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DOES DIGITALIZATION WIDEN INCOME INEQUALITY? A COMPARATIVE ASSESSMENT FOR ADVANCED AND DEVELOPING ECONOMIES

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Abstract

The paper raises two questions: (1) Does digitalization contribute to wealth and income inequality? (2) Does it affect inequality differently between advanced and developing economies? For the answers, the paper investigates the impact of digitalization on inequality for a balanced panel dataset of advanced economies and a balanced panel dataset of developing economies from 2002 through 2020. It applies the system-GMM and PMG estimators for estimation and robustness check. Some exciting results it provides. First, digitalization narrows inequality in developed economies and widens in developing economies. Second, the economic growth – income inequality relationship is U-shaped as real GDP per capita increases from low (developing economies) to high (advanced economies). Third, unemployment enhances inequality in two groups. The results note some necessary implications to develop digital technology and reduce income inequality in these economies.

Keywords: *digitalization, income inequality, advanced economies, developing economies.*

JEL classification: *C33, D31, J31, O33*

1. Introduction

Income inequality in society is one of the severe problems in both advanced and developing economies under rising digitalization and globalization because it can lead to social stabilization. Narrowing inequality across countries has become one of the eight worldwide Millennium Development Goals (MDGs) suggested by United Nations. At the same time, digitalization is currently emerging as a globally dominant and irreversible process. Governments in several developing economies hope that digitalization improves economic activities and enhances economic growth to catch up with advanced economies. Thus, digitalization is expected to be an appropriate solution to reduce income and wealth inequality in the development agendas of policy-makers in these economies. Unfortunately, economists still do not consensus about its effect on inequality. From the beginning of the GINI index in 1912 to measure global income inequality by Corrado Gini, a strand of literature on income inequality has investigated the determinants of income inequality. Notably, digital progress with the digital divide in society leads to several efforts to test

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the impact of digitalization on inequality. However, no papers study the different impacts of digitalization on inequality between advanced and developing economies.

In practice, advanced economies have many resources to solve the severe problem of inequality. Most advanced economies have high levels of economic development and high living standards with high income. In particular, these economies have a rule-based governance environment that enables them to better coordinate resources and run their economies (Li and Filer 2003). As a result, policies for addressing income inequality in these economies have also become more effective. Notably, high levels of education along with a universally applied digital background is also an advantage in helping these economies deal with income inequality if digital technology has a meaningful impact on income inequality in these economies. However, developing economies do not have enough necessary resources and appropriate solutions to decrease income and wealth inequality. Most developing economies have low levels of economic development and low living standards with low income. These economies have a relation-based governance environment (Li and Filer 2003). Governments in these economies try to formulate and implement regulations and policies to enhance digital development and reduce the income difference in society. Digitalization also helps to reform governance in developing economies in terms of E-government. Unfortunately, the digitalization process indicates a global digital divide in society in which high-income people have better access to digital technology than low-income people. It comes from the knowledge and cost required to access digital technology facing low-income people. More importantly, this challenge is more severe in developing economies because low-income people spend their income on accommodation and food. As such, differences in economic development reflected in living standards, income levels, education levels, and digital technology platforms between developed and developing economies can lead to differences in the effect of digitalization on income inequality between these two groups of economies. In particular, if digitalization has a significant effect on income inequality, the differences in this effect become even more pronounced between these two groups. Therefore, this paper suggests two research questions: (1) Does digitalization contribute to wealth and income inequality? (2) Does it affect income inequality differently between advanced and developing economies?

In short, narrowing inequality is one of the main goals of development policies in advanced and developing economies, and digitalization affects significantly this goal. In particular, the digital divide can lead to the different contributions of digitalization to income and wealth inequality between developing and advanced economies. Given these facts, this paper studies the impact of digitalization on inequality for a panel dataset of 30 advanced economies and a panel dataset of 35 developing economies between 2002 and 2020. It employs the system-GMM Arellano-Bond estimator (S-GMM) and Pooled Mean Group estimator (PMG) for estimation and robustness check.

The study presents its structure as follows. Section 1 (Introduction) provides the theoretical framework and motivation, while Section 2 presents the global income inequality and the global digital divide. Section 3 (Literature review) notes the impact of digitalization on income and wealth inequality, whereas Section 4 (Methodology) describes the empirical model, the characteristics of estimators, and the data. Section 5 provides the findings and discussion. Finally, Section 6 is a conclusion with some implications.

2. Some facts on the global digital divide and global income inequality

2.1. Global digital divide

According to UNCTAD (2021), there is a highly uneven digital development across countries. Today, the world is characterized by a big difference between less connected and hyper-digitized economies. Compared to four in five in advanced countries, just one out of five in developing countries accesses the Internet. It only reflects one aspect of the digital gap. This gap is significant in some industries like frontier technology and digital data. Both Latin America and Africa, for example, occupy below 5% of global data centers.

Notably, ITU (2018) reports that 51.2% of the global population accessed the Internet in 2018 with 3.9 billion people online. Although it reflects the advancement in digitalization, there remains a significant gap in Internet access. The Internet access growth has driven from developing economies, standing for about 90% of the global rise, with the highest rates going to developing countries. However, the Internet use growth rate these days has slowed down, implying that several middle- and low-income countries can increase Internet use for their citizens. The decrease in new online persons is partly related to their incapability to link to related devices and basic Internet. Just 40% of middle- and low-income countries have Internet access. African people have the highest average cost of Internet use compared to those in other developing regions.

Geographically, UNCTAD (2021) reports that digitalization-based economies do not mirror a traditional gap between North and South. Indeed, United States (a developed country) and China (a developing country) are still leading. They occupy more than 50% of global expenditure for the Internet of things, 75% of blockchain-based patents, and 75% of the world market for public cloud computation. Among 70 global biggest digital platforms, they capture 90% capitalization value, whereas Europe captures 4% and Latin America and Africa 1%. Thus, in the advancement of digital technology, the remaining world (notably Latin America and Africa) is following the United States and China.

2.2. Global income inequality

The rate of increase in income inequality has varied across regions of the world in recent decades. A report by Alvaredo et al. (2018) informs that income inequality in Europe is the lowest, but that in the Middle East is the highest. The share of the top 10% income earners to national income in 2016 was 37% in Europe, 41% in China, 46% in Russia, 47% in the Canada-United States, 55% in Brazil, Sub-Saharan Africa, India. The Middle East is the most unequal region, where 61% of national income belongs to the top 10%. Since 1980 global income inequality has increased sharply. In Asia, the high growth rate has led to growth in income at the 50% bottom. Globally, since 1980 the top 1% of the world's richest have captured double the growth compared to the 50% of the global bottom group due to increasing income inequality across countries. However, the rise in global income inequality has not yet stabilized. After reaching 22% in 2000, the income share of the top 1% globally decreased slightly to 20% from 16% in 1980. Furthermore, the bottom 50% of global income has hovered around 8% since 1980.

Notably, Alvaredo et al. (2018) emphasize the importance of regulations and policies (governance/institutional quality) in dealing with differences in income and wealth inequality across economies, even across economies with the same level of development. Income inequality has risen in North America, Russia, India, China, while it has been moderately in Europe since 1980. In contrast, inequality in Brazil, the Middle East, Sub-Saharan Africa has still kept relatively steady. The statistical report across countries indicates that institutional and political contexts have had impacts on income inequality dynamics since 1980. Good trends on inequality in India, Russia, China point out the positively targeted policies in these nations. However, since 1980 the gap in inequality between the United States and Western Europe has seemed too high. The income share of the top 1% in 2016 slightly rose to 20% in the United States and 12% in Western Europe from approximately 10% in 1980 in these regions. Besides, the income share of the bottom 50% in the United States decreased from nearly 20% in 1980 to 13% in 2016.

3. Theoretical framework and literature review

3.1. Theoretical framework

Given the relevance of the research topic, Mirza et al. (2019) and Prettner and Strulik (2020) have recently suggested some theoretical frameworks. A stylized social-ecological model by Mirza et al. (2019) indicates that a positive connection between digitalization and wealth enhances local income inequality, which increases poverty and natural resource degradation. In addition, the analytical results show how individuals in society access digital technology determine the distribution of wealth. Meanwhile, an R&D-driven growth model by Prettner and Strulik (2020) assumes that education is endogenous in which low-skilled labor is displaced by machines and high-skilled labor is complementary to them. The analytical results project that digitalization (automation) promotes college graduates, leading to rising income and wealth inequality. Notably, this paper discovers the opposite effect of digitalization on inequality between developing and advanced economies. We provide arguments to point out it as follows. In advanced economies with high levels of development, due to a low digital gap and high levels of education, the poor (low-income people) can easily access digital technology to enhance their skills and knowledge (UNCTAD 2021). They are easier to find high-income jobs, which narrows the income gap between low-income and high-income individuals, thereby decreasing inequality. In developing economies with low levels of development, by contrast, due to a high digital gap and low levels of education, the poor (low-income people) can not easily access digital technology. The rich (high-income people) can financially access progress in digital technology to enhance skill and knowledge. They are easier to find a high-income job and get promoted, which widens the income difference between low-income and high-income individuals, thereby increasing income inequality.

3.2. Literature review

Qureshi (2020) notes that income inequality within economies has risen as digital progress has reshaped markets of goods, business, and work. Wealth and income inequalities have increased between not only workers but firms. In the same vein, Zilian and Zilian (2020) find inequality in socio-economic digitalization in Austria through survey data from 2011 to 2012. However, so far, the number of papers on the impact of digitalization on inequality is not much. Some studies report that progress in digital technology decreases income inequality (Richmond and Triplett 2018; Canh et al. 2020), while some note that digitalization increases it (Mönnig, Maier, and Zika 2019; Mohd Daud, Ahmad, and Ngah 2020; Law et al. 2020). For the negative impact, Richmond and Triplett (2018) use the fixed effects estimator for 109 countries between 2001 through 2014. They discover that the impact of digitalization on inequality is subject to the type of digital technology and the proxy of inequality. Canh et al. (2020) apply the twostep system-GMM estimator for 87 countries from 2002 to 2014. They note that digital progress and communication are a way to narrow inequality. Mobile and Internet use should be encouraged as a means of economic policy to reduce income inequality. For the positive impact, Mönnig, Maier, and Zika (2019) use the analytical approach to study the impact of digital technology on wage inequality. They conclude that digitalization enhances income inequality. Meanwhile, Law et al. (2020) use the panel mean group (PMG) estimator for 23 developed countries from 1990 to 2015, while Mohd Daud, Ahmad, and Ngah (2020) apply the onestep system-GMM estimator for 54 countries from 2010 to 2015. Both papers note that digital technology widens income inequality.

Furthermore, some papers investigate the impact of institutional quality on wealth and income inequality. Most of them like Nadia and Teheni (2014), Josifidis (2017), Law and Soon (2020), Kunawotor (2020), Blancheton and Chhorn (2021) report that institutional improvement reduces income inequality. Nadia and Teheni (2014) apply non-parametric correlations tests for 39 countries from 1996 to 2009, while Josifidis (2017) employs the Fixed Effects Vector Decomposition (FEVD) method for 21 OECD economies between 1990 and 2010. Similarly, Law and Soon (2020) use the twostep system-GMM estimator for 65 advanced and developing economies, while Kunawotor (2020) applies the twostep difference-GMM estimator for 40 African economies over the period 1990 – 2017. More recently, Blancheton and Chhorn (2021) employ FMOLS and the DOLS estimations for 8 Asian economies during the period 1988 – 2014. They also report that public spending narrows income inequality. By contrast, Perera and Lee (2013) find that institutional quality increases inequality for a panel dataset of 9 Asian developing economies from 1985 to 2009 via the onestep system-GMM GMM estimator. They suggest that measures for institutional improvement in East and South Asian developing economies should focus on income distribution and poverty. Notably, Asamoah (2021) discovers the opposite effect of institutional/governance quality on wealth and income inequality between 24 advanced and 52 developing economies between 1996 and 2017 using the dynamic panel threshold model. Institutional improvement widens inequality in developing economies but narrows in advanced economies. He also notes a nonlinear impact of economic growth on inequality from developing to advanced economies.

Notably, some studies (Asogwa et al. 2021; Berisha, Gupta, and Meszaros 2020; Deyshappriya 2017; Hailemariam, Sakutukwa, and Dzhumashev 2021) investigate the determinants of income inequality. Deyshappriya (2017) uses the onestep difference-GMM estimator for a group of 33 Asian economies from 1990 to 2013. He finds that education, labor force, official assistance reduce inequality, but political risk, unemployment, trade openness, inflation enhance. In particular, he notes a nonlinear impact of economic growth on inequality in these economies. Meanwhile, Berisha, Gupta, and Meszaros (2020) apply the PMG estimator and the common correlated effects estimator for the BRICS economies between 2001 and 2015 and discover that interest rates, economic growth, and inflation widen income inequality. More recently, Asogwa et al. (2021) employ the GMM (pooled OLS and fixed effects) estimators for a group of 28 African economies during the period 2001- 2016. They note that education and unemployment increase income inequality while labor force, inflation, and economic growth decrease. Likewise, Hailemariam, Sakutukwa, and Dzhumashev (2021) use the panel vector auto-regression method for a sample of 17 advanced economies from 1870 to 2016 and reveal that public spending, financial development, interest rate, and education reduce inequality while growth rate enhances.

In short, in the view of literature, this paper shows two highlights that can be different from related studies. First, it provides empirical evidence to indicate the distinct contributions of digitalization on inequality between advanced and developing economies. Second, it applies the system-GMM and PMG estimators for estimation and robustness check.

4. Methodology and research data

4.1. Methodology

Following Law et al. (2020), the empirical equation is extended as follows:

$$GIN_{it} = \lambda_0 + \lambda_1 GIN_{it-1} + \lambda_2 DIG_{it} + Z_{it}\lambda' + X_{it}\lambda'' + \mu_i + \zeta_{it} \quad (1)$$

where t and i are the time and country index. GIN_{it} is the Gini index, a proxy for income inequality. Its value ranges from 0 to 100 where 0 notes complete equality (everyone has the same income) and 100 reports the highest level of income inequality. $GIN_{it\text{-}1}$ is the initial level, and DIG_{it} is digitalization. Z_{it} is a set of control variables (economic growth, education, and unemployment), while X_{it} is a set of annual time dummies. μ_i is a country-specific, time-invariant, unobserved effect and ζ_{it} is an observed error term. λ_0, λ_1, λ_2, λ', and λ" are estimated coefficients. According to Roodman (2009), the difference and system GMM Arellano-Bond estimators are built on the assumption that errors are correlated only within individuals, not across them. Because of this, following the suggestion by Roodman (2009), we include annual time dummies to remove universal time-related shocks from the errors.

We apply Equation (1) to study the impact of digitalization on inequality for a panel dataset of advanced economies and a panel dataset of developing economies. We use fixed broadband subscriptions and Individuals using the Internet as proxies of digitalization in this paper. There are several measures to proxy for digitalization in a country. They are two measures (fixed broadband subscriptions and Individuals using the Internet) released by World Bank and some digital metrics (Digital Economy Metrics, Digital Society Metrics, Digital Industry Metrics, Digital Enterprise Metrics, Digital Client Metrics, and Digital Investment Metrics) recommended by Kotarba (2017). However, this paper employs only two measures released by World Bank because so far some digital metrics recommended by Kotarba (2017) are not available.

Some severe problems in econometrics arise from estimating Equation (1). Firstly, government revenue, public spending, economic growth, and unemployment can be endogenous. They may correlate with μ_i, which results in the endogenous phenomenon. Secondly, some unobserved effects such as culture, geography, customs, and anthropology (fixed effects) can correlate with the independent variables. These fixed effects exist in μ_i. Thirdly, a high autocorrelation comes from the presence of $GIN_{it\text{-}1}$. Finally, panel data contain a large unit of economies (M = 30) and a short length of observation (L = 19). These problems can make the OLS regression biased. The random-effects model (REM) and the fixed-effects model (FEM) could not handle serial autocorrelation as well as endogenous phenomena. The IV-2SLS estimator needs some suitable instruments out of independent variables in the empirical model. Following Judson and Owen (1999), we apply the system-GMM Arellano-Bond estimator and the PMG estimator for estimation and robustness check.

Holtz-Eakin, Newey, and Rosen (1988) are the first to propose the general method of moments (GMM) Arellano and Bond (1991). Two kinds of GMM Arellano-Bond estimators are developed: the difference and the system. The past values of persistent regressors in the empirical models do not provide information for their changes, making their lags become weak instrumental variables in the difference GMM estimator. Therefore, the S-GMM (system-GMM estimator) is better than the D-GMM (difference-GMM estimator) (Arellano and Bover 1995).

For estimation, the twostep S-GMM can be more efficient than the onestep S-GMM. However, employing the twostep S-GMM in small research samples like our sample has a problem (Roodman 2009). It is the instrumental variables proliferation that quadratically rises as the dimension of time increases, which causes the number of instruments to be larger than the number of panel units. The solution is to employ the thumb rule to keep the number of panel units more than or equal to the number of instruments (Roodman 2009). The study uses Arellano-Bond, Sargan, and Hansen statistics to test the instruments' validity in the S-GMM. The Arellano-Bond test AR(2) searches the serial autocorrelation of errors in the first difference while the Sargan and Hansen tests detect endogenous phenomena.

The study applies the PMG estimator by Pesaran, Shin, and Smith (1999) to validate the robustness of the S-GMM estimates. It presents the PMG-based model as follows:

$$Y_{it} = \psi X_{it-1} + \sum_{j=1}^{p} \pi_{ij} \Delta Z_{it-j} + \sigma_{it}$$
$$where \ \ X_{it-1} = Y_{it-1} - \lambda Z_{it-1} \quad (2)$$

where Y_{it} is the Gini index, a proxy for income inequality; $X_{it\text{-}1}$ is the deviation from long-run equilibrium for group i at any period t, and ψ is the error-correction coefficient. The vector λ captures the long-run coefficients. They express the long-run elasticity of inequality corresponding with every variable in $Z_{it\text{-}1}$. Meanwhile, the vector π captures the short-run responses of the Z_{it} variables. σ_i is a fixed effect and τ_{it} is an error term. The study uses the value and significance level of the speed of adjustment ψ (negative, smaller than 1) to examine the validity of the PMG estimates.

4.2. Research data

The dataset contains GINI index, fixed broadband subscriptions, individuals using the Internet, GDP per capita, school enrollment, and unemployment. The paper exacts them from the World Bank database. The research sample contains 30 advanced economies[1] and 35 developing economies[2] from 2002 to 2020. The Appendix presents the definition as well as descriptive statistics. Table C and Table D indicate the correlation coefficient between fixed broadband subscriptions and individuals using the Internet is relatively high; hence, the paper uses them separately in the empirical equations.

5. Findings

5.1. Estimated results

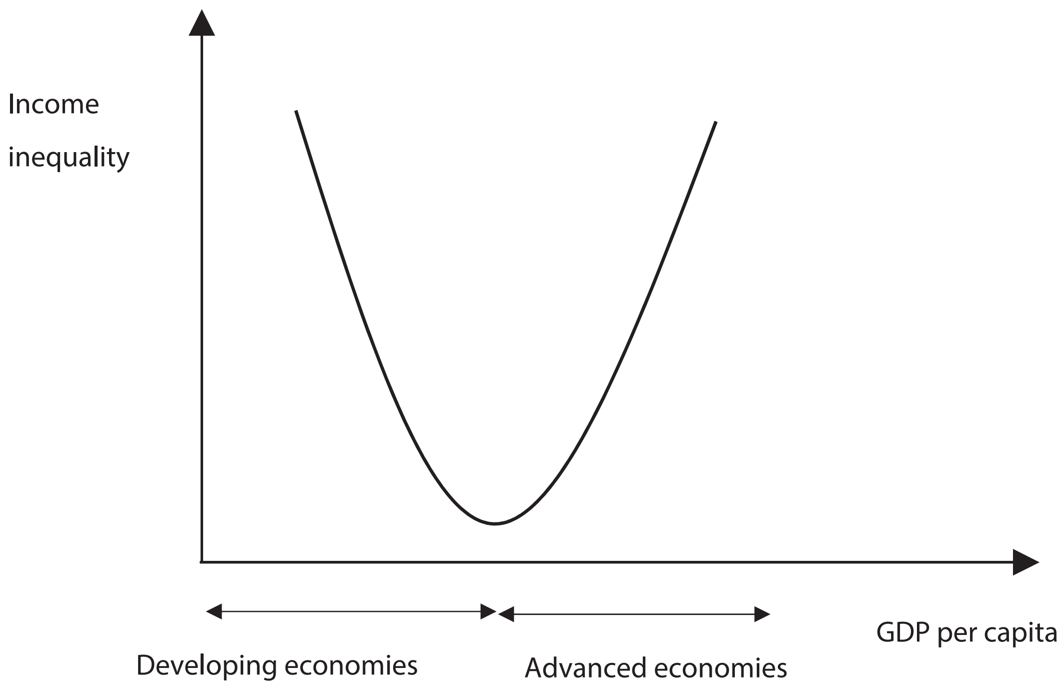
The paper presents the twostep S-GMM estimates in Table 1 and Table 2 and the one-step S-GMM estimates in Table 3 and Table 4. Table 1 and Table 3 indicate the effect of fixed-broadband subscriptions, while Table 2 and Table 4 show the effect of individuals using the Internet. We discover that economic growth is endogenous in estimations; hence, we use economic growth as an instrumented variable in GMM style and income inequality, digitalization, education, unemployment as instrumental variables in IV style.

The results across all empirical models in Table 1 (fixed-broadband subscriptions) and Table 2 (individuals using the Internet), as well as Table 3 (fixed-broadband subscriptions) and Table 4 (individuals using the Internet), indicate that digitalization narrows inequality in developed economies but widens in developing economies. By contrast, economic growth enhances inequality in advanced economies but decreases in developing economies. Furthermore, education in developing economies and unemployment in both groups enhance inequality.

The opposite effect of digitalization on income inequality between advanced and developing economies stems from differences in the digital divide between these groups. Governments in advanced economies have several resources to deal with domestic problems, particularly narrowing income inequality between the rich and the poor. These resources include a high level of economic development, a good governance environment, high income per capita, and high living standards, so governments in these economies can use public spending (even borrowing) to finance education and narrow the digital divide for the poor. In particular, education in these economies is almost free and universal for everyone. As a result, a low digital gap and high levels of education in advanced economies help low-income individuals (the poor) easily access progress in digital technology to improve their skills and knowledge. They can find a job with a high income, which reduces the income difference between high-income and low-income individuals, thereby narrowing income inequality. In contrast, developing economies do not have several resources to handle domestic problems, especially income inequality. Most developing economies have a low level of economic development, a poor governance environment, a low income per capita, and low living standards, so they cannot use public spending to finance education and improve the digital platform for the poor. Borrowing to finance public spending in these economies is also relatively hard due to the difficulty of repayment for loans. In addition, the poor also have to pay school costs for education in these economies. As a result, a high digital gap and low levels of education in developing economies prevent low-income individuals (the poor) from accessing progress in digital technology. However, high-income individuals (the rich) have enough money to access progress in digital technology to enhance their skills and knowledge. They can easily find a job with high income and get promoted, which increases the income difference between high-income and low-income individuals, thereby widening income inequality. In short, the effect of digitalization on income inequality is different between advanced and developing economies. Therefore, governments in developing economies should focus on policies that enhance public spending to finance education and reduce the digital divide to narrow the income gap between the poor and the rich.

Notably, the economic growth narrows inequality in developing economies but widens in developed economies, given in Figure 1 with the U-shape curve of income inequality. In the view of a whole, in economies with low levels of development (developing economies), income inequality decreases against per capita income throughout economic development;

Figure 1. The U shaped curve of income inequality



Source: Author's drawing

then, it increases when these countries have a higher level of development (advanced economies). This finding contrasts the hypothesis by Kuznets (1955) on the inverted U-shape curve when considering the shift of income inequality against per capita income from low (developing economies) to high (advanced economies). Wong (2017) and Asogwa et al. (2021) discover that economic growth reduces inequality in Latin American economies, while Berisha, Gupta, and Meszaros (2020), Apergis (2021), and Hailemariam, Sakutukwa, and Dzhumashev (2021) confirm it enhances income inequality in 21 advanced economies.

Education enhances income inequality in developing economies. Education is a public good that governments supply for free, and students do not pay the money to attend public schools. However, wealthy families agree to pay charges to send their children to high-quality private schools. Students from these families receive better knowledge and skills than those from average families. Therefore, students from wealthy families easily find high-income jobs and get more promoted, which increases income inequality. This finding can be found in Asogwa et al. (2021), Demir et al. (2020), Kaulihowa and Adjasi (2018).

The high unemployment often falls into the poor who lack the necessary knowledge and skills to get a high-income job, boosting the income gap in society. Deyshappriya (2017) and Asogwa et al. (2021) support it. This finding implies that governments in advanced economies should pay more attention to the poor and help them access education and healthcare to get high-income jobs.

Table 1. Digitalization (fixed broadband subscriptions) and income inequality: two-step S-GMM estimates, 2002 – 2020

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Income inequality (-1)	0.944***	0.934***
	(0.011)	(0.004)
Digitalization	-0.0018***	0.0046***
	(0.0001)	(0.0001)
Economic growth	0.005***	-0.012***
	(0.0002)	(0.001)
Education	-0.027	0.048***
	(0.113)	(0.006)
Unemployment	0.031***	0.009**
	(0.003)	(0.006)
Year2003	-3.209	9.078
	(8.673)	(6.980)
Year2004	-2.940	8.243
	(8.930)	(6.088)
Year2005	-3.176	8.842
	(8.986)	(5.830)
Year2006	-3.079	7.437
	(9.128)	(5.727)
Year2007	-2.978	7.517
	(9.368)	(5.508)
Year2008	-2.996	7.384
	(9.361)	(5.431)
Year2009	-3.149	6.999
	(9.418)	(5.407)
Year2010	-3.204	7.464
	(9.389)	(5.288)
Year2011	-3.006	7.255
	(9.354)	(5.319)
Year2012	-2.927	7.549
	(9.400)	(5.222)
Year2013	-2.889	7.370
	(9.523)	(5.262)
Year2014	-3.083	7.014
	(9.471)	(5.178)
Year2015	-2.965	7.403
	(9.443)	(5.196)
Year2016	-3.109	7.331
	(9.501)	(5.189)
Year2017	-3.196	7.167
	(9.503)	(5.129)
Year2018	-3.059	7.434
	(9.577)	(5.173)
Year2019	-3.067	7.205
	(9.599)	(5.127)
Year2020	-3.020	7.196
	(9.656)	(5.125)
Instrument	30	34
Country/Observation	30/540	35/630
AR(2) test	0.211	0.445
Sargan test	0.380	0.602
Hansen test	0.986	0.791

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 2. Digitalization (individuals using the Internet) and income inequality: two-step S-GMM estimates, 2002 – 2020

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Income inequality (-1)	0.973***	0.912***
	(0.028)	(0.011)
Digitalization	-0.002***	0.007***
	(0.000)	(0.001)
Economic growth	0.012***	-0.001***
	(0.001)	(0.000)
Education	-0.021	0.112***
	(0.040)	(0.003)
Unemployment	0.031***	0.027**
	(0.010)	(0.001)
Year2003	-12.559	10.284
	(6.980)	(5.385)
Year2004	-12.369	10.191
	(7.031)	(5.324)
Year2005	-12.752	9.242
	(7.055)	(5.137)
Year2006	-12.868	10.297
	(7.205)	(5.286)
Year2007	-12.875	10.024
	(7.281)	(5.194)
Year2008	-12.911	10.279
	(7.275)	(5.229)
Year2009	-13.283	10.267
	(7.463)	(5.200)
Year2010	-13.361	9.719
	(7.483)	(5.143)
Year2011	-13.106	9.897
	(7.435)	(5.146)
Year2012	-13.057	9.550
	(7.488)	(5.200)
Year2013	-13.143	9.430
	(7.623)	(5.136)
Year2014	-13.259	9.845
	(7.558)	(5.046)
Year2015	-13.261	9.390
	(7.574)	(5.092)
Year2016	-13.387	9.375
	(7.615)	(5.003)
Year2017	-13.579	9.461
	(7.641)	(4.975)
Year2018	-13.458	9.204
	(7.675)	(5.009)
Year2019	-13.524	9.458
	(7.722)	(4.938)
Year2020	-13.585	9.301
	(7.800)	(4.946)
Instrument	30	33
Country/Observation	30/540	35/630
AR(2) test	0.227	0.392
Sargan test	0.334	0.125
Hansen test	0.994	0.736

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 3. Digitalization (fixed broadband subscriptions) and income inequality: one-step S-GMM estimates, 2002 – 2020

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Income inequality (-1)	0.929***	0.931***
	(0.012)	(0.009)
Digitalization	-0.011**	0.0005**
	(0.002	(0.000)
Economic growth	0.005**	-0.004***
	(0.001)	(0.001)
Education	-0.018	0.072***
	(0.049)	(0.015)
Unemployment	0.034**	0.014
	(0.016)	(0.013)
Year2003	-1.509	1.749
	(3.306)	(2.800)
Year2004	-1.196	1.311
	(3.356)	(2.588)
Year2005	-1.302	0.650
	(3.415)	(2.521)
Year2006	-1.478	1.814
	(3.467)	(2.457)
Year2007	-1.080	1.468
	(3.510)	(2.431)
Year2008	-1.043	1.686
	(3.537)	(2.400)
Year2009	-1.248	1.885
	(3.543)	(2.373)
Year2010	-1.423	1.026
	(3.538)	(2.359)
Year2011	-1.116	1.490
	(3.529)	(2.338)
Year2012	-1.026	1.246
	(3.532)	(2.329)
Year2013	-0.896	1.198
	(3.563)	(2.318)
Year2014	-1.301	1.480
	(3.553)	(2.310)
Year2015	-1.143	1.184
	(3.565)	(2.299)
Year2016	-1.261	1.189
	(3.570)	(2.293)
Year2017	-1.301	1.157
	(3.591)	(2.287)
Year2018	-1.146	1.087
	(3.598)	(2.294)
Year2019	-1.165	1.316
	(3.605)	(2.299)
Year2020	-1.116	1.194
	(3.626)	(2.285)
Instrument	30	34
Country/Observation	30/540	35/630
AR(2) test	0.215	0.107
Sargan test	0.380	0.618

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 4. Digitalization (individuals using the Internet) and income inequality: one-step S-GMM estimates, 2002 – 2020

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Income inequality (-1)	0.925***	0.936***
	(0.017)	(0.009)
Digitalization	-0.010**	0.023***
	(0.003)	(0.004)
Economic growth	0.003**	-0.006***
	(0.0001)	(0.003)
Education	-0.004	0.083***
	(0.016)	(0.023)
Unemployment	0.020*	0.010
	(0.010)	(0.014)
Year2003	-1.431	1.326
	(4.224)	(3.542)
Year2004	-1.211	1.035
	(4.234)	(3.523)
Year2005	-1.397	0.397
	(4.265)	(3.503)
Year2006	-1.622	1.572
	(4.307)	(3.477)
Year2007	-1.253	1.268
	(4.351)	(3.485)
Year2008	-1.213	1.527
	(4.396)	(3.467)
Year2009	-1.378	1.795
	(4.436)	(3.437)
Year2010	-1.520	1.011
	(4.454)	(3.409)
Year2011	-1.201	1.542
	(4.452)	(3.379)
Year2012	-1.092	1.385
	(4.472)	(3.351)
Year2013	-0.967	1.375
	(4.516)	(3.324)
Year2014	-1.359	1.732
	(4.513)	(3.294)
Year2015	-1.208	1.504
	(4.526)	(3.261)
Year2016	-1.324	1.597
	(4.537)	(3.229)
Year2017	-1.377	1.623
	(4.562)	(3.203)
Year2018	-1.223	1.618
	(4.573)	(3.204)
Year2019	-1.239	1.916
	(4.588)	(3.203)
Year2020	-1.192	1.860
	(4.624)	(3.179)
Instrument	30	34
Country/Observation	30/540	35/630
AR(2) test	0.220	0.109
Sargan test	0.334	0.139

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

5.2. Robustness check

The paper employs the PMG estimator for Equation (2) to test the robustness of S-GMM estimates. The PMG estimator is a kind of panel Error Correction Model (ECM) that requires co-integration between regressors and the dependent variable. The PMG estimator requires the panel co-integration among regressors and the dependent. So, the paper examines the stationary of all variables in the empirical model to ensure that they all have the same order of co-integration. Then, it performs the panel co-integration tests by Westerlund (2007).

The stationary tests in Table 5 (advanced economies) and Table 6 (developing economies) show that income inequality, fixed broadband subscriptions, individuals using the Internet economic growth, education, unemployment are stationary at a significance level of less than 10%, meaning that they have co-integration of zero-order I(0). The Westerlund tests in Table 7 and Table 8 note that three of four tests deny the null hypothesis of no co-integration, suggesting that income inequality co-integrates with fixed broadband subscriptions, individuals using the Internet economic growth, education, unemployment.

The estimated results by PMG across all empirical models are indicated in Table 9 (advanced economies) and Table 10 (developing economies). Similar to those by the two-step S-GMM, estimates by the PMG estimator note that (i) digitalization widens inequality in developing economies but narrows in developed economies, (ii) economic growth increases inequality in advanced economies but reduces in developing economies. The significance level and value of the speed of adjustment at the bottom of tables report that PMG estimates are highly reliable.

Table 5. Fisher type unit root tests: 2002 – 2020 (Advanced economies)

Variables	Augmented Dickey-Fuller test		Phillips-Perron test	
	Prob > chi2		Prob > chi2	
	Without trend	With trend	Without trend	With trend
Income inequality	67.430	92.163***	69.072	102.602***
Fixed broadband subscriptions	176.981***	529.239***	1781.414***	1082.451***
Individuals using the Internet	196.841***	85.751***	521.950***	205.598***
Economic growth	93.364***	60.155	71.661	23.079
Education	181.606***	232.144***	46.100	55.226
Unemployment	116.632***	88.899***	61.361	39.757

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 6. Fisher type unit root tests: 2002 – 2020 (Developing economies)

Variables	Augmented Dickey-Fuller test		Phillips-Perron test	
	Prob > chi2		Prob > chi2	
	Without trend	With trend	Without trend	With trend
Income inequality	63.328	142.940***	105.919***	216.918***
Fixed broadband subscriptions	390.697***	171.170***	1445.687***	526.533***
Individuals using the Internet	69.036	51.241	101.519***	77.903
Economic growth	96.342**	51.023	138.331***	42.294
Education	127.279***	175.431***	113.106***	127.065***
Unemployment	80.369	62.171	109.798***	47.855

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 7. Westerlund panel co-integration tests: 2002 – 2020 (Advanced economies)

Normalized variable: GINI index (income inequality)

Covariates	G_t	G_α	P_t	P_α
Fixed Broadband subscriptions	-2.732^{***}	-6.267	-10.959^{***}	-6.206^{***}
Individuals using the Internet	-3.063^{***}	-14.053^{**}	-15.194^{***}	-11.490^{***}
Economic growth	-3.279^{***}	-14.273^{**}	-14.411^{***}	-10.694^{**}
Education	-3.604^{***}	-17.113^{***}	-16.414^{***}	-13.677^{***}
Unemployment	-3.819^{***}	-18.611^{***}	-18.735^{***}	-13.095^{***}

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 8. Westerlund panel co-integration tests: 2002 – 2020 (Developing economies)

Normalized variable: GINI index (income inequality)

Covariates	G_t	G_α	P_t	P_α
Fixed broadband subscriptions	-3.657^{***}	-17.556^{***}	-20.710^{***}	-16.913^{***}
Individuals using the Internet	-3.647^{***}	-17.219^{***}	-26.950^{***}	-21.849^{***}
Economic growth	-3.573^{***}	-15.648^{***}	-23.656^{***}	-19.289^{***}
Education	-3.186^{***}	-21.928^{***}	-17.618^{***}	-16.089^{***}
Unemployment	-3.399^{***}	-24.842^{***}	-18.066^{***}	-18.603^{***}

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 9. Digitalization (fixed broadband subscriptions) and income inequality: PMG estimates, 2002 – 2020

Long run co-integrating vectors

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Digitalization	-0.004^{***} (0.001)	0.002^{***} (0.000)
Economic growth	0.046^{***} (0.013)	-0.146^{***} (0.007)
Education	-0.148^{***} (0.041)	0.023 (0.020)
Unemployment	0.076^{**} (0.033)	0.085^{***} (0.027)
Error correction	-0.472^{***}	-0.454^{***}
Observation	540	630
Log likelihood	-359.442	-706.422

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

Table 10. Digitalization (individuals using the Internet) and income inequality: PMG estimates, 2002 – 2020

Long run co-integrating vectors

Dependent variable: Income inequality (GINI index)

Variables	Advanced economies	Developing economies
Digitalization	-0.049***	0.001*
	(0.007)	(0.000)
Economic growth	0.046***	-0.148**
	(0.008)	(0.010)
Education	-0.000	0.008***
	(0.020)	(0.015)
Unemployment	0.087***	-0.014
	(0.032)	(0.044)
Error correction	-0.371***	-0.378***
Observation	540	612
Log likelihood	-360.768	-743.219

*Note: ***, **,* note significance level at 1%, 5%, 10% respectively*

6. Conclusion

Income inequality in society is one of the global problems in advanced and developing economies under rising globalization and digitalization. Narrowing income inequality is one of the main goals in the development agendas. Meanwhile, digital progress is an irreversible process, significantly contributing to economic growth in these economies. Unfortunately, the digital divide is also emerging in society. Given these facts, the paper tests the impact of digitalization on inequality for 30 advanced economies and 35 developing economies between 2002 and 2020. The study applies the S-GMM and PMG estimators for estimation and robustness checks. The results indicate that (i) Digitalization narrows income inequality in developed economies, but widens it in developing economies, (ii) the economic growth – income inequality relationship is U-shaped as real GDP per capita rises from low (developing economies) to high (advanced economies). Third, unemployment increases inequality in two groups.

The findings suggest some crucial implications to design, formulate, and implement regulations and policies related to digital development. The implication is that digitalization is an irreversible process in countries but significantly affects income inequality. Notably, severe income inequality can lead to social instability. Developing economies should adjust the strategies and methods of digital technology development to reduce the digital divide and its adverse impact on income inequality. In particular, governments in developing countries should use public spending to focus on digital education programs for the poor and help them better access digital technology to enhance job search and improve income.

The limitation of this paper is that it uses two measures released by World Bank to proxy for digitalization, while some digital metrics recommended by Kotarba (2017) can use to measure digitalization better. They are Digital Economy Metrics, Digital Society Metrics, Digital Industry Metrics, Digital Enterprise Metrics, Digital Client Metrics, and Digital Investment Metrics. However, these metrics are not available now. It needs more time to develop and collect the database.

Future research should focus on the impact of digitalization on inequality by sector/industry. Furthermore, the contribution of institutional/governance quality to the digitalization – inequality relationship is another suggestion for future research.

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Endnotes

1 Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Italy, Israel, Ireland, South Korea, Luxembourg, Lithuania, Latvia, Malta, Norway, Netherlands, Portugal, Switzerland, Slovak Republic, Spain, Slovenia, Sweden, United Kingdom, United States.

2 Armenia, Argentina, Belarus, Bolivia, Bulgaria, Brazil, Costa Rica, Chile, Colombia, China, Croatia, Dominican Republic, El Salvador, Ecuador, Georgia, Honduras, Hungary, Indonesia, Kazakhstan, Kyrgyz Republic, Malaysia, Moldova, Mexico, Pakistan, Paraguay, Panama, Poland, Peru, Russian Federation, Romania, Thailand, Turkey, Ukraine, Vietnam, West Bank & Gaza.

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Appendix

Table A. Data description

Variable	Definition	Type	Source
Income inequality (GIN)	Gini index on the income distribution.	value	World Bank
Fixed broadband subscriptions (BRO)	Refers to fixed subscriptions for high-speed access to the public Internet (TCP/IP connections), at downstream speeds greater than or equal to 256 kbit/s.	log	World Bank
Individuals using the Internet (INT)	Internet users are persons who have used the Internet within the last three months (from any location). They can use the Internet through mobile phones, computers, game consoles, digital TVs, digital assistants,...	%	World Bank
Economic growth (GDP)	Real per capita GDP (constant 2015 US$)	log	World Bank
Education (EDU)	School enrollment, primary (% gross)	%	World Bank
Unemployment (UNE)	Refers to the proportion of the workforce who are unemployed but available and looking for work.	%	World Bank

Table B. Descriptive statistics for advanced economies

Variable	Obs	Mean	Std. Dev.	Min	Max
GINI index	570	31.607	4.250	23.7	42.5
Fixed broadband subscriptions	570	25.966	11.738	0.075	48.334
Individuals using the Internet	570	72.302	19.354	14.67	99.7
GDP per capita	570	1047.25	54.117	898.825	1162.597
School enrollment, primary	570	102.194	4.207	95.648	127.2
Unemployment	570	7.648	4.134	2.01	27.466

Table C. Descriptive statistics for developing economies

Variable	Obs	Mean	Std. Dev.	Min	Max
GINI index	665	40.332	8.633	24	59.5
Fixed broadband subscriptions	665	7.970	8.074	0.0002	34.452
Individuals using the Internet	665	37.806	24.126	1.587	89.555
GDP per capita	665	854.062	76.461	651.6592	977.395
School enrollment, primary	665	103.661	8.992101	70.894	146.827
Unemployment	665	7.347	4.767	0.398	27.465

Table D. Matrix of correlation coefficients for advanced economies

	GIN	BRO	INT	GDP	EDU	UNE
GIN	1					
BRO	-0.054	1				
INT	-0.254***	0.780***	1			
GDP	-0.136***	0.330***	0.472***	1		
EDU	0.179***	0.029	-0.081**	0.000	1	
UNE	0.271***	-0.135***	-0.258***	-0.418***	0.025	1

*Note: ***, **, * note significance level at 1%, 5%, 10% respectively*

Table E. Matrix of correlation coefficients for developing economies

	GIN	BRO	INT	GDP	EDU	UNE
GIN	1					
BRO	-0.133***	1				
INT	-0.204***	0.786***	1			
GDP	0.136***	0.565***	0.569***	1		
EDU	0.511***	0.007	-0.102***	0.236***	1	
UNE	-0.174***	-0.010	0.056	0.076**	-0.008	1

*Note: ***, **, * note significance level at 1%, 5%, 10% respectively*