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Regional Income Inequality in Indonesia: The Role of Public and Private Investment

(Ketidaksamaan Pendapatan Serantau di Indonesia: Peranan Pelaburan Awam dan Swasta)

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ABSTRACT

This study analyzed the effect of investment on regional income inequality in Indonesia using a panel dataset on 33 provinces for the period 2006 -2021. We distinguished among three forms of investment, namely, regional public investment (RDI), private domestic investment (PDI), and foreign direct investment (FDI). By employing a dynamic panel system generalized method of moment (Sys-GMM) estimation, this study revealed that PDI exacerbated regional income inequality Even though PDI alongside FDI positive affect regional economic growth. Among other findings, school participation rate and internet access reduced regional income inequality. But average years of schooling is associated is increased regional inequality suggesting that the school completion benefited middle- and high-income groups. The regional government needs to open up greater access to secondary education and create more proper digital infrastructure in remote areas.

Keywords: Education; regional income inequality; internet; investment
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ABSTRAK

Kajian ini menganalisis kesan pelaburan terhadap ketidaksamaan pendapatan serantau di Indonesia menggunakan set data panel di 33 wilayah bagi tempoh 2006 -2021. Kami membezakan antara tiga bentuk pelaburan, iaitu, pelaburan awam serantau (RDI), pelaburan domestik swasta (PDI), dan pelaburan langsung asing (FDI). Dengan menggunakan anggaran kaedah momen umum sistem panel dinamik (Sys-GMM), kajian ini mendedahkan bahawa PDI memburukkan lagi ketidaksamaan pendapatan serantau Walaupun PDI bersama FDI secara positif menjejaskan pertumbuhan ekonomi serantau. Antara penemuan lain, kadar penyertaan sekolah dan akses internet mengurangkan ketidaksamaan pendapatan serantau. Tetapi purata tahun persekolahan adalah dikaitkan dengan peningkatan ketidaksamaan wilayah yang menunjukkan bahawa lepasan sekolah memberi manfaat kepada kumpulan berpendapatan sederhana dan tinggi. Kerajaan wilayah perlu membuka akses yang lebih besar kepada pendidikan menengah dan mewujudkan lebih banyak infrastruktur digital yang sesuai di kawasan terpencil.

Kata kunci: Pendidikan; ketidaksamaan pendapatan serantau; internet; pelaburan

INTRODUCTION

Global income inequality increased dramatically at the end of 2021 with an individual from the 10% highest income population earning USD 122,100 per year while someone from the lowest income group earning only USD 3,920 (Chancel et al. 2022). From the aspect of wealth point of view, 10% of the population controls 76% of the world's total wealth. This sad situation must be taken seriously, especially by developing countries, because enormous income inequality harms economic growth (Barro 2008). During the Covid-19 pandemic, developing countries too have been affected though often with significant in-country spatial variation. According to the Indonesian Central Statistics Bureau, at the regional level, income inequality in 16 of 34 provinces increased at the end of 2021. In a socially fragmented country like Indonesia, high-income inequality could not only trigger political instability, this can also harm regional economic growth in the long term (Amri & Nazamuddin 2018).

The drivers of income inequality are many and, among others, related to educational attainment inequality (Coady & Dizioli 2017), internet access (Canh et al. 2020), and investment (Kaulihowa & Adjasi 2018). While these three variables have been extensively studied, most studies focus are either global in scope or country-specific. These studies report mixed results that make it difficult to implement policy. Therefore, this current study examines the effect of educational attainment, internet access, and investment on regional income inequality in Indonesia. As far as we know, no other studies attempted this focus.

Moreover, a meta-regression study by Abdullah et al. (2015) noted considerable heterogeneity across studies regarding the relationship between education and income inequality, caused by several factors, such as differences in measurement methods and model specifications. Education has a more significant effect on increasing the income share of the poor than reducing the income share of the rich. Moreover, secondary schooling is reported to have a more significant effect than primary schooling in reducing inequality.

For Indonesia, access to education remains one of the key means for the poor and disadvantaged children to become more productive and escape from poverty (Asadullah & Maliki 2017). In this context, the secondary school net participation rate (SSNPR) is a proxy for educational attainment related to access to education. In Indonesia, SSNPR is also a proxy for educational attainment that is proportional in measuring the opportunity to access education and the timeliness of education travel.

Furthermore, the rich-poor gap in digital access can also increase the income gap at the regional level (Porfaraj 2018). Closing the digital divide is still a policy challenge for developing countries like Indonesia, particularly in the country's deepest and outermost regions. With the spread of internet access, people's economic activities, such as small micro and medium enterprises, e-commerce, culinary business, and transportation services, can be more developed. Among others, internet access also help reduce income inequality via educational development (Tchamyou et al. 2019) and favor economic growth (Noh & Yoo 2008). Several studies have attempted to examine the relationship between internet access and income inequality. While Ningsih and Choi (2018), Liu (2017), Asongu and Odhiambo (2019), and Canh et al. (2020) support the proposition that internet penetration reduces income inequality, Daud et al. (2020) present evidence against this view.

According to Martin and Robinson (2007), the level of education, regional conditions, and income could themselves affect the digital divide. In this context, investments in infrastructure and the business sector, especially those related to digital infrastructure, are essential in reducing the digital divide and income inequality. However, previous studies did not show a convincing result regarding the effect of investment on income inequality. The effect of investment on income inequality is debatable and additionally varies by investment type. While Bandelj and Mahutga (2010) noted that foreign direct investment (FDI) widens income inequality, Chintrakarn et al. (2012) and Herzer and Nunnenkamp (2013) found the opposite. On the other hand, Chatterjee and Turnovsky (2012) found that public investment could increase the average income but exacerbate income inequality. Moreover, the effect of investment on income inequality depends on the investment target and the types of the development sector (Mendoza 2017).

Given the ambiguous nature of the effect of investment on income inequality, this study employed three proxies to re-examine the relationship between investment and regional income inequality. This study employed regional government investment (RDI), foreign direct investment (FDI), and private domestic investment (PDI) as investment proxies.

The rest of the paper is organized as follows. Section 2 offers a critical overview of the related literature. Section 3 is methodology while section 4 reports the main findings. We conclude in section 5.

LITERATURE REVIEW

This section reviews the literature on regional inequality reduction in three aspects: (1) the role of public investment in general (2) the role of education and lastly (3) the role of digital divide.

1. The role of public investment

Mendoza (2017) explained that the effect of investment on income inequality depends on the investment target type of development. Although public investment would increase average income, it could trigger income inequality (Chatterjee & Turnovsky 2012). Wahyuni et al. (2014), and Ishak et al. (2018) found a positive effect between investment on income inequality. Other studies find no evidence that domestic investment affects income inequality. For instance, Bandelj and Mahutga (2010); Soeharjoto (2020); Salim et al. (2020) found no relationship between investment and income inequality. On the other hand, Kentor (2001) found evidence that domestic investment negatively affects income inequality. Kentor (2001) mentioned that this effect is likely because domestic investment expands job opportunities. Therefore, domestic investment considered would be able to reduce income inequality.

Researchers have also examined the relationship between FDI and income inequality. Mahutga and Bandelj (2008) found that FDI positively affects income inequality. Bogliaccini and Egan (2017) explained that FDI in the service sector is likely more associated with income inequality than in other sectors. Skill biases and technological changes in service sector work patterns are the reasons. Bogliaccini and Egan (2017) argued that FDI could not reduce income inequality in developed countries. FDI in developed countries is likely to have more skill biases that can increase the income of highskilled workers. Meanwhile, developing countries need to consider the type of FDI that does not increase income inequality (Bogliaccini & Egan 2017).

Triyono et al. (2021) did not find any effect of FDI on regional income inequality. Meanwhile, several other studies such as Halmos (2011), Figini and Görg (2011), Clark and Highfill (2011), Herzer et al. (2014), Irma et al. (2018), and Khan and Nawaz (2019), mentioned that FDI exacerbated income inequality. Basu and Guariglia (2007) mentioned that FDI increases income inequality and economic growth but reduces the agricultural sector's contribution to GDP. It verifies the theory of agrarian sector migration towards industrialization from Kuznets (2019). Many studies, such as Franco and Gerussi (2013) and Teixeira and Loureiro (2019), failed to find a significant effect of FDI on income inequality. The effect of FDI on income inequality depends on education and GDP per capita (Mihaylova 2015). Mihaylova (2015) revealed that FDI increases income inequality in countries with low human capital and economic development. However, if human capital and economic growth are high, FDI could reduce income inequality.

Huang et al. (2020) explained that FDI exacerbates inequality in low-income countries but reduces it in high-income countries. At the beginning of a country's economic development, FDI could exacerbate income inequality. However, along with higher levels of development, FDI could reduce inequality (Huang et al. 2020). On the contrary, Kaulihowa and Adjasi (2018) document a U-shaped effect of FDI on income inequality. FDI increased equality, but this effect diminishes with a higher level of FDI. Because of that, although FDI could increase growth, the growth originating from FDI does not certainly reduce income inequality (Kaulihowa & Adjasi 2018).

In contrast, Deng and Lin (2013) explained that inward FDI could reduce inequality in low-income countries with limited human resources. However, FDI increases income inequality in middle-income countries with abundant human resources. Many studies, such as Jensen and Rosas (2007), Chintrakarn et al. (2012), and Herzer and Nunnenkamp (2013) found that FDI could reduce income inequality. Ucal et al. (2015) mentioned that FDI reduced Turkey's income inequality in the short and long run. Moreover, Xu et al. (2021) found that income inequality will decrease along with the increase in FDI and income per capita.

2. The role of educational attainment

One of the popular strategies for reducing income inequality is strengthening and spreading education. The human capital theory posits that individual investment in education and training would increase income so that an increase in human capital among low income groups would increase labor share of the GDP, thus reducing overall inequality. However, this will be untrue of if the education access is unequal (Pose & Tselios 2009); (Lee & Lee 2018). Coady and Dizioli (2017) noted that expanding education access will reduce income inequality though its effect will decrease at a later stage of economic development. Several empirical studies proved that educational attainment reduced income inequality in developing countries (e.g. see Khan et al. 2015) and Qazi et al. (2018) in Pakistan, Kudasheva et al. (2015) in Kazakhstan, Arshed et al. (2018) in South Asian Association for Regional Cooperation (SAARC) countries, and Shimeles (2016) in developing African countries).

Several researchers, including Coady and Dizioli (2017), Istiqomah et al. (2020), and Sehrawat and Singh (2019), employed years of schooling or MYS as educational attainment proxy. Their studies proved that MYS reduces income inequality. In this context, educational attainment can be defined as a person's achievement of a level of education. However, several other studies believed that MYS is an inaccurate proxy for measuring educational attainment. Time spent in schools does not guarantee the quality of learning (Angrist et al. 2019) and Asadullah et al. (2019). Another proxy to measure educational attainment -- student enrollment – suffers from the same limitation (for studies, employing this proxy, see Benos and Karagiannis (2010), Tsai et al. (2010), Suri et al. (2011), and Ramos and Mourelle (2019) and (Keller 2010).

Moreover, the enrollment ratio proxy tends to ignore the dropout rate aspect. Students who register for school do not guarantee to complete their education on time. Because of these reasons and in the absence of data on test scores (or learning outcomes), this study prefers to employ the secondary school net participation ratio (SSNPR) as another alternative proxy for measuring educational attainment. SSNPR reflects the education spread at the secondary level, so this proxy is predicted to reduce regional income inequality, assuming that the correlation between schooling and learning is satisfactory.

3. The role of internet access

Mayer (2010) explained that reducing income inequality by expanding education was not promising. Particular policies such as tax redistribution, transfer systems, and wage control are needed. This opinion is in line with the findings of Breen and Chung (2015) that education policy could only have a minor impact on income inequality in the United States. Climent and Doménech (2014) found no evidence that educational attainment reduced income inequality. Skill-biased technological change is one reason for that insignificant effect (Murphy & Topel 2016). Therefore, educated workers do not always have the competencies to master the leading and supporting technology for production factors. Because of that reason, it is necessary to increase access to information technology via the internet.

Tchamyou et al. (2019) proved that the interaction between internet use in primary and secondary education would reduce income inequality. It means that education needs to be balanced by the internet to produce educated workers who master technology. Several studies have attempted to examine the role of internet access in reducing income inequality. The effect of the internet on income inequality depends on its economic and political characteristics (Richmond & Triplett 2018). Omar and Inaba (2020) explained that internet access could increase financial inclusion, which reduces income inequality. Some studies mentioned the internet as Information Communication Technology (ICT). Bauer (2018) mentioned that ICT affects direct and indirect income distribution. Meanwhile, Demir et al. (2020) mentioned that financial technology (Fintech) is the ICT aspect that affects income inequality. Demir et al. (2020) stated that Fintech reduced income inequality through financial inclusion.

Studies regarding the link between internet access and income inequality have been deployed in many countries. For instance, Ningsih and Choi (2018) in Southeast Asia, Asongu and Odhiambo (2019) in African countries, Liu (2017) in 51 developing and developed countries, and Canh et al. (2020) with data from 46 developing countries and 41 developed countries. They found that internet access reduced income inequality.

On the contrary, Daud et al. (2020) explained that Fintech could widen income inequality. With digital access to technology, this Fintech tends to be only used by higher-income groups. This situation showed that internet penetration also needs to be well-distributed. Education level, areas, and income level could determine the affordability of internet access (Martin & Robinson 2007). In other words, if internet access positively affects income inequality, it indicates a digital divide. Investments in infrastructure and the business sector, especially those related to digital infrastructure, are essential in reducing the digital divide.

METHODOLOGY

The data in this study was extracted from the Indonesian Central Statistics Bureau at the national and regional levels. Indonesia's total number of provinces is 34, but only 33 have relatively complete data. Therefore, this study only employed panel data for 33 Provinces from 2006 to 2021. The dependent variable in this study is regional income inequality proxied by the Gini coefficient (GINI). Meanwhile, the explanatory variables in this study are educational attainment, internet access, and investment. Education attainment is proxied by MYS and SSNPR. In contrast, investment is proxied by regional public investment (RDI), domestic private investment (DPI), and foreign direct investment (FDI). As for internet access, this study used the percentage of households accessing the internet (INT).

According to the World Bank, the GINI measures income or consumption distribution. In the context of this study, we calculated the GINI based on the consumption approach as a proxy for income. Therefore, this study employed this formula to estimate the GINI:

$$\text{GINI} = 1 - \sum_{i=1}^{n} \text{f.pi x} \left(\text{FC}_i + \text{FC}_{i-1}\right)(1) \qquad (1)$$

Where GINI= Gini Coefficient, fpi = population frequency on the i^{th} spending class, and Fci = cumulative frequency from total spending in the i^{th} spending class.

MYS is calculated based on the following formula:

$$\text{MYS} = \frac{1}{n} \times \sum_{i=n}^{n} \text{xi}(2) \qquad (2)$$

Where MYS = mean years of schooling residents aged 25 and over, *xi* = years of schooling of the i^{th} residents aged 25 and over, n = total population of residents aged 25 and over

This study also used the SSNPR as one of the education attainment proxies. The SSNPR shows how many school-age residents can access the educational facilities according to their level of education. If all school-age children can attend school on time, the SSNPR will reach 100 percent. The SSNPR in this study is calculated based on the following formula:

$$\text{SSNPR} = \frac{\sum a}{b} \text{x100\%}(3) \qquad (3)$$

Where α = students aged 16 to 18 years, b = total population aged 16 to 18.

We do not employ the primary net participation rate for several reasons. Primary schooling data in Indonesia tends to be less varied because it is relatively spread out in each province. In addition, some studies, such as Keller (2010), state that primary schooling could increase income inequality. This finding is reinforced by a meta-analysis study from Abdullah et al. (2015), which states that secondary schooling significantly reduces income inequality compared to primary schooling. However, we test the primary schooling net participation rate as part of the robustness checks.

Furthermore, the internet access variable in this study is measured by the percentage of households accessing the internet using cellular telephones or computers in the last three months. In contrast, the Indonesian Central Statistics Bureau only provided the total investment, FDI, and provincial government investment in capital expenditure data. The PDI data are unavailable, so this study estimates PDI by subtracting total investment by RPI and FDI. This study defines FDI as investment made by companies, individuals, or the government outside the country. Meanwhile, RPI is the total investment of the provincial government in the form of capital expenditures. At the same time, PDI is the investment made by domestic companies, citizens, or households. All investment proxies in this study used a million USD unit of measure. In order to get a more precise estimation, we logged the FDI, RPI, and PDI.

This study used dynamic panel data analysis. According to Baltagi (2005), the general equation for dynamic panel analysis is as follows:

$$Y_{it} = \delta Y_{i,\ t-1} + \beta X_{it} + u_{it} (4) \quad (4)$$

Where δ = scalar, X_{it} = 1 x K, and β = K x 1. Furthermore, i = 1,….N, t = 1,…..T. Therefore, u_{it} = μi + νit follows the one-way error component model.

Based on the fundamental equation above, the model specification in this study is as follows:

$$\begin{aligned} GINI_{it} &= \delta GINI_{it-1} + \beta_1 MYS_{it} \\ &+ \beta_2 SSNPR_{it} + \beta_3 INT_{it} \\ &+ \beta_4 LogFDI_{it} + \beta_5 LogRPI_{it} \\ &+ \beta_6 LogPDI_{it} + u_{it} \end{aligned} \quad (5)$$

Based on the model above, this study formulates six hypotheses to be tested. This study suspects that educational attainment proxied by MYS and SSNPR could reduce regional income inequality (H_1 and H_2). This study also suspects that internet access could reduce regional income inequality (H_3), and investment proxied by FDI, PDI, and RPI could reduce regional income inequality (H_4, H_5, and H_6). However, this study also estimated the effect of income inequality and all those explanatory variables on regional economic growth to support the hypothesis results. It is necessary to understand whether income inequality inhibits economic growth or vice versa. The growth in this study is the percentage of real regional GDP growth. Therefore, the second model specification of this study is as follows:

$$\begin{aligned} GROWTH_{it} &= \delta GROWTH_{it-1} + \beta_1 GINI_{it} \\ &+ \beta_2 MYS_{it} + \beta_3 SSNPR_{it} \\ &+ \beta_4 INT_{it} + \beta_5 LogFDI_{it} \\ &+ \beta_6 LogRPI_{it} + \beta_7 LogPDI_{it} + u_{it} \end{aligned} \quad (6)$$

According to Baltagi (2005), static models on dynamic panel data are prone to bias and inconsistency. Moreover, relative economic variables may deliver endogeneity problems, or Y_{it-1} is correlated with u_{it}. There is also the possibility of an omitted variable and simultaneity. Therefore, it is necessary to estimate the instrumental variables to overcome these possible problems (Arellano & Bond 1991). Concerning instrumental variables, the simple instrumental variable and the generalized method of moment (GMM) are the most widely used method.

According to Baum et al. (2003), GMM is more efficient under heteroscedasticity conditions than simple instrumental variables. In this case, there are two types of GMM: the first difference generalized method of moment (FD-GMM) and the dynamic panel system generalized method of moments (Sys-GMM). Blundell and Bond (1998) mentioned that Sys-GMM is more efficient than FD-GMM in limited time series data conditions. In this study, the time series data is lower (16) than the cross-sectional data (33), so this study chose Sys-GMM to estimate the model.

Sys-GMM is a method developed by Arellano and Bover (1995) and Blundell and Bond (1998). Apart from the fact that T is more significant than N, this study uses Sys-GMM for several reasons. It is to anticipate endogeneity bias, control for time-unvarying country-specific effects, and avoid model assumption problems. One of the advantages of GMM is that it does not require homoscedastic assumptions and independent serials. In addition, using Sys-GMM in this study can increase precision and reduce finite sample bias (Blundell et al. 2000).

Baltagi (2005) states that studies using economic indicators such as the relationship between investment, imports, exports, and production tend to produce an endogeneity bias. We used two lag-dependent for instruments to anticipate this potential endogeneity bias. It refers to Ullah et al. (2018), who state that lags dependent is used as an instrument to control endogeneity. According to Ullah et al. (2018), using two lag-dependent variables is relatively sufficient to capture the persistence of the dependent variable. This dependent variable lag can be a valid instrument for first-differences and levels equations (Arellano & Bover 1995).

RESULTS

This study describes the general condition of the data by descriptive statistical analysis. The results are as follows:

Table 1 shows that Indonesia's MYS for the last 16 years was only 8.14. If converted into the educational stage, the Indonesian people only finish senior high school. MYS achievement at the regional level has not yet reached the 9-year compulsory schooling limit. Conditions that are still concerning can also be seen in the value of the SSNPR, which has only reached 54.66%. In other words, only 54.66% of school-age residents can access secondary education on time. The sad two conditions of educational attainment are exacerbated by the percentage of internet access which tends to be low. In the last 16 years, only 36.86% of households in Indonesia have access to the internet.

Table 1 also shows that the investment with the lowest value comes from RDI, which averages

TABLE 1. Descriptive Statistics

	Obs	Mean	Std.Dev	Min	Max
MYS	528	8.148	0.948	5.76	11.17
GINI	528	0.356	0.04	0.236	0.506
SSNPR	528	54.669	9.892	29.16	74.82
FDI	528	695.386	1222.36	0	9927.6
GROWTH	528	5.247	3.671	-17.14	28.47
INT	528	36.861	26.344	0.97	95.44
PDI	528	5125.737	8787.296	-1681.04	57150.61
RPI	528	100.674	192.343	8.169	2444.489

Notes: The measurement unit for MYS is years. At the same time, SSNPR is a percentage that shows what percentage of the participation rate of citizens aged 16 to 18 can access secondary education. The unit of measurement for internet access is the percentage that shows how many households access the internet. The measurement unit for FDI, PDI, and RPI is millions of USD

TABLE 2. Correlation matrix

	MYS	GINI	SSNPR	GROWTH	INT	LogFDI	LogPDI	LogRPI
MYS	1							
GINI	-0.003	1						
SSNPR	0.526	0.042	1					
GROWTH	-0.052	0.070	-0.195	1				
INT	0.446	0.134	0.715	-0.296	1			
LogFDI	0.246	0.196	0.277	-0.075	0.409	1		
LogPDI	0.288	0.232	0.252	-0.119	0.393	0.682	1	
LogRPI	0.339	0.157	0.176	-0.173	0.318	0.561	0.654	1

Notes: This study was multicollinearity free because the correlation matrix between the independent variables is less than 0.8

TABLE 3. System GMM estimation overall data sample

	I	II
MYS	0.0041** (3.13)	0.3419 (0.4)
SSNPR	-0.0006** (-2.91)	0.0287 (0.21)
INT	-0.0001** (-2.53)	-0.1282*** (-6.15)
LogFDI	-0.0001 (-0.13)	0.6553** (2.43)
LogPDI	0.0114*** (5.13)	1.004** (2.06)
LogRPI	-0.0018 (-0.75)	-0.4171 (-0.82)
GINI	-	-11.326 (-0.93)
Sargan *p*-value	518.921 (0.0953)	223.0169 (0.062)
AR (1) *p*-value	-3.9278 (0.0001)	-3.1381 (0.0017)
AR (2) *p*-value	-1.8217 (0.0685)	-0.2933 (0.7693)
Observations	450	260

Notes: *significant at α=0.10, **significant at α=0.05, ***significant at α=0.01. Column I results from dynamic panel system GMM estimation with GINI as the dependent variable. Column II results from dynamic panel system GMM estimation with growth as the dependent variable. All explanatory variables in this study were treated as potential endogenous variables. The Sargan coefficient tests the validity of instruments by determining the correlation between residues and the overidentifying restrictions. If the p-value of Sargan is higher than 0.05, the system GMM instruments are valid. In this study, the number of lags dependent used as an instrument variable depends on the Sargan test. For the model in column I, the instrument is valid at the lag dependent 2. In contrast, in the column 2 model, the instrument passes the Sargan test at lag 8. Thus, the system GMM is consistent if the probability value of AR 2 is higher than 0.05. On that basis, the estimation of this model is declared consistent. It does not contain autocorrelation in the second-order error difference. The lagged dependent variables are not shown for brevity. Value in parentheses are robust t-statistics

100 billion USD annually. When compared to the total investment value, RDI only contributed 1.7%. Meanwhile, FDI contributed 11.7% and PDI 86.5%. Thus, the number of standard deviations for FDI, PDI, and RDI shows inequality. FDI, for example, is still relatively concentrated in urban areas. Furthermore, Indonesia's Gini coefficient average for the last sixty years is 0.356. It makes Indonesia one of the broadest income inequality countries in Southeast Asia. Besides, regional economic growth tends to be relatively high at 5.24%.

Before employing the Sys-GMM estimation, this study diagnosed multicollinearity by correlating all independent variables. The results are as follows:

Table 2 shows that a reasonably high correlation occurs between proxies that are similar to variables. FDI is relatively correlated with PDI and PI because they are investment measures. Likewise, MYS also has a reasonably high correlation with SSNPR because both are proxied for education attaintment. Internet access has a reasonably significant correlation with SSNPR because there is a fairly close relationship between education attainment and internet access. Tchamyou et al. (2019) mentioned that secondary education and internet access have interacted. Furthermore, the results of the Sys-GMM estimation are as follows:

In model 1 (column 1), we only use two lag-dependent variables as instruments. In contrast, we use eight lag-dependent variables in model 2 (column 2). It is because, in model 2, the dependent variable used is economic growth which may have more potential omitted variable bias. The results of the Sargan test verified the use of the lags-dependent value. Many researchers (e.g. see Tsai et al. 2010) and Khan and Nawaz (2019) also employed relatively many lags dependent variables as the instruments.

Table 3 shows that internet access and educational attainment proxied by SSNPR reduced regional income inequality. However, MYS increased regional income inequality. From the investment aspect, public and foreign investment have an insignificant negative effect on income inequality. Meanwhile, private domestic investment has been proven to exacerbate income inequality. On the other hand, this study found that internet access reduced regional economic growth rates. In contrast, this study found the positive effect of FDI and PDI on regional economic growth.

Furthermore, to get additional proof regarding the consistency of effects between variables, this study conducted a Sys-GMM estimation by clustering data based on the level of regional GDP. The regional middle limit of GDP is 3% (100/33), so a province with a regional GDP above 3% will be categorized as an upper level, while a lower level is below that limit. In this case, there are only eight provinces that are included in the upper-level group: DKI Jakarta, Jawa Timur, Jawa Barat, Jawa Tengah, Riau, Kalimantan Timur, Sumetara Utara, and Banten. Provinces with the upper-level category are far less than the lower level because there is a large regional GDP gap. For example, DKI Jakarta, Jawa Timur, Jawa Barat, and Jawa Tengah each have a regional composition of GDP of 16.95%, 14.69%, 13.44%, and 8.58%. The four provinces control 53.67% of the Indonesian economy if accumulated. The lower level group contains 25 provinces with a regional GDP contribution below 3%. The results of the Sys-GMM for the two regional groups are as follows:

Table 4 shows that MYS and domestic private investment increase regional income inequality in provinces with high or low GDP. Meanwhile, SSNPR and internet access reduced regional income inequality in all provinces. These results are consistent with the Sys-GMM for the overall data sample. The main difference that can be seen from the analysis based on this regional GDP group is in column II. In provinces with high regional GDP, FDI and PDI affect regional economic growth positively. However, FDI and PDI do not affect regional economic growth in lower-level regional GDP provinces.

ROBUSTNESS CHECKS

This study checks robustness in several ways. We employ the Williamson Index (WI) as an alternative measure of income inequality. However, due to data availability, WI can only be estimated from 2010 to 2021. This study calculates the WI with the following formula:

$$WI = \frac{\sqrt{\Sigma_i \left(Y_i - \bar{Y}\right)^2 n_i / n}}{\bar{Y}} (7) \qquad (7)$$

where, Y_i is per capita GDP at regional level i, while Y is per capita GDP at the national level. Thus, n_i is the population in region i, and n is the population at the national level.

The results of the Sys GMM estimation on robustness checking in this study are as follows:

Table 5 shows that SSNPR and internet access reduce income inequality while MYS exacerbates it. These results are similar to the main results of this study (see table 3). Furthermore, from column 2 of table 5, internet access reduces economic growth while FDI increases it. This result is also in line with table 3. The difference between the primary results and this robustness check appears from regional public investment's effect on income inequality. In table 5, the RPI has a positive effect on income inequality, in contrast to table 3, which shows that the RPI reduced income inequality, although the effect is insignificant. It is because WI tends to record clearer disparities between provinces, where one of the causes is the size of regional income and expenditure between provinces.

TABLE 4. System GMM estimation based on regional GDP province group

	Upper Level		Lower Level	
	I	II	I	II
MYS	0.0031** (2.48)	-0.0000 (0.00)	0.0064** (3.33)	0.9348* (1.92)
SSNPR	-0.0004** (-2.23)	-0.0358 (-1.12)	-0.0009*** (-3.83)	0.0264 (0.41)
INT	-0.0002** (-3.22)	-0.0479*** (-4.93)	-0.0002** (-3.01)	-0.0814*** (-4.15)
logPDI	0.0091*** (6.9)	0.7006*** (3.93)	0.0106** (3.44)	-0.007 (-0.02)
logFDI	0.0021 (0.81)	0.3293*** (4.88)	0.0004 (0.36)	0.0881 (0.43)
logRPI	0.0008 (0.33)	-0.1665 (-0.48)	-0.0014 (-0.54)	-0.2987 (-0.77)
GINI	-	2.4478 (0.59)	-	0.2638 (0.03)
Sargan *p*-value	180.9686 (0.8415)	202.0959 (0.7267)	409.0576 (0.0961)	357.3231 (0.0794)
AR (1) *p*-value	-2.4031 (0.0163)	-2.7422 (0.0061)	-4.013 (0.000)	-2.5385 (0.0111)
AR (2) *p*-value	-1.6001 (0.1096)	-0.0007 (0.999)	1.5256 (0.1271)	0.8119 (0.4168)
N of observation	120	120	318	271

Notes: *significant at α=0.10, **significant at α=0.05, ***significant at α=0.01. The dependent variable in column I is GINI, while in column II is Growth. The initial observations in the upper-level group were 128, while those in the lower-level group were 400. However, the number of observations will decrease along with the number of instruments employed. The more dependent lags are used as instruments, the less the number of observations will be. The lagged dependent variables are not shown for brevity. Robust t-statistics are in parentheses.

TABLE 5. System GMM estimation for Williamson Index

	I	II
MYS	0.0034** (2.79)	0.2287 (0.21)
SSNPR	-0.0004** (-2.28)	0.2212 (0.9)
INT	-0.0001** (-2.09)	-0.1473*** (-6.47)
LogPDI	-0.002 (-0.99)	-0.7661 (-0.38)
LogRPI	0.0055** (2.36)	-0.3144 (-0.24)
LogFDI	-0.0017 (-1.39)	2.1649** (2.06)
WI	-	1.7701 (0.63)
Sargan *p*-value	294.0693 (0.0718)	227.5313 (0.0609)
AR (1) *p*-value	-2.563 (0.0104)	-3.5586 (0.0004)
AR (2) *p*-value	-1.6297 (0.1032)	-1.8899 (0.0588)
Observations	260	194

Notes: *significant at α=0.10, **significant at α=0.05, ***significant at α=0.01. The dependent variable in column I is Williamson Index, while in column II is Growth. We used two lag-dependent variables to estimate the models, but we have not shown them here for brevity. Robust t-statistics are in parentheses

TABLE 6. System GMM estimation for GINI without PDI

	I	II	III
MYS	0.0096*** (6.92)	-	-
INT	-0.0003*** (-6.79)	-0.0002*** (-5.08)	-0.0003*** (-7.68)
LogRPI	0.0028 (0.50)	0.0239*** (4.77)	0.0088 (1.62)
LogFDI	0.0032 (1.3)	0.0051** (2.39)	0.0045** (2.02)
SSNPR	-	-0.0001 (-0.51)	-
PRIMARY_NPR	-	-	0.0009*** (5.21)
Sargan *p*-value	436.2887 (0.1968)	442.4626 (0.379)	449.7631 (0.0967)
AR (1) *p*-value	-4.7778 (0.000)	-4.4196 (0.000)	-4.809 (0.000)
AR (2) *p*-value	2.1891 (0.0286)	-1.6906 (0.0909)	1.3345 (0.182)

Notes: *significant at α=0.10, **significant at α=0.05, ***significant at α=0.01. The dependent variable for all columns is GINI. We employed two lag-dependent variables as the instrument to estimate this model. However, we have not shown them here for brevity. Robust t-statistics are in parentheses

Furthermore, we removed the PDI variable from the model to obtain convincing results. We use the primary school net participation rate (Primary NPR) as an alternative proxy for education attainment. In addition, we also separate the MYS variable with SSNPR and Primary NPR as follows:

Table 6 shows that the results are relatively unchanged when PDI was excluded from the model and when we separated the MYS, SSNPR, and PRIMARYNPR. Internet access plays a significant role in reducing income inequality, while MYS continues to exacerbate it. Meanwhile, when MYS excluded from the model (column 2), internet access still reduces income inequality significantly. At the same time, the negative effect of SSNPR on income inequality becomes insignificant. In this condition, RPI and FDI exacerbate the level of income inequality.

On the other hand, the proxy of primary schooling net participation rate increases income inequality. This result strengthens the findings of Abdullah et al. (2015). They found that secondary schools have a more significant role in reducing income inequality than primary schools. Overall, from this robustness check, internet access is the most robust variable in reducing income inequality.

DISCUSSION

How should we interpret our estimates obtained from our econometric models? Particularly puzzling is the finding that internet access and school participation rate reduced regional income inequality while average years of schooling had the opposite effect. A good starting point is the recognition that there is considerable variation at the region level in Indonesia in Inequality trends. This is also confirmed by Figure 1 which plots income inequality data for the period 2006-2021 for all regions. In regions such as Papua and Lampung, inequality has been on the decline since 2006 while in others such as Di Yogjakarta, it has been on the rise. Regardless, during 2020-2021, most provinces did not experience an increase in regional income inequality. Only provinces with big cities such as Jakarta, West Java, and East Java, experienced a high increase in regional income inequality during the pandemic. The contrasting experience vis-à-vis COVID-19 pandemic between high-income populous areas and low-income provinces suggest that the social security program to protect the poor during the pandemic was better implemented in the latter group. In this paper, however, we are mostly interested in the long-term trends and their drivers.

In this section, we summarize our findings on regional inequality reduction with a focus on (i) the role of education (ii) the role of digital divide and lastly (iii) the role of public investment in general. We do so by focusing on region specific trends.

This study revealed that educational attaintment measured by MYS is not sufficient to reduce income inequality. If anything, in some instances, MYS has been positively correlated with income inequality. Figure 2 confirms this association for each Indonesian province while Figure 3 offers an overview of SSNPR at the provincial level..

FIGURE 1. The trend of regional income inequality in Indonesia from 2006 - 2021

As per Figure 2, urban areas have higher MYS than others. Several provinces with the largest MYS include DKI Jakarta, DI Yogyakarta, Kep. Riau, and Maluku. Meanwhile, in provinces quite far from the center of government, such as Papua, Papua Barat, Nusa Tenggara Timur, and Kalimantan Barat, MYS tends to be very low. One of the reasons for the high MYS is access to higher education. In this context, regions with limited access to higher education tend to have lower MYS. The more middle and upper-class people can access higher education, the bigger the MYS will trigger an increase in income inequality. However, in the absence of data,

FIGURE 2. Mean years of schooling across provinces

FIGURE 3. Secondary school net participation ratio across provinces

we could not investigate the role of differential access to higher education in inequality reduction. We cannot rule other interpretations. The positive association between MYS and income inequality could be owing to the ineffectiveness of education services in improving human resources and education simply being valued for consumption (i.e. signaling) purposes. Alternatively, the effect of education on income inequality could suffer from a diminishing marginal return. Pose and Tselios (2009) offer some evidence that educational attaintment could not reduce income inequality due to social gaps in access and quality which contrasts with the findings of Coady and Dizioli (2017), Istiqomah et al. (2020), and Sehrawat and Singh (2019). Equally, skill-biased technological change in various economic sectors might be the leading cause of why MYS could not reduce income inequality (Murphy & Topel 2016).

In table 3, MYS has no positive and significant effect on regional economic growth in the overall data sample, while Table 4 shows that MYS positively affects regional economic growth in provinces with low GDP. On the other hand, our study revealed that educational attaintment measured by SSNPR is negatively associated with regional income inequality, a finding that is supported Coady and Dizioli (2017). However, Table 4 also confirms that the role of SSNPR in reducing regional income inequality in the lower level of GDP provinces was higher than in the upper level of GDP.

Overall, our findings indicate that the provincial government's role in increasing access to education is crucial to reducing regional income inequalities. Some provinces such as DI Yogyakarta already have education policies that effectively spread access to education. DI Yogyakarta has become a region with a relatively high 12-year compulsory education program achievement. In addition, Yogyakarta also has various educational facilities that support the creation of a learning climate. Several are the Yogyakarta Learning Gateway Internet Library Network, providing international standard schools. Yogyakarta is one of the provinces with the most education awards in Indonesia for its success in education. Figure 3 shows that SSNPR is relatively wider than MYS. Several provinces with high SSNPR levels include DI Yogyakarta, Aceh, Kalimantan Timur, and Kep. Riau. This better spread of SSNPR reduces regional income inequality. To provide a clearer picture of the relationship between MYS, SSNPR, and regional income inequality, Figure 4 summarizes the three trends.

Figure 4 shows that the MYS trend with SSNPR has similarities. Meanwhile, income inequality fluctuated; from 2009 to 2014, there was a sharp increase in income inequality. From 2015 to 2019, it decreased but began to rise again in 2020 until now. Based on data from the Central Statistics Bureau, Indonesia's Gini coefficient as of March 2022 has reached 3.84. The trend of income inequality is quite the opposite of MYS and SSNPR, mainly starting in 2014. However, statistically, MYS has been proven to exacerbate regional income inequality. In contrast, SSNPR reduces income inequality. The reverse role between MYS and SSNPR in regional income inequality is because their characteristics were different. MYS only measures the average length of schooling without estimating how much participation of citizens between regions in accessing education. The amount of MYS can mean that the education level of the upper middle class has increased. Moreover, in Figure 2, MYS is not evenly distributed. Meanwhile, SSNPR measures the

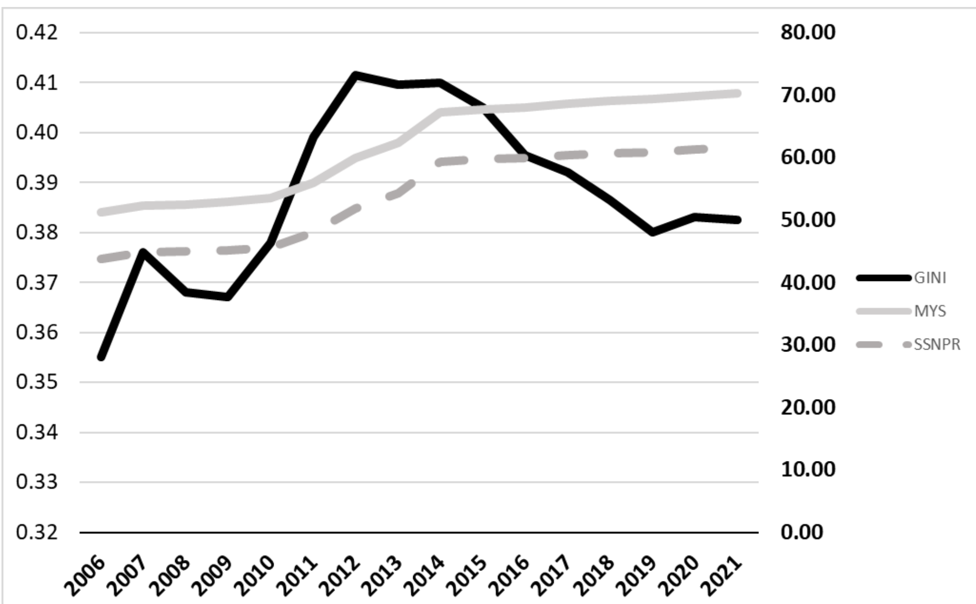

FIGURE 4. The trend of GINI, MYS, and SSNPR at the National Level in Indonesia

participation and timeliness of citizens in each region in accessing secondary education.

On the role of internet access, there are only a handful of provinces with poor internet access such as Papua, Maluku Utara, Sumatera Selatan, Bengkulu, and Sulawesi Barat. The provinces with the lowest internet access are archipelagic and mountainous areas that tend to be challenging to reach. In general, the time trend in internet access is positive in almost all provinces (Figure 5). Our study revealed that internet access helped reduce regional income inequality, a finding that is true in both the groups of provinces with low and high GDP. This is reassuring given the rapidly expanding Gig-economy in Indonesia where millions of low-income citizens have taken advantage of internet access to join e-hailing service and e-commerce sector. Expanding internet access may have helped reduce regional income inequality through supporting business activities of small and medium enterprises (SMEs). With adequate internet access, SMEs can use several e-commerce platforms to support their business development. In addition, according to Demir et al. (2020), and Omar and Inaba (2020), internet access also reduces regional income inequality by increasing access to financial inclusion. The result of this study was in line with Ningsih and Choi (2018), Liu (2017), Asongu and Odhiambo (2019), and Canh et al. (2020) They also proved that internet access reduced income inequality. An overview of the regional trend in internet access is available from figure 5. Other channels include the positive impact of growing internet penetration on education though we have not formally tested for this. Besides, the literature on digital access and learning remains inconclusive (Asadullah & Bhattacharjee (2022).

Lastly, our analysis revealed that FDI has an insignificant negative effect on regional income inequality. FDI could only affect economic growth positively. This finding aligns with most previous studies that FDI could not reduce income inequality (Franco and Gerussi 2013; Teixeira and Loureiro 2019). This null result could indicate poor absorptive capacity and technology. If Indonesian human capital has an excellent absorptive capacity, FDI could have reduced income inequality (Wu and Hsu 2012). Poor education quality might be the reasons for the insignificant effect of FDI on income inequality in our data, as is also suggested by Huang et al. (2020). The insignificant negative effect of FDI could also reflect insufficient job creation by foreign owned companies. Three sectors in Indonesia relatively receive the most foreign capital. Among them are the services sector, mining, and the metal industry. In terms of their characteristics, those sectors have a small impact on expanding employment opportunities. Among others, we also revealed that RDI has an insignificant negative effect on regional income inequality. This condition shows the limited capacity of the provincial government budget to build equity through investment. Most of the provincial government's budget is still dominated by wage expenditures. The low local revenue makes it quite difficult for the provincial government to invest in

FIGURE 5. The trend of regional internet access in Indonesia from 2006 - 2021

financial conditions. In contrast, this study found that PDI increased regional income inequality. This result supported Chatterjee and Turnovsky (2012), Wahyuni et al. (2014), and Ishak et al. (2018). They also found that domestic investment has a positive effect on income inequality.

CONCLUSION

As much as 53.67 of Indonesia's national economy is dominated by four provinces and that too all located in Java island. This study therefore re-examined the pattern of regional income inequality in the past two decades. We found evidence that if measured by SSNPR, educational attainment reduced regional income inequality. In contrast, MYS is associated with widening regional income inequality. We also find evidence that internet access reduces income inequality. On the other hand, this study finds an insignificant negative effect of FDI and RDI on income inequality. However, this study found that PDI exacerbates regional income inequality. FDI and PDI affect regional economic growth positively. Overall, the results suggest that infrastructure development in Indonesia is still unequal. The finding implies that, instead of relying on national level economic growth, the regional government needs to support equitable investment distribution so that it is not concentrated only in high-income areas. As for the federal government policy, FDI and government investment need to be increased and directed towards underdeveloped areas because, although not significant, these two investment channels have the potential to reduce income inequality.

Lastly, the study has a number of limitations when it comes to measures of human capital used. We only employed educational attainment which does not comprehensively reflect education's effect on income inequality. We also did not employ specific measures of higher education expansion. Lastly, we only employed the percentage of households accessing the internet to measure internet access. This proxy does not estimate the speed of internet access. Therefore, future studies may fill these shortcomings by replicating the study with better data.

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