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Indatu Journal of Management and Accounting

Vol. 3, No. 1, 2025



Business Confidence and Economic Complexity in Indonesia: Evidence from Technology, Trade, and Research Dimensions

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Article History

Received 12 April 2025
 Revised 10 June 2025
 Accepted 24 June 2025
 Available Online 30 June 2025

Keywords:

Economic complexity
 Business confidence
 Technology
 Trade
 Research
 DOLS

Abstract

This study investigates the impact of business confidence on economic complexity in Indonesia, focusing on three key dimensions: research, technology, and trade. Using quarterly data from 2003 to 2021 and applying the Dynamic Ordinary Least Squares (DOLS) estimation method, the analysis incorporates business confidence, economic growth, and gross fixed capital formation as explanatory variables. The DOLS results reveal that an increase in business confidence has a positive and significant effect on technological and trade complexity. However, it is associated with a negative effect on research complexity. Economic growth is positively linked to trade complexity but negatively associated with both technological and research complexity, while gross fixed capital formation contributes positively to technological and research complexity but negatively to trade complexity. These findings highlight the need for integrated policy strategies that align business sentiment and investment behavior with long-term innovation and export development goals in Indonesia.



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1. Introduction

Economic complexity functions as a vital metric which shows how well a nation develops its advanced production abilities and its ability to achieve enduring growth through innovation [1–5]. Unlike gross domestic product (GDP), which reflects aggregate economic output, measures of economic complexity assess the diversity and technological sophistication embedded within a country's production and export structure [6–8]. Recent advancements in this field have emphasized the multidimensional nature of complexity, encompassing not only the composition of traded goods, but also the country's capacity for technological advancement and

scientific research [1, 9, 10]. Specifically, complexity can be analyzed through three interrelated dimensions: trade-based complexity, which captures the diversification and knowledge intensity of exports; technological complexity, which reflects the level of innovation and industrial sophistication; and research-based complexity, which indicates a country's ability to produce and disseminate new knowledge [1, 9, 11, 12]. Together, these dimensions provide a holistic view of how nations acquire, apply, and diffuse productive knowledge [9, 12]. Empirical evidence suggests that countries with greater complexity across these domains tend to achieve higher long-term economic growth, improved income

distribution, and enhanced resilience to external shocks [13].

Business confidence serves as a key indicator of firms' perceptions and expectations regarding current and future economic conditions [14]. It reflects how optimistic or pessimistic businesses are about factors such as market demand, investment climate, profitability, and regulatory stability [15–18]. High levels of business confidence typically encourage firms to expand operations, invest in capital and innovation, and hire more workers, thereby stimulating broader economic activity. Conversely, low business confidence can lead to reduced investment, hiring freezes, and cautious inventory management, which may dampen economic growth [19–21]. According to the Organisation for Economic Co-operation and Development (OECD), business confidence indicators are often used as leading signals of economic turning points, as they capture real-time sentiment before changes are reflected in actual output or investment data [22]. While widely used in macroeconomic forecasting, the role of business confidence in influencing structural variables, such as economic complexity, has been largely underexplored. Understanding this behavioral dimension is particularly important in emerging economies, where private sector expectations can significantly shape the trajectory of industrial transformation and innovation.

Previous studies have extensively examined the relationship between economic complexity and broader development outcomes such as growth, diversification, and inequality. Zhu & Li [23], in a cross-country analysis of 210 economies, explored the combined effects of human capital and economic complexity on economic growth. They found that both factors significantly contribute to short- and long-term growth, with higher income countries exhibiting greater complexity than their low- and middle-income counterparts. Tabash et al. [7], focusing on 24 African countries from 1995 to 2017 using the Generalized Method of Moments (GMM) model, confirmed that economic complexity has a positive impact on GDP growth. Further evidence by Canh & Thanh [6], based on 70 countries from 1996 to 2014, reveals that economic complexity not only promotes growth stability, especially in high income nations, but also maintains a bidirectional relationship with export diversification, varying across levels of development and time. In addition to growth-oriented outcomes, Hartmann et al. [24] demonstrated that countries exporting more complex products tend to exhibit lower income inequality. This inverse relationship remains significant even after controlling for income, institutional quality, and human capital, suggesting that a nation's

productive structure meaningfully shapes its distributional outcomes.

However, there is a lack of studies that investigate the role of business confidence, representing firms' expectations and risk appetite, in shaping economic complexity. Business confidence is well-known to affect investment decisions, innovation efforts, and expansion strategies [22, 25, 26], yet it is rarely integrated into empirical ECI models. This represents a critical gap in the literature. Moreover, although macroeconomic factors such as GDP growth and gross fixed capital formation (GFCF) are commonly associated with economic performance, their influence on different dimensions of complexity, especially when combined with business sentiment, remains largely unexplored. While empirical gaps are evident, a stronger theoretical foundation is also needed to explain how business sentiment influences economic complexity. Economic complexity, which reflects a country's capacity to produce and export sophisticated products, depends not only on existing capabilities but also on firms' willingness to invest in knowledge-intensive sectors. Business confidence captures forward-looking expectations, risk tolerance, and perceived economic stability. These factors directly shape firms' strategic decisions in areas such as innovation, diversification, and upgrading of production structures. In this context, business sentiment can be viewed as a behavioral channel that helps explain how macroeconomic conditions influence structural economic outcomes. Based on previous studies, there is no evidence of business confidence toward economic complexity in Indonesia. Prior research has examined the impact of business confidence on renewable energy (Hardi et al. [27]), investment (Khan & Upadhayaya [16]), emissions (Akan [28]), and economic growth (Jongh & Mncayi [20]).

Indonesia provides a compelling context for this study. As Southeast Asia's largest economy, Indonesia has experienced steady GDP growth and expanding investment over two decades [29–33], but its progress in economic complexity has remained modest [34, 35]. Commercial initiatives like "Making Indonesia 4.0" and mineral downstreaming programs aim to drive structural transformation, yet the country continues to rely heavily on commodity exports and shows limited growth in high-tech exports and research output. Investigating how business confidence alongside GDP and GFCF shapes the research, technology, and trade complexity offers important policy insights.

This study investigates the impact of business confidence on economic complexity in Indonesia, using quarterly data from 2003 to 2021. Employing Dynamic Ordinary

Table 1. Variable Descriptions and data sources.

Variable Symbol	Variable Full Name	Unit of Measurement	Source
ECI_Technology	Economic Complexity of Technology	Score (-2.5 to +2.5)	OECD [36]
ECI_Trade	Economic Complexity of Trade	Score (-2.5 to +2.5)	OECD [36]
ECI_Research	Economic Complexity of Research	Score (-2.5 to +2.5)	OECD [36]
BC	Business Confidence	Index (100 as the central point)	OECD [22]
GDP	Gross Domestic Product	Constant 2015 USD (log-transformed)	WDI [37]
GFCF	Gross Fixed Capital Formation	Constant 2015 USD (log-transformed)	WDI [37]

Least Squares (DOLS) estimation, the analysis explores how business sentiment, GDP, and GFCF impact three dimensions of economic complexity: technology (ECI_Technology), trade (ECI_Trade), and research (ECI_Research). By integrating business confidence into the complexity framework, this study fills a critical gap in the literature and expands understanding of structural transformation in emerging economies. It offers original empirical evidence on the interplay between behavioral, macroeconomic, and investment factors in shaping complexity. The findings provide guidance for policymakers seeking to harness business sentiment to advance technology, research, and trade sophistication in Indonesia.

2. Materials and Methods

2.1. Data and Variables

This study utilizes quarterly time series data for Indonesia covering the period from 2003 to 2021. The analysis focuses on three dependent variables representing different dimensions of economic complexity: the Economic Complexity Index (ECI) for Technology (ECI_Technology), Trade (ECI_Trade), and Research (ECI_Research). The primary explanatory variable is Business Confidence (BC), with two control variables included: Gross Domestic Product (GDP) and Gross Fixed Capital Formation (GFCF). Data on economic complexity are sourced from the Observatory of Economic Complexity (OEC) [36], while Business Confidence Index data are obtained from the OECD [22]. Macroeconomic indicators such as GDP and GFCF are collected from World Development Indicators (WDI) [37] and are expressed in natural logarithmic form (lnGDP and lnGFCF) to account for scale differences and reduce potential heteroscedasticity, and allow for easier interpretation of coefficients in percentage terms. Details of all variables are presented in Table 1.

2.2. Model Specification

To explore the long-run impact of business confidence and macroeconomic factors on economic complexity, the following three models are specified, each with a different dimension of ECI as the dependent variable: Model 1 is for ECI_Technology, Model 2 for ECI_Trade, and

Model 3 for ECI_Research. These models are presented in Equations 1–3.

Model 1:

$$ECI_{Technology}_t = f(BC_t, \ln GDP_t, \ln GFCF_t) \quad (1)$$

Model 2:

$$ECI_{Trade}_t = f(BC_t, \ln GDP_t, \ln GFCF_t) \quad (2)$$

Model 3:

$$ECI_{Research}_t = f(BC_t, \ln GDP_t, \ln GFCF_t) \quad (3)$$

In each model, the economic complexity index serves as the dependent variable, while BC, GDP, and GFCF act as explanatory variables. This approach allows for the separate estimation of how behavioral and macroeconomic factors influence different aspects of structural economic development.

2.3. Dynamic Ordinary Least Squares (DOLS) Estimation

To estimate the long-run relationships between the variables, the study employs DOLS method [38–41]. DOLS is particularly suitable when the regressors are non-stationary but cointegrated, as it corrects for serial correlation and endogeneity by including leads and lags of the first-differenced regressors [42, 43]. This approach has also been applied in previous studies, such as Mukhtarov et al. [44], Doğan et al. [45], van Ledden et al. [46], and Yahyaoui & Bouchoucha [47], to analyze long-run economic relationships.

The general form of the DOLS model is presented in Equation 4.

$$ECI(Technology/Trade/Research)_t = \alpha + \beta_1 BC_t + \beta_2 \ln GDP_t + \beta_3 \ln GFCF_t + \sum_{k=-q}^q \delta_k \Delta X_{t+k} + \varepsilon_t \quad (4)$$

In Equation 4, ECI_t denotes the dependent variable representing each dimension of economic complexity, including technology ($ECI_{Technology}_t$), trade (ECI_{Trade}_t), and research ($ECI_{Research}_t$) at time t . The explanatory variables include business confidence (BC_t), the natural logarithm of economic growth ($\ln GDP_t$), and the natural logarithm of gross fixed capital formation ($\ln GFCF_t$). The term ΔX_{t+k} captures the leads and lags of the first differences of the regressors, which are incorporated to address potential endogeneity and serial

Table 2. Variable definitions and data sources.

Variable	Mean	Median	Max.	Min.	Std. Dev.
BC	100.1722	100.2904	102.7678	96.7303	1.2020
ECI_Technology	-0.2607	-0.2560	-0.0045	-0.7976	0.2207
ECI_Trade	-0.2837	-0.2822	0.0203	-0.5977	0.1488
ECI_Research	-0.1820	-0.1741	0.1652	-0.6531	0.1936
lnGDP	27.3063	27.3306	27.6947	26.8287	0.2820
lnGFCF	26.1438	26.2255	26.5785	25.4721	0.3438

Table 3. Phillips-Perron unit root test results.

Variable	Level		1 st Diff.	
	t-stat.	Prob.	t-stat.	Prob.
BC	-2.8287	0.0591	-6.8520*	0.0000
ECI_Technology	-2.1385	0.2305	-8.4922*	0.0000
ECI_Trade	-9.1759*	0.0000	-9.1759*	0.0000
ECI_Research	-2.0423	0.2686	-8.4976*	0.0000
lnGDP	-1.5893	0.4830	-12.8727*	0.0001
lnGFCF	-3.4746**	0.0114	-10.6857*	0.0001

Note: * (1%) and ** (5%) significance levels.

correlation. The error term is denoted by ε_t , and q represents the number of leads and lags included in the model. This specification enables robust estimation of the long run equilibrium relationships between the explanatory variables and each component of economic complexity. Before estimating the DOLS model, preliminary tests were conducted, including stationarity tests for all variables using the Phillips-Perron (P-P) method [48], and a cointegration test based on the Johansen approach [49].

2.4. Empirical Flow and Estimation Steps

The analysis begins with descriptive statistics to provide an overview of the data. A unit root test using the Phillips-Perron (P-P) method is then conducted to assess stationarity. Next, the Johansen cointegration test is used to examine long-run relationships among the variables. Upon confirming cointegration, the Dynamic Ordinary Least Squares (DOLS) method is applied to estimate these relationships, addressing potential serial correlation and endogeneity.

3. Results and Discussion

3.1. Descriptive Statistics

The descriptive statistics, presented in Table 2, reveal several key patterns in the dataset. BC has a mean of 100.17 and a median of 100.29, with values ranging from 96.73 to 102.77 and a low standard deviation of 1.20, indicating relatively stable sentiment among Indonesian firms over time. All three ECI dimensions (technology, trade, and research) have negative mean values, suggesting that Indonesia's complexity levels remain below the global average. ECI_Technology shows a mean of -0.2607, with a range from -0.7976 to -0.0045 and a

standard deviation of 0.2207, while ECI_Trade has the lowest variability, with a mean of -0.2837, standard deviation of 0.1488, and values spanning from -0.5977 to 0.0203. ECI_Research presents a mean of -0.1820, ranging from -0.6531 to 0.1652, with a standard deviation of 0.1936, reflecting moderate dispersion in research complexity. For macroeconomic indicators, lnGDP has a mean of 27.31 and a standard deviation of 0.2820, while lnGFCF averages 26.14 with slightly higher variability, shown by a standard deviation of 0.3438 and a range from 25.47 to 26.58.

3.2. Unit Root Test

The stationarity test results shown in Table 3 indicate that most variables are non-stationary at level but become stationary after first differencing. Variables such as BC, ECI_Technology, ECI_Research, and GDP are not stationary at level, as their respective p-values exceed the 0.05 threshold. However, all of them become stationary at first difference with p-values of 0.0000, indicating strong statistical significance. ECI_Trade and GFCF show different behavior: ECI_Trade is already stationary at level ($p = 0.0000$), while GFCF is marginally stationary at level ($p = 0.0114$) and clearly stationary at first difference.

3.3. Cointegration Test

The Johansen cointegration test results presented in Table 4 indicate the presence of at least one cointegrating relationship for each ECI dimension, confirming a long-run equilibrium among the variables in the models. For ECI_Technology, both the trace statistic and the maximum eigenvalue test are significant at the 5% level at the first rank, indicating one cointegrating vector. Similarly, for ECI_Trade, the null hypothesis of no cointegration is rejected based on both trace ($p = 0.0111$)

Table 4. Results of Johansen cointegration test.

Hypothesized	Eigenvalue	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
<i>Model 1: ECI_Technology</i>					
None	0.3115	61.5404*	0.0016	27.2509	0.0551
At most 1	0.2700	34.2895**	0.0142	22.9715**	0.0273
At most 2	0.1048	11.3181	0.1927	8.0803	0.3706
At most 3	0.0434	3.2378	0.0720	3.2378	0.0720
<i>Model 2: ECI_Trade</i>					
None	0.3430	54.2755**	0.0111	30.6660**	0.0195
At most 1	0.2098	23.6095	0.2174	17.1895	0.1632
At most 2	0.0602	6.4200	0.6459	4.5287	0.7998
At most 3	0.0256	1.8913	0.1690	1.8913	0.1690
<i>Model 3: ECI_Research</i>					
None	0.3288	61.5205*	0.0016	29.1000**	0.0317
At most 1	0.2305	32.4205**	0.0244	19.1223	0.0933
At most 2	0.1174	13.2981	0.1043	9.1124	0.2769
At most 3	0.0557	4.1857**	0.0408	4.1857**	0.0408

Note: * (1%) and ** (5%) significance levels.

Table 5. DOLS estimation results.

Variable	Coeff.	Std. Err.	t-stat.	Prob.
<i>Model 1: ECI_Technology</i>				
BC	0.0985**	0.0404	2.4411	0.0187
lnGDP	-2.1446	1.4585	-1.4705	0.1485
lnGFCF	2.1716***	1.2003	1.8092	0.0773
C	-8.3281	10.5837	-0.7869	0.4356
R ²	0.8172	-	-	-
Adj. R ²	0.7175	-	-	-
<i>Model 2: ECI_Trade</i>				
BC	0.0450***	0.0232	1.9391	0.0589
lnGDP	2.0506**	0.8393	2.4433	0.0186
lnGFCF	-1.3926**	0.6907	-2.0162	0.0499
C	-24.3319*	6.0905	-3.9951	0.0002
R ²	0.8630	-	-	-
Adj. R ²	0.7882	-	-	-
<i>Model 3: ECI_Research</i>				
BC	-0.2283*	0.0464	-4.9181	0.0000
lnGDP	-3.5677**	1.6771	-2.1273	0.0390
lnGFCF	2.5098***	1.3803	1.8183	0.0758
C	54.3490*	12.1704	4.4657	0.0001
R ²	0.7819	-	-	-
Adj. R ²	0.6629	-	-	-

Note: * (1%), ** (5%), *** (10%) significance levels.

and max-eigen statistics ($p = 0.0195$), supporting one cointegrating relationship. For ECI_Research, both trace ($p = 0.0016$) and max-eigen ($p = 0.0317$) tests also confirm the existence of at least one cointegrating vector. These results validate the use of the Dynamic OLS method, as the variables in each model are cointegrated, indicating stable long-term relationships among business confidence, GDP, GFCF, and the respective ECI measures.

3.4. DOLS Estimation Test Results

The Dynamic Ordinary Least Squares (DOLS) estimation provides robust insights into the relationship between business confidence and the multidimensional structure of economic complexity in Indonesia, specifically across

technology (ECI_Technology), trade (ECI_Trade), and research (ECI_Research), as presented in Table 5.

In Model 1, where ECI_Technology serves as the dependent variable, BC exhibits a positive and statistically significant effect ($\beta = 0.0985$, $p = 0.0187$). This finding suggests that a one-point increase in BC is associated with a 0.0985-point increase in ECI_Technology. Furthermore, GFCF also demonstrates a positive and significant effect on ECI_Technology ($\beta = 2.1716$, $p = 0.0773$), indicating that a 1% increase in GFCF will boost ECI_Technology by 2.1716 points. Conversely, GDP growth is negatively associated with ECI_Technology, though the effect is not statistically significant ($p = 0.1485$).

Model 2, which examines ECI_Trade, reveals that BC positively affects ECI_Trade at a marginal level of significance ($\beta = 0.0450$, $p = 0.0589$), meaning that a one-point increase in BC will raise ECI_Trade by 0.0450 points. Notably, GDP growth exerts a positive and statistically significant impact ($\beta = 2.0506$, $p = 0.0186$), where a 1% increase in GDP will increase ECI_Trade by 2.0506 points. In contrast, GFCF displays a negative and significant relationship with ECI_Trade ($\beta = -1.3926$, $p = 0.0499$), indicating that a 1% increase in GFCF will reduce ECI_Trade by 1.3926 points.

In Model 3, where ECI_Research is the dependent variable, the impact of BC on research complexity is negative and highly significant ($\beta = -0.2283$, $p < 0.0001$), suggesting that a one-point increase in BC will reduce ECI_Research by 0.2283 points. Additionally, GDP growth is negatively and significantly associated with ECI_Research ($\beta = -3.5677$, $p = 0.0390$), meaning that a 1% increase in GDP will reduce research complexity by 3.5677 points. Conversely, GFCF shows a positive effect on ECI_Research ($\beta = 2.5098$, $p = 0.0758$), where a 1% increase in GFCF will raise ECI_Research by 2.5098 points.

The three models demonstrate strong explanatory power, as reflected by R^2 values ranging from 0.7819 to 0.8630 and adjusted R^2 values between 0.6629 and 0.7175. These results indicate that a substantial portion of the variation in economic complexity across technology, trade, and research is well explained by business confidence, GDP, and GFCF. The adjusted R^2 values, which account for model complexity, further support the validity of the estimations by confirming that the models are not overfitted and remain robust in capturing Indonesia's long-run economic complexity dynamics.

3.5. Discussion

Business confidence has a positive and significant impact on technological complexity. This indicates that when firms are optimistic about the economic environment, they are more inclined to adopt or upgrade technology [50]. This pattern aligns with Indonesia's recent trajectory, where improved business sentiment, supported by macroeconomic stability, digital transformation, and industrial modernization, has encouraged firms to enhance their technological capabilities [51, 52]. Programs such as Making Indonesia 4.0 and government incentives for technology-intensive manufacturing have enabled businesses to integrate automation, digital platforms, and process innovation more effectively. The responsiveness of technological complexity to changes in business confidence suggests that the private sector is willing to invest in applied

technologies when conditions are favorable, showing a pragmatic approach to modernization that yields immediate operational and competitive benefits. Although the impact of business confidence on technological complexity has not been specifically examined before, this study is supported by Kim et al. [53], who explored the relationship between firms and technology, and by Li & Ye [54], who examined information technology and firm performance.

Business confidence also exerts a positive impact on trade complexity. This suggests that rising optimism among firms encourages more diversified and sophisticated participation in international markets. In Indonesia, this result aligns with ongoing policy efforts to improve trade logistics, promote non-commodity exports, and support small and medium enterprises in accessing global markets. Initiatives such as export credit facilities, digital trade platforms, and participation in multilateral agreements like the Regional Comprehensive Economic Partnership (RCEP) have helped create an environment that facilitates complex trade behavior [55, 56]. However, the relatively modest effect of business confidence on trade complexity suggests that while firm sentiment plays a role, long-term export sophistication continues to depend on broader structural factors such as competitiveness, production capacity, and value-added capabilities. While not directly specific, studies by Sepehrdoust et al. [11] and Zaccaria et al. [57] support this study's findings.

In contrast, business confidence has a negative impact on research complexity. This result, although unexpected, may reflect the limited involvement of private enterprises in Indonesia's research and development ecosystem. While rising business optimism often signals a favorable investment climate, in the Indonesian context it appears to drive expansionary and commercial behavior rather than long-term investment in research [58, 59]. Most research activities remain concentrated in universities and public institutions, with minimal private sector contribution or collaboration [60, 61]. This structural imbalance suggests that during periods of economic optimism, firms may deprioritize research in favor of activities that offer quicker returns. Enhancing private sector engagement in innovation through fiscal incentives, public-private research partnerships, and targeted grant programs will be necessary to shift this dynamic and foster a more research-oriented private sector. Our findings are supported by González-Varona et al. [62], and Eden & Nielsen [63].

GDP growth shows a positive relationship with trade complexity, supporting the idea that economic expansion can improve a country's export structure [64]. In

Indonesia, this is evident through progress in shifting from raw commodity exports toward more refined products, driven by government-led downstreaming efforts in sectors like minerals and energy. However, GDP is negatively associated with technology and research complexity, indicating that growth remains concentrated in low-knowledge sectors such as extractives, construction, and domestic consumption. This highlights a structural concern: growth without innovation risks entrenching low complexity and long-term vulnerability. In contrast, gross fixed capital formation presents a more optimistic outlook, showing a positive impact on both technology and research complexity. Investment in infrastructure, industrial zones, and modern facilities has contributed to building technological capacity and research potential. Nevertheless, gross fixed capital formation negatively correlates with trade complexity, likely due to capital being directed toward non-tradable or low-complexity sectors like real estate and utilities [65]. To translate investment into export sophistication, Indonesia must redirect capital toward high-tech and export-oriented manufacturing sectors.

4. Conclusions, Implications and Limitations

This study investigates the relationship between business confidence and economic complexity in Indonesia, using quarterly data spanning from 2003 to 2021. Employing the Dynamic Ordinary Least Squares (DOLS) estimation technique, the analysis explores how business confidence, alongside macroeconomic factors such as economic growth and gross fixed capital formation, influences three key dimensions of economic complexity: Technology, trade, and research. The findings reveal that an increase in business confidence has a positive and significant effect on both technological and trade complexity, but a negative effect on research complexity. Economic growth is positively associated with trade complexity but negatively linked to both technological and research complexity. Meanwhile, gross fixed capital formation contributes positively to technological and research complexity but shows a negative relationship with trade complexity.

Based on the findings, business confidence plays a critical role in shaping the complexity of Indonesia's economy, particularly in the areas of technology, trade, and research. The positive effect of business confidence on technological and trade complexity suggests that firms are more likely to pursue innovation and expand into diverse export markets when confidence is high. However, the observed negative association with research complexity indicates that business optimism does not automatically lead to increased investment in research and development activities. This highlights a

strategic gap that businesses should address by aligning their growth strategies with long-term innovation goals, rather than focusing solely on short to medium term commercial expansion. Business leaders should consider allocating resources toward internal research capabilities, partnerships with academic institutions, or collaborative innovation networks to strengthen their position in research-intensive sectors. For policymakers, these findings suggest that incentive structures such as tax reliefs or matching grants should be designed to encourage confident firms to engage more in research-oriented initiatives. While economic growth and gross fixed capital formation play a role, their relatively limited influence reinforces the idea that business sentiment is a more dynamic and behaviorally driven driver of economic complexity.

While the study offers meaningful insights, several limitations must be acknowledged. First, the analysis focuses solely on Indonesia, which may limit the generalizability of the findings to other developing economies with different institutional and industrial structures. Second, although the DOLS model accounts for long-run relationships, it may not fully capture short-term shocks or structural breaks, particularly those related to major policy reforms or external crises. Third, business confidence is treated as an aggregate index, which may mask sectoral differences in sentiment and response to policy changes. Future research could address these limitations by incorporating panel data across countries, applying non-linear or regime-switching models, and disaggregating business confidence by sector or firm size to gain a more granular understanding of its effects on economic complexity. Moreover, exploring interactions between business sentiment and innovation-specific policies could further enrich the policy relevance of this line of inquiry.

Author Contributions: Conceptualization, G.M.I. and D.B.W.; methodology, G.M.I. and D.B.W.; software, G.M.I. and D.B.W.; validation, D.B.W.; formal analysis, G.M.I. and D.B.W.; investigation, G.M.I.; resources, G.M.I. and D.B.W.; data curation, D.B.W.; writing—original draft preparation, G.M.I. and D.B.W.; writing—review and editing, G.M.I.; visualization, G.M.I.; supervision, D.B.W.; project administration, D.B.W.; All authors have read and agreed to the published version of the manuscript.

Funding: There is no institutional funding for this research.

Data Availability Statement: The data used in this study is available upon request from the corresponding author.

Acknowledgments: The authors express their gratitude to their institutions and universities.

Conflicts of Interest: All the authors declare no conflicts of interest.

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