

# The impact of technological innovations on economic complexity in South Africa

## Someleze Sithole, Thobeka Ncanywa, Dorah Dubihlela\*

Department of Business Management & Economics, Faculty of Economic and Financial Sciences, Walter Sisulu University, Mthatha 5099, South Africa

\* Corresponding author: Dorah Dubihlela, ddubihlela@wsu.ac.za

#### CITATION

Article

Sithole S, Ncanywa T, Dubihlela D. (2024). The impact of technological innovations on economic complexity in South Africa. Journal of Infrastructure, Policy and Development. 8(9): 7355. https://doi.org/10.24294/jipd.v8i9.7355

#### ARTICLE INFO

Received: 23 June 2024 Accepted: 24 July 2024 Available online: 6 September 2024





Copyright © 2024 by author(s). Journal of Infrastructure, Policy and Development is published by EnPress Publisher, LLC. This work is licensed under the Creative Commons Attribution (CC BY) license. https://creativecommons.org/licenses/ by/4.0/

Abstract: Technological innovation allows nations to produce sophisticated products more efficiently and at higher quality to increase exports. Countries that aim to produce and export sophisticated products can improve their economic complexity and lead to the country's economic development. Hence, the study investigates the impact of technological innovation on economic complexity in South Africa. Technological innovation, exports, and manufactured products were used as variables to examine South Africa's economic complexity index. The study employed the ARDL method to determine the relationship among the variables. The ARDL F-bounds test reflected the long-run cointegration among the selected variables. The study produced long-run positive estimates of technological innovation, exports, and manufactured products on economic complexity, however, manufactured products and exports were insignificant. Granger causality indicated unidirectional causality on economic complexity to manufactured products, exports to technological innovation, and a bi-directional causal effect from exports to economic complexity and technological innovation to economic complexity. The study recommends that South Africa focus on innovation, create more diversified and sophisticated products and processes, and promote more manufacturing firms, particularly Agri-processed products.

**Keywords:** economic complexity; technological innovation; exports; manufactured products; autoregressive distributed lag model (ARDL); granger causality

## **1. Introduction**

Countries that aim to produce and export sophisticated products can improve their economic complexity and realize economic development (Hidalgo, 2021). Economic complexity is a phenomenon that necessitates an economy's enhancement of its productive capability by exporting a combination of sophisticated products (Ralarala and Ncanywa, 2019). If a country can export many exclusive complex commodities, it can enhance its economic complexity. Complexity represents the progress of economies' knowledge and technology, from manufacturing to exports (Erkan and Yildirimci, 2015). Economic complexity index (ECI) is utilized to measure each economy's productive ability by examining the knowledge it invested in its products and exports (Claudia et al., 2021). Economic complexity reflects the country's exportation and production of diverse and ubiquitous products. Products considered the most complex range from machinery to metals to chemicals, while the least uncomplex products are raw products such as raw gold, agricultural products, or textiles (Hidalgo, 2021).

Countries leading in economic complexity globally are Japan, Switzerland, Germany, and South Korea, while the least in economic complexity are Papua New

Guinea, Gabon, Liberia, and Angola (Atlas of Economic Complexity, 2021). Molele and Ncanywa (2022) reflect on some recent studies that show countries with expanding production and technological advancement can be at the top of the ranking list on ECI and have an advantage in export competitiveness. Rubbo et al. (2021) state that low-income countries export fewer complex products, implying that the inability to export the product results in low productivity or quality. High-income economies export more complex products, resulting in high income, high production, and improved economic development.

Innovation is crucial for economic progress that benefits the whole economy (Claudia et al., 2021). Economically, innovation significantly contributes to clarifying the economic performance of institutions and regional development over time. According to the European Central Banks (ECB) (2023), innovation encompasses creating and utilizing the application of technologies that enhance products, services, or efficient production to enhance value. Technology is an essential driver of the economic growth of nations, and technological innovation permits nations to produce goods and services more efficiently and at higher quality to promote exports (Ricardo and Jose, 2023). Solow's model states that an increase in the stock of knowledge available for production is caused by technological innovation (Wang and Xu, 2021). South Africa possesses abundant natural resources, including agricultural products and minerals, but structural transformation is still needed (Monga, 2018; Ncanywa, 2021; Perez and Claveria, 2020).

Monga (2018) considers South Africa a trapped country in exporting unprocessed minerals. It is rated 59 in the ECI (Atlas of Economic Complexity, 2021). Most countries have formed partnerships in anticipation of attracting economic innovation that would reflect on their economies. Brazil, Russia, India, China and South Africa (BRICS) economies have the potential to equip themselves economically and technologically as world leaders, and BRICS presents higher levels of economic development (Nuno et al., 2021). For instance, South Africa partnered with BRICS and exported to various countries. Brazil is rated 49, Russia 45, India 41, China 25, and South Africa 59 on the ECI ranking list (The Observatory of Economic Complexity, 2021). The emerging countries' production characteristics differ from the developed countries as China is a global producer, Brazil is a great grain exporter, India is a great exporter of a qualified technological workforce, and Russia is a global energy exporter (Rubbo et al., 2021). Hence, this paper examines the impact of technological innovations on economic complexity in South Africa.

This study intends to add value to the literature by examining the knowledge on the topic of technological innovation and economic complexity in South Africa. Some scholars have contributed to the literature regarding the essence of economic complexity as a significant factor on developed and developing nations (Erkan and Yildirimci, 2015; Hidalgo, 2021; Ncanywa, 2021). This study uses a time series data Moreover, ARDL method is utilized to determine both the short-and long-term impact of technological innovations on economic complexity and encompassing the Granger causality test permits to explore the cruciality of the causal effects of amongst the variables. The findings are expected to give a valuable guidance for policymakers in building an effective economic complexity.

## 2. Literature review

## 2.1. Theoretical literature

The Solow Growth model entails innovation and knowledge, leading to the economy's growth rate, as technology is important. The study employed Solow and Swan's (1956) Growth model. This model explains the stable growth rate of an economy when the economic forces are into play: Capital, labour, and technological progress. This study focuses on the production function side of the model. The Solow growth model theory states that labour and capital determine the economic short-term equilibrium in the production process and argues that technological change significantly influences the functioning of an economy (Corporate Finance Institute, 2022). Additionally, the total output is determined by labour and capital. Still, the significant increase in total output is caused by the implementation of technology progress through increasing efficiency of labour productivity (CFI, 2022). However, technological knowledge in product diversification emphasizes the intense application of economic complexity (Serhrdoust et al., 2019).

The Posner (1961) model explains a country that adopted technological advancement as a major source of trade to expand its production specialization and exports. Dosi et al. (2015) and Soete (1981) addressed the technology gaps as a technological innovation that some of the countries achieved. Technological advancements significantly pose an effective export via enhancements in production efficiency (Oliveira, 2017). According to Oliveira (2017), technological innovations are crucial in trade and expanding product specialization.

Vernon (1966) further extended the technology gap model, explaining that technological changes have become the new vital key factor of economic trade. Pasinetti (1981) raised the Ricardian comparative advantage as an imperative key to innovation, and Dosi et al. (1990) believed technological advancement to be a key factor in absolute advantage. The endogenous growth model production function is formulated through the "AK (Knowledge, Capital)" growth model identified in the work of Romer (1986). In this formulation, the growth of capital and knowledge (technology) depends on capital expansion because capital intensification encourages technological spill-overs that increase the capital's marginal productivity throughout the economy. Any increase in total K will, therefore, raise A and the productivity of all firms. Developing economies should specialize in comparative advantage in production and export (Seperhrdous et al., 2019). Additionally, export and production diversification leads to improved technological progress in economic development that improves economic complexity.

The export-led growth strategy was developed by W. Max Corden in the 1950s. This strategy was based on the idea that an economy could enhance economic growth by deepening its exports (Palley, 2012). Smith (2001) postulated that export diversification is crucial in boosting economic growth. This strategy elaborated that the overall growth of economies can be generated not only by expanding the amounts of capital and labour, but also by increasing exports. Max Corden believed that export diversification is imperative for a country's growth (Smith, 2001). Shirazi and Manap (2005) note that this theory explains export augmentation foremost to improve

resource distributions, generate production efficiency through technological advancement, employment, and capital formation, and enhance economies of scale and production.

#### 2.2. Empirical literature

Zhou and Gao (2017) computed the economic complexity of provinces in China by analysing data from over 25 years. The study estimated the geographical economic complexity index (ECI), and it emerged that the ECI of the regions had generally been slow and steady over time. In applying economic complexity to economic development and income disparity, it was found that the descriptive power of ECI was constructive for the former but negative for the latter. However, the study contrasted how the monetary macroeconomic indicators related to economic diversity. The findings showed that ECI and non-linear iteration-based fitness index were comparable, and both had a tremendously more descriptive power than other benchmark metrics. Additionally, multivariate regressions observed that the study outcomes were powerful, after adjusting for other socioeconomic factors.

Coskun et al. (2018) conducted a study to locate the ranking of Turkey among dissimilar economies. Furthermore, they analyzed why Turkey has a small GDP per capita according to export structure and current production. To determine the number of economic complexity factors (export sophistication, product sophistication, diversification, and open forest), the study used the export data (STIC Rec. 4-3 digit). According to the study, Turkey is a highly industrialized nation, but the existing industrial structure focuses on producing fewer complex goods. As a result, the nation's GDP per capita is regarded as below its potential in PPP terms.

Neagu (2019) investigated the link between carbon emissions and economic complexity in 25 chosen European Union nations from 1995 to 2017. The Environmental Kuznets Curve (EKC) model was employed. The paper examined the cointegrating polynomial regression (CPR) for penal data framework and simple time series for separate economies. According to the model, the primary factor influencing carbon emissions is energy intensity. The model showed that pollution accumulates when economies strengthen the product sophistications they export. After a certain point, the augment in economic complexity suppresses the pollutant emissions. The carbon emission patterns revealed an inverted U-shaped curve depending on the economic complexity. The long-run cointegration among carbon emissions, economic complexity, and energy intensity were examined. The results reflected that an increase of 10% in energy would lead to a 3.9% deepen in carbon emissions.

In Africa, William and Shodi (2021) examined the role of economic complexity in the sustainable development and environmental sustainability of Africa's 10 uppermost exporting economies, constituting 78% of the total trade for the continent from 2000–2018. The study employed a non-parametric time-varying technique with a fixed effect method and a parametric common correlated effects mean group estimation method. The paper revealed that, while economic complexity is a justifiable factor in determining export competitiveness, the study showed that its impact was not extremely influential, like trade openness, GDP, foreign direct investment, and exchange rate. The researchers recommended that the government embrace substantial trade policy reforms that consider the country's economic complexity alongside other factors such as economic growth, exchange rate, foreign direct investment, and trade openness. Rojas and Correa (2021) investigated economic growth, economic complexity, and CO<sub>2</sub> emission in 86 countries, and this study incorporated African countries such as Ghana, Algeria, Cameroon, and Angola from 1971 to 2014. The Sasabuchu-Lind-Mehlum (SLM) test, Dynamic panel data methodologies, and the Adaptive Neuro-Fuzzy Inference system (ANFIS) model were utilized in the study. The outcomes showed no explicit evidence in favour of the EKC theory, production quantities, and production intelligence. The study also stated that only high-income economies experience a symmetrical decline in pollution levels and a surge in ECI.

Ngueda and Kelly (2022) examined the correlation between economic complexity and foreign direct investment in the Sub-Saharan nations from 1998 to 2018. The ordinary least square technique was employed, and the research illustrated that foreign direct investment was advantageous to global economic complexity. The results were obtained using Quantile regression and Fixed effects Hypothesis Estimations. The outcomes indicated that trade, GDP, education, and urbanization had a beneficial effect on the economic intelligence of the economies in Sub-Saharan nations. The researchers recommended that policies such as the provision of credits, investment promotion, innovation, and the adoption of transparent governance should be implemented to boost the FDI and contribute to the economic complexity of the economies.

Ralarala and Ncanywa (2019) investigated the link between the economic complexity index and monetary policy lending rates in selected Sub-Saharan African countries. The study used panel ARDL to examine the ECI-lending rate nexus. Both Kao and Johansen's cointegration exhibited a substantial long-term relationship. The long-run outcomes demonstrated that ECI is adverse and significant on monetary lending rates. At a significant rate of 25 percent, the equilibrium could be corrected. The findings suggested new ideas that could enhance the formulation of appropriate economic policies to decrease interest rates for borrowing. Chauke and Ncanywa (2021) investigated the impact of investing in infrastructure development on economic complexity in South Africa from 1960 to 2018. The ARDL technique was employed to determine the short-run and long-run equation. The study outcomes reflected that investing in government economic infrastructure is significant and affects economic complexity. Investing in social and public corporations' infrastructure can be beneficial to economic complexity. The study suggested that to enhance the lives of the citizens, stimulate the economy, attract the FDI, and generate employment, the government should improve policies that aid industrial development that is targeted to encourage the economic infrastructure and should particularly prioritize special economic zones.

Kelly et al. (2022) investigated the effect of economic complexity on the depletion of natural resources in Sub-Saharan Africa from 1998 to 2019, and South Africa was selected. The study utilized the ordinary least squares fixed effects estimation method. The study outcomes indicated that economic sophistication and urbanization contribute to the depletion of natural resources. The generalized least squares random effects are employed to check robustness, and quintile regression aligns the natural resources and economic complexity depletion to have a relationship

in Sub-Saharan economies. Djeunankan et al. (2023) examined the long-run effects of economic complexity on energy efficiency in 93 economies. Algeria, Cameroon, and South Africa were among the countries. The data spanned the years 1995–2015. The investigation outcomes showed that economic complexity enhances energy efficiency. The study observed that economic growth and population density escalate energy efficiency and hinder trade. The mediation analysis was used and revealed that 38% and 63% of the effect of economic complexity on energy efficiency were mediated through human capital accumulation and income inequality reduction respectively.

Can et al. (2022) explored the effect of economic complexity on energy consumption in 21 developed nations and 44 developing nations, and South Africa was among the list of developing nations. The period of the study was from 1971 to 2014. The study employed cointegration with structural breaks and Durbin-H panel cointegrations to examine the long-run relationship. The Augmented mean group technique was employed. The outcomes showed that in developing nations, higher economic complexity leads to increased energy consumption. In contrast, in developed nations, economic complexity results in declined energy consumption. Taha et al. (2022) explored the dynamic link between FDI, economic complexity, renewable energy, natural resources, urbanization, and CO<sub>2</sub> emission in BRICS economies using a panel data for 1990–2019. The augmented mean group and fully modified-ordinary least squares estimators were employed. Study outcomes, through the pollution haven hypothesis, suggest that FDI enhances environmental degradation in BRICS economies. Renewable energy, urbanization, and ECI were found to have a detrimental effect on emissions, while urbanization and natural resources had a constructive contribution to the environment. Dumitrescu and Hurlin causality showed a bidirectional causality between the economic complexity and CO<sub>2</sub> emission. Similarly, ECI, urbanization, and CO<sub>2</sub> were found to be bidirectional and between FDI and CO<sub>2</sub>, the causality was unidirectional.

## 3. Research methodology

## 3.1. Model specification and data

The study used annual data from 1998–2022 to inspect the impact of technological innovations on economic complexity in South Africa. Data for the ECI were obtained from the MIT Atlas of Economic Complexity, and for the independent variables (Export products and Manufactured products), data were extracted from the World Bank. Data for Technological innovation was acquired from the South African Reserve Bank (SARB). The period is chosen based on data availability. The study found it essential to examine the impact of three independent variables (technological innovations, export products, and manufactured products) on ECI. Coskun et al. (2018) observe that an improved economic complexity matters for economic performance. This study adapted Ncanywa's (2021) model, examining how information systems can affect economic complexity in South Africa. The model of the study is presented below:

$$ECI_t = \alpha + INV(IS)_t + CPI_t + GDP_t + \varepsilon_t$$
(1)

ECI represents economic complexity; INV(IS) is an investment in information systems proxy by Gross fixed capital formation on information, computer, and communications equipment, and GDP represents the gross domestic product. Therefore, the model of this study is formulated as follows:

$$ECI = f(TCN, EXP, MP)$$
(2)

From the above equation, the economic complexity index is assumed to be a function of technological innovation (patents), exports, and manufactured products. Therefore, the Equation (2) can be presented as follows:

$$ECI_t = \beta_0 + \beta_1 TCN_t + \beta_2 EXP_t + \beta_3 MP_t + \varepsilon_t$$
(3)

In Equation (3), *ECI* represents the economic complexity index, *TCN* is the technological innovations (patents), *EXP* is the export and *MP* denotes the manufactured products. The study adopted the empirical model of Ncanywa (2021), Ricardo and Oliveira (2017), Balland et al. (2021), and other reviewed scholars to exploit the link between the dependent and independent variables. The study adopted *ECI*; *TCN* is the technological innovations as a new variable, *EXP* is the export products adopted and *MP* is added manufactured product (processed goods and services),  $\beta_0$  represents the model's intercept,  $\beta_1 - \beta_3$  are unknown parameters of the model to be estimated, and the  $\varepsilon_t$  the error term was adopted to incorporate all other factors that are not included but impact the model.

## **3.2. Estimation techniques**

Firstly, this study makes use of unit root tests suggested by David Dickey and Wayne Fuller, known as the Augmented Dickey-Fuller test (1979), and Peter C.B. Phillips and Pierre Perron, known as Phillips Perron (1988) and employed the informal graphical method of testing for unit root. The Dickey-Fuller (1979) test holds significance in evaluating the null hypothesis of the presence of a unit root in an autoregressive (AR) time series model. The alternative hypothesis varies according to the version of the test utilized but generally follows either trend stationarity or nonstationarity (Tugcu et al., 2020). The Phillips Perron test (1988) is a unit root test utilized to determine whether a time series is integrated at order 1 (Myovella and Kisava, 2017). The Dickey-Fuller test (DF) of the null hypothesis p equals 0 determines the first difference operator in the equation; increments difference operator in the equation,  $\Delta y_t = P y_{t-1} + \mu_t$ ,  $\Delta$  (Sanderson, 2018). PP identifies the issue that autoregressive  $y_t$  might have a higher order than what is conceded in the equation forming  $y_{t-1}$  endogenous, which would undermine the DF test (Tugcu et al., 2020). The problem of generating regressors in the test equation by using lag  $\Delta y_t$  as a regressor is addressed by the ADF test, and the PP test creates a non-parametric correlation with the appropriate *t*-test statistic (Tugcu et al., 2020). PP test is vigorous in terms of undefined autocorrelation and heteroscedasticity in the disturbance process of the test equation.

#### 3.3. Co-integration: ARDL test

To investigate the impact of technological innovations on economic complexity in South Africa, this study employed an Autoregressive distributed lag (ARDL) method to review the short-run and long-run among variables. The ARDL model bound test was created by Pesaran et al. (2001) and permits ascertaining long-run relations existing in variables (Nasrullah et al., 2021). The ARDL model follows the least square method by incorporating values of both dependent and independent variables as predictors (Molele, 2022). This study's data properties accommodate the use of Autoregressive Distributed Lag (ARDL) approach. Firstly, the ARDL works when the variables are stationary on I (0), I (1), or both. Additionally, we cannot use ARDL if any of the variables under investigation is stationary at the second difference (Chetty, 2018). Secondly, ARDL concurrently represents the short-run and long-run equations (Nkoro and Uko, 2016). Thirdly, the technique is appropriate for a small amount of observation. This method can also integrate structural breaks in time series data (Molele, 2022). This condition is imperative for examining the long-run relationship among economic complexity, technological innovation, exports and manufactured products have different integration orders. Next, the study employed the Granger causality test to determine that one variable is a factor and provides useful information for predicting another variable (Li, 2020). The Granger causality holds a key that a variable  $\{x_i, t\}$  is Granger causality of another variable  $\{x_i, t\}$  and incorporation of the past values of  $x_i$  improves the projection of  $x_j$  over the useful information of the past value of  $x_i$  alone. Impulse response and variance decomposition and diagnostic tests were performed, as well.

# 4. Results and discussion

#### 4.1. Correlation

**Table 1** examines the correlation between the timeseries variables of the study. Qoko, Sibanda and Senzangakhona (2024) concur in their study that this test is very crucial in determining that the model is free from the issues of multicollinearity or collinearity. **Table 1** shows that Exports (EXP) is correlated with value of -309026 to manufactured products (MP), followed by -0.360700, which is exports (EXP) to technological innovation (TCN) and followed by -0.231968, which is technological innovation (TCN) to manufactured products (MP). Therefore, there is no signs of multicollinearity between the explanatory variable in any of the values.

Table 1. Conclutions matrix.					
	EXP	МР	TCN		
EXP	1	-0.309026	-0.360700		
MP	-0.309026	1	-0.231968		
TCN	-0.360700	-0.231968	1		

Table 1. Correlations matrix.

Source: Authors' computation from Eviews10.

## 4.2. Formal unit root test

The ADF test and PP test are utilized in this section to present the stationarity of the selected time series variables. The study made use of the Autoregressive Distributed Lag (ARDL) model as it accounts that the variables should be stationary at I (0) or I (1), not I (2) (Nkoro and Uko, 2016). In **Table 2**, the ADF and PP outcomes are demonstrated, indicating that all variables are stationary after the first difference. The study noted that the ECI as a dependent variable is stationary after first differencing I (1), and the independent variables (Technological innovation, exports,

and manufactured products) are stationary after first differencing I (1). These results permit the use of the ARDL model suggested by Pesaran et al. (2001).

Variables	Test Method	<b>Test Equation</b>	Level	First Difference
		Intercept	-1.426	-8.475***
ECI	ADF	Intercept and trend	-2.862	-3.821***
		None	-1.834*	-
		Intercept	-1.292	-8.532***
-	PP	Intercept and trend	-2.981	-10.557***
		None	-2.062***	-
		Intercept	-1.380	-6.830***
LTCN	ADF	Intercept and trend	-2.843**	-
		None	-0.581	-6.926***
		Intercept	-1.282	-6.830***
-	PP	Intercept and trend	-2.843***	-
		None	-0.357	-6.926***
		Intercept	-2.107	-4.992***
LEXP	ADF	Intercept and trend	-4.139***	-
		None	0.853	-4.905***
		Intercept	-2.033	-5.566***
-	PP	Intercept and trend	-2.831	-5.385***
		None	1.704**	-
		Intercept	-1.131	-3.660***
LMP	ADF	Intercept and trend	-0.820	-3.651***
		None	-2.949***	-
		Intercept	-1.131	-3.660***
-	PP	Intercept and trend	-1.034	-3.680***
		None	-2.949***	-

Table 2. ADF and PP tests.

Source: Authors' computation from Eviews10.

Note: \*, \*\*, \*\*\* represent significance at 10%, 5%, and 1%, respectively.

## 4.3. Optimal lag length selection criterion

According to Nguyen et al. (2020) an unfit selection of lag criterion can result inan ineffective model, specifically, a lag period that is too short will result in an inaccurate representation of data generation process, while a lag period that is too big will cause the model to suffer from a lack of degrees of freedom and inaccurate estimations. Hence, to ensure the fit of the model, we follow the standard method in the literature (Nguyen et al, 2020) and choose a lag of 3 as provided by LR, FPE, AIC, SC and HQ criteria in **Table 3**.

Lag	LogL	LR	FPE	AIC	SC	НО
0	53.56360	NA	$1.30 \times 10^{-7}$	-4.505781	-4.307410	-4.459051
1	114.9335	94.84444	$2.17 \times 10^{-9}$	-8.630320	-7.638464	-8.396669
2	133.2795	21.68166	$2.08 \times 10^{-9}$	-8.843595	-7.058253	-8.423022
3	179.3332	37.68025*	$2.23\times10^{-10} *$	-11.57574*	-8.996916*	-10.96825*

Table 3. Optimal selection lag criterion.

Source: Authors' computation from Eviews10.

Note: \* Indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion and HQ: Hannan-Quinn information criterion.

#### 4.4. ARDL-Bounds test

The study exploits the ADRL bounds test formulated by Pesaran et al. (2001) to examine if there is a long-run relationship between Economic complexity, Technological innovation, Exports, and Manufactured products as they are the selected variables.

**Table 4** reflects the ARDL Bounds test for the Cointegration test. The evaluated F-stats is 12.46, surpassing the upper bound of the critical value of 1% (5.61) and 5% (4.35). Hence, the null hypothesis of no cointegration is rejected, implying that any deviations from this cointegration will be corrected over time. Scholars such as Nkoro and Uko (2016), Amir and Bashair (2019), Ncanywa (2021), Molele and Ncanywa (2022), Nkoro and Uko (2023) concurred that the presence of cointegration between the series signifies the long-run link among the variables.

Null hypothesis: No levels relationship					
Test statistics	Value	k			
F-statistics	12.45694	3			
<b>Critical Value Bounds</b>					
Significance	I (0)	I (1)			
10%	2.72	3.77			
5%	3.23	4.35			
2.5%	3.69	4.89			
1%	4.29	5.61			

Table 4. ARDL approach to cointegration.

Source: Authors' computation from Eviews10.

#### 4.5. ARDL long-run results

Content deleted as requested. **Table 5** provides the long-run equation of technological innovation (LTCN), exports (LEXP), and manufactured products (LMP) on economic complexity (ECI).

The results in **Table 5** show that technological innovation, exports, and manufactured products positively affect economic complexity. Exports are positive for economic complexity and statistically insignificant in South Africa. Based on this specific variable (Technological innovation), these results produced alignment will consider the theory of Posner (1961) that explains if an economy adopts technological advancement as an imperative source of trade to increase its production specialization

and exports. Pasinetti (1981) outstretched that technological progress is an indispensable key to innovation and production specialization. Oliveira (2017) mentioned it as a crucial factor in trade and enhancing economic growth and the development of economies.

**Table 5.** ARDL long-run outcomes.

Variables	coefficients	Std. Error	t-stats	Prob	
LTCN	0.664587	0.342170	1.942271	0.0054	
LEXP	4.636977	3.922375	1.182186	0.3586	
LMP	0.736406	0.765583	0.961889	0.4376	

Source: Authors' computation from Eviews10.

Note: Dependent variable: Economic complexity index.

According to the study by Breitenbach et al. (2021), low-income economies have limited diversity and complexity in their exports, which leaves them more vulnerable to external shocks. Manufactured products positively affect economic complexity and insignificant. The positive effect shows that any 1% rise in manufactured products contributes to a 0.736% increase in economic complexity. Scholars such as Bhorat et al. (2019) elaborate that less developed economies, such as South Africa, are involved in exports of agricultural commodities, and the production sector is rooted in the export of less complex goods. The study considered the Slow Growth theory to transform the economic structures from agricultural productivity into more modern industrialized heterogeneous manufacturing products.

## 4.6. ARDL short-run equation and error correction model results

This subsection examines the estimates of short-run equation and an error correction term among the variables utilizing an ARDL method.

As exhibited in **Table 6**, the positive correlation shows that any 1% increase in exports contributes a positive input increase of 0.80 on economic complexity. These results concur with Moralles et al. (2022) indicated that export diversification of complexed products enhances economic complexity.

Variables	Coefficient	Std. Error	t-Statistic	Prob.
С	-8.464100	0.756892	-11.18271	0.0079
D(LEXP)	0.804789	0.074555	10.79463	0.0085
D(LMP)	1.186139	0.139499	8.502825	0.0136
D(LTCN)	0.027472	0.012817	2.143424	0.1653
CointEq (-1)	-0.393898	0.035292	-11.16107	0.0079

Table 6. ARDL short-run equation and ECM outcomes.

Source: Authors' computation from Eviews10.

Note: CointEq (-1) means cointegrating equation.

The positive correlation shows that any 1% increase in manufactured products contributes a positive input of 1.18 increase in economic complexity. This outcome aligns with Ngueda and Kelly (2022) findings, which shows diversification of products and complexed products play an indispensable role in improving economic complexity and contributes significant economic growth.

The positive correlation shows that any 1% increase in technological innovation contributes a positive input of 0.02 increase on economic complexity. (Koelble, 2021) argues that South Africa is viewed as a low-income country and technological innovation is seen as a challenge to implement and is seen as lacking human capital and Hlongwane (2020) mentioned that the attraction of foreign direct investment might improve the technological progress in less developed economies.

The error correction term (ECM) should be a negative numeral and significant to ascertain the speed of adjustment and correlation between the short- and long-run variables and the return to its equilibrium (Biswas and Durgia, 2020). The adjustment speed is negative at a rate of -0.39 and statistically significant at the 1% level, which was expected. Therefore, there is a stable long-term relationship. This elucidates that any short-run imbalances will be corrected back to equilibrium and 40% of these imbalances will be resolved within the initial period. In conclusion, all the determined variables were found to improve economic complexity index significantly. Therefore, the error correction significance level magnifies the evidence of a stable long-term relationship.

## 4.7. Granger causality test results

Table 7 provides the causality test results among the variables for 1998–2022. The causality checks on economic complexity to exports, the *p*-value obtained is 0.14, indicating that economic complexity does not cause exports according to the Granger causality test, and the null hypothesis of no causality is failed to be rejected. These causality outcomes concur with Tabash et al. (2024) findings, in which their study also found the bidirectional causal linkage between exports and economic complexity. Moreover, according to the Granger causality test, manufactured products do not foremost to economic complexity. This means there is no causal interrelation among these variables, as demonstrated by a *p*-value of 0.23, which fails to reject the null hypothesis of no causality. Conversely, there is a causal link between economic complexity and manufactured products based on an economic complexity-causing manufactured products with a value of 0.0254 at a 5% significance level, rejecting the null hypothesis. Lima et al. (2022) produced similar finding such of this study that manufactured products and economic complexity produce a unidirectional causal effect. Regarding technological innovation's impact on economic complexity, the pvalue is at 0.21, indicating no direct influence. Likewise, on whether economic complexity indicates no causal effect on technological innovation, the p-value was maintained at 0.39, and both variables did not reject the null hypothesis of causality. Yu et al. (2022) also found the bidirectional causal effect between economic complexity and technological innovation in N-11 countries. Manufactured products Granger causes exports at 0.0183 at a significance level obtained at *p*-value at 1%, rejecting the idea of no causality. The empirical evidence that was conducted by Uysal and Sat (2019) is consistent with the result of this study, in which they found unidirectional causal between manufactured products and exports as this study also obtained unidirectional effect between the two variables. Technological innovation does not impact exports, as indicated by the *p*-value of 0.4411, failing to reject the null hypothesis of no causality. Moreover, exports have a causal influence on technological innovation, with a *p*-value of 0.0058, which is significant at 1%, rejecting the null hypothesis of no causality. According to the empirical evidence of Filipescu et al. (2013) exports and technological innovation have a direct relationship and their causality outcomes were unidirectional between the two variables. Also, Maradana et al. (2017) found consistent outcome that exports, and technological innovation have a unidirectional causal effect. Technological innovation has no causal effect on manufactured products at 0.4234 *p*-values, which cannot reject the null hypothesis. Nonetheless, manufactured products have a direct influence on technological innovation with a value of 0.0059 at a 1% significance level, rejecting the null hypothesis. Mohamed et al. (2022) conducted a study significantly rooted in the causality between technological innovation and economic growth in developing nations and their study findings produced similar findings as unidirectional effect between technological innovation and manufactured products.

Null Hypothesis:	Obs	F-Statistic	Prob.
LEXP does not Granger Cause ECI	23	1.80339	0.1933
ECI does not Granger Cause LEXP	23	2.22946	0.1364
LMP does not Granger Cause ECI	23	1.61260	0.2269
ECI does not Granger Cause LMP	23	4.53456	0.0254
LTCN does not Granger Cause ECI	23	1.71222	0.2086
ECI does not Granger Cause LTCN	23	0.97929	0.3947
LMP does not Granger Cause LEXP	23	5.03536	0.0183
LEXP does not Granger Cause LMP	23	0.14452	0.8664
LTCN does not Granger Cause LEXP	23	0.85686	0.4411
LEXP does not Granger Cause LTCN	23	6.95238	0.0058
LTCN does not Granger Cause LMP	23	0.90174	0.4234
LMP does not Granger Cause LTCN	23	6.90761	0.0059

Table 7. Causality test.

Source: Authors' computation from Eviews10.

#### 4.8. Diagnostic results

The study used the Jarque-Bera test for normality, the Ljung Box test for serial correlation between the variables, and homoscedasticity using Breusch-Pagan Godfrey.

**Table 8** shows the computed chi-squared value indicates a *p*-value of 0.008 lower than the 0.05 level and significant, at 1% leading to rejection of the null hypothesis and indicating correlation among variables.

Table 8. Breusch-Godfrey serial correlation LM test.

F-statistic	0.499646	Prob. F	0.6083		
Obs × R-squared	6.996694	Prob. Chi-squared	0.0082		
Source: Authons' commutation from Eviewa10					

Source: Authors' computation from Eviews10.

According to **Table 9**, Breusch-Pagan Godfrey test, the *p*-value is 0.28, which fails to reject the null hypothesis regarding homoscedasticity confirming its existence. In other words, there are no indications of heteroscedasticity in the residuals.

		8 3	
F-statistic	13.80340	Prob. F (18, 2)	0.0696
Obs R-squared	20.83231	Prob. Chi-squared	0.2880
Scaled explained SS	0.168448	Prob. Chi-squared	1.0000

Table 9. Breusch-Pagan-Godfrey.

Source: Authors' computation from Eviews10.

Note: Obs R-squared- the number of observation multiply to R-square.

Table 10 and Figure 1 provide the JB model, which exhibits a bell-shaped distribution and meets the normal conditions. The kurtosis is 2.78, less than 3 (platykurtic), and skewness is negative -0.107 (long left tail). The diagnostic results of the Jarque-Bera test yield a *p*-value of 0.96, which exceeds the 5% significance level. This shows that the null hypothesis is not rejected at 0.05 level, indicating the distribution of residuals.

 Table 10. Normality test.

 Kurtosis
 2.782

 Skewness
 -0.107

 Jarque-Bera
 0.082

 Prob
 0.95

Source: Authors' computation from Eviews10.



**Figure 1.** Results of the test for skewness of the residuals (Jarque-Bera). Source: Authors' computation from Eviews10.

#### **4.9.** Impulse response function results (IRF)

The IRF is shown in **Figure 2** between the selected variables (economic complexity, exports, technological innovation, and manufactured products), 1998–2022, in South Africa.

The response is positive from all the variables, but LMP is negative until the 7th, then, to the last period, has a positive shock effect on the economic complexity (LMP). These results are in line with empirical findings of Kahn et al. (2022) that South Africa lagging in technological progress and innovation (Kahn et al., 2022).

## Response to Cholesky One S.D. (d.f. adjusted) Innovations



Figure 2. Response of ECI.

Source: Authors' computation from Eviews10.

#### 4.10. Variance decomposition results

The contribution of each variable in the model is discerned by their changes over time (Sepehrdoust et al., 2019), and for that, the variance of decomposition analysis was used.

**Table 11** reports that economic complexity elucidates 100% of its variation in the first period. The 2nd period explains 79% variance of its own; all other variables show the remaining 19% of innovative shock. The economic complexity seems to have significant values of innovative shock from the 1st to the 5th quarter, which stipulated that economic complexity is mainly shocked by its innovation.

Periods	S. E	ECI	LEXP	LTCN	LMP
1	0.042214	100.0000	0.000000	0.000000	0.000000
2	0.047958	79.51385	7.979466	3.861880	8.644804
3	0.063296	57.56356	18.69676	17.55479	6.184888
4	0.067984	54.10640	23.66503	16.75793	5.470636
5	0.073567	49.99549	20.90116	20.64342	8.459934
6	0.076334	48.89039	19.44735	21.25434	10.40792
7	0.079444	46.72296	17.97464	20.98452	14.31788
8	0.082636	44.28718	16.86283	19.87370	18.97628
9	0.086433	41.37536	16.32454	18.23667	24.06343
10	0.090870	38.15000	16.34861	16.50042	29.00097

Table 11. Variance decomposition of ECI outcomes.

Source: Authors' computation from Eviews10.

## 4.11. CUSUM test and CUSUM of square results

**Figure 3** provides the results for the CUSUM test and CUSUM of squares test of selected time series variables. The hypothesis exhibits the relationship's stability to the interval fixed between two lines (Amir and Bashir, 2019). The outcome provides

that all estimated model coefficients are stable as the bound within the 5% critical interval. Therefore, parameter stability is present in South Africa. Figure 3a provide the CUSUM test states that the presence of parameter stability must remain within the 5% critical level to ensure the stability of the short- and long-run coefficient. Therefore, the results provide that there is a presence of parameter stability in South Africa. Figure 3b proved the results of CUSUM of squares test of selected time series variables. The outcome provides that all coefficients of the model estimated are stable as the bound within the 5% critical interval. Therefore, there is the presence of parameter stability in South Africa.



Figure 3. Results for the CUSUM test and CUSUM of squares test of selected time series variables: (a) the results for the CUSUM test; (b) the results of CUSUM of squares test.

Source: Authors' computation from Eviews10.

#### 5. Conclusion and recommendations

This present study examined the impact of technological innovations on economic complexity in South Africa. The selected variables (technological innovation, exports, and manufactured products) contribute positively to South Africa's economic complexity index. The recommendations of this study are formulated from long-run findings and are made to enhance South Africa's ECI results, economic growth and development, and, subsequently, the production structure. Therefore, the study proffers the following recommendations based on the long-run observations that authentically established a relationship between economic complexity and selected variables (technological innovation, exports, and manufactured products). The study puts forward recommendations to the government, trade industry policy, the Department of Trade Industry and Competition, and policymakers.

 Technological innovation in South Africa is described as lagging far behind other economies (developed and developing) (Kahn et al., 2022). The study established a positive significant contribution towards the economic complexity of South Africa. It is recommended that policymakers should promote and invest in immeasurable innovation or knowledge that will immensely build its economic complexity, adopts advanced technology that will allow for the more efficient production of finished goods and services that will enhance the sophistication of export.

- South Africa is considered immensely rich in the agricultural sector and to be a net exporter of farming products (Sihlobo, 2023). The study revealed a positive impact on the economic complexity of South Africa, but insignificant. When putting forward its recommendations specifically on this variable (exports of sophisticated products), the study considered the theory of product lifecycle developed by Vernon Raymond (1966), explaining that economies should concentrate on manufacturing and exporting higher value-added products. The study recommends that policy markers discern which specific products or industries could pivot on to augment the sophistication of its exports or specialize in exporting products it can manufacture and export. It also recommends that South Africa create a propitious environment in adopting an innovative domestic value chain that produces knowledge-based products for the export market.
- South Africa is said to be on the wrong track regarding its economic complexity and largely dependent on less complex products and agricultural commodities, and its production structure remains primarily resource-based. The study produced positive outcomes towards the economic complexity of South Africa. It is highly recommended that policymakers should centre on innovation, research, and development to create more diversified and sophisticated products and processes and focus on developing its human capital through investment in education and training programs. Moreover, there is a need for foreign direct investment that will bring new technologies and markets. Additionally, there is a need to modernize its agricultural sector with more Agri-processed products.

# 6. Limitations of the study

The major limitation of this study was the missing data, particularly the variable economic complexity index data that was available until 2021 and that will continue be a major limitation for future studies because ECI data is updated yearly. However, the econometric methods, such as an autoregressive distributed lag that were used, assisted to overcome the challenges of the small sample size.

# 7. Recommendation for future studies

For the future research, it is recommended to study deep to comprehend the underlying factor that drives the significant impact of technological innovation on economic complexity in South Africa, as well as the factors that contribute significantly to economic complexity index. Moreover, we encourage future research to conduct comparative studies across different nations or to SACU countries, SADC region and BRICS economies with variables such as economic complexity, human capital, trade openness and foreign direct investment. Additionally, longitudinal studies that track the impact of technological innovations on economic complexity over an extended period can shed light on the dynamic nature of this relationship and examining efficient of policy interventions as they play the core when strengthening the economic complexity of South Africa.

Author contributions: Conceptualization, SS, TN and DD; methodology, SS; software, SS; validation, SS, TN and DD; formal analysis, SS; investigation, SS; resources, SS; data curation, SS, TN and DD; writing—original draft preparation, SS; writing—review and editing, TN and DD; visualization, TN and DD; supervision, TN and DD; project administration, TN; funding acquisition, DD. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

## References

- Akinwale, Y. O. (2022). Towards understanding the triangular relationship between technology innovation, human capital and economic growth in South Africa. International Journal of Learning and Change, 14(3), 258. https://doi.org/10.1504/ijlc.2022.122521
- Amir, A., & Bashir. A. (2019). Relationship between government expenditure on education and GDP per capita in Pakistan: An ARDL approach to cointegration. Advances and Applications in Statistics, 55(1), 77-103.
- Banton, C. (2021). Serial Correlation: Definition, How to Determine, and analysis. Investopedia.
- Bhorat, H., Whitehead, C. A. (2021). Understanding Economic Complexity: An Application to the MER sector. Development Policy Research Unit.
- Bhorat, H., Ewinyu, A., Lilenstein, K., et al. (2019). Economic complexity and employment expansion: The case of South Africa. Working Papers idredprusouthafrica, University of Cape Town, Development Policy Research Unit.
- Breitenbach, M. C., Chisadza, C., & Clance, M. (2021). The Economic Complexity Index (ECI) and output volatility: High vs. low-income countries. The Journal of International Trade & Economic Development, 31(4), 566–580. https://doi.org/10.1080/09638199.2021.1995467
- Can, M., Brusselaers, J., & Mercan, M. (2022). The effect of export composition on energy demand: A Fresh Evidence in the context of economic complexity. Review of Development Economics, 26(2), 687–703. https://doi.org/10.1111/rode.12854
- CFI Team. (2022). Theories of Growth. Available online: www.corporatefinanceinstitute.com/resource/economics/theories-of-growth/ (accessed on 3 May 2023).
- Chauke, R., & Ncanywa, T. (2021). Infrastructure Development and Economic Complexity in South Africa: Can Infrastructure Development Influence Economic Complexity? Technium Social Sciences Journal.
- Chetty, P. (2018). Autoregressive Distributed Lag Model (ARDL) and its advantages. Available online: https://www.Projectguru.in/auto-regressive-distributed-lag-model-ardl/ (accessed on 3 May 2023).
- Claudia, T. P., Luiz, A. P., & Priscila, R. (2021). Innovation and Economic complexity in BRICS. International journal of knowledge Management Studies.
- Coskun, N., Lopcu, K., Tuncer, I. (2018). Economic Complexity Approach to Development Policy: where Turkey stands in comparison to OECD plus China? In: Proceeding of the Middle East Economic Association.
- Djeunankan, R., Njangang, H., & Tékam, H. (2023). How does economic complexity improve energy efficiency? Mechanism discussion and empirical test. Environmental Science and Pollution Research, 30(43), 96906–96925. https://doi.org/10.1007/s11356-023-28920-z
- Erkan, B., & Yildirimci, E. (2015). Economic Complexity and Export Competitiveness: The Case of Turkey. Procedia Social and Behavioral Sciences, 195, 524–533. https://doi.org/10.1016/j.sbspro.2015.06.262

European Central Bank. (2017). How does Innovation lead to growth? Available online: https://www.ecb.europa.eu/ecb/educational/explainers/tell-memore/html/growth.en.html#:~:text=what%20is%20innovation%3F,make%20their%20production%20more%20efficient (accessed on 3 May 2023).

Filipescu, D. A., Prashantham, S., Rialp, A., et al. (2013). Technological Innovation and Exports: Unpacking Their Reciprocal

Causality. Journal of International Marketing, 21(1), 23-38. https://doi.org/10.1509/jim.12.0099

- Gao, J., & Zhou, T. (2018). Quantifying China's regional economic complexity. Physica A: Statistical Mechanics and Its Applications, 492, 1591–1603. https://doi.org/10.1016/j.physa.2017.11.084
- Hidalgo, C. A. (2021). Economic complexity theory and applications. Nature Reviews Physics, 3(2), 92–113. https://doi.org/10.1038/s42254-020-00275-1
- Kahn, A., Sithole, M., & Buchana, Y. (2022). An analysis of the impact of technological innovation on productivity in South African manufacturing firms using direct measures of innovation. South African Journal of Economics, 90(1), 37–56. https://doi.org/10.1111/saje.12310
- Kelly, A. M., Ketu, I., & Tchouto, J. E. T. (2022). Investigating the Link between Exhaustion of Natural Resources and Economic Sophistication in Sub-Saharan Africa. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4103121
- Laverde-Rojas, H., & Correa, J. C. (2021). Economic Complexity, Economic Growth, and CO2 Emissions: A Panel Data Analysis. International Economic Journal, 35(4), 411–433. https://doi.org/10.1080/10168737.2021.1975303
- Maradana, R. P., Pradhan, R. P., Chetterjee. D. et al. (2017). Does innovation promote economic growth? Evidence from European countries. Journal of Innovation and Entrepreneurship, 6(1). https://doi.org/10.1186/s13731-016-0061-9.
- Menegaki, A. N. (2019). The ARDL Method in the Energy-Growth Nexus Field; Best Implementation Strategies. Economies, 7(4), 105. https://doi.org/10.3390/economies7040105
- Mohamed, M. M. A., Liu, P., & Nie, G. (2022). Causality between Technological Innovation and Economic Growth: Evidence from the Economies of Developing Countries. Sustainability 2022, 3586. https://doi.org/10.3390/su14063586.
- Molele, S., & Ncanywa, T. (2022). Interrogating the association between current account and economic complexity. International Journal of Research in Business and Social Science (2147- 4478), 11(10), 160–170. https://doi.org/10.20525/ijrbs.v11i10.2081
- Nasrullah, M., Rizwanullah, M., Yu, X., et al. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. Journal of Water and Climate Change, 12(6), 2256– 2270. https://doi.org/10.2166/wcc.2021.030
- Neagu, O. (2019). The Link between Economic Complexity and Carbon Emissions in the European Union Countries: A Model Based on the Environmental Kuznets Curve (EKC) Approach. Sustainability, 11(17), 4753. https://doi.org/10.3390/su11174753
- Nguéda, R. D. N., & Kelly, A. M. (2022). The Nexus between Economic Complexity and Foreign Direct Investment in Sub-Saharan Africa. South Asian Journal of Social Studies and Economics, 41–52. https://doi.org/10.9734/sajsse/2022/v14i230377
- Nguyen, H. T., Luu, H. N., & Do, N. H. (2020). The dynamic relationship between greenfield investments, cross-border M&As, domestic investment and economic growth in Vietnam. Economic Change and Restructuring, 54(4), 1065–1089. https://doi.org/10.1007/s10644-020-09292-7
- Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) Cointegration technique: Application and Interpretation. Journal of Statistical and Econometric Methods, 5, 63-91.
- Nkoro, E., & Uko, A. K. (2023). Foreign Direct Investment and Inclusive Growth: Financial Sector Development in Nigeria, 1981-2020. Applied Econometrics and International Development, Euro-American Association of Economic Development, 23(1), 77-100.
- Pérez, C., & Claveria, O. (2020). Natural resources and human development: Evidence from mineral-dependent African countries using exploratory graphical analysis. Resources Policy, 65, 101535. https://doi.org/10.1016/j.resourpol.2019.101535
- Qoko, A., Sibanda, K and Senzangakhona, P. (2024). Health Capital and Economic performance in selected Southern African Development Community (SADC) countries. Cogent Economics and Finance, 12(1), 1–7, https://doi.org/10.1080/2332039.2024.2337479
- Ralarala, O., & Ncanywa, T. (2019). Investigating the Link between Economic Complexity Index and Monetary Policy Lending Rates in Selected Sub-Saharan African Countries. Journal of Reviews on Global Economics, 8, 1339–1350. https://doi.org/10.6000/1929-7092.2019.08.117
- Rojas, H. L., & Correa, J. C. (2021). Economic Complexity, Economic Growth, and C02 Emissions: A penal data analysis. International Economic Journal. https://doi.org/10.1080/10168737.2021.1975303.
- Sepehrdoust, H., Davarikish, R., & Setarehie, M. (2019). The knowledge-based products and economic complexity in developing countries. Heliyon, 5(12), e02979. https://doi.org/10.1016/j.heliyon.2019.e02979

Sihlobo, W. (2023). South Africa is Exporting more food, but it needs to find new growth frontiers. Stellenbosch University.

Tabash, M. I., Farooq, U., Aljughaiman, A. A., et al. (2024). Does economic complexity help in achieving environmental sustainability? New empirical evidence from N-11 countries. Heliyon, 10(11), e31794. https://doi.org/10.1016/j.heliyon.2024.e31794

Taha, A., Bekun. F. V., Agozie. D. Q. et al. (2022). Environmental Kuznets Curve hypothesis from lens of economic complexity index for BRICS: Evidence from second generation panel analysis. Sustainable Energy Technologies and Assessments.

Wang, X., & Xu, L. (2021). The Impact of Technological Innovation on Economic Growth: Evidence from China. Atlantis Press.

William, G. O., & Oshadi, F. A. (2021). Can Africa raise Export Competitiveness through Economic Complexity? Evidence from (non)-Parametric panel techniques. African Development Review.

Zhou, T., & Goa, J. (2017). Quantifying China's regional Economic Complexity. Physica. https://doi.org/10.1016/j.physa.2017.11.084.