as summarized in Table 5, the OLS and RLS estimations reveal heterogeneous short-run effects of economic complexity on Indonesia's economic growth. Research-based and trade-based complexities exert positive and statistically significant effects on output, indicating that knowledge creation and export sophistication immediately enhance short-term productivity through innovation diffusion and learning-by-exporting channels. In contrast, technological complexity exerts a negative short-run effect, reflecting transitional frictions and limited absorptive capacity that delay the realization of productivity gains from advanced technologies. Collectively, these findings suggest that the short-run effects of multidimensional complexity are highly contingent upon structural readiness and institutional maturity, consistent with Stojkoski et al. [46], who emphasize that the benefits of complexity materialize unevenly across knowledge domains and development stages.

3.5. Dynamic Estimation Results: FMOLS, CCR, and DOLS

The dynamic estimations using FMOLS, CCR, and DOLS provide robust evidence of long-run cointegration between economic growth and its explanatory variables across all three models. These estimators address potential issues of serial correlation, endogeneity, and small-sample bias, ensuring that the coefficients capture genuine long-run equilibrium. As reported in Table 6, all models exhibit high explanatory power, with R^2 values exceeding 0.99, indicating that the specified variables explain nearly all variations in GDP over the long run.

Consistent with the short-run results, research-based complexity (ECI_Research) continues to exert a positive and statistically significant influence on GDP across all estimators, with coefficients ranging between 0.0407 and 0.0418. This suggests that a one-score increase in research-based complexity leads to approximately 4% higher long-run economic growth, highlighting the sustained role of research-driven innovation in maintaining productivity expansion. Unlike Stojkoski et al. [46], who found research-based complexity statistically insignificant at the cross-country level, Indonesia's positive long-run result indicates that the country is making significant progress through an early transition toward a knowledge-oriented economy, where



(A) (B) (C) (D)

Figure 4. Graphical results of the Quantile Regression for Model 1: (A) ECI_Research, (B) GLB, (C) GFCF, and (D) LF on GDP.

the diffusion of research output into productive sectors has begun to take effect. This is consistent with Kaur and Singh [57], who emphasized that the influence of knowledge and innovation on growth in developing economies tends to emerge over time, once investments in R&D, education, and institutional frameworks interact systematically to support technological adaptation. Similarly, Sokolov-Mladenović et al. [58] demonstrated that sustained R&D expenditure exerts a significant and positive impact on long-run economic growth in EU economies, with the magnitude of the effect strengthening after accounting for time lags, underscoring the delayed but persistent contribution of research investment to productivity gains. Consistent with Risso & Sánchez-Carrera [59], the growth effects of R&D are often non-linear and lagged, initially limited or insignificant below certain efficiency thresholds but becoming stronger as human capital and absorptive capacity improve. Evidence from Kaneva & Untura [60] further supports that long-term R&D and innovation expenditures yield growth-enhancing effects primarily in economies with evolving rather than fully mature innovation systems. Therefore, Indonesia's modest yet significant elasticity of ECI_Research reflects the early but meaningful impact of research-based complexity, marking an incremental step toward building a more resilient and knowledge-driven growth trajectory.

In contrast, technology-based complexity (ECI_Tech) remains negative and statistically significant across all estimators, with coefficients between -0.0624 and -0.0726. This suggests that a one-score increase in technological complexity results in a 0.06% to 0.07% decline in GDP, underscoring Indonesia has yet to translate its technological sophistication into sustained productivity gains. Compared with Stojkoski et al. [46], who employ a multidimensional ECI framework and find that technological complexity supports long-term growth once absorptive capacities are established, Indonesia's result indicates a structural gap between technological advancement and institutional readiness. Empirical evidence from Mewes and Broekel [61] shows that regions with higher technological complexity experience faster growth only when local knowledge bases and learning capabilities are well developed, while Broekel & Klarl [62] highlight that such positive effects emerge gradually through the cumulative evolution of technologies and sustained capability building. In Indonesia, however, technological upgrading remains largely import-driven and concentrated in low value-added sectors, limiting knowledge diffusion and domestic innovation. Consequently, even in the long run, technological sophistication has not yet evolved into a self-sustaining driver of growth, reflecting a premature complexity trap, where the economy appears

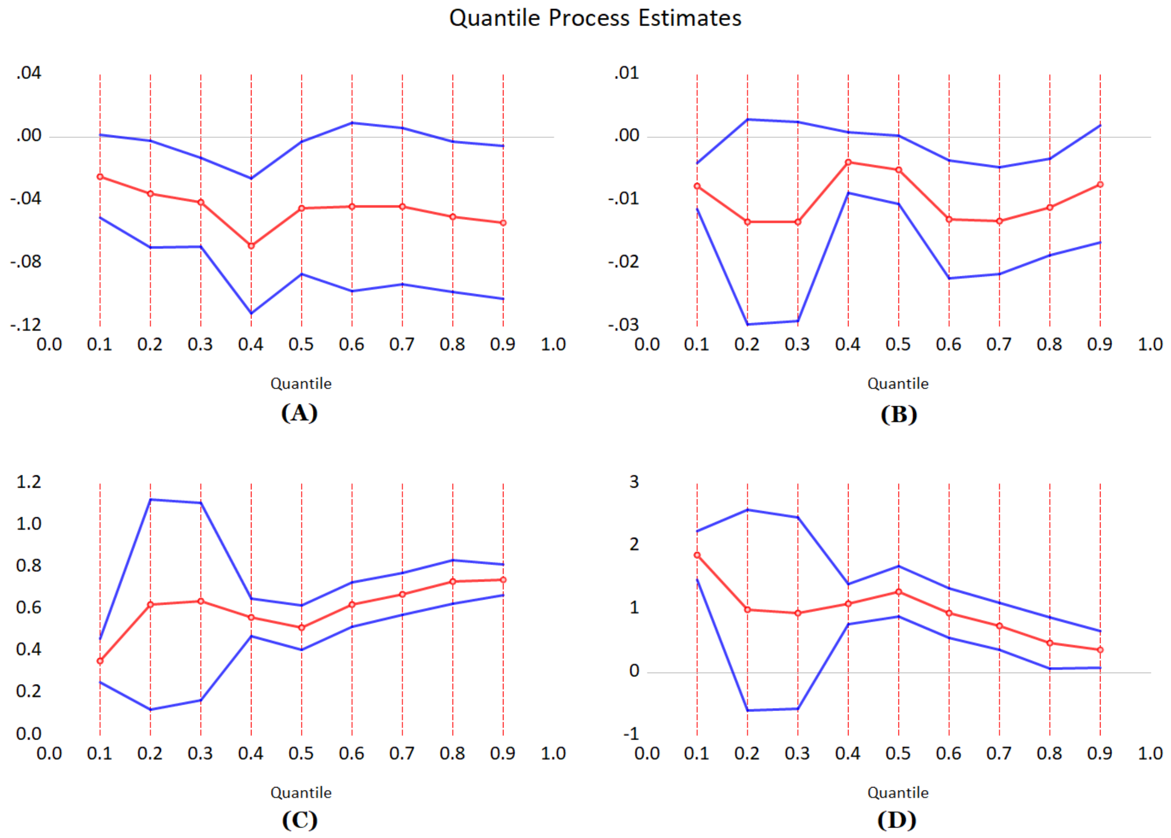


Figure 5. Graphical results of the Quantile Regression for Model 2: (A) ECI_Tech, (B) GLB, (C) GFCF, and (D) LF on GDP.

technologically advanced but lacks the institutional and human capacity to internalize and fully realize its complexity advantages.

Meanwhile, trade-based complexity (ECI_Trade) remains consistenly positive and significant across all estimators, with coefficients between 0.0882 and 0.0923. A one-score rise in trade-based complexity increases GDP by roughly 8–9%, underscoring the cumulative role of export diversification and domestic value-added upgrading in driving long-term growth. This finding aligns with Hidalgo [11] and Stojkoski et al. [46], who show that trade-based complexity embodies cumulative productive knowledge and predicts sustained income growth. Similarly, Zhang et al. [63], who develop the value-added–based ECI (ECI_VADP), emphasize that when export sophistication is driven by domestic value creation rather than gross trade volume, it becomes a stronger predictor of sustainable income growth. Complementary studies by Li et al. [53] and Hartmann et al. [9] further suggest that export complexity strengthens institutional quality and inclusivity, ensuring that growth driven by complex trade structures becomes more resilient and equitable. In Indonesia's case, the persistent long-run contribution of ECI_Trade indicates that structural diversification, from raw commodity exports toward semi-manufactured and technology-based products, has begun to yield productivity spillovers and learning-by-exporting effects. However, the relatively modest magnitude of the coefficient also reflects that the transformative potential of export complexity remains constrained by limited R&D intensity and uneven institutional coordination.

For the control variables, both GFCF and labor LF retain their positive and statistically significant effects across all estimators, reaffirming their fundamental role in supporting long-run growth. A 1% increase in GFCF raises GDP by approximately 0.56–0.64%, while LF contributes between 0.77% and 1.2%. Consistent with the endogenous growth theory [64], which emphasizes that continuous capital accumulation and human capital development drive sustained productivity growth through innovation, technological progress, and knowledge spillovers, these results highlight the importance of investment and labor inputs in maintaining long-term output expansion. Empirical evidence from Idroes et al. [31] and Sarsar and Echaoui [54] similarly supports this pattern in emerging economies, showing that productive investment and labor dynamics remain key determinants of persistent economic growth. Conversely, GLB remains negative and significant, reducing GDP by around 1.0–1.6% over the long run. This outcome is consistent with the findings of Latif et al. [55], who demonstrated that globalization exerts a negative and statistically significant long-run impact on economic growth in emerging economies.

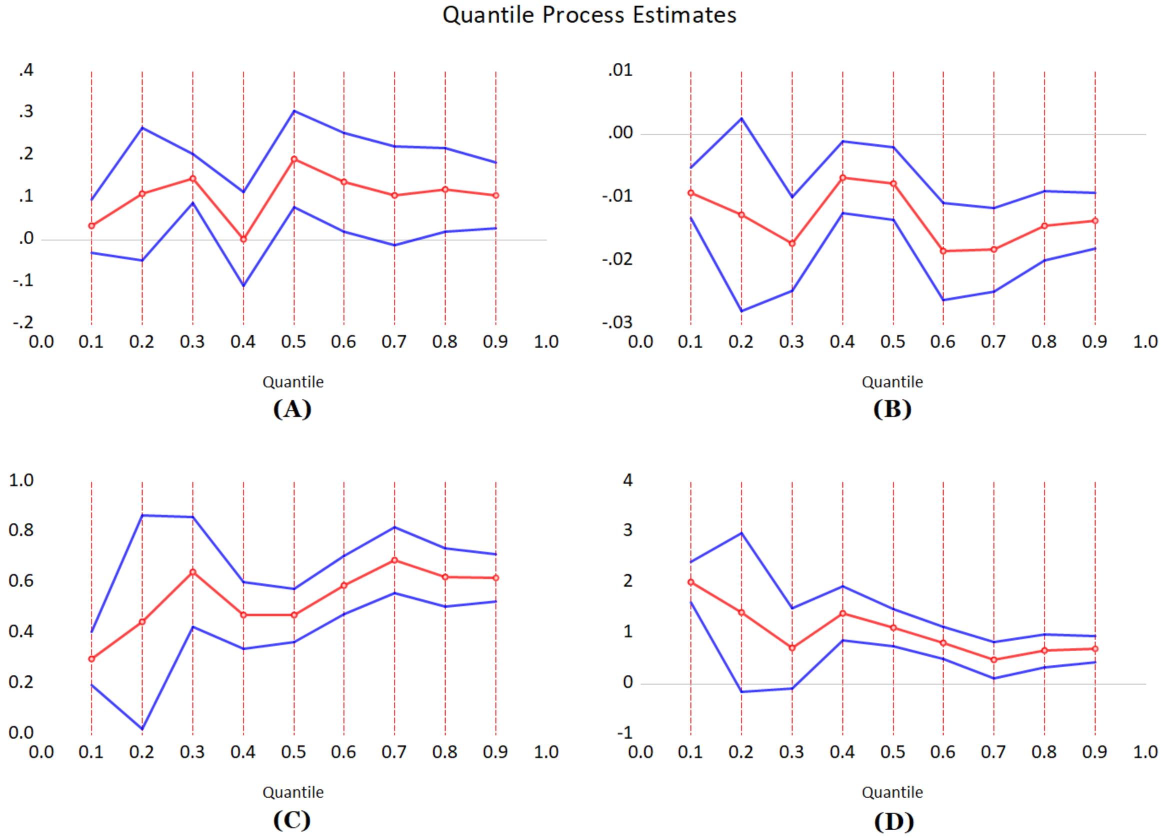


Figure 6. Graphical results of the Quantile Regression for Model 3: (A) ECI_Trade, (B) GLB, (C) GFCF, and (D) LF on GDP.

Their study emphasizes that the benefits of openness tend to erode over time when countries experience persistent import dependence and limited absorptive capacity. Similar evidence from Hassan et al. [65] and Acheampong et al. [66] further supports this pattern, showing that weak institutional quality and structural fragility can transform globalization from a growth catalyst into a long-term constraint. In Indonesia's case, the sustained negative association observed here highlights that global integration must be accompanied by stronger industrial development, technological progress, and institutional reform to ensure that openness contributes positively to long-run productivity and sustainable growth.

Overall, the FMOLS, CCR, and DOLS results confirm a consistent long-run cointegrating relationship between economic complexity and growth, while highlighting that the effects differ across dimensions. Research-based and trade-based complexities support structural transformation and productivity improvement, whereas technology-based complexity still poses transitional challenges. These findings suggest that the developmental stage of an economy shapes which dimension of complexity delivers the most sustainable growth outcomes. In Indonesia, the long-run benefits of complexity depend on aligning research, technology, and trade capabilities with domestic absorptive capacity, institutional quality, and integration into global markets.

3.6. Quantile Regression

The quantile regression analysis, based on Indonesia's time-series data with GDP as the dependent variable, provides a nuanced understanding of how different dimensions of economic complexity influence growth across various phases of economic performance. Rather than comparing countries, this approach captures how these relationships evolve within Indonesia over time, during periods of low, medium, and high growth. By examining the conditional distribution of GDP rather than its mean, the quantile regression framework reveals heterogeneous effects of complexity across development stages, offering a deeper view of Indonesia's growth dynamics. The estimation results are presented in Table 7, while Figures 4–6 illustrate the variations across quantiles, emphasizing the asymmetric and state-dependent behavior of economic complexity throughout Indonesia's growth trajectory.

3.6.1. Quantile Regression Results for ECI Research (Model 1)

In Model 1, which employs research-based complexity (ECI_Research), the effect on GDP is positive and statistically significant at the lower quantiles (as shown in

Figure 4), particularly at Q0.10 (0.0538, 95% confidence level), Q0.20 (0.0567, 90% confidence level), and Q0.30 (0.0738, 95% confidence level). This indicates that during periods of weaker economic performance, increases in research-oriented complexity contribute more strongly to GDP growth by stimulating innovation diffusion and strengthening scientific capacity. However, the effect diminishes and becomes statistically insignificant beyond the median quantile, suggesting that research-based activities are most effective when the economy operates below its potential. This pattern aligns with Sokolov-Mladenović et al. [58], who found that R&D's positive effects on EU growth typically materialize after downturns, underscoring the countercyclical role of innovation in restoring productivity. It is also consistent with Risso & Sánchez-Carrera [59], who demonstrate that R&D impacts are non-linear, becoming significant only once efficiency thresholds and absorptive capacities improve. Likewise, Kaur & Singh [57] emphasize that in developing economies, the benefits of knowledge accumulation and research investment emerge gradually as education and institutional systems evolve. Hence, Indonesia's case reflects an early-stage innovation environment, where research-based complexity helps stabilize growth during slower phases but loses its strength in stronger expansion periods due to limited absorptive and technological scalability.

3.6.2. Quantile Regression Results for ECI Technology (Model 2)

Model 2, incorporating technology-based complexity (ECI_Tech), reveals a consistently negative and statistically significant relationship with GDP across most quantiles (as displayed in Figure 5), with the strongest adverse impacts observed between Q0.30 and Q0.60. The largest negative coefficients occur at Q0.40 (-0.0688, 99% confidence level) and Q0.90 (-0.0538, 95% confidence level), suggesting that even as GDP rises, higher technological complexity exerts contractionary pressure on output. This implies that technological sophistication, when unsupported by adequate absorptive capacity, human capital, and institutional readiness, tends to generate structural inefficiencies rather than productivity gains. According to Stojkoski et al. [46], technological complexity interacts nonlinearly with trade and research complexity and its benefits appear only when complementary capabilities exist to internalize knowledge spillovers. In Indonesia's case, the persistently negative coefficients across middle and upper quantiles indicate that even higher-income states have not yet reached the threshold where complex technologies enhance productivity. This finding contrasts with advanced-economy results [61] and reflects Indonesia's premature complexity phenomenon, where technological upgrading outpaces skill accumulation and institutional adaptation. As Broekel & Klarl [62] argue, the positive growth effects of technological complexity unfold gradually after sustained capability building, highlighting that technological sophistication alone does not guarantee growth but may exacerbate transitional frictions when innovation systems and absorptive infrastructures remain underdeveloped.

3.6.3. Quantile Regression Results for ECI Trade (Model 3)

Model 3, which focuses on trade-based complexity (ECI_Trade), shows a heterogeneous but overall positive impact on GDP, as presented in Figure 6. The effect is insignificant at lower quantiles (Q0.10–Q0.20) but becomes positive and statistically significant from Q0.30 upward, reaching its peak between Q0.70 and Q0.90 with coefficients around 0.105. This pattern indicates that the growth-enhancing role of export sophistication strengthens as the economy reaches higher levels of performance. Consistent with Hidalgo [11], diversified and knowledge-intensive exports generate stronger productivity spillovers once a country attains sufficient absorptive and institutional capacity. Similar evidence from Doğan et al. [51] and Zhu & Li [52] confirms that complex export structures yield uneven but increasingly positive effects as economies advance toward higher industrial maturity. Furthermore, Li et al. [53] and Stojkoski et al. [46] show that the benefits of trade-embedded complexity expand at upper quantiles, where innovation diffusion and technological learning become more effective. In Indonesia's case, the upward trend of ECI_Trade across quantiles suggests that trade-driven complexity becomes a major catalyst for growth once the economy approaches its potential output, reflecting a threshold mechanism in which diversification and export upgrading reinforce productivity after foundational capacities are established.

For the control variables, both gross fixed capital formation (GFCF) and labor force (LF) remain positive and statistically significant across all quantiles, although their marginal effects gradually weaken at higher GDP levels. This pattern indicates that capital and labor accumulation play a stronger role in the lower and middle quantiles, where economies rely heavily on factor inputs, but yield diminishing returns at the upper quantiles as the economy transitions toward efficiency-driven growth. This result aligns with Sarsar & Echaoui [54] and Idroes et al. [31], who report that investment and employment significantly boost early-stage output but taper off as structural maturity is reached. Hayyat et al. [67] further confirm this nonlinear pattern using a global quantile regression framework, showing that both GFCF and employment exhibit diminishing or even adverse effects beyond certain thresholds due to infrastructural saturation and declining labor efficiency. These findings imply that economies at higher development stages require greater innovation, human capital upgrading, and technological diffusion to sustain productivity growth. Conversely, globalization (GLB) maintains a mild but persistent negative association with GDP across quantiles, with stronger adverse effects at the lower and middle levels of output. This suggests that less-developed economies are more vulnerable to external competition and trade imbalances, whereas more advanced economies are better positioned to absorb the benefits of openness. As Acheampong et al. [66] and Xu et al. [56] emphasize, the net effect of globalization depends heavily on governance quality, domestic linkages, and technological readiness, conditions that remain critical for Indonesia to transform openness into an engine of inclusive and sustainable growth.

Overall, the quantile regression results highlight the asymmetric and state-dependent nature of economic complexity's impact on Indonesia's growth trajectory. Research-based complexity provides countercyclical support during periods of low growth, technology-based complexity introduces transitional frictions during mid-development stages, and trade-based complexity emerges as the dominant driver of output expansion at higher levels of performance. This nonlinear pattern underscores that the benefits of complexity evolve with structural maturity and institutional readiness, reflecting the path-dependent nature of capability accumulation. Accordingly, policy interventions should be phase-specific, strengthening research and innovation capacity at early stages, enhancing technological absorption and institutional quality during industrial transformation, and deepening export diversification and value-chain integration once higher growth thresholds are achieved.

4. Conclusions

This study empirically investigates how economic complexity, viewed through the dimensions of research, technology, and trade, affects Indonesia's economic growth between 2000 and 2021. The results show that research- and trade-based complexities are the main long-run drivers of growth, while technology-based complexity exerts a negative effect due to limited absorptive capacity and institutional readiness. Research-based complexity enhances productivity and stabilizes growth during low-performance periods, whereas trade-based complexity supports expansion through export diversification and participation in global value chains. In contrast, technological sophistication still entails adjustment costs, reflecting that innovation diffusion in Indonesia remains at an early stage. Capital formation and labor remain key short-run growth inputs, while the mixed effect of globalization underscores the need to strengthen domestic competitiveness to mitigate external vulnerabilities.

From a policy perspective, the findings emphasize the need for a stage-specific development strategy. At early stages, policies should focus on strengthening research and innovation ecosystems through investments in education, R&D, and university–industry collaboration. During transitional phases, emphasis should shift to improving technological diffusion, digital infrastructure, and regulatory efficiency to convert complexity into productivity. As the economy matures, strategic attention must be directed toward advancing export sophistication, value-added production, and deeper integration into global value chains to ensure long-term competitiveness and resilience. Despite providing robust empirical evidence, this study acknowledges several limitations. The use of aggregate time-series data may overlook regional and sectoral heterogeneity across Indonesia's economy. Future studies could extend this framework using panel or spatial approaches and incorporate institutional and environmental variables to provide a more comprehensive understanding of how economic complexity supports inclusive and sustainable growth.

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