JIET
Jurnal Ilmiah Ekonomi Terapan

JURNAL ILMU EKONOMI TERAPAN
https://e-journal.unair.ac.id/JIET/index

THE INFLUENCE OF ECONOMIC COMPLEXITY INDEX ON INCOME INEQUALITY IN G20 FORUM COUNTRIES

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ABSTRACT

This research examines the influence of the economic complexity index, GDP per capita, gross higher education participation ratio, government spending on education, and fertility rates on income inequality in G20 Forum member countries from 2010 to 2019. The dynamic panel data regression method with the two-step System Generalized Method of Moments (SYS-GMM) estimation technique is used to analyze the data in this study. The findings reveal that the economic complexity index, GDP per capita squared, government spending on education, and fertility levels have a negative and significant effect on income inequality. Meanwhile, GDP per capita and gross enrollment rates in tertiary education have a significant positive effect on income inequality. This study shows that the economic complexity index and the quality of human resources can reduce income inequality. Therefore, policies that focus on improving the quality of human resources need to be considered to encourage innovation, increase GDP per capita, and ultimately reduce income inequality.

Keywords: *Income Inequality, Gini Index, Economic Complexity Index (ECI), SYS-GMM*

ARTICLE INFO

Received: May 16th, 2024
Revised: May 26th, 2024
Accepted: May 31st, 2024
Online: June 25th, 2024

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ABSTRAK

Penelitian ini menguji pengaruh indeks kompleksitas ekonomi, PDB per kapita, rasio partisipasi pendidikan tinggi bruto, pengeluaran pemerintah untuk pendidikan, dan tingkat kesuburan terhadap ketimpangan pendapatan di negara-negara anggota Forum G20 tahun 2010 – 2019. Teknik analisis yang digunakan adalah metode regresi data panel dinamis dengan teknik estimasi two-step System Generalized Method of Moment (SYS-GMM). Hasil penelitian menunjukkan bahwa indeks kompleksitas ekonomi, PDB per kapita kuadrat, pengeluaran pemerintah untuk pendidikan, dan tingkat kesuburan berpengaruh negatif dan signifikan terhadap ketimpangan pendapatan. Sedangkan PDB per kapita dan angka partisipasi kasar pendidikan tersier berpengaruh positif signifikan terhadap ketimpangan pendapatan. Studi ini menunjukkan bahwa indeks kompleksitas ekonomi dan kualitas sumber daya manusia dapat mengurangi ketimpangan pendapatan. Oleh karena itu, kebijakan yang fokus pada peningkatan kualitas sumber daya manusia perlu dipertimbangkan untuk mendorong inovasi, meningkatkan PDB per kapita, dan pada akhirnya mengurangi ketimpangan pendapatan.

Kata Kunci: *Ketimpangan Pendapatan, Indeks Gini, Economic Complexity Index (ECI), SYS-GMM*
JEL: D63, C33

To cite this document: Subekti, M. J. M. & Sari, D. W. (2024). The Influence of Economic Complexity Index on Income Inequality in G20 Forum Countries. *Jurnal Ilmu Ekonomi Terapan, 9*(1), 137-150. https://doi.org/10.20473/jiet.v9i1.57677

Jurnal Ilmu Ekonomi Terapan; p-ISSN: 2541-1470; e-ISSN: 2528-1879
DOI: 10.20473/jiet.v9i1.57677

Introduction

Income inequality has become a problem in the world of economics. Research on this problem has been going on for a long time and is still being developed today. One of the most well-known studies is Simon Kuznets' study on the "Inverted-U" Curve which implies that income distribution tends to deteriorate in the initial phases of economic growth, followed by an improvement in the subsequent phases (Todaro & Smith, 2011). Rapid economic growth and increasing inequality have been closely related in recent decades. Better economic conditions will drastically reduce poverty and significantly improve people's welfare. However, widening income inequality will be a quite serious problem. In fact, income inequality is an important concern for the economy (Lee & Wang, 2021).

This concern arises because all countries in the world want stable economic conditions with equal income distribution. Income inequality in a country is associated with decreased trust, life and work satisfaction, and happiness which will later lead to low economic growth (Herzer & Vollmer, 2012). Various efforts have been made, but achieving economic balance by reducing income inequality is still relatively difficult. Research conducted by researchers continues to develop today because high inequality can threaten a nation's welfare.

Research developments have increased over the last few years along with increasing academic interest in income inequality. The majority of previous research has focused on factors that impact income distribution, such as life expectancy, trade openness, foreign direct investment, etc. On the other hand, there are still differences in empirical evidence regarding the Kuznets Curve theory (Lee & Vu, 2020). This conflicting empirical evidence may arise due to the complexity of income inequality and limitations in measuring economic development (Chu & Hoang, 2020).

Aggregate metrics of economic development, such as gross domestic product (GDP), GDP per capita, and the contribution of all economic sectors to GDP are still being debated (Hartmann et al., 2017). The reason for this lies in the fact that GDP measurements solely capture the quantitative aspect of economic development and overlook qualitative dimensions such as the "sophistication" of output (Chu & Hoang, 2020). As pointed out by Lee & Vu (2020), the performance and economic value of a product can vary. Hence, utilizing GDP as an aggregate monetary gauge of economic output provides only a limited depiction of a country's economic development (Hartmann et al., 2017).

Then, clarifying the factors that determine income inequality is not easy. This is caused by the development of income distribution, which is influenced by various economic, social and institutional variables including endowment factors, institutions, social capital, historical trajectories, technological innovation, and returns on capital (Hartmann, 2014). As a result, calculations of a country's productive structure cannot accurately reflect differences in industrial structure because the categories measured are too broad, including manufacturing, services, and agriculture (Hartmann et al., 2017). Consequently, a new metric called the economic complexity index has recently been introduced, representing a new concept that can influence inequality.

Hidalgo & Hausmann (2009) utilized the reflection method to construct an economic complexity index. The economic complexity index is utilized to assess a country's production capacity, which is represented in the form of "diversity" and "ubiquity" (Chu & Hoang, 2020). Due to its very high probability of predicting future economic growth, this concept has also attracted a lot of attention (Hartmann et al., 2017). This is the background for conducting research on how economic complexity affects income inequality.

The G20 Forum is comprised of 19 major countries, including the European Union (EU), and serves as an international forum for economic cooperation. Several issues such as macroeconomic concerns, trade, sustainable development, health, agriculture, environment, energy, climate change, and anti-corruption are the main focus of discussion at the G20 annual summit. Because the G20 forum plays an important role in building and improving global architecture and governance related to all major international economic issues, the G20 member countries were chosen as the objects of this research. Moreover, there has been no previous research discussing G20 member countries.

According to World Bank data, the economic growth of all G20 members increases every year. However, in 2020, the Covid-19 pandemic caused a drop in economic growth. Economic growth accelerated again in 2021. The economic complexity index, utilized for forecasting future economic income levels, is related to GDP per capita (Hidalgo, 2021).

As discussed earlier, the use of GDP per capita still causes many problems because the categories are too broad. Therefore, other factors are needed to analyze what can influence income inequality and economic complexity. These factors include education level, health, investment, and other factors. High income inequality is a sign that a country is facing obstacles in improving social consensus, health, education, and investment (Lee & Vu, 2020).

According to the background provided, this research will investigate how the economic complexity index, GDP per capita, gross higher education enrollment ratio, government expenditure on education, and fertility rate affect income inequality in the G20 Forum member countries. This study employs secondary panel data from 2010 to 2019 obtained from the World Bank, OEC World, and The Standardized World Income Inequality Database (SWIID) 9.4, with research locations in 20 member countries of the G20 Forum. The dynamic panel data regression method with the two-step system generalized method of moments (SYS-GMM) estimation technique will be applied in this study.

This study has some differences from previous studies. The impact of economic complexity on income inequality has been the focus of several previous studies. However, no specific research has been found that discusses G20 member countries in the 2010-2019 period. Existing research is relatively limited to a few countries that have great economic opportunities and only developed countries. In addition, many previous studies have produced mixed results. Therefore, research is still needed on the effect of economic complexity indexes, GDP per capita and squared, gross enrollment rates of higher education, government spending on education, and fertility rates on income inequality.

Literature Review

Income Inequality

Todaro & Smith (2011), define income inequality as the unequal distribution of total national income among a country's households. Income inequality often occurs in both developing and developed countries. Differences in income inequality in each country in the world occur for many reasons, but two main factors are most important. The first factor is wage dispersion, which refers to the difference in wages between workers with high and low incomes. The next factor is the role of the state in collecting income tax and returning it in the form of transfers. The second factor is the state's role, which takes income in the form of taxes and returns it in the form of transfers. Income inequality can be reduced by these taxes and transfers (Keeley, 2015).

The concept of an inverted U-curve explaining the relationship of per capita income to income inequality was first proposed by Kuznets (1955). According to Kuznets (1955), income inequality will increase in the initial phase of economic growth along with an increase in GDP per capita. This continues until income inequality reaches its peak point. Subsequently, income inequality can decrease when a country experiences rapid industrialization, urbanization, democratization, and economic growth. Building upon Kuznets' concept, Robinson (1976) further elaborated on this theory by directing his analysis towards the societal shift from an agricultural base to an industrial one. Within this model, the agricultural and rural sectors comprise the dominant part of the economy at the outset. These sectors are characterized by low per capita income and relatively equal income distribution. Meanwhile, the industrial and urban sectors are initially small parts of the economy that have high per capita income and may also have relatively high levels of inequality.

Galor & Moav (2004) and Galor (2011) argue that income distribution plays a crucial role in human capital formation and the development process. During the initial stages of industrialization, inequality can enhance the development process. This occurs because physical capital accumulation serves as the primary driver of growth. However, as development progresses, human capital becomes the key engine of growth and equality, encouraging the formation and growth of human capital. Equality will facilitate the accumulation of human resources which will then stimulate the growth process.

Income inequality can be quantified using various methods. A commonly employed technique is the Gini Index. Formally, the Gini Index is defined as the ratio of the difference between the average income of all couples in a population and twice the average income of that population. Notably, the Gini Index is recognized for its greater sensitivity in capturing income inequality compared to other metrics (Solt, 2020).

The Standardized World Income Inequality Database (SWIID) serves as the source of the Gini index database for all countries. The most important thing in collecting data to estimate the results of cross-country comparisons carried out with SWIID is that there are observations for the same country in the same year but with different definitions of welfare and equality scales or from different sources (Solt, 2020).

Economic Complexity Index

The productive structure of a country, as emphasized by Hartmann et al. (2017), is a fundamental determinant of its capacity to generate and distribute income. However, accurately measuring a country's productive structure presents a major challenge due to the complexity of its measurement (Chu & Hoang, 2020). To overcome this problem, the concept of economic complexity was formed. This idea can serve as a measure of the knowledge stock accumulated within a population, also referred to as knowledge productivity or production complexity. The economic complexity method, which is based on the premise that countries are connected through the products they export, uses export competitiveness and product quality as metrics to measure the complexity of a country's economy (Hidalgo & Hausmann, 2009).

The Economic Complexity Index (ECI) utilizes a reflection method to gauge a country's economic complexity (Mariani et al., 2015). Revealed Comparative Advantage (RCA) measures a country's effectiveness in exporting certain products, which is used to indicate the level of economic complexity. Based on this concept, two aspects of economic complexity—"diversity" and "ubiquity"—can be defined (Chu & Hoang, 2020). "Diversity" refers to the number of products a country can export with RCA, while "ubiquity" captures the number of countries that hold an advantage in exporting certain products. Therefore, countries with high diversity or that can export more products with RCA are considered more complex. Meanwhile, a product is considered complex if only a few countries are able to export it (Lee & Vu, 2020).

Economic complexity metrics measure a country's economic capacity by applying dimensionality reduction methods such as Singular Value Decomposition (SVD) or Principal Component Analysis (PCA). These techniques identify the combination of factors that most effectively explain the geography of various economic activities. Dimensionality reduction techniques, unlike traditional growth models that assume properties of factors, are used to learn factors directly from data. Furthermore, economic complexity metrics are also utilized to forecast economic growth, income inequality, and greenhouse gas emissions (Hidalgo, 2021).

Several studies show an inverse relationship between economic complexity and income inequality (Hartmann et al., 2017). Countries exhibiting extensive knowledge diversification are poised to foster sophisticated industries and promote more balanced employment frameworks (Constantine & Khemraj, 2019; Hartmann et al., 2017). Consequently, this diversification expands employment opportunities for high-skilled, low-skilled, and even unskilled workers, ultimately reducing income inequality by empowering them with appropriate remuneration (Hartmann, 2014).

Conversely, studies by Chu & Hoang (2020) and Lee & Vu (2020) posited a positive relationship between income inequality and economic complexity. In other words, as the economy undergoes a structural transformation towards more sophisticated products, an increase in income inequality will follow.

Previous Studies

Several studies have been conducted to analyze the influence of the economic complexity index on income distribution. Employing data covering more than 150 countries between 1963-2008, Hartmann et al. (2017) examined the influence of the economic complexity index on income distribution. Their findings reveal that the economic complexity index has a negative impact on income inequality. The study further reveals that economic competitiveness for complex products depends on a wider network of skilled workers, related industries, and inclusive institutions (Hartmann et al., 2017). These characteristics foster a more equal society. Conversely, competitiveness in simple industries, resource exploitation activities that often depend on natural resource abundance, low labor costs, repetitive activities, and economies of scale are characteristics that can exacerbate income inequality (Hartmann et al., 2017).

Other research presents evidence showing that the economic complexity index drives income inequality. An increase in the economic complexity index correlates with a widening wage disparity between low-skilled and high-skilled workers, thereby contributing to a rise in income inequality (Lee & Vu, 2020). Research by Lee & Vu (2020) estimates the influence of productive structure in 113 countries with an average of 5 years for the period 1965–2014 using the SYS-GMM dynamic panel and finds a positive influence of the economic complexity index on income inequality. In addition, another study applying SYS-GMM estimates based on data from 88 countries in 2002-2007 revealed that the economic complexity index is associated with higher income inequality (Chu & Hoang, 2020). Another study using mixed models in 43 countries over the period 1991–2016 also reported a positive influence of the economic complexity index on income inequality (Lee & Wang, 2021).

As a continuation of these findings, several studies have identified evidence indicating a non-linear relationship between the economic complexity index and income inequality. Hausmann et al. (2014) emphasize the significance of this non-linear relationship. This study explores the concept of opportunity value, which refers to the benefits derived from the accumulation of knowledge, and its relationship to economic complexity. The data indicates that countries with a low economic complexity index exhibit limited appreciation for knowledge. This is likely because these countries lack the capacity to effectively utilize knowledge for productive endeavors. Conversely, countries that have high levels of productive knowledge also have low knowledge rewards. In these countries, a significant portion of the product space is already occupied by productive knowledge, thereby limiting the benefits of further knowledge accumulation. In countries with medium levels of complexity, opportunity values become more variable.

Le et al. (2020) conducted an analysis to assess the influence of export diversification on income inequality utilizing panel data from 90 countries in 2002–2014. The results suggest an inverted U-shaped relationship. Although economic complexity offers a more holistic measure of a country's productive framework compared to export diversification, the results reinforce the concept of a non-linear correlation between economic complexity and income inequality. Therefore, economic complexity plays a crucial role in either increasing or reducing income inequality.

Other factors that influence income inequality include the gross enrollment ratio in tertiary education, government spending on education, and fertility rates. Barro (2000) finds that higher education participation is positively correlated with income inequality. Lee & Vu (2020) also suggest that increasing participation at higher levels of education will be associated with increasing economic complexity and will increase income inequality.

Meanwhile, Palmisano et al. (2022) state that increasing opportunities to continue higher education will have an impact on reducing income inequality (even distribution of income). The strong influence of parents' education level tends to influence their offspring. This will increase opportunities to obtain higher education and increase income equality for the nation's next generation. Chu & Hoang (2020) also stated that increasing participation in higher education will improve the quality of human resources and thus reduce income inequality.

Research by Artige & Cavenaile (2023), Celikay & Sengur (2016), Köse & Güven (2007), and Sylwester (2002) found a positive influence of government spending on education on income inequality. Increased government spending on education can encourage better income distribution. Apart from that, it will also increase human resources which will ultimately increase a country's economic growth. Meanwhile, Barro (2000) found that government spending on education has a negative influence on income inequality.

Fertility levels can also influence income inequality. As pointed out by De La Croix & Doepke (2003), increasing income inequality can lead to increased fertility. This happens because parents with low incomes tend to have more children than wealthier parents. Subsequently, parents with low incomes tend to allocate fewer resources to their children's education. This, in turn, can contribute to a decline in a country's human capital and hinder economic growth.

Otherwise, Deaton & Paxson (1997) discover a negative relationship between income inequality and fertility. According to this study, inequality increased significantly with age. This can have a big impact. The low rate of population growth seen from the low fertility rate will increase income inequality between groups because the proportion of older age groups is increasing.

According to the previous discussion, this study posits a hypothesis that the economic complexity index, GDP per capita and squared, gross participation ratio of tertiary education, government spending on education, and fertility rates have an influence on income inequality.

Data and Research Methods

This study employs a quantitative approach, utilizing a two-step system generalized method of moment (SYS-GMM) estimation technique. The Sargan-Hansen test is then used to test the model specification, while the Arellano-Bond AR (2) is used to test serial correlation in error terms.

This study utilizes secondary panel data obtained from various sources. The time series data used covers the period 2010-2019 and the cross-sectional data used covers 20 member countries of the G20 Forum. These countries include South Africa, United States, Saudi Arabia, Argentina, Australia, Brazil, India, Indonesia, England, Italy, Japan, Germany, Canada, South Korea, Mexico, France, Russia, China, Turkey, and the European Union. A detailed description of the variables used in the study is provided in Table 1.

Table 1: Variables, Definitions, and Sources

Variable	Definition	Source
Gini Index	The Gini index variable (GINI) used is Gini disposable income which is an estimate of the Gini index for household inequality that has been equalized (square root scale) and can be spent (after tax, post transfer), using Luxembourg Income Study Data as a standard. The Gini index ranges from 0 to 100, with 0 indicating perfect equality and 100 indicating perfect inequality.	The Standardized World Income Inequality Database (SWIID) 9.4
Economic complexity index	The economic complexity index is a calculation that estimates a country's productive knowledge, which is known from the diversity of countries in making products and seeing the ubiquity of the products made. A higher economic complexity index indicates a country's economy is more complex, while a lower index indicates the opposite.	The Observatory of Economic Complexity (OEC) World
GDP per capita	This research uses GDP per capita based on constant prices in 2015 in US Dollars. $GDP\ per\ capita = \frac{GDP}{Mid-year\ population}$	World Bank
Gross enrollment ratio of tertiary education	This indicator is the ratio of total enrollment regardless of age in the age group officially corresponding to the indicated level of education.	World Bank
Government spending on education	Government expenditure on education is government expenditure on education funded by transfers from international sources to the government. The method used to calculate government expenditure on education is to divide the entire amount spent on education at all levels by GDP, then multiply the result by 100.	World Bank
Fertility rate	The fertility rate is a calculation that shows the number of children a woman gives birth to during her fertile period in a particular year. The unit used is births per woman.	World Bank

The empirical model in this research uses dynamic panel data regression. The model used is as follows:

$$\begin{aligned} GINI_{i,t} = {} & \beta_0 + \beta_1 L1.GINI_{i,t-1} + \beta_2 ECI_{i,t} + \beta_3 GDP_{i,t} + \beta_4 GDP2_{i,t} + \beta_5 EDU_{i,t} \\ & + \beta_6 EDUEXP_{i,t} + \beta_7 TRF_{i,t} + \mu_{i,t} \end{aligned} \tag{1}$$

Where:

$GINI$: Gini Index
ECI : Economic complexity index
GDP : GDP per capita
$GDP2$: GDP per capita squared
EDU : Gross enrollment ratio of tertiary education
$EDUEXP$: Government spending on education
TFR : Fertility rate
$L1$: Lag
$\mu_{i,t}$: Error term
β_0 : Intercept
$\beta_1, \ldots, \beta_7$: Regression coefficient
i : Cross section
t : Time series

This study employs the two-step SYS-GMM technique for data analysis. The generalized method of moments (GMM) is an estimation method that ignores the error component structure of the disturbance and estimates a generalized variance-covariance matrix along the time dimension (Baltagi, 2005). The GMM method is employed due to its ability to overcome the simultaneity bias that arises when some explanatory variables are endogenous. Furthermore, the GMM method can also control for country-specific effects that cannot be addressed with country-specific dummies due to the dynamic nature of the regression equation.

This study adopts the SYS-GMM procedure due to its advantages over the Difference GMM (DIFF-GMM) approach. The SYS-GMM technique combines level similarities and differences. Furthermore, the lagged differences from the regression serve as additional instruments for level equations (Blundell & Bond, 1998). Meanwhile, DIFF-GMM has several limitations. It can provide misleading results when the explanatory variables are fixed and the level of the lagged variable becomes a weak instrument (Arellano & Bover, 1995).

The suitability of the selected model and the consistency of the GMM estimator are evaluated through the application of two tests. First, the validity of the instrument is determined using the Sargan-Hansen test. The null hypothesis (H_0) of the Sargan-Hansen test states that the instrument is valid, meaning there are no problems with the instrument used. H_0 is rejected if the probability value is lower than the significance level of 1%, 5%, or 10%, which indicates that the instrument and model used are invalid. Conversely, failing to reject H_0 indicates that the instruments and models used are valid.

Furthermore, to determine whether there is a correlation between variables, a serial correlation test is carried out using Arellano-Bond AR (2). This test utilizes z-statistics where the null hypothesis (H_0) is that there is no serial correlation. H_0 is not rejected if the probability value exceeds the significance level of 1%, 5%, or 10%. This indicates that there is no autocorrelation between the variables. On the other hand, H_0 is rejected if the probability value is smaller than the significance, indicating that there is autocorrelation between variables.

Statistical tests are conducted using partial tests (t-test) and simultaneous tests (F-test). The t-test is employed to determine the influence of each independent variable on the dependent variable. This is accomplished by comparing the t-statistics from the estimation results with the critical value of t obtained from the t-distribution table. Rejection of the null hypothesis (H_0) occurs when the t-statistic value exceeds the t-table value, indicating a significant effect of the independent variable on the dependent variable. In addition, decision making in the t-test can also be done using the p-value. A p-value lower than the significance level of 1%, 5%, or 10% leads to the rejection of H_0, implying a statistically significant effect of the independent variable on the dependent variable.

A simultaneous test or F test is carried out to determine whether the independent variables simultaneously influence the dependent variable or not. H0 is rejected, indicating that the independent variables simultaneously have an influence on the dependent variable, if the Prob>F value is smaller than the significance level of 1%, 5%, or 10%.

Finding and Discussion

Descriptive statistics

Table 2: Descriptive statistics

Variable	Obs.	Mean	Std. Dev	Min	Max
GINI	196	38.042	8.025	28.7	63,4
ECI	200	0.932	0.659	-0.359	2,58
GDP	200	24743.94	17483.16	1244.4	60687.2
GDP2	200	9.16e+08	1.01e+09	1548447	3.68e+09
EDU	183	61.368	24.442	17.834	120.966
EDUEXP	143	4.717	0.985	2.669	8.510
TFR	200	1.867	0.405	0.918	2.853

Table 2 displays descriptive statistics for each variable utilized in this study. This table includes the variables employed in the analysis, the number of observations for each variable, the mean, standard deviation, minimum value, and maximum value. The varying number of observations for each variable indicates that the data used is unbalanced panel data.

GMM Estimation Results

This study employs a dynamic panel data regression with the SYS-GMM estimation technique. First, a one-step SYS-GMM estimation is performed to determine whether the estimate is correct. If the results are still not correct, further estimation is needed using the two-step SYS-GMM. The validity of the instrument is then determined by performing the Sargan-Hansen test. Finally, to determine if there is a correlation between the variables, the AR(2) test is performed.

The outcomes of the one-step and two-step SYS-GMM estimate are displayed in Table 3. The AR(2) test value for one-step estimation meets the criteria, however there is no value for the Sargan-Hansen test. Therefore, one-step estimation cannot be used because it is invalid. To evaluate the validity of the instrument and the presence of autocorrelation in the model, a two-step estimation is required.

Table 3: SYS-GMM Estimation Results

Variable	***One-step estimation***		***Two-step estimation***	
	Coefficient	**P-*value***	**Coefficient**	**P-*value***
C	-3.191	0.003*** (1.031)	-3.463	0.000*** (0.796)
L1.GINI	1.092	0.000 *** (0.024)	1.100	0.000*** (0.018)
ECI	-0.131	0.209 (0.103)	-0.234	0.091* (0.131)
GDP	0.00008	0.000*** (0.000)	0.0001	0.000*** (0.000)
GDP2	-1.09e-09	0.000*** (2.81e-10)	-1.46e-09	0.001*** (3.56e-10)
EDU	0.009	0.022** (0.003)	0.010	0.001*** (0.002)
EDUEXP	-0.229	0.002*** (0.073)	-0.253	0.011** (0.089)
TFR	-0.508	0.004*** (0.172)	-0.591	0.001*** (0.149)
AR(1) (p-*value*)	0.030		0.060	
AR(2) (p-*value*)	0.982		0.961	
Hansen test (p-*value*)	-		0.608	
Prob > F	0.000		0.000	
Number of instruments	16		16	
Number of groups	20		20	
Number of observations	116		116	
Number of countries	20		20	

Information: Numbers in parentheses ( ) are standard errors; ***significant at 1%; ** significant at 5%; and * is significant at 10%

Specification Test Results

The validity of the instruments and models employed in this study is determined utilizing the Sargan-Hansen test. Meanwhile, the AR(2) test is used to determine whether there is autocorrelation between variables. As shown in Table 3, the Hansen test probability value for the two-step estimation procedure is 0.608, which exceeds the significance level. This indicates that H_0 is not rejected, implying the validity of the instruments and models. The next stage is the AR(2) test. The AR(2) test statistic for the two-step estimation in Table 3 is 0.961, which also exceeds the significance level. This finding leads to the decision not to reject H_0, thus indicating the absence of autocorrelation between variables.

Statistical Test Results

The results of the partial test (t-test) based on Table 3 show that the GDP and EDU variables have a positive and significant influence on the income inequality variable, with a significance level for both of them of 1%. Meanwhile, the variables ECI, GDP2, EDUEXP, and TFR exhibit a negative and statistically significant influence on income inequality variable with significance levels of 10%, 1%, 5%, and 1%, respectively. Subsequently, the Prob > F value of 0.000 indicates that the independent variables simultaneously have a significant influence on income inequality.

Discussion

The estimation results shown in Table 3 show a coefficient of -0.234 for the economic complexity index variable. This means that when the economic complexity index variable increases by 1 point, the income inequality variable will decrease by -0.234 points assuming other variables are considered constant. Thus, the economic complexity index variable is able to reduce the income inequality variable significantly.

These findings align with the studies conducted by Lee & Wang (2021) and Hartmann et al. (2017). The economic complexity index has the potential to reduce income inequality by improving the employment structure, expanding employment and educational prospects, and producing high-value products (Lee & Wang, 2021). In addition, expanding the index of economic complexity, skills, knowledge, and class consciousness can also reduce income inequality (Constantine & Khemraj, 2019).

The coefficient for the GDP per capita variable is 0.0001, indicating that a 1% increase in GDP per capita will lead to a 0.0001% increase in income inequality with the other variables remain constant. Meanwhile, the coefficient for the squared GDP per capita variable is -1.46e-09. This implies that a 1% increase in the squared GDP per capita variable will result in a -1.46e-09% decrease in income inequality, assuming other variables remain constant. Therefore, an increase in GDP per capita can lead to an increase in income inequality. Meanwhile, the squared GDP per capita variable has a negative and significant influence on income inequality. These positive and negative influences correspond to the Kuznets Inverted U Curve.

Research by Chu & Hoang (2020) and Lee & Vu (2020) also shows that there is a significant positive and negative influence of the GDP per capita variable and its square on income inequality. These findings reinforce Kuznets' Inverted U-Curve theory which reveals that during the initial phases of economic development, income inequality tends to increase until it reaches a certain threshold of GDP per capita. Additionally, advancements in industrialization, urbanization, democracy, and overall prosperity contribute to reducing economic inequality (Kuznets, 1955).

Then, the variable gross participation ratio of tertiary education has a coefficient of 0.010. This indicates that a 1% increase in the gross enrollment ratio for the tertiary education variable results in a 0.010% increase in income inequality, assuming other variables remain constant. Therefore, the gross participation ratio of higher education variables significantly increases income inequality.

This is in accordance with research by Barro (2000), Rodríguez-Pose & Tselios (2009), and Lee & Vu (2020). As shown by Rodríguez-Pose & Tselios (2009), higher levels of education are associated with higher income inequality. Rising levels of education tend to exacerbate income inequality due to imperfect competition for roles that require higher education. This will also further increase the wages of educated people. In addition, increasing the level of education will increase a person's opportunities to develop as well. However, this impact tends to be felt more by the rich group than the poor group, so the rich group has a greater opportunity to earn higher wages.

The government expenditure variable for education has a coefficient of -0.253. This means that when the government spending variable for education increases by 1%, the income inequality variable will decrease by 0.253% assuming other variables are considered constant. Thus, the variable government spending on education significantly reduces income inequality.

This negative influence is in accordance with research from Sylwester (2002). Research findings show that support for education is useful in increasing human resources to spur economic growth. This phenomenon is more evident in developing countries. Other research conducted by Celikay & Sengur (2016) also shows that in the long term, government spending on education can contribute to the reduction of income inequality. Artige & Cavenaile (2023) also state that most countries can increase growth and reduce income inequality through government spending on higher education by increasing taxes.

Finally, the fertility level variable has a coefficient of -0.591. This means that if the fertility rate variable increases by 1 birth per woman, then the income inequality variable will decrease by -0.591 births per woman assuming other variables are held constant. Thus, the fertility level variable is able to reduce the income inequality variable significantly.

This negative and significant influence is in accordance with research by Deaton & Paxson (1997) and Husain (2022) which states that there is a negative relationship between fertility levels and income inequality. Husain (2022) associated these findings with the concept of a trade-off between the quantity and quality of established and persistent offspring. In developing countries, increasing inequality can increase the opportunity costs of raising children. In addition, market or institutional assistance will not be able to significantly mitigate the cost burden of child-rearing for parents. Consequently, this will reduce the preference for having children.

Conclusion

The findings of this research reveal that the economic complexity index variable has a negative and significant impact on the income inequality variable. In other words, a high economic complexity index can reduce income inequality. Income inequality can be reduced through improving employment structures, increasing employment opportunities, enhancing learning opportunities, producing higher-value products, expanding skills and knowledge, raising class awareness.

Furthermore, the GDP per capita variable and its square respectively have a significant positive and negative influence on the income inequality variable. This aligns with Kuznets' inverse U-curve hypothesis, which states that the early stages of economic development are accompanied by high income inequality. However, after reaching a certain point, further development characterized by industrialization, urbanization, democratization, and increased prosperity will lead to a gradual reduction in income inequality.

Then, the variable gross participation ratio of tertiary education has a positive and significant impact on income inequality. An increase in the gross enrollment ratio in higher education can exacerbate income inequality due to imperfections in the labor market for positions demanding higher educational qualifications. This will also further increase the wages of educated people. In addition, there is a higher tendency for rich people than poor people to earn high wages even though they have the same level of education.

The government spending variable for education has a negative and significant effect on the income inequality variable. This suggests that increased government spending on education can be a tool for increasing human resources to spur economic growth. This increase can be done by increasing taxes. Finally, the fertility level variable has a negative and significant effect on the income inequality variable. In developing countries, as inequality increases, the costs of raising children also increase. Therefore, parents tend to reduce their preferences for having children.

There are several suggestions that can be taken from the discussion of this research. For policy makers in every country, increasing economic complexity must start with increasing human resources first. This can be done by increasing government spending in the education sector which will help poor people to get better education and improve their quality and skills so that they are unable to compete with the workforce of the rich. Apart from that, policy makers or the government must also provide assistance for community welfare, such as life support, health, and so on. Improving the quality of a country's human resources can encourage an increase in GDP per capita and create the latest product innovations for export. This will increase the complexity of the country's economy and reduce income inequality.

This research still has research limitations. Data on each variable is incomplete due to limitations in data collection. In addition, the year period studied was only ten years. This research also has not added other variables that influence income inequality, such as unemployment rate, labor force level, investment level, etc. Therefore, it is hoped that in future research, we can add wider research locations with a longer research period. Apart from that, further research can also add other variables which are factors that influence income inequality so that the research results become more accurate.

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