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Digital Divide, Globalization and Income Inequality in sub-Saharan African countries: Analysing cross-country heterogeneity

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Hermann Ndoya
Department of Economic policy Analysis
University of Dschang (Cameroon)
E-mail: hermannondoya@gmail.com

Simplice A. Asongu
African Governance and Development Institute,
P.O. Box 8413, Yaoundé, Cameroon
E-mails: asongus@afridev.org
/ asongusimplice@yahoo.com

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Digital Divide, Globalization and Income Inequality in sub-Saharan African countries: Analysing cross-country heterogeneity

Hermann Ndoya & Simplice A. Asongu

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Abstract

The aim of this paper is to analyse the impact of digital divide on income inequality in sub-Saharan Africa over the period 2004-2016. In applying a finite mixture model (FMM) to a sample of 35 sub-Saharan African (SSA) countries, this study posits that digital divide affects income inequality differently. Our findings show that the effect of digital divide on income inequality varies across two distinct groups of countries, which differ according to their level of globalization. In addition, the study shows that, most globalized countries are more inclined to be in the group where the effect of digital divide on income inequality is negative. The results are consistent to several robustness checks, including alternative measures of income inequality and additional control variables. The study complements that extant literature by assessing linkages between the digital divide, globalization and income inequality in sub-Saharan African countries contingent on cross-country heterogeneity.

Keywords: Digital Divide, Income Inequality, Globalization, Finite Mixture model
JELClassification:C14, O15, O33, O55

1. Introduction

The last decades have highlighted the proliferation of information and communication technologies (ICTs) worldwide, with strong implications for the labor market (Chun & Tang, 2018; Roztocki *et al.*, 2019; Ngono, 2021), women empowerment (Asongu & Odhiambo, 2018; Ngoa & Song, 2021) and governance and transparency (Maiti & Awasthi, 2020).

Although the emergence and the rapid diffusion of ICTs in African countries is creating great opportunities for marginalized groups, the digital revolution has brought with it, unequal access to new technologies, leading to what is now known as the “digital divide”. We understand digital divide (DD) according to Castells (2002) as being the difference in access to and use of ICTs between individuals.

The concept of DD has evolved significantly over time, from the first level of digital divide based on connectivity to the second level, which deals with the abilities and skills that individuals must develop to use the internet; to the third level which measures the tangible results of internet usage (Scheerder *et al*., 2017; Hidalgo *et al*., 2020).

While it is true that there is an important literature on the impact of ICT on economic outcomes, including economic growth (Stanley *et al*., 2018; Vu *et al*., 2020), financial inclusion (Tchamyou *et al*., 2019a) and human development (Asongu & le Roux, 2017), little is known concerning the effects of DD. According to Zhang *et al*. (2020), the opportunities provided by ICTs could lead to a DD so that some people benefit more than others because they have greater access to them but also use them more to generate a higher level of productivity due to their higher initial level of human and financial capital. Indeed, while Evans (2019) shows that as the digital revolution has taken place at an unprecedented speed in sub-Saharan Africa (SSA), the debate must now turn to the resulting DD, thus raising the issue of poverty reduction and income inequality. As wealth, gender, education, geography have been identified as the main drivers of DD (Afshar Ali et al., 2020; Lindblom & Rasanen, 2017; Salemink et al., 2017), this study focuses on its socio-economic effects, and mainly on income distribution.

Theoretically, DD could affect income inequality in two different ways. First, since ICTs contribute to economic growth, they provide a multidimensional approach to fighting poverty and strengthening economic development, by touching both social and human capital (Wavermann *et al*., 2005). Reducing inequalities in access to and use of technology and promoting inclusive diffusion of ICTs is particularly useful in facilitating access to resources, and information. It also allows firms to increase their productivity and improves income-generating opportunities for poor individuals and households (Aker & Mbiti 2010; Qureshi, 2011). In addition, as Downes (2009) shows, equal access to ICT has particularly strong positive network impacts, limits rent accumulation, and curbs existing wealth concentrations (Antonelli & Gehringer, 2016; Richmond & Triplett, 2018). Second, in an environment characterized by inequalities in opportunity, education, gender and wealth, improvements in the distribution of ICTs may further widen income gaps between individuals (Lindsay, 2005). This phenomenon is referred to as the "Matthew effect," where those who "have", expand their range of opportunities while those who "don't have", are increasingly marginalized and excluded from the advantaged class (Tewathia *et al*., 2020). As mentioned by Acemoglu (2002) and Piketty and Saez (2003), the ever-increasing income inequality in most developed countries can be traced back to the diffusion of information technology, which increases the sources of income of people leveraging on ICT. The focus is no longer solely on access to ICT services, but more on use, since poor people do not have sufficient skills or financial means to use ICT-enabled services. In the same vein Aghion *et al*. (2019) added that the recent evolution of income inequality in the upper brackets is largely caused by innovation. As an illustration, when *Forbes magazine* ranks the richest people in the United States (US) of America, 11 out of 50 turn out to be inventors and U.S patent holders and most are owners of trademarked companies. To sum up, DD could produce different effects on income distribution and according to Richmond and Triplett (2018), this relationship is highlighted by other economic and political aspects.

The aim of this paper is to complement the extant literature (highlighted above and expanded in Section 2) by assessing the nexus between DD, globalization and income inequality in SSA. Our study differs from previous works and contributes to the literature in three levels. First, as previous studies have assessed the impact of ICT on income inequality (see Section 2.2 for a summary of corresponding research); this study is in our knowledge one of the first to assess the impact of digital divide on income distribution in Africa. Second, while previous studies have used basic panel data methods, such as ordinary least squares (OLS), fixed effects, two stage least squares (2SLS) and generalised method of moments (GMM) regressions, which are based on a single inequality model in the panel (e.g. Tchamyou *et al*., 2019a, 2019b; Adams & Akobeng, 2021; Njangang *et al*., 2021), in this work we use a model that focuses on unobserved in-sample heterogeneity. This is the finite mixture model (FMM). The FMM incorporates a latent variable to group countries by considering any existing potential unobserved heterogeneity. As a result, different marginal effects of covariates can be observed from one group of countries to another. In this case, the DD may therefore have a positive impact in one group and a negative effect in another group. Third, we investigate whether globalization can contribute to explaining the differences in inequality across classes. Previous studies have often included an interactive variable in the model to account for the role of globalization (Ezcurra & Del Villar, 2021; Nchofoung & Asongu, 2022). In this paper, we include the overall index of globalization and its political, economic and the social dimensions as coexisting variables, in addition to being explanatory variables. By doing so, we can explain group memberships of sampled countries.

Using data from a sample of 35 SSA countries over the period 2004-2016, our results show that countries in our sample converge into two distinct classes. Thus, in the first class, DD has no significant effect on income inequality, while in the second class; the effect of DD on income inequality is negative and significant. Our results then present a heterogeneous effect of DD on income inequality in SSA. In addition, we use the overall index of globalization and its political, economic, and social dimensions to investigate whether they contribute to explaining country group membership. We find that the results are related to the globalization variables: the most globalized countries are more likely to be in the group where DD is negatively associated with income inequality.

It is also worthwhile to articulate that the success of digital technology is based on substantial insights into nexuses with socio-economic and profitability objectives, *inter alia*, inclusive human development, corporate green innovation, stakeholder-focused goals, within the remit of business models that are tailored to increase profitability simultaneously with upholding social values. Hence, corporate social responsibility (CSR) is also an indirect focus of the present study, not least, because the underlying phenomenon consists of going beyond shareholders' interest to pay attention to all stakeholders. Accordingly, digital transformation is closely connected to CSR because companies are also motivated to promote inclusive development by means of digital technologies (Na et al., 2022).

The rest of the paper is organised as follows. Section 2 covers the theoretical underpinnings and literature while Section 3 presents the methodology and data used. Section 4 discloses and discusses the empirical results while Section 5 concludes with implications and future research directions.

2. Theoretical underpinnings and literature review

2.1 Theoretical underpinnings

It is worthwhile to complement the theoretical underpinnings highlighted in the introduction with insights from other theoretical underpinnings on the nexus between digital technologies and inclusive development outcomes such as the mitigation of income inequality. In accordance with the extant studies on the adoption of ICTs (Cusick, 2014; Nikiforova, 2013; Yousafzai *et al*., 2010; Asongu *et al*., 2018) and more recently the nexus between ICT, literacy and inclusive development (Asongu & Odhiambo, 2019a), there are three fundamental theories that articulate the underlying nexus, notably: the theory of reasoned action (TRA), theory of planned behavior (TPB) and technology acceptance model (TAM).

First, the TRA is premised on a supposition that individuals are rational from an inherent perspective, especially as it pertains to acknowledging actions being taken by such individuals (Fishbein & Ajzen, 1975; Bagozzi, 1982; Ajzen & Fishbein, 1980). Second, it is hence, noteworthy that the TPB is an expanded version of the TRA, essentially because from the view of Ajzen (1991), emphasis is placed on two types of individuals: on the one hand, those who demonstrate a conscious influence linked to the actions they take and on the other, individuals who fail to demonstrate the corresponding influence. Third, looking at the TAM, the assumption motivating the desire by an individual to adopt a specific form of technology can be elicited by an individual's voluntary decision to adopt and utilize the specific technology (Davis, 1989). Consistent with the corresponding literature, a denominator that is quite apparent in the three theories can be further articulated on two fronts: (i) the formation of individual belief and (ii) composite constituents such personal, psychological, behavioral and utilitarian features.

The underlying individual features which are derived from the underpinning theories can be further contextualized using the following views (Asongu & Odhiambo, 2019a). First, according to the utilitarian view, users of digital technologies adopt corresponding technologies because such users are anticipating that these technologies will help them improve their wellbeing and living standards and by extension, contribute towards income inequality reduction. Second, looking at the behavioral view, digital technologies can be adopted by some individuals owing to the fact that they want to be part of a social order, particularly if they anticipate that attaining the social order is related to a reduction of income inequality. Third, personal and psychological underpinnings also motivate the decision of whether to adopt a digital technology when individuals are influenced by other tendencies such as globalization on the potential benefits of digital technologies in mitigating income inequality. It follows from the underlying three elements that an individual's decision to adopt a specific digital technology is contingent on a plethora of factors which are both systemic and idiosyncratic motivations.

2.2 Literature review

The available literature on the relevance of digital technology has been surveyed by Reddy and Sharma (2020). Hence, for brevity and lack of space, we summarize the corresponding strands motivating this study below but invite the interested reader to peruse the relevant literature for more expanded insights of the extant knowledge on the subject. According to the underlying study, the corresponding benefits are largely in terms of health care, education, environmental sustainability and employment. Nchofoung and Asongu (2022) are broadly consistent with Reddy and Sharma (2020) in the corresponding literature on the importance of digital technologies in socio-economic outcomes. The corresponding literature can be discussed in three main strands, especially as it pertains to the nexus between: (i) ICT and environmental sustainability; (ii) ICT and social development and (iii) ICT, education and income inequality. The underlying three strands are expanded in the same order as highlighted.

First, with respect to the connection between ICT and environmental sustainability, there is a strand of authors arguing that ICT mitigates carbon dioxide (CO_2) emissions in order to boost environmental sustainability (Ahmed & Le, 2021; N'dri *et al.*, 2021; Wang & Xu, 2021; Chien *et al.*, 2021). Hence, with the increase of ICT or related investment in ICTs, CO_2 emissions are correspondingly reduced. Accordingly, financial development and economic prosperity contribute towards CO_2 emissions within the remit of all quantiles whereas the effect of ICT on CO_2 emissions is significantly apparent exclusively in lower quantiles (Chien *et al.*, 2021). Moreover, the consolidation of ICT via a plethora of electronic commodities adoption mitigates the usage of traditional goods and services. According to the narrative, traditional meetings have been increasingly replaced with online meetings. Furthermore, travelling has been reduced owing to electronic (e)-commerce, e-books have replaced traditional books and e-mails have almost replaced letters. The underlying change is also associated with a reduction of resources linked to the usage of such traditional modes of using products and services which by extension, is associated with a promotion of environmental sustainability owing to a corresponding reduction in CO_2 emissions. The narrative is consistent with a recent stream of literature supporting the perspective that ICTs have facilitated transport systems, engendering less CO_2 emissions and energy consumption (Haseeb *et al*., 2019; Ahmed & Le, 2021).

Second, on the connection between ICT and social development, there is a stream of literature which has concluded that ICT generally promotes socio-economic development outcomes mostly in terms of inclusive human development (Asongu *et al*., 2017). In essence, policies that are founded on the promotion of ICT ultimately boost inclusive human development; an effect that is contingent on features such as landlockedness, resource wealth, legal origin, political stability and income level (Asongu & le Roux, 2017). Furthermore, Asongu *et al*. (2019) establish that ICT can be used to reduce the unfavorable incidence of CO_2 emissions on inclusive human development. The corresponding reducing incidence is higher in oil-wealthy, middle-income and English common law countries compared to oil-poor, low-income and French civil law countries. Moreover, social development could also been viewed from the health angle (Dutta *et al*., 2019; Majeed & Khan, 2019; Kouton *et al*., 2020). Accordingly, for the incidence on health standard to be more apparent, economic freedom is needed to facilitate the diffusion of ICT in order to reduce infant mortality in Africa (Kouton *et al*., 2020). Furthermore, according to Lee and Lio (2016), ICT diffusion is linked to reduced infant mortality and higher life expectancy.

Third, with respect to linkages between ICT, education and income inequality, it is argued by Asongu and Odhiambo (2019b) that ICT has differing incidences on the quality of education, especially in above-median countries in terms of poor quality education. The authors also maintain that internet and mobile phone penetration rates ameliorate education quality. According to Tchamyou *et al*. (2019b), primary education interacts with ICT to mitigate income inequality, negative net impacts are apparent from the role of secondary education, while the nexus from tertiary education is not significant. Moreover, the authors opine that some critical masses of income inequality should not be exceeded in order for ICT to continuously have a favorable role on inclusive education (Asongu *et al*., 2019). According to Adams and Akobeng (2021), ICT mitigates income inequality and the nexus is consolidated by government quality. Moreover, the effect of ICT on income inequality depends on ICT type and the manner in which income inequality is measured. According to Richmond and Triplett (2018), the magnitude of the impact of ICT on the redistribution of income can be compared with economic infrastructure of traditional nature while politico-economic factors influence the nexus between ICT and income inequality. According to Njangang *et al*. (2021), ICT boosts wealth inequality by increasing the wealth of billionaires in the society and, the unfavorable incidence on wealth distribution can be dampened by democracy. The manner in which the present study contributes to the extant literature has been discussed in the introduction.

3. Methodology and data

3.1. Econometric specification

As mentioned above, many empirical models that estimate the effects of the DD are based on the assumption of parameter homogeneity, yet there are several reasons to believe that the effects of DD are not homogeneous. Therefore, there are several ways for the level of the DD to be heterogeneous according to the individual characteristics of countries and for its process to vary according to the characteristics of individuals or groups. The heterogeneity of the effects of DD is therefore driven by the heterogeneity of each of these dimensions. Thus, traditional estimation methods may fail to detect changes in behavior across groups. In this work, we propose a different approach that overcomes the problems raised in the literature by applying the FMM, which enables us to relax the assumption of a single model (Ouédraogo et al., 2020; Sawadogo & Semedo, 2021).

FMMs have been the subject of multiple econometric applications, including the health field (Deb et al., 2011; Geweke et al., 1997; Heckman & Singer, 1984). However, this method has not yet been applied in the context of the relationship between the digital divide, globalization and income inequality.

To specify the FMM, it is supposed that each country is associated with one of a set of latent classes *j*, and that the corresponding countries exhibit heterogeneity across classes. Contingent on the observed covariates, within a given class *j*, there is homogeneity.

For the i^{th} latent class with *n* response variables, the conditional joint density function for a given observation is:

$$f_i(y \mid x, \theta) = \prod_{j=1}^{n} f_{ij}(y_j \mid x, \theta) \tag{1}$$

Where $f_i(y \mid x, \theta)$ describes the income inequality distribution conditional on belonging to a class*j* and on covariates *x*.The FMM uses the multinomial logistic distribution to model the probabilities for the latent classes. Thus, for the i^{th}latent class, the probability is given by:

$$\pi_i = \Pr(c_i = 1 | x) = \frac{\exp(y_i)}{\sum_{j=1}^{g} exp(y_j)} \quad \text{, with } 0 < \pi_i < 1 \text{ and } \sum_{c=1}^{C} \pi_i = 1 \tag{2}$$

Where the linear prediction for the i^{th} latent class is $z_i = x'\gamma_i$; γ_i is the associated vector of coefficients. If the first latent class is the base level, γ_1 is a vector of zeros so that $z_1 = 0$ and $\exp(z_1) = 1$. The vector θ is therefore the set of unique model parameters taken from γ_i which is the vector of coefficients for the i^{th}latent class. Auxiliary parameters are those that result from some of the distribution families. Indeed, each latent class will have its own set of these parameters.

The estimation of the FMM can be performed using the Dempster *et al.* (1977) maximum likelihood with the Expectation Maximization *(*EM) algorithm, in the light of the following procedure:

$$\max_{\pi,\theta} \log L = \sum_{i=1}^{N} \left(\sum_{c=1}^{C} \pi_c f_c(y | \theta_c) \right) \tag{3}$$

Moreover, consistent with Hawkins *et al.* (2001) in the case of a mixture of linear regression, we use two information criteria to select the number of components: the Bayesian Information Criterion (BIC), developed by Schwarz (1978) and the Akaike Information Criterion (AIC) developed by Akaike (1974). The BIC is defined as:

$$BIC = -2\log(L) + K\log(N) \tag{4}$$

The AIC is defined as:

$$AIC = -2\log(L) + 2K \quad , \tag{5}$$

where log (L) represents the estimated value of the log-likelihood in Equation (3), K denotes the number of free parameters, and N reflects the number of observations.

3.2. Data

The study covers a sample of 35 SSA countries over the period 2004-2016. The choice of sample and study period was conditioned by the availability of data at the time of study. The data are mainly from secondary sources.

We proxy income inequality with the Gini index, extracted from the *Standardized World Income Inequality Database* (SWIID) constructed by Solt (2014). The Gini index measures the annual distribution of net income in a country and ranges from 0 to the 100th percentile. A value close to zero represents an equitable distribution of income among individuals, while a value close to 100 represents an extremely unequal income distribution. The Gini index is the most widely used indicator for comparing the unequal distribution of income across countries (Hermes, 2014). We use the Palma ratio as well as the Atkinson index as alternative measures of income inequality to check the robustness of our results. The digital divide (DD) encompasses the ICT divide. As demonstrated by Song et al. (2020), DD can be analysed using three categories of indicators: Access[1], Usage[2], and Outcomes[3]. In this study, five indictors are retained to construct the DD index, because of the lack of data in several African countries. These are: mobile broadband, mobile telephone, fixed broadband, fixed telephone and the internet. The construction of the DD index is inspired by works of Rice and Katz (2003) and Migniamissi and Djijo (2021). First, the divide is calculated as the difference between 100% (the total penetration rate) and the level of the ICT indicators mentioned above. We therefore obtain: the mobile broadband divide, the mobile telephone divide, the fixed broadband divide, the fixed telephone divide and the internet divide. Secondly, the overall DD is calculated by averaging the five divide indicators obtained in the first step. The data used are extracted from the international telecommunication union (ITU).

For the control variables, we include the gross domestic product per capita (GDPPC), the total natural resources rent, government expenditures, human capital proxied by the mean years of schooling, and the institutions proxied by the rule of law. The choice of control variables is based on the determinants of income inequality identified in the literature (Persson & Tabellini 2000; Lee & Lee, 2018; Richmond & Triplett, 2018; Tchamyou, 2019, 2021; Nchofoung *et al*., 2021, 2022). We include GDPPC to account for economic development. We also include natural resources rents. In developing countries generally, natural resources have often been evidenced as a curse and a driver of income inequality, especially when institutions are poor (Richmond & Triplett, 2018). The human capital proxied by education has been proven by Lee and Lee (2018) for being a strong determinant of income inequality. According to the authors, education is an important lever for reducing income inequality. As far as the institutional framework is important for income distribution (Persson & Tabellini 2000), we control for institutions by including the rule of law variable, which captures the quality of contract enforcement, property rights, the police, and the court system.

[1] It refers to computer penetration, cell phone penetration, internet service providers per capita and internet access prices.
[2]It is related to internet users per capita, broadband subscribers per capita, connection time and internet bandwidth per capita.
[3]It refers to e-commerce economics, e-procurement benefits, e-learning outcomes and e-government.

All these variables are extracted from the World Bank's *World Development Indicators*, with the exceptions of: (i) the mean years of schooling which comes from United Nations Development Program (UNDP) and (ii) rule of law which comes from *Worldwide Governance Indicators* (WGI) of the World Bank. Table 1 presents the descriptive statistics.

Table 1: Descriptive statistics and sources of variables

Variables	Obs	Mean	Std. Dev.	Min	Max	Sources
Gini Index	505	.580	.039	.440	.851	SWIID
Digital Divide Index	223	26.187	15.278	1.293	64.390	Authors' calculation from ITU
Mobile Telephone Divide	545	56.228	42.007	.209	165.649	Authors' calculation from ITU
Mobile Broadband Divide	249	16.461	18.574	.003	82.190	Authors' calculation from ITU
Fixed Broadband Divide	479	1.442	4.071	0	29.054	Authors' calculation from ITU
Fixed Telephone Divide	527	4.396	6.985	.005	33.614	Authors' calculation from ITU
Internet Divide	522	12.315	15.618	.155	76.481	Authors' calculation from ITU
GDP per Capita	537	2501.72	3376.389	285.545	18247.01	WDI
Natural Resources	546	11.673	10.954	.001	58.650	WDI
Government Expenditures	493	15.022	6.224	4.157	43.483	WDI
Years of Schooling	545	4.926	2.428	1.3	12.8	UNDP
Rule of Law	546	-.612	.580	-1.816	1.029	WGI

Note: GDP: Gross Domestic Product SWIID: Standardized World Income Inequality Database; ITU: International Telecommunication Union; WDI: World Development Indicators; UNDP: United Nations Development Program; WGI: Worldwide Governance Indicators. Source: Authors' calculations.

4. Empirical Results

4.1. Baseline Results

As an initial step, we choose the number of classes using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The AIC and BIC values for each number of classes are reported in Table 2 below. Indeed, the AIC and BIC values are high for C = 3, which correspond to three groups for the sampled countries. Moreover, the BIC and AIC values are lower when the number of classes is 2. Whereas the BIC and AIC are decreasing from C = 1 to C = 2 and later improving or C = 3, the BIC and AIC values are minimised for C = 2. Hence, we retain the two groups.

Table 2: Selection of the number of groups

	C=1	C=2	C=3	C=4
AIC	1390.308	1595.005	1868.95	Not Concave
BIC	1354.521	1519.454	1753.636	Not Concave

Note: BIC uses N = number of observations. BIC: Bayesian Information Criterion; AIC: Akaike Information Criterion

Table 3 presents the baseline results obtained using the fixed effects ordinary least squares (FE-OLS), the fixed effects instrumental variable (FE-IV) and the finite mixture model (FMM) with two classes. We start by the FE-OLS while, this method suffers from endogeneity problems, we rely on the FE-IV method to avoid the problem of simultaneity. We follow Migniamissi and Djijo (2021) by using the overall DD two periods lagged as an instrumental variable.

The results show that the coefficients associated with DD are negative and not statistically significant when using both FE-OLS (Column 1) and FE-IV (Column 2). Thus, according to FE-OLS and FE-IV models, DD does not significantly have an effect on income inequality. Thus, as mentioned above, these econometric models only offer a limited view of the heterogeneous impacts across countries, therefore the need to go further with the analysis by applying the FMM.

In Table 3, Columns (2) and (3) report the estimation results of the FMM, with the annual Gini coefficient as our dependent variable. We report the results C = 2, or for two groups. As far as the BIC and AIC criteria were minimised for C = 2, we retain a FMM with 2 groups. The findings differ across the two groups of countries. In our sample, there is a latent class of about 60.21% where DD has no significant effect (Class1). On the other hand, Class 2 is the smallest, recording a proportion of about 39.79%, and in which, DD significantly affects income inequality. Furthermore, to test whether the coefficient associated with DD is similar in the two groups of countries, we use a joint Wald p-value test and report the results at the bottom of Table 3. Given that the p-value is less than 5%, we reject the hypothesis that the coefficients are equal in the two groups.

Table 3: Baseline results

	(1)	(2)	(3)	(4)
	FE-OLS	FE-IV	FMM	
			Class 1	Class 2
Digital Divide	-0.0030	-0.0186	0.0045	-0.0349***
	(0.006)	(0.011)	(0.0032)	(0.0107)
Natural resources	0.0081***	0.0073**	-0.0190***	0.0157***
	(0.003)	(0.004)	(0.0016)	(0.0027)
GDPPC	-0.0074	-0.0000	-0.0279***	-0.0209**
	(0.013)	(0.016)	(0.0022)	(0.0099)
Government Expenditures	0.0127*	0.0222**	-0.0086***	0.0344**
	(0.007)	(0.009)	(0.0033)	(0.0175)
Years of Schooling	0.0032	0.0108	0.0080***	0.0636***
	(0.018)	(0.026)	(0.0031)	(0.0167)
Urbanisation	-0.1389***	-0.1199***	0.0096**	-0.0043
	(0.029)	(0.038)	(0.0046)	(0.0155)
Rule of Law	-0.0041	0.0030	-0.0125***	0.0557***
	(0.007)	(0.007)	(0.0030)	(0.0095)
Constant	1.0823***	0.9671***	0.758***	0.700***
	(0.142)	(0.183)	(0.0228)	(0.0566)
Observations	394	334	394	394
R^2	0.7983	0.8115		
Hansen Overid (p-value)		0.785		
Number of countries	35	35	35	35
Posteriorprobability			0.6021	0.3979
Wald Test (p-value)			0.0002	

Standard errors in parentheses. * p<0.1 significant at 10 %; ** p<0.05 significant at 5 %; *** p<0.01 significant at 1 %. Note: GDPPC: per capita Gross Domestic Product; FE-OLS: Fixed-effects Ordinary Least Squares; FE-IV: Fixed-effects Instrumental Variable; FMM: Finite Mixture Model.

The results show that DD affects income inequality differently across two classes of countries. In the first class, the coefficient associated with DD is positive and insignificant, while the coefficient is negative and significant at the 1% level in the second class. Indeed, the result in the second class shows that, a 1 percentage point increase in the DD index will reduce income inequality by 0.0349 percentage point. This finding is in line with the recent debate in the literature, concerning the effect of ICT on income inequality. Indeed, the effects of digital divide on income inequality may also be ambiguous as far as the results confirm two conflicting views. First the unequal access to ICTs (digital divide) may reduce income gaps between individuals. This first strand of result is in line with the works of Aghion *et al*. (2019) and Schradie (2020), who showed that the proliferation of ICTs around the world is leading to more innovations, helping the richer to increase their wealth further and widening the gap among the poorest. Second, the results also support the strand of the literature that ICT reinforces unequal income distribution between individuals and corroborate previous studies that found that ICT penetration reduces economic inequalities globally, and income inequality more precisely (Francis & Francis, 2022; Adams & Akobeng, 2021; Evans, 2019; Tchamyou *et al*., 2019a, 2019b).

From the results reported in Table 3, we calculate the posterior probabilities. To do so, we classify country *i* in Group 1 if and only if the probability of belonging to this group is higher than that of being in the second group. Table 4 below presents the composition of the countries in the sample with the average posterior probabilities of belonging to one group of countries or another for the study period considered. As presented in Table 4, countries as Algeria, Ghana and Lesotho tend to end-up in Class 1, where DD increases income inequality, while countries like Botswana, Mauritius and Zambia tend to converge towards Class 2, where DD decreases income inequality.

At the bottom of Table 4, we also report the average values of the Gini index and DD index for the two classes of countries. Thus, we observe significant differences between the country classes for these two variables. The average Gini index is 0.5743 point for Class 1 countries, while it is 0.5827 point for Class 2 countries. Regarding the level of the DD index, we find that it is lower in Class 1 compared to Class 2. It is 20.987 for Class 1 and 31.836 for Class 2.

Table 4:Classes memberships

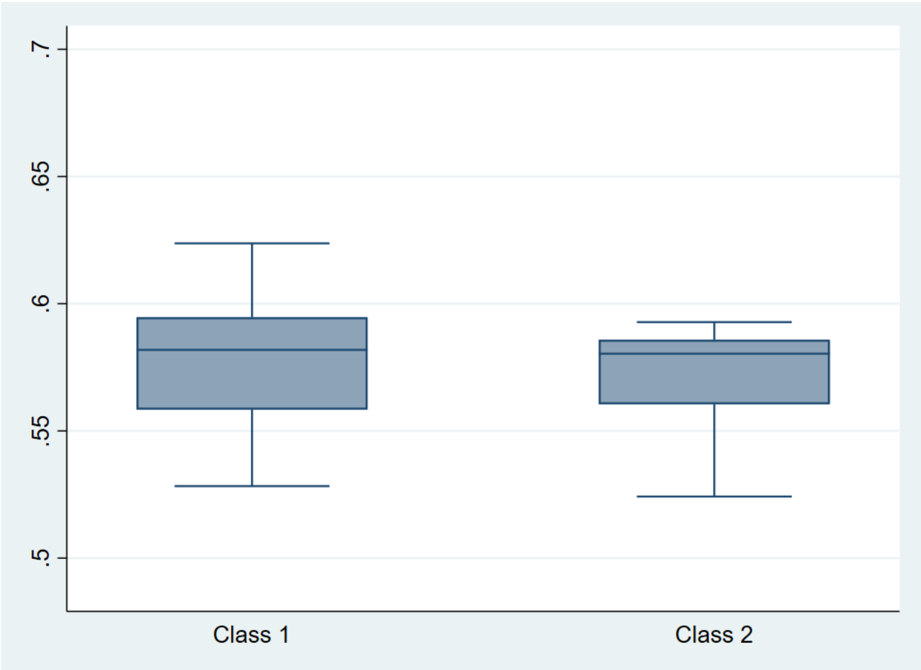
Country	Probability of Class 1	Country	Probability of Class 2
Algeria	0.908	Botswana	0.999
Angola	0.506	Congo, Rep.	1
Benin	0.875	Djibouti	0.836
Burkina Faso	0.816	Gabon	0.999
Burundi	0.835	Mauritius	0.999
Cameroon	0.792	Namibia	0.574
Central African Rep.	0.923	Nigeria	0.795
Chad	0.918	Rwanda	0.678
Egypt, Arab Rep.	0.757	Seychelles	0.757
Ethiopia	0.721	South Africa	1
Gambia	0.897	Zambia	0.999
Ghana	0.947		
Kenya	0.691		
Lesotho	0.954		
Madagascar	0.792		
Mali	0.71		
Mauritania	0.652		
Morocco	0.651		
Mozambique	0.76		
Niger	0.736		
Senegal	0.818		
Sudan	0.829		
Togo	0.739		
Tunisia	0.764		

Table 5: Probability of membership and mean of key variables

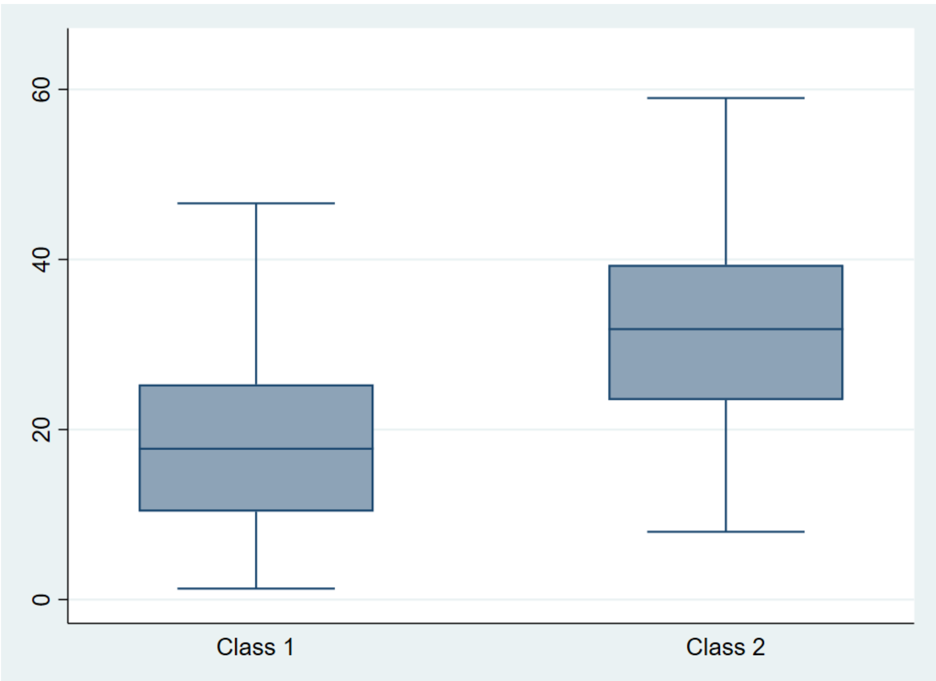
	Class 1	Class 2
Gini Index	0.5743	0.5827
Digital Divide Index	20.987	31.836
Posteriorprobability	0.6021	0.3979

Figure 1: Difference in income inequality and digital divide between classes

(i) Gini index



(ii) Digital divide



Source : Authors

4.2. Explaining class membership: The role of globalization

In this sub-section, we analyze the role of globalization in the nexus between DD and income inequality. The finite mixture model allows us to explain the convergence of a country to one class using concurrent variables. Accordingly, the concomitant variables allow us to evaluate which variables best explain the convergence of a country to a particular class. Thus, our goal is then to show that globalization explains a country's class membership, and we use the concurrent variables to estimate whether the probability of belonging to a specific class is because of globalization. In all regressions related to this analysis, we will use Class 2 as the reference class since in this class DD negatively and significantly affects income inequality. Therefore, we assume a dummy variable that takes the value 1 if the country belongs to Class 2 and 0 otherwise. We then employ the random effects model of Mundlak (1978) to estimate the odds of belonging to Class 2. Mundlak's random effects model has the advantage, unlike the fixed effects model, of including in the analysis countries that do not belong to Class 2.

Moreover, the Mundlak random-effects model considers heterogeneities between countries, controlling for all country-specific and time-invariant features that may affect the probability of a country belonging to Class 2. As far as globalization is concerned, we consider the overall index of globalization and three disaggregated variables, linked to the economic, social and political dimensions. The globalization index was first introduced by Dreher (2006) and further updated by Gygli et al. (2019). Economic globalization considers commercial and financial globalization. Social globalization entails interpersonal, informational and cultural globalization aspects. These variables range from 0 (low globalization) to 100 (high globalization).

The results are reported in Table 6 and as can be seen, the coefficients associated with the globalization indicators are positive and significant. These results suggest that countries with a higher level of globalization are more likely to belong to Class 2. Therefore, SSA countries with higher levels of globalization, including the overall index, economic, social, and political globalization dynamics, are more likely to be in the group of countries where DD reduces income inequality. In short, the results in Table 6 imply that a country's level of globalization can help explain its convergence to a class. This may be because the higher the level of globalization, the greater the openness, but the more unequal the access to ICT, which could have different implications for income distribution. Thus, the results reinforce our preliminary conclusion that Class 2 includes most SSA countries with high income inequality. This finding corroborates the argument in the literature that globalization increases inequalities worldwide and therefore represent a driver of income disparities between individuals in developing countries (Haseeb *et al*., 2020; Lee *et al*., 2020). Consistent with Richmond and Triplett (2018) and Nolan et al. (2019), globalization enhances the effect of DD on inequality.

Table 6: Digital divide and income inequality: the role of globalization

	(1)	(2)	(3)	(4)
Overall Index	0.619***			
	(0.235)			
Economic Globalization		0.619***		
		(0.235)		
Political Globalization			0.309*	
			(0.159)	
Social Globalization				0.200
				(0.223)
Constant	0.498**	0.498**	0.510***	0.430**
	(0.205)	(0.205)	(0.195)	(0.216)
Observations	383	383	394	394
Wald (P-value)	0.028	0.027	0.100	0.667

Standard errors in parentheses. $^{*}p< 0.1$, $^{**}p< 0.05$, $^{***}p< 0.01$

4.3. Robustness Checks

In the baseline analysis, we used the Gini index to measure income inequality. Although this is the most widely used indicator, it does not fully explain income inequality. Our results could therefore be affected by alternative indicators. In addition, in the baseline model specification, we do not take into account all the determinants of income inequality in our regressions; other important variables could have been omitted in controlling the model. For all these reasons, we conduct two main robustness checks. (i) the use of alternative measures of income inequality and (ii) the change of model specification by including additional control variables.

4.3.1. Alternative measures of income inequality

This first robustness analysis addressed the concern that our results might be different when using alternative measures of income inequality. In this subsection, we repeat the same estimations as above, using two alternative measures of income inequality: the Palma ratio, which captures the differences between those at the top and bottom of the income ladder, and the Atkinson index, which calculates the proportion of total income that is required to achieve an equal level of social welfare if the distribution of income were fair. The use of these alternative income inequality indicators for robustness check is consistent with contemporary income inequality literature (Asongu & Odhiambo, 2021; Odhiambo, 2022).

The results of this robustness analysis are presented in Tables 7 and 8. As in the previous case, the coefficient associated with income inequality is negative and statistically significant in Class 2. Hence, the findings of the regressions using the Palma ratio and the Atkinson index corroborate those discussed above. However, we observe that the DD index increases inequality in Class 1 at the 5% significance level when the Palma ratio is used, whereas its impact was not significant in the baseline results. In addition, the signs of the coefficients of the control variables are almost identical to those established above.

Table 7: Robustness check: Using the Palma ratio as an alternative measure of inequality

	(1)	(2)	(3)	(4)
	FE-OLS	FE-IV	FMM	
			Class 1	Class 2
Digital Divide	-0.4241**	-1.002***	0.223**	-2.414***
	(0.199)	(0.359)	(0.092)	(0.352)
Natural resources	0.2835***	0.2725**	-0.350***	0.309***
	(0.103)	(0.114)	(0.027)	(0.109)
GDPPC	-0.0464	0.4360	-1.176***	-2.060***
	(0.485)	(0.542)	(0.053)	(0.306)
GovernmentExpenditures	0.3739	0.6728**	-0.302***	0.717**
	(0.233)	(0.277)	(0.106)	(0.335)
Years of Schooling	1.3627**	1.4928*	-0.332***	3.332***
	(0.622)	(0.805)	(0.094)	(0.392)
Urbanisation	-5.4981***	-4.6631***	1.429***	1.768***
	(1.066)	(1.356)	(0.107)	(0.492)
Rule of Law	-0.2158	0.0584	-0.398***	2.369***
	(0.239)	(0.257)	(0.090)	(0.294)
Constant	23.6404***	17.5417***	9.552***	18.33***
	(5.205)	(6.311)	(0.519)	(1.948)
Observations	394	334	394	394
R^2	0.8727	0.8820		
Hansen Overid (p-value)		0.889		
Number of countries	35	35	35	35
Posteriorprobability			0.5965	0.4035
Wald Test (p-value)			0.0001	

Standard errors in parentheses. * p<0.1 significant at 10 %; ** p<0.05 significant at 5 %; *** p<0.01 significant at 1 %. Note: GDPPC: per capita Gross Domestic Product; FE-OLS: Fixed-effects Ordinary Least Squares; FE-IV: Fixed-effects Instrumental Variable; FMM: Finite Mixture Model.

Table 8: Robustness check: Using the Atkinson index as an alternative measure of inequality

	(1)	(2)	(3)	(4)
	FE-OLS	FE-IV	FMM	
			Class 1	Class 2
Digital Divide	-0.0174**	-0.0273**	0.0018	-0.0485***
	(0.007)	(0.014)	(0.010)	(0.012)
Natural resources	0.0080*	0.0067	-0.0220***	0.0167***
	(0.005)	(0.005)	(0.002)	(0.003)
GDPPC	-0.0081	-0.0075	-0.0631***	-0.0155**
	(0.024)	(0.028)	(0.005)	(0.008)
GovernmentExpenditures	0.0279*	0.0462***	-0.0413***	0.0922***
	(0.015)	(0.018)	(0.008)	(0.011)
Years of Schooling	0.0490	0.0278	-0.0138*	0.0938***
	(0.031)	(0.038)	(0.008)	(0.011)
Urbanisation	-0.2660***	-0.2414***	0.0740***	-0.0347**
	(0.053)	(0.072)	(0.009)	(0.015)
Rule of Law	-0.0169	0.0103	-0.0434***	0.0490***
	(0.012)	(0.013)	(0.008)	(0.009)
Constant	1.5732***	1.5228***	0.976***	0.727***
	(0.269)	(0.342)	(0.052)	(0.054)
Observations	394	334	394	394
R^2	0.8278	0.8487		
Hansen Overid (p-value)		0.332		
Number of countries	35	35	35	35
Posteriorprobability			0.4873	0.5127
Wald Test (p-value)			0.0003	

Standard errors in parentheses. * p<0.1 significant at 10 %; ** p<0.05 significant at 5 %; *** p<0.01 significant at 1 %. Note: GDPPC: per capita Gross Domestic Product; FE-OLS: Fixed-effects Ordinary Least Squares; FE-IV: Fixed-effects Instrumental Variable; FMM: Finite Mixture Model.

4.3.2 Additional control variables in the specifications

Our second robustness check is related to including additional control variables in the specification. The included variables are inflation, trade openness and remittances. The inflation variable aims to capture the macroeconomic instability in the country (Agénor, 2005; Li & Zou, 2002; Milanovic, 2005). The trade openness variable assesses the sensitivity of the country due to the openness of its economy and remittances assess the impact of additional income received by households (Bang et al., 2016; Ebeke & Le Goff, 2011; Meniago &Asongu, 2018). All these variables are obtained from WDI database.

The results in Table 9 are consistent with the baseline findings. Thus, adding additional control variables does not change our main results obtained.

Table 9: Robustness checks: additional variables in the specifications

	(1)	(2)	(3)	(4)
	FE-OLS	FE-IV	FMM	
			Class 1	Class 2
Digital Divide	-0.0048	-0.0218*	0.0027	-0.0261**
	(0.006)	(0.012)	(0.003)	(0.010)
Natural resources	0.0079**	0.0074*	-0.0232***	0.0089***
	(0.003)	(0.004)	(0.002)	(0.003)
GDPPC	-0.0027	0.0083	-0.0271***	-0.0281***
	(0.014)	(0.018)	(0.002)	(0.009)
GovernmentExpenditures	0.0138	0.0253**	-0.0165***	0.0699***
	(0.008)	(0.010)	(0.003)	(0.018)
Years of Schooling	0.0009	0.0057	-0.0138*	0.0938***
	(0.019)	(0.026)	(0.008)	(0.011)
Urbanisation	-0.1271***	-0.1086***	0.0085***	0.0554***
	(0.032)	(0.042)	(0.003)	(0.016)
Rule of Law	-0.0035	0.0044	0.0073*	0.0177
	(0.007)	(0.008)	(0.004)	(0.016)
Inflation	0.0003	0.0001	0.0002	-0.0007
	(0.000)	(0.000)	(0.000)	(0.001)
Openess	-0.0001	-0.0002	0.0002***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Remittances	0.0001	0.0001	0.0001	-0.0059**
	(0.001)	(0.001)	(0.000)	(0.002)
Constant	1.0029***	0.8665***	0.770***	0.607***
	(0.157)	(0.205)	(0.018)	(0.064)
Observations	379	323	394	394
R^2	0.8020	0.8159		
Hansen Overid (p-value)		0.952		
Number of countries	35	35	35	35
Posteriorprobability			0.5806	0.4194
Wald Test (p-value)			0.0002	

Standard errors in parentheses. * p<0.1 significant at 10 %; ** p<0.05 significant at 5 %; *** p<0.01 significant at 1 %. Note: GDPPC: per capita Gross Domestic Product; FE-OLS: Fixed-effects Ordinary Least Squares; FE-IV: Fixed-effects Instrumental Variable; FMM: Finite Mixture Model.

5. Concluding implications and future research directions

The aim of this paper was to assess the impact of the digital divide on income inequality in Sub-Saharan Africa, under the assumption that there is strong heterogeneity across countries.

We then tested the hypothesis that globalization explains differences in the effect of the digital divide on income inequality, using a robust empirical strategy. Therefore, we applied a finite mixture model, which unlike the traditional econometric methods for panel data, is the most appropriate for this study.

Using a sample of 35 sub-Saharan African countries over the period 2004-2016, we find a differential effect of the digital divide on income inequality across country classes. Moreover, the results showed that the effect of the digital divide on income inequality is positive and insignificant in the first class, while it is negative in the second class. These results highlight the role of globalization in explaining the differences in effect in the two classes. As a result, we find that countries with the highest levels of globalization are more likely to belong to Class 2, the class where the digital divide negatively affects income inequality.

The significant nexus between digital divide and income distribution is consistent with the theoretical postulations in Section 2, especially as it pertains to the underlying motivations of individuals who adopt a specific technology. More specifically, from a broad theoretical standpoint, the significant linkages established in this study, suggest from a theoretical angle that, *inter alia*: the decision to adopt a digital technology is a reasoned action by the user (i.e. theory of reasoned action), a planned behaviour (i.e. theory of planned behaviour) and acceptance of a given technology in the light of anticipated potential rewards (i.e. technology acceptance model).

In terms of policy implications, our results clearly show that Sub-Saharan African countries need to undertake robust reforms to bridge the digital divide to stem income inequality and achieve Sustainable Development Goal 10, which calls for the reduction of inequality of all kinds. To do so, these reforms must ensure inclusive access to and use of digital technologies, as well as improve people's skills. To facilitate access, policies must ensure that individuals can afford the purchase and maintenance of digital technologies. Once people have easy access to ICT, their use becomes easy, but they need to improve their skills for effective use. Policy makers should therefore invest more in providing individuals with quality education to ensure this. Digital technologies can be enhanced by consolidating ICT policies, via, *inter alia*: schemes that are worthwhile in favouring universal access to ICT, improving the relevant ICT infrastructure and favouring low pricing channels. Moreover, ICT networks of distribution should be examined before the corresponding policies are adopted so that such are tailored to local needs, not least, because corresponding challenges could vary from one country to another.

Finally, with respect to globalization, reforms should be undertaken to limit its perverse effects and make the most of it, as the literature generally presents globalization as an accelerating factor in world inequality. Policies must therefore put in place effective measures to control this phenomenon and promote more inclusive development. The corresponding policies can build on what has worked elsewhere, especially in countries with similar initial economic development conditions that have leveraged on extant digital technologies to alleviate poverty and decrease income inequality.

The study obviously leaves room for future research especially as it pertains to considering how the digital divide is affecting other development outcomes in the light of the United Nations' sustainable development agenda. Moreover, considering this study within the remit of cryptocurrencies can also improve insights into the relevance of digital currencies in income distribution.

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