The Influence of Technological Progress on Regional Income Inequality in Indonesia

Nefo Indra Nizar[1], Ahmad Nazir[2], Achmad Nur Sholeh[3]

[1,2,3]Faculty of Economics and Business, University of Pamulang, Indonesia

Abstract

The aim of this research is to determine the influence of technology on regional economic development as well as prove whether technology can cause income inequality in Indonesia. This research method uses panel data regression estimation. Panel data is a combination of cross section and time series data. Meanwhile, a technology index was calculated based on indicators of smartphone, internet and computer use to see the characteristics of the technological dimensions of each province in Indonesia. The data used is secondary data from provinces throughout Indonesia for the 2016-2022 time period. The data source was taken from the Indonesian Central Statistics Agency. The panel data regression estimation results are estimated smartphone owners ratio and computer user rasio do not affect regional income inequality significantly meanwhile internet access rasio affect regional income inequality partially. All variables affected regional Income simultaneously or tecnological progress has affected regional income inequality in Indonesia.

***Keyword*: Internet, Smartphones, Computers, Income Inequality**

JEL Classification : G40

Corresponding author's email : dosen01479@unpam.ac.id

Background

Since the first industrial revolution with the discovery of the steam engine in the 18th century, humans have changed the way and methods of managing resources and the process of producing goods and services, becoming increasingly easier and faster. Currently, technological advances in the era of industrial revolution 4.0 have been able to change the way people live both in relation to economic activities and community life.

As an archipelagic country, the role of technological infrastructure is very important in Indonesia. Indonesia has built the Palapa Ring as network infrastructure so that people throughout Indonesia have the opportunity to access the internet equally. Currently the world and Indonesia are entering the era of Industrial Revolution 4.0. an era where there is very rapid development of digital technology. Adiningsih, et al. (2019) stated that the digital revolution was driven by four types of technology that had a huge impact on people's lives, namely:

1) Mobile Internet via smart phones, where currently it is estimated that 60% of internet traffic uses smart phones;

2) Cloud Computing, faster and relatively cheaper internet networks and accessibility have a huge impact on remote and isolated areas.

3) Internet of Thinks (IoT), a way of working that aims to expand the benefits of continuously connected internet connectivity. The impact of this type of technology gives birth to new business models, production methods, and new technological applications.

4) Big Data & Advanced Analytics. The large amount of data is a result of the very high data and information exchange process via computers and the internet. This information can help businesses because supply chain information processes become more efficient.

To be able to measure and compare the development of Information Communication Technology (ICT) at regional, country and global levels, the International Telecommunication Union (ITU) has compiled a composite ICT Development Index (ICT Index). The ICT Index indicator is adopted in almost all countries to describe their respective ICT developments, including by the Central Statistics Agency to measure ICT development in Indonesia. The formation of the ICT Development index is based on several stages, namely:

1. ICT readiness, reflects the level of infrastructure that has networks and access to ICT

2. ICT intensity, reflects the level of ICT use in society;

3. ICT impact, reflects the results of the efficiency and effectiveness of ICT use.

Previous research conducted by Rath & Hermawan (2019) shows that ICT development has a positive and significant influence on economic growth. Research conducted by Makun & Jayaraman (2020), which examined the spread of ICT use in Pacific island countries on economic growth, showed the same results, that ICT positively and significantly influenced economic growth.

Based on economic growth theory, such as the Solow model (Juhro & Trisnanto, 2018), even though it places technology as an exogenous factor in the model, it recognizes that technology has an important role in economic growth. Endogenous growth theory (Juhro & Trisnanto, 2018) emphasizes that technological factors are the main driving factor of economic growth. Fitriana's research (2019), one of the conclusions, states that strengthening the creative industry needs to be supported by innovation capabilities and strengthening infrastructure, especially information technology, which can be utilized by creative business actors, especially creative industries in rural areas.

The process of regional and rural development cannot be separated and requires the role of technology. The use of the internet, computers and smartphones is a supporting force for rural communities to have access to information and make a real contribution to development. Raeskiesa and Erica's research (2019) shows that ICT is able to provide a positive and significant impact. Providing ICT infrastructure and easy access to information through ICT is not enough, it needs to be supported by human resources who are able to master and have sufficient knowledge of technology. The technological infrastructure gap between urban and rural areas causes a gap in the income of rural residents compared to urban residents because they do not have access to ICT.

Internet technology has proven capable of supporting the Indonesian economy. During the Covid-19 pandemic, regulations were implemented to maintain distance. Many companies closed and were forced to lay off their employees. The MSME sector, which is the backbone of the Indonesian economy, has not escaped the Covid-19 storm. The impact of the Covid-19 pandemic resulted in pressure on the economy, economic growth grew negatively by -5.32% in the second quarter of 2020. The digital economic sector was able to slow down the decline in economic growth. The digital economy is able to grow very significantly through e-commerce and financial technology and makes a real contribution to economic growth (Nizar & Sholeh, 2021).

On the other hand, technology can potentially cause problems with population income inequality (Peng, 2014). This condition is caused by the inability to access technology and information as well as the ability to utilize the technology itself. The technology gap results in income inequality (Ndoya & Asongu, 2022). The inequality in access to technology that occurs between rural-urban areas, Java Island and areas outside Java is one of the factors that causes income inequality in Indonesia. The progress of ICT infrastructure development between regions is not the same because it depends on investment in the ICT sector, innovation capacity in the technology sector, and the availability of ICT itself. Research by Antonelli & Tubiana (2020) states that technological progress has an impact on income inequality due to exploitation in technology-based industries and labor polarization as a consequence.

Based on the description of the background of the problem above, the formulation of the problem in this research is whether has an effect smartphone owners ratio, internet access ratio, computer users rasio and technological progress on region on income inequality in Indonesia partially. The aim of this research is to determine the influence of technology on regional income inequality in Indonesia.

Literature Review

Understanding Technology

The definition of Information and Communication Technology refers to all technical equipment for processing and conveying information, covering two aspects, namely information technology and communication technology. Information technology includes everything related to processes, use as tools, manipulation and management of information, while communication technology is everything related to the use of tools to process and transfer data from one device to another. Therefore, information technology and communication technology are two inseparable concepts. Minister of Communication and Information Regulation No. 23 of 2012 defines Information and Communication Technology (ICT) as all activities related to the processing, management and delivery or transfer of information between facilities/media.

Communication Information Technology (ICT) is a component consisting of hardware, software, networks and media used to collect, store, process the transmission and presentation of information in the form of voice, data, text, images, starting from telephone, radio, television and Internet. ICT is one of the backbones of the economy which is an effective tool for encouraging economic growth and regional development. One of the most obvious benefits associated with the use of ICT is the increased flow of information and knowledge. ICT allows information to be transmitted relatively cheaply and cost efficiently. The use of ICT tends to reduce uncertainty and transaction costs for participating in economic transactions. This, in turn, tends to lead to increased transaction volumes leading to higher levels of output and productivity. In addition, with the increasing flow of information, technology can be acquired and adapted more easily, leading to increased innovation and productivity.

ICT is able to overcome geographical boundaries. Therefore, international buyers and sellers are increasingly able to share information, reduce uncertainty, reduce transaction costs, and increase cross-border competitiveness, all of which results in more efficient global markets. Additionally, production processes can be outsourced based on comparative advantage, across national boundaries resulting in further global efficiency improvements. Market access and coverage is also likely to expand, as access to global supplies increases.

Income Inequality Theory

Kuznets was the first to explain the relationship between economic growth and income inequality. According to Kuznets, in the early stages of development, income inequality will first rise and then fall as economic growth increases and becomes more developed because trickle-down development occurs through workers earning higher average wages. The relationship between growth and inequality is depicted as an inverted U curve. Although the Kuznets hypothesis is not supported by sufficient data quality, since the publication of the Kuznets hypothesis it has encouraged other researchers to test the Kuznets hypothesis. Some studies find empirical evidence for a U-shaped curve, but on the other hand some empirical studies do not find clear evidence for the existence of a Kuznets curve (Buceli, 2017).

Meanwhile, the causes of income inequality can be caused by many factors, including educational factors. An interesting study was conducted by Arshed et al. (2019) in ASEAN developing countries. His research confirmed Kuznetz's hypothesis in the context of the relationship between education and income inequality. The results of his research reveal a positive relationship between primary level education and income inequality, but the large-scale spread of primary education will reduce the level of inequality. Furthermore, in the first stage of school enrollment, increasing secondary school enrollment will increase the level of income inequality, but a further increase in school participation will reduce income inequality.

Enrollment at a higher level of education shows a negative relationship with income inequality at an early stage. This means that increasing higher education will decrease income inequality but its large scale implications will increase income inequality because individuals who achieve higher levels of tertiary education will demand higher wages. compared to primary and secondary school graduates, further increasing income inequality.

The paper from McKnight (2019) tries to review several studies related to the relationship between inequality and economic growth. Several research results show ambiguous results, because several studies show inconsistent results. The relationship between inequality and economic growth is non-linear. The idea of the Kuznets hypothesis leads to a broader relationship, namely inequality, poverty and economic growth, or what is known as the poverty-growth-inequality-poverty triangle.

Bourguignon is considered to be the first to put forward the concept of the poverty-growth-inequality triangle. Absolute poverty and poverty reduction are caused by two things, namely the growth effect and the income distribution effect. The conclusion that can be drawn from Bourguignon's hypothesis is that the better the changes in the distribution effect of average income, the ability to increase income so that it crosses the poverty line, the result will be reduced poverty (McKnight, 2019). Likewise, if the results of equitable economic growth are able to reduce absolute poverty.

Bergstrom (2020) conducted research on the role of income inequality in reducing poverty using World Bank data, concluding that changes in income inequality by increasing average income can reduce poverty levels. Growth can also reduce poverty. Meanwhile, there is a trade-off between income inequality and economic growth. Which effect has the greatest change in inequality and growth in reducing poverty depends on how much it is calculated from the elasticity value. For this reason, studies are needed for policy makers to examine the influence of various policies on inequality and growth.

Technology and Income Inequality

Research related to technology as a cause of income inequality conducted by Peng (2014) states that technological progress will increase productivity, then increase status in consumption. Status in consumption is only enjoyed by a small portion of the population who have high incomes. Growth resulting from increasing status in consumption is an immiserating growth because it creates income inequality. Antonelli & Tubiana (2020) state that the transition to a knowledge economy brings about radical changes, especially because technological progress has an impact on income inequality due to the exploitation of knowledge in technology-based industries and labor polarization as a consequence.

Ndoya & Asongu's (2022) research regarding the technology gap in several African countries concluded that there are two groups affected by the technology gap. In the first group, the technology gap has a positive and significant effect on income inequality. Meanwhile, in the second group, the technology gap has a negative and significant effect on income inequality. The impact of globalization on the technology gap is very high for countries in the first group. The implication is that strong policies are needed to overcome the income gap in the case of African countries in the first group.

Research from Richmond & Triplett (2017) on 109 countries states that technological growth can increase economic growth quickly, but technology can also increase and decrease income inequality, depending on mastery and ease of access to the technology itself. Simple and effective technology tends to be able to reduce income inequality in a country. Research results from Biyase, et al (2023) in BRICS countries concluded that technological innovation tends to increase income inequality.

Theoritical Framework

The rationale for this research is based on the idea that technology is an engine for regional economic growth and development, but on the other hand it also causes income inequality. To prove the hypothesis that there is an influence of technology on economic development and income inequality, the following framework scheme was created. As an dependent variable, income inequality uses the Gini Index. On the other hand, the independent variable for technology uses three indicators, namely the percentage of smartphone, internet and computer use.

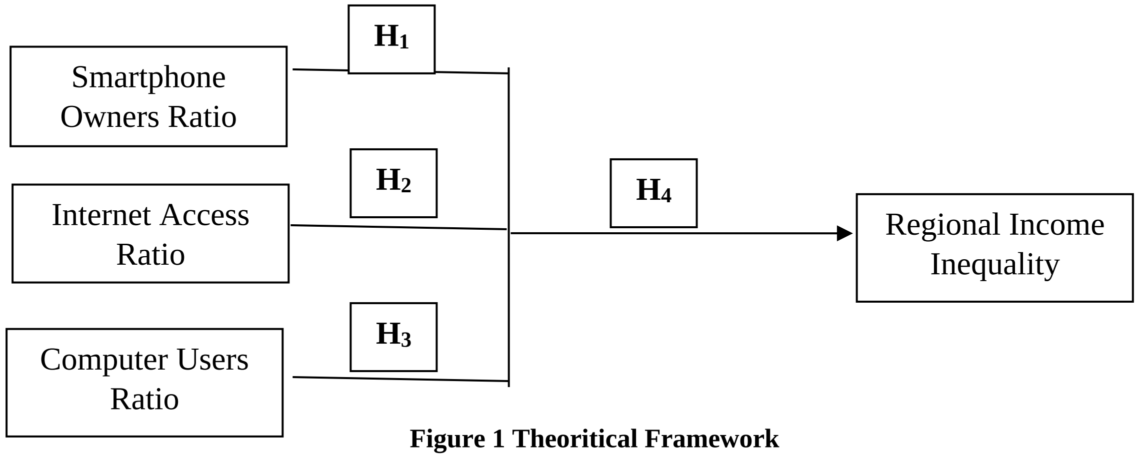

Figure 1 Theoritical Framework

Methods

This study uses a quantitative approach. The data used is secondary data, covering 34 provinces in Indonesia, for the time period 2016 – 2022. Data source is from the publication of the Central Statistics Agency. The operational definitions of the variables used in this research can be seen in Table 1.

Table 1 Operational Variables

The Type of Variables	Variabels	Unit	The Source of Data
Dependent Variable	Regional Income Inequality	Indexes	Central Bureau of Statistics Indonesia
Independent Variable (X1)	Smartphone Owners Ratio	Percentage	Central Bureau of Statistics
Independent Variable (X2)	Internet Access Ratio	Percentage	Central Bureau of Statistics
Independent Variable (X3)	Computer User Ratio	Percentage	Central Bureau of Statistics

To find out whether there is a heteroscedasticity problem, the Wald test is used, while to find out serial correlation, the Wooldridge test is used. The multicollinearity problem can be seen from the variance inflation factor (VIF) value or from the high correlation value between the independent variables. Meanwhile, for heteroscedasticity and time series (autocorrelation) solutions, regression is carried out using the robust standard error technique (Wooldrige, 2016).

The regression analysis used is panel data regression analysis, using the Stata application. There are several advantages to using panel data in regression models, namely that it can provide more complete information, is more satisfactory for determining dynamic changes, helps studies to analyze more complex behavior, for example phenomena of economic scale and technological change and can minimize the bias produced by aggregation. individual or company because there are more data units. There are three estimation techniques used in conducting panel data analysis, namely as follows:

Pooled Least Square (PLS)

This technique is the simplest panel data technique because it only combines cross section data and time data. This technical approach does not pay attention to time and cross section indicators, and estimates using the same approach as ordinary least squares (OLS) or least squares techniques to estimate panel data models.

Random Effect (RE)

This technique assumes that the error has an inter-time and inter-cross section relationship. Therefore, the estimation results using Random Effect will adjust the constant value (intercept) to the error of each cross section. The Random Effect technique is also known as the Generalized Least Square (GLS) technique so that the assumption of homoscedasticity is definitely met (there is no heteroscedasticity).

Fixed Effects (FE)

This technique assumes that differences between cross sections are accommodated by a constant value (intercept). When using this method, estimation will be carried out using a dummy variable which will capture constant differences between cross sections. This technique approach is also known as the Least Squares Dummy Variables (LSDV) approach.

The explanation of the panel data estimation model selection test can be explained as follows:

Lagrange Multiplier (LM) Test

The LM test is used to determine whether an estimate should use the Random Effect model rather than the Pooled Least Square model. This test was developed by BreuschPagan.

Testing the significance of the Random Effect model is based on the residual values from the OLS method. The LM test is based on a chi-square distribution with a degree of freedom equal to the number of independent variables. If the LM statistical value is greater than the critical value of the chi-squares statistic, then the null hypothesis is rejected, which means that the estimate is correct using the random effects method rather than OLS.

Hypothesis:

H0: Choose Pooled Least Square

H1: Choose Random Effect

Chow Test

Chow testing is used to determine which model is best, whether an estimate should use the Fixed Effect model or use the Pooled Least Square model, with the hypothesis:

H0: Choose Pooled Least Square

H1: Select Fixed Effect

Hausman test

The Hausman test was developed by Hausman in 1978 (Gujarati, 2004). The Hausman test is used to determine which estimation model should be used, between the Random Effect model or the Pooled Least Square model. In this test, is there a correlation between the error terms and the independent variables. If correlation occurs, then Fixed Effect is a better model to use.

H0: Choose Random Effect

H1: Select Fixed Effect

Result and Discussion

Results

Table 2 Pool Regression

Dependent Variable: Y
Method: Panel Least Squares
Date: 03/01/24 Time: 23:21
Sample: 2016 2022

Periods included: 7

Cross-sections included: 34

Total panel (balanced) observations: 238

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.419202	0.018120	23.13466	0.0000
X1	-0.003286	0.000560	-5.864525	0.0000
X2	0.001019	0.000260	3.920078	0.0001
X3	0.004474	0.000577	7.750952	0.0000

R-squared	0.216406	Mean dependent var	0.351441
Adjusted R-squared	0.206360	S.D. dependent var	0.038815
S.E. of regression	0.034579	Akaike info criterion	-3.874466
Sum squared resid	0.279798	Schwarz criterion	-3.816109
Log likelihood	465.0615	Hannan-Quinn criter.	-3.850947
F-statistic	21.54136	Durbin-Watson stat	0.251603
Prob(F-statistic)	0.000000		

Source: Eviews-9

Table 2 shows pool regression. X1, X2, and X3 have probability under 5%. It show that smartphone owners ratio, internet access ratio, and computer user ratio have impacted regional regional income inequality partially. Technological progress have impacted regional income inequality simultaneously.

Table 3 Lagrange Multiplier Test

Lagrange Multiplier Tests for Random Effects

Null hypotheses: No effects

Alternative hypotheses: Two-sided (Breusch-Pagan) and one-sided (all others) alternatives

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	473.9756	0.830985	474.8065
	(0.0000)	(0.3620)	(0.0000)
Honda	21.77098	0.911584	16.03899
	(0.0000)	(0.1810)	(0.0000)
King-Wu	21.77098	0.911584	9.377816
	(0.0000)	(0.1810)	(0.0000)

Standardized Honda	22.69942 (0.0000)	1.761903 (0.0390)	13.72958 (0.0000)
Standardized King-Wu	22.69942 (0.0000)	1.761903 (0.0390)	7.759678 (0.0000)
Gourierioux, et al.*	--	--	474.8065 (< 0.01)

*Mixed chi-square asymptotic critical values:

1%	7.289
5%	4.321
10%	2.952

Source: Eviews 9

Table 3 shows lagrange multiplier test. Both Ho is rejected. It means random effect prefer to pooled least square.

Table 4 Fixed Effect Regression

Dependent Variable: Y
Method: Panel Least Squares
Date: 03/01/24 Time: 23:23
Sample: 2016 2022
Periods included: 7
Cross-sections included: 34
Total panel (balanced) observations: 238

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.365013	0.020693	17.63976	0.0000
X1	0.000222	0.000428	0.519045	0.6043
X2	-0.000490	0.000126	-3.878649	0.0001
X3	0.000368	0.000310	1.184943	0.2374

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.941590	Mean dependent var	0.351441
Adjusted R-squared	0.931129	S.D. dependent var	0.038815
S.E. of regression	0.010186	Akaike info criterion	-6.193567
Sum squared resid	0.020856	Schwarz criterion	-5.653760
Log likelihood	774.0344	Hannan-Quinn criter.	-5.976015

F-statistic	90.00606	Durbin-Watson stat	1.668445
Prob(F-statistic)	0.000000		

Source: Eviews 9

Table 4 shows fixed effect regression. X1 and X3 have not significantly impacted Y. It means smartphone owner ratio and computer user ratio do not impact income equality. In contrast, X2 impact Y partially. It means internet access rasio impact regional income inequality. Technological progress has significantly affected regional income inequality.

Table 5 Chow Test

Redundant Fixed Effects Tests
Equation: Untitled
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	75.621738	(33,201)	0.0000
Cross-section Chi-square	617.945924	33	0.0000

Source: Eviews

Table 5 shows chow test. Ho is rejected. It means fixed effect prefer to pooled effect.

Table 6 Random Effect Regression

Dependent Variable: Y
Method: Panel EGLS (Cross-section random effects)
Date: 03/01/24 Time: 23:25
Sample: 2016 2022
Periods included: 7
Cross-sections included: 34
Total panel (balanced) observations: 238
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.366541	0.019483	18.81340	0.0000
X1	9.31E-05	0.000397	0.234442	0.8148
X2	-0.000432	0.000122	-3.523484	0.0005
X3	0.000537	0.000301	1.784851	0.0756

Effects Specification

	S.D.	Rho

Cross-section random		0.032371	0.9099
Idiosyncratic random		0.010186	0.0901

Weighted Statistics			
R-squared	0.292185	Mean dependent var	0.041507
Adjusted R-squared	0.283110	S.D. dependent var	0.012305
S.E. of regression	0.010419	Sum squared resid	0.025401
F-statistic	32.19829	Durbin-Watson stat	1.363391
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.036657	Mean dependent var	0.351441
Sum squared resid	0.343981	Durbin-Watson stat	0.100679

Source: Eviews 9

Table 6 shows random effect. X1 and X3 do not signify Y. It means smartphone owners and computer user ratio

Table 7 Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	13.799954	3	0.0032

Source: Eviews 9

Table 7 shows hausman test. Ho is rejected. It menas fixed effect prefer to random effect.

Discussion

The model data panel that chosen is fixed effect regression. Smartphone owners ratio add the income equality 0.00022. Increasing smartphone 1% will increase regional income inequality 0,00022%. Internet access ratio minus regional income inequality 0.000490. Increasing internet access ratio 1% will decrease regional income inequality 0.00049%. Computer user ratio add the regional income inequality 0.000368. Increasing computer users ratio 1 % will increase regional income inequality 0.000368%.

Conclusion

In conclusion, The smartphone owners ratio does not impact regional income inequality. The internet access ratio signify regional income inequality. Computer users rasio does not signify regional income inequality. Technological progress/ICT significantly impact regional income inequality.

Acknowledgement

This research is self-funded.

References

Adiningsih S, Lokollo EM, Setiaji SN, Ardiansyah SR, Islam M, Rahmawaty UFR. (2019). *Transformasi Ekonomi Berbasis Digital di Indonesia. Lahirnya Tren Baru Teknologi, Bisnis, Ekonomi, dan Kebijakan di Indonesia*. PT Gramedia Pustaka Utama

ITU Report. (2017). *Measuring the Information Society Report*. International Telecommunication Union. United Nations

Rath BN, Hermawan D. (2019). Do Information and Communication Technologies Foster Economic Growth in Indonesia? *Bulletin of Monetary Economics and Banking*. Vol. 22, No. 1 (2019). pp. 103 – 122

Makun K, Jayaraman TK. (2020). Spread Of Ict And Economic Growth In Pacific Island Countries: A Panel Study. *Bulletin of Monetary Economics and Banking*. Special Issue 2020. pp. 109 - 128

Juhro S, Trisnanto B. (2018). Paradigma Dan Model Pertumbuhan Ekonomi Endogen Indonesia. *Working Paper*. Bank Indonesia Institute

Fitriana W. 2019. Model Ekonomi Kreatif Inklusif di Sumatera Barat. *Disertasi*. IPB. Bogor

Raeskyesa, Sidan DG, Erica NL. 2019. Does Digitalization Increase Economic Growth? Evidence from ASEAN8 Countries. *Jurnal Ekonomi Indonesia*. 8, no.2 (2019). http://jurnal.isei.or.id/index.php/isei/article/view/33

Nizar NI, Sholeh AN. 2021. Peran Ekonomi Digital Terhadap Ketahanan Dan Pertumbuhan Ekonomi Selama Pandemi Covid-19. *Jurnal Madani*. Vol. 4, No. 1, Maret 2021. Lembaga Kajian Demokrasi dan Pemberdayaan Masyarakat

Peng B. 2014. Status and income inequality in a knowledge economy. *The Journal of Economic Inequality*. Springer. Society for the Study of Economic Inequality. vol. 12(4). pages 581-595, December

Ndoya H, Asongu SA. (2022). Digital divide, globalization and income inequality in sub-Saharan African countries: analysing cross-country heterogeneity. *Social Responsibility Journal*. Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/SRJ-07-2022-0277

Antonelli C, Tubiana M. (2020). Income inequality in the knowledge economy. Structural Change and Economic Dynamics. *Elsevier*, vol. 55(C), pages 153-164

Korres. G. M. (2018). *Technical Change and Economic Growth : Inside the Knowledge Based Economy*. Taylor & Francis Group.

Buceli, I. (2017). Understanding the Links between Inequalities and Poverty (LIP). CASE Papers /204. Centre for Analysis of Social Exclusion. LSE

Arshed N, Awais A, Muhaf mmad SH, Samra B. 2019. Education stock and its implication for income inequality: The case of Asian economies. *Review of Development Economics*, Wiley Blackwell, vol. 23(2), pages 1050-1066, May. https://doi.org/10.1111/rode.12585

McKnight, A. 2019. Understanding the relationship between poverty, inequality and growth: a review of existing evidence. *CASE Papers /216*. Centre for Analysis of Social Exclusion, LSE.

Richmond K & Triplett RE. (2017). ICT and income inequality: a cross-national perspective. *International Review of Applied Economics*. DOI:10.1080/02692171.2017.1338677

Mduduzi Biyase M, Zwane T, Mncayi P, Maleka M. 2023. *Do Technological Innovation and Financial Development Affect Inequality? Evidence from BRICS Countries*. International Journal of Financial Studies. MDPI

Wooldridge, JM. 2016. *Introductory econometrics: A modern approach*. Six Edition. International Student Edition. 20 Channel Center Street, Boston, MA 02210, USA. Cengage Learning.