ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

THE EFFECT OF HUMAN CAPITAL ON INCOME INEQUALITY: EVIDENCE FROM SELECTED SUB-SAHARAN COUNTRIES

MSc THESIS SUBMITTED TO THE DEPARTMENT OF ECONOMICS IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR A DEGREE OF MASTERS OF SCIENCE IN DEVELOPMENT ECONOMICS

BY; TSEDENIA TIBEBU

ADVISOR: MESELE ARAYA (PHD)

SEPTEMBER, 2023

ADDIS ABABA, ETHIOPIA

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis titled "The Effect of Human Capital on Income Inequality: Evidence from Selected Sub-Saharan Countries" is prepared by Tsedenia Tibebu and is submitted in partial fulfillment of the requirements for the Degree of Master of Science in Developmental Economics.

Signed by the Examining Committee:

Advisor: _____ Signature _____ Date_____

Internal Examiner: _____ Signature _____ Date_____

External Examiner: _____ Signature _____ Date _____

Declaration

The researcher hereby declares that the thesis "The Effect of Human Capital on Income Inequality: Evidence from Selected Sub-Saharan Countries" is the original work and that all sources that have been referred to and quoted have been duly indicated and acknowledged with complete references.

Name_____

Signature_____

Date_____

Acknowledgement

First and foremost glory is to the almighty God for giving me the wisdom and strength in my entire life journey. I would like to express my sincere gratitude to my advisor, Dr. Mesele Araya, for his invaluable guidance and support throughout my master's program. His expertise and encouragement helped me to complete this research and write this thesis.

I would also like to thank Petros Terefe for his feedback on my research proposal and thesis and Yimer Ali for his assistance in conducting estimation techniques in STATA. I would like to thank my family and friends for their love and support. My deep and warmest appreciation extends to my beloved mother Aselef Mekonnen. I am here because of her.

Finally, I wish to express my appreciation to all individuals who have contributed to the completion of this paper in one way or the other.

Table of Contents

Contents **Pages**

List of Tables

List of Figures

Acronyms

GDL: Global Data Lab

GDPpc: Gross Domestic Product per capita

GMM: Generalized Method of Moments

HDI: Human Development Index

IMF: International Monetary Fund

IWI: International Wealth Index

PRC: Pew Research Center

SDGs: Sustainable Development Goals

UN DESA: United Nation Department of Economic and Social Affairs

ABSTRACT

The study explores the impact of human capital on income inequality in 24 selected Sub-Saharan African countries during the period from 2010 to 2020. The study used Gini coefficient as a measure of income inequality. To conduct the econometric data analysis, a two-step System Generalized Method of Moments (GMM) was employed. Other explanatory variables, including Domestic Credit to the Private Sector, GDP per capita, Inflation, and Population Growth, were controlled for in the analysis. The results obtained from the two-step system GMM indicate that human capital has a significant positive effect on income inequality. This implies that as human capital improves within a society, income inequality worsens. The positive relationship between the Gini coefficient and human capital can be attributed to the highly unequal distribution of access to and quality of education in Sub-Saharan Africa. Another variable found to have a significant effect is inflation. The findings demonstrate that inflation significantly and negatively impacts income inequality in Sub-Saharan Africa. Overall, this study provides valuable insights into the relationship between human capital, inflation, and income inequality in Sub-Saharan Africa, shedding light on the factors that contribute to income disparities within the region.

CHAPTER ONE

1. INTRODUCTION

1.1. Background of the Study

In terms of social justice, especially high income inequality caused by social inequality over time is undesirable. In addition, inequitable income distribution can be an obstacle to economic growt h. Greater inequality gives talented but disadvantaged individuals less education and destabilizes communities and discourages investment. Therefore, countries seek to improve the wellbeing of t he poor and vulnerable by using redistributive policies, creating social security and reducing wea lth and income inequality (Lee and Lee, 2018).

The impact of human capital on income distribution and economic growth is growing in significance. More educated people are expected to have a considerable favorable impact on social, political, and economic outcomes. In general, higher levels of human capital performance will boost economic growth, lower rates of poverty, and narrow income disparities. Through knowledge, information, and respectable cultural practices, human capital will also contribute to the development of a more civilized society. In order to improve and preserve the quality of its human resource, a nation must consistently invest in human capital. (Ismail and Yussof, 2010).

Focusing on the link between economic growth and income inequality, Kuznets (1955) predicted that as economies develop, income inequality would initially increase, reach its peak, and then begin to drop after reaching a critical threshold in terms of both income level and development stage. Kuznets backed up this assertion using cross-country and time series data. The Kuznets curve is an inverted U-shaped pattern of income inequality that is usually measured using the Gini coefficient, a scale on which zero is perfect equality and one is perfect inequality. It is a stylized fact about long-run processes of economic development.

Globalization and technological advancements have altered how economies operate and what skills are needed for future employment (World Economic Forum and PricewaterhouseCoopers 2021). Therefore, the development of human capital has been given top priority in government policies around the world, especially in developing nations that have a history of having low levels of human capital. The promotion of the development of necessary skills for successful

participation in the twenty-first century economy has not, however, benefited from the prioritization of human capital production. (Keese and Tan 2013).

Since it has been shown that we cannot discuss equitable economic growth without addressing human capital and income inequality, these major development challenges have taken centre stage in today's development debates. Additionally, it is impossible to solve the problem of wealth disparity without simultaneously tackling the issue of societal human capital. As a result, economic development and income disparity are closely intertwined, and both can have a significant impact on the nation's economic development over the long and short terms. The researcher was inspired to pursue research in this area as a result of these pressing development challenges and their unprecedented contribution to economic development.

1.2. Statement of the Problem

Although many African countries have experienced tremendous economic growth over the past few decades, indicators of human development and the fight against poverty have not progressed as expected. Indeed, according to world Bank statistics on the implementation of the Millennium Development Goals, poverty has been declining everywhere in the globe save for the African continent (World Bank, 2015). This is in contrast to data that indicates that since the middle of the 1990s, African countries have experienced a major uptick in growth (Fosu, 2015). The solution to this conundrum has increased attention in the study of inequality as one of the possible causes of the low elasticity of growth for poverty reduction in Africa (Fosu, 2009; Thorbecke, 2013).

The achievement of a more equitable income distribution among the various societal segments is one of the key goals of economic development. However, despite achieving a noticeably high rate of economic growth, poverty and income inequality continue to be the main issues in developing nations. High economic development cannot guarantee equal income distribution because this requires government action and cannot be left to market forces alone. This is due to the fact that not everyone has an equal opportunity to possess and utilize resources. Even with good government policy, if such policy is inefficient, income disparity will still be a problem. (Ismail and Yussof, 2010).

Human capital is one of the things that can increase people's income and hence reduce income disparity, as has long been understood. The creators of the Human Capital Theory, Schultz

(1960) and Becker (1964), highlighted the ability of human capital to increase an individual's profits. Other researchers have since backed up this claim, and the majority of studies conclusively demonstrate a significant and favorable relationship between the attainment of human capital and income or earnings (Denison, 1967; Barro, 1990; Mankiw et al., 1992; De Gregario, 1992; Otani & Villanueva, 1993; Hanson & Knowles, 1997; Murthy and Chien, 1997; Barro & Lee, 1996 & Pritchett, 1996). They also concur that income distribution will be more equitable when human capital, particularly education, is spread equitably throughout the society (Hammermesh,1984).

In many nations and areas, educational attainment has increased recently, and educational disparity has decreased, but economic inequality has increased at the same time. This pattern is perplexing given that experts anticipate rising average educational attainment and educational equality to reduce income inequality. By evaluating the roles of all the significant components in income distribution, we must pinpoint the precise contribution of education to income distribution. For instance, globalization and technical advancement have accelerated significantly in the recent past. While numerous studies have examined the origins of income disparity, none have yet in-depth examined the precise role that education plays in it, particularly in cross-national and intertemporal situations (Ibd!).

Gary Becker (1964) asserted that human capital is a factor in production that is influenced by factors like education, training, and medical care. The difference in income for graduates can be explained by increased human capital. Human capital is determined by national educational standards, which evaluate skills, education, capacity, and labor traits that influence a person's capacity for output and earning potential. Therefore, understanding the connection between income inequality and human capital will be crucial to solving the present development-related issues in developing countries. In light of the fact that income inequality and subsequent rates of economic growth are thought to be highly influenced by human capital, this variable is thought to be of particular interest for this study.

Human capital has been cited as one of the key variables influencing the degree of economic inequality in numerous past studies. A key factor in determining a worker's lifetime earnings is their human capital, which is determined by the level of education they have attained. Parents view investing in their children's education as a key strategy for increasing their future wages.

Increased education investment is a popular strategy used by many governments to combat income disparity by reducing educational inequality. Despite the popular perception and interest among the public and policymakers regarding the significance of education for income distribution, the relationship between educational attainment and its distribution in communities experiencing income equality is not always clear in theoretical and empirical investigations (Lee and Lee 2018).

There are, however, not many studies on the relationship between income inequality and human capital in Africa. Most studies in SSA focused on trends, determinants, institutional determinants, other determining variables, and consequence of income inequality in the region (Okojie and Abebe,2006; Nicolas,2009; Zizzamia et al, 2021; Ambassa,2021; Avom et al, 2022). And other researchers in this field tend to concentrate on a particular country level; there are a few cross-country analysis that focuses on the relationship between Income Inequality and Human Capital in developing countries and SSA (Friderichs et al, 2023; Lee and Lee,2018; Singh, 2023) . Few researchers who studied the relationship between the two in SSA, used other estimation techniques (Getaye,2021).

In order to establish a long-term relationship between these two variables, this study conducted a cross-country analysis consisting of 24 countries by using a more reliable estimation technique-system GMM. In light of this, the purpose of this article is to investigate how Human Capital affects Income disparity and identify other significant variables that influence income disparity across Sub Saharan Countries using a Panel Data.

1.3. Basic research questions

The study has tried to answer these questions:

1. What is the trend between Human Capital and Income Inequality in Sub-Saharan countries?
2. What is the effect of human capital on Income Inequality across Sub-Saharan countries?
3. How is Human Capital and income inequality related across Sub-Saharan countries?

1.4. Objectives of the study

1.4.1. General objective

The general objective of this study is to assess the effect of Human Capital on income inequality by using panel data for 24 selected countries from Sub Saharan Africa for the period covering 2010-2020.

1.4.2. Specific objectives

The study has the following specific objectives:-

- To show the trends of human capital and Income Inequality in Sub Saharan countries.
- To assess the effect of human capital on Income Inequality across Sub-Saharan countries
- To show how Human Capital and income inequality are related across Sub-Saharan countries

1.5. Significance of the study

This study could have importance for various parties. The study about income inequality, unemployment, human capital, and economic growth has policy and national strategy features that could be used as input for policy makers. As a result, the research's findings can be used by strategists and policymakers for a variety of decision-making processes.

The other significance of this study also relies in the fact that it attempted to empirically establish the major determinant variables that are affecting income inequality in selected countries, it would serve as a references material for the respective countries in order to formulate their development policies.

Last, but not least, the study could add value to the existing knowledge in the subject area, and its findings can be important since it could serve as a references for academics, students, and other interest groups or people.

1.6. Scope of the study

This study was delimited to investigate the effect of Human Capital on Income Inequality. It is largely a proven fact that Income inequality is not only an economic phenomena and affected not only by economic factors rather it is largely affected by many socio-economic, political and

historical factors of the country. However, because of the cost and time limitations coupled with limited purpose of the study, which is for partial fulfillment of the degree of the Masters of sciences in development economics, the scope of this study is limited to investigate the effect of Human Capital on Income Inequality in Sub Saharan Countries. Further, the study will examine macroeconomic factors that affect Income Inequality by using panel data collected from 24 countries from Sub Saharan Africa for the period covering 2010 – 2020 G.C.

1.7. Organizations of the Thesis

The paper is organized into five main chapters. The first chapter deals with an approach to the problem. The second chapter focuses on reviewing related literature. Research design and methodology of the study is presented in chapter three and the fourth chapter is descriptive and empirical analysis of the study. Then the final chapter includes conclusions and policy implications.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Theoretical Literature Review

2.1.1. Income Inequality: Global and National Perspective

The widening income inequality is the most urgent issue of our day. Currently, advanced economies are experiencing their largest wealth imbalance. The patterns of inequality in emerging markets and developing countries (EMDCs) have been more diverse; while some countries have experienced decreased inequality, there are still significant disparities in the access to finance, healthcare, and education. Therefore, it should not come as a surprise that some of the most hotly debated issues among politicians and academics are the severity of inequality, its causes, and remedies to the problem (IMF, 2015).

Since then, income disparity has received more attention in discussions of policy. "Leave no one behind" is the motto of the 2030 Agenda for Sustainable Development. With good reason, Goal 10 of the Sustainable Development Goals (SDGs) seeks to lessen inequality within and between nations. The vast differences between and within countries have not been eliminated despite the last decades' high economic growth and substantial improvements in wellbeing. Significant social, economic, and environmental factors are influencing the income gap. There are many implications of these global influences, also referred to as megatrends. While some can aid in equalizing possibilities, others are putting increasing pressure on income inequality, especially through their impact on labour markets, 2020 (UN DESA)

In most developed countries as well as some middle-income countries, such as China and India, the income gap has widened since 1990. The majority (71%) of the world's population lives in countries with rising inequality. The trend toward increasing inequality is not pervasive, though. Most countries in Latin America and the Caribbean, as well as others in Africa and Asia, have seen a decline in the Gini coefficient of income inequality over the previous twenty years. Even while some countries have made progress, income and wealth are more concentrated at the top. The share of income going to the richest 1% of the world's population increased in 46 of the 57 countries and regions with data from 1990 to 2015. In comparison, the bottom 40% of the

population earned less than 25% of total income in all 92 nations with data (United Nations, 2019).

Consequently, growing inequality is a major concern. Growing income inequality among the most developed and emerging markets and developing countries (EMDCs) is a topic that has drawn significant attention; former American President Barack Obama termed it the "defining challenge of our time." More than 60% of people worldwide said that the gap between the rich and the poor is a key concern in a recent Pew Research Centre survey (PRC 2014), and Pope Francis has spoken out against the "economy of exclusion." Indeed, the PRC poll revealed that while having a good education and working hard were considered to be vital for moving up, it was also important to have the appropriate connections and come from a wealthy family, suggesting potential significant barriers to social mobility.

Equality and fairness are fundamental principles in the vast majority of nations. Regardless of their philosophy, culture, or religion, individuals are concerned about inequality. Inequality is a sign of poor income mobility and opportunity but it can also be a sign of long-term disadvantage for some social groupings. Growing inequality can also lead to the concentration of political and governing authority in the hands of a few number of people, the ineffective use of human resources, political and economic instability that deters investment, and a rise in crisis risk. Due to the economic and social effects of the global financial crisis and the consequent obstacles to global growth and employment, rising income disparity is attracting more attention. (Ibd!).

2.1.2. Income Inequality Problem and Economic Growth

Over the past 40 years, technology has greatly reduced the cost of transportation and improved automation and communication. The opening of new markets has led to growth opportunities in both rich and poor countries, lifting hundreds of millions of people out of poverty. The skill-biased technical advancement that has come after economic expansion or other aspects of the growth process may be to blame for the rise in inequality. (IMF, 2015)

Additionally, despite significant economic growth over the past few decades in many African nations, indexes of human development and poverty have not changed as anticipated. Indeed, according to globe Bank statistics on the implementation of the Millennium Development Goals, poverty has been declining everywhere in the globe save for the African continent (World Bank,

2015). This contrasts with data demonstrating that from the mid-1990s, African countries have experienced a major uptick in growth. (Fosu, 2015).

After figuring out this puzzle, researchers are now more interested in studying inequality as one of the possible causes driving the weak poverty-reduction elasticity of growth in Africa (Fosu, 2009; Thorbecke, 2013).

Human capital is one of the things that can increase people's income and hence reduce income disparity, as has long been understood. The creators of the Human Capital Theory, Schultz (1960) and Becker (1964), highlighted the ability of human capital to increase an individual's profits. Other researchers have since backed up this claim, and the majority of studies conclusively demonstrate a significant and favourable relationship between the attainment of human capital and income or earnings (Denison, 1967; Barro, 1990; Mankiw et al., 1992; De Gregario, 1992; Otani & Villanueva, 1993; Hanson & Knowles, 1997; Murthy and Chien, 1997; Barro & Lee, 1996 & Pritchett, 1996). They also concur that economic distribution will be more equitable when human capital, particularly education, is spread equitably throughout society (Hammermesh, 1984).

Numerous empirical studies have attempted to explain income disparity or distribution from a variety of perspectives. As in Mocan (1999) and Blejer and Guererro (1990), some studies, especially those based on time series data, are frequently preoccupied with figuring out the effects of particular macroeconomic variables (such as inflation and unemployment level) on income distribution, while other time-series studies look at the effects of fiscal policy, particularly tax rate, on inequality, as in Auten and Carroll (1999) and Feenberg and Poterba (1993). Such studies are not very pertinent to the current cross-country analysis because they have been reported mostly for industrialized nations with sufficient time series on income distribution. (UN WIDER, 2001)

The majority of empirical studies on income inequality have focused on two issues: determining the causes of the pattern and degree of disparity that have been observed, as well as the direction—whether positive or negative—of the impact of inequality on economic growth. Contradictory results have, however, frequently been reported, in part due to the theory's limited direction. Additionally, the majority of these researches have relied on cross-country data (or panel data, in some cases) for a specific area or for all nations with relevant data. However, few

studies have been reported exclusively for Africa due to the lack of income distribution data points for African countries, and even when all countries with data are included, the percentage of African countries covered is frequently negligible. (Ibd!)

The paradox continues at the empirical level. While some studies, such as Perotti (1996) and those compiled in Benabou (1996), provide data that generally support the idea that inequality has a detrimental impact on growth, other studies, such as Li and Zou (1998), have indicated the opposite. More recently, Barro (2000) has provided evidence that tends to "reconcile" them by demonstrating that "the relationship between inequality and growth is positive for rich countries but negative for poor countries." However, this "reconciliation" is still far from convincing, and the current study, which is almost entirely based on data for developing nations, makes an effort to further clarify the situation. (Odedokun and Round, 2001)

2.1.3. Human Capital Theory and Income Inequality

Technology innovation, the rise in the talent premium that has emerged, and the deterioration of some institutions governing the labor market have all led to an increase in inequality in both advanced economies and EMDCs. A little but persistent impact of globalization has been seen. It's significant to observe that although financial depth is linked to growing inequality in EMDCs, rising skill premium is linked to widening income gaps in advanced countries, opening the door for policies that promote financial inclusion. Policies that put the middle class and the disadvantaged first can lessen inequality. Increased access to social programs such as healthcare, education, and welfare together with steps to ensure that the poor are not disproportionately penalized by labor market institutions can help improve the income share for the poor, regardless of the rate of economic growth (IMF, 2015).

According to the human capital Model, the level and distribution of education within a population affects how income is distributed (Becker and Chiswick, 1966; Mincer, 1974). As a result, the model claims that the level of income inequality in a society is influenced by the availability and demand for education. The average number of years spent in school has an impact on income inequality, but depending on how the rates of return on education have changed, that impact could be positive or negative even though the model predicts a clear positive relationship between income inequality and educational inequality as measured by the variance of schooling. 2018 (Lee and Lee).

The creators of the Human Capital Theory, Schultz and Becker, made this point about the ability of human capital to increase individual earnings. Other researchers have since backed up this claim, and the majority of studies strongly demonstrate a significant and positive relationship between human capital attainment and earnings or income (Denison, 1967); Barro, 1990; Mankiw et al., 1992; De Gregario, 1992; Otani and Villanueva, 1993; Hanson & Knowles, 1997; Mur They also concur that economic distribution will be more equitable when human capital, particularly education, is spread equitably throughout society (Hammermesh, 1984).

The majority of earlier studies indicate a favourable correlation between income distribution and human capital. For instance, Podder (2003) investigates how human capital affected the disparity in incomes between 1997 and 1998 in Australia. He discovers that inequality and discrimination are related using the Mincer quadratic earnings equation. Grimm (2004) utilizes a micro simulation dynamic model to examine how changes in Cote d'Ivoire's educational system have affected household income. He discovers a correlation between these two factors that is positive, showing that returns to education and labour demand have a significant impact on income distribution and poverty. A rise in the rate of returns to education, according to a different study by Arabsheibani, Carneiro, and Hanley (2003), will lessen income disparity.

2.2. Empirical Literature Review

The majority of the research on the development of human capital examines how income disparity affects economic growth. Galor and Zeira (1993) make the point that the impoverished have little money to spend on the growth of human capital. Because financial restrictions are always a major barrier to investing in the creation of human capital, poor nations either lack the resources to do so or invest very little. Every economy must focus on building up its human capital in order to begin the redistribution of income and attain specialisation. Less developed countries gained less from this process than developed countries with strong rates of human capital formation.

Human capital characteristics have a favorable association with earnings through increased productivity, according to Schultz (1960) and Becker (1964). Since earnings make up a significant amount of income, an equal distribution of educational opportunities will result in a more equitable distribution of income. Becker (1964) divided the components of human capital into four categories: migration, education, training, and health. However, over time, these

elements have changed to fit the surroundings. For instance, the components are expanded to include variables like knowledge, abilities, and information (Becker, 1993; Fedderke et al, 1999; Djamaludin Ancok; 2007).

Appiah and McMahon (2002) emphasized the necessity of ongoing, significant, and long-term investments in both physical and human capital in order for African nations to get to the level of development now attained by industrialized nations. According to the study, political stability and a sufficient level of human capital are requirements for the effectiveness of investments in physical capital. Therefore, significant investments in human resource development together with political and economic reform can quicken Africa's economic progress.

Shahpari and Davoudi (2013), they studied Effects of Human Capital on Income Inequality in Iran. It has been discovered by using the ARDL technique between 1969 and 2007 that raising physical and human capital can lower the Gini Index and hence improve the fairness of income distribution. On the other hand, rising GDP, inflation, and unemployment rates can all increase the Gini index and worsen the inequality of income distribution.

Jong-Wha Lee and Hanol Lee (2018) conduct an empirical investigation of the relationship between human capital, as determined by educational attainment, and income distribution. The regressions, which make use of a panel data set spanning a wide range of nations between 1980 and 2015, demonstrate how considerably a more even distribution of education lowers income disparity.

In his 2003 study, Podder examined how human capital contributed to Australia's earnings disparity for the year 1997-1998. He discovers that inequality and discrimination are related using the Mincer quadratic earnings equation. Additionally, using a micro simulation dynamic model in Cote d'Ivoire, Grimm (2004) evaluates the effect of educational development on household income. He discovers a positive correlation between these two variables, with income distribution and poverty heavily reliant on returns to education and labour demand. A rise in the rate of returns to education, according to a different study by Arabsheibani, Carneiro, and Hanley (2003), will lessen income disparity.

In Taiwan from 1976 to 2003, Lin (2007) examines the expansion of education, educational inequality, and income inequality. According to his research, Taiwan has seen a decline in educational inequality and an increase in the mean number of school years. As a result, Taiwan's

income disparity has decreased. Rahmah and Poo Bee Tin (2002) used Malaysian data from the 1970 to 2000 time periods to investigate the factors that affect income distribution in Malaysia. They discover a significant positive association between the Gini coefficient and foreign direct investment, unemployment rate, and foreign labour. This suggests that a rise in those factors will result in less income disparity, While transfer payments, manufacturing employment, and GDP growth have a negative correlation with income inequality.

According to Knight and Sabot (1983), increasing educational attainment may or may not have an impact on how income is distributed. They demonstrate that increased educational attainment has two opposing effects on income distribution: the "composition effect," which indicates that wage inequality initially rises as a result of the increase in the proportion of more educated workers; and the "wage compression effect," which suggests that as a result of increased educational attainment, the premium for educated workers will eventually decline and, as a result, wage inequalities.

2.3. Conceptual Framework of the Study

A conceptual framework, according to Upton (2011), can be characterised as a collection of overarching concepts and guiding principles drawn from pertinent fields of inquiry and utilised to organise subsequent studies. As a result, a conceptual framework is a research instrument created to help a researcher gain knowledge of the issue being studied, understand it, and interact with the study (Upton, 2011). In order to demonstrate the relationship between Income Inequality and Human Capital and other explanatory variables, the study developed conceptual framework models, as shown in figure 2.3 below.

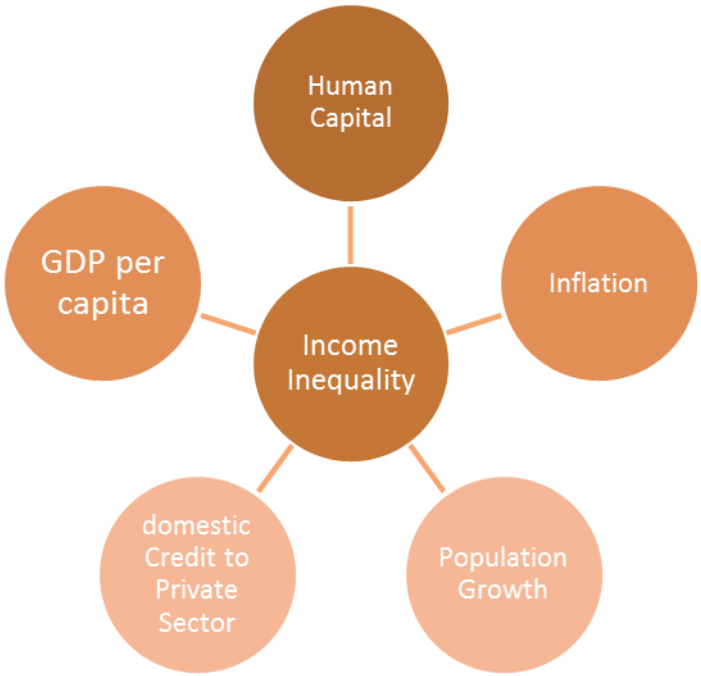

Figure 1 Conceptual Framework

Source: Own computation from Literature review

CHAPTER THREE

3. RESEARCH METHODOLOGY

3.1. Source and data type

The study is based on secondary data type. The study used panel data, which is time series data from year 2010 to 2020 for 24 selected countries from Sub Saharan Africa. Secondary data on dependent variable Income Inequality is collected from International Wealth Index (IWI). The interest variable Human Capital is collected from Subnational HDI Database of the Global Data Lab (GDL). The remaining variables such as Domestic Credit to Private Sector, GDP per capita, Inflation, and Population Growth are collected from World Development Indicator. The analysis is based on 24 selected Sub Saharan African countries. Those countries are selected based on availability of data. The selected countries are Benin, Burundi, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Nigeria, Rwanda, Sao Tome & Principe, Senegal, Sierra-Leone, South Africa, and Togo.

3.2Research Design

Both descriptive and econometric data analysis techniques were used in this investigation. Empirically this study investigated how human capital, is related to income distribution by using a panel data set covering 24 Sub Saharan African countries between 2010 and 2020. The two-step system GMM model is applied to dig deep into Human Capital and income inequality based on recent data. The GMM model controls for Endogeneity by internally transforming the data and by including lagged values of the dependent variable. In this way, the GMM model offers a superior estimation technique compared to the other panel data models.

3.2.1 Model Specification

Based on research in the literature and in empirical studies, the independent variables are chosen. To identify whether Human Capital, Domestic Credit to Private Sector, GDP per capita, Inflation, and Population Growth determine income inequality in sub-Saharan African countries, we must identify the important model. The model can be provided as follows in light of the literature already in existence (Getaye,2021; Ambassa,2021; Avom et al, 2022).

$$GINI_{it} = \beta 0 + \beta 1 HC_{it} + \beta 2 Dcp_{it} + \beta 3 GDPpc_{it} + \beta 4 Inf_{it} + \beta 5 PG_{it} + \varepsilon_{it}$$

And the Generalized Method of Moment (GMM) model is specified as follow:

$$GINI_{it} = \beta 0 + \beta 1 GINI_{it-1} + \beta 2 HCit + \beta 3 Dcp_{it} + \beta_4 GDPpc_{it} + \beta_5 Inf_{it} + \beta_6 PG_{it} + Xit + \alpha i + \square t + \varepsilon it$$

Where, $GINI_{it}$ is Gini index a measure of income inequality ad $GINI_{it-1}$ is its lagged value. HC is Human Capital measured by Mean Years of Schooling for country i and time t. Dcp_{it} is Domestic Credit to Private Sector for time t and country i. $GDPpc_{it}$ is per capita gross domestic product for every individual country i and time t. Inf_{it} is Inflation rate of country i for time t. PG_{it} is population growth of the countries i with time t. X_{it} is a vector of other control variables that affect the distribution of Gini coefficient. i and t indicates the individual country and time respectively. β0 indicates the value of a constant and β1, β2, β3, β4,and β5 are coefficients on the explanatory variables. αi and □t are unobserved country-specific and time-specific fixed effects respectively.

3.3 Definition and Measurement of Variables

The dependent and explanatory variables that the model used in this study are described and measured as follows:

Income Inequality: This is the Independent variable of the study. It measures how unequally income is distributed among a population. It is measured by many indexes; however, for this study the researcher used Gini Index as a measure of Income inequality for empirical assessment. The data is collected from International Wealth Index (IWI).

Human Capital Index: For empirical assessment under this paper, the researcher used Mean Years of Schooling. It is the average number of years of a country's population aged 20+ and older has completed their education. The data is collected from Subnational HDI Database of the Global Data Lab (GDL). Human capital is expected to affect income inequality negatively.

Domestic credit to private sector: It refers to financial resources provided to the private sector by formal financial corporations/institution for business purpose. It is measured as domestic credit which is provided to private sector as a percentage of Gross Domestic Product. The data is collected from World Development Indicator. Domestic Credit to Private Sector is expected to have a negative impact on income inequality. .

Inflation Rate: it is the persistent increases in the general price level for the long period of time for the country. It is measured by the annual growth rate of the GDP implicit deflator which shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency. The data is collected from World Development Indicator**.** A positive relationship is expected between this variable and income inequality.

GDP Per Capita: It is a financial indicator that quantifies the economic output per person in a nation and is computed by dividing GDP by population. The data for this variable is collected from World Bank development indicators. It is expected to affect income inequality negatively.

Population Growth: The population growth rate is the percentage change in the population over time. It is computed by dividing the total number of people added to the population at the start of the period by the total population at the start of the period. The expected sign of this variable is positive.

3.4 Method of Data Analysis and Estimation Technique

A variety of economic variables interact in dynamic ways. They can be identified by the lagged dependent variable being included among the right-side regressors, which shows that the influence of the dependent variable's earlier periods tends to persist in the dependent variable's current period. A type of data called panel data includes observations on the same units over a range of time periods. Numerous phenomena can be studied using this kind of data. Working with panel data presents a number of difficulties, including the possibility of endogenous data. This implies that the dependent variable and the error term might be associated. This may result in biased estimates. The possibility of serial correlation in the data adds another difficulty to working with panel data. This implies that the model's errors might correlate over time. This can also result in biased estimates.

In their 1999 publication, "System GMM Estimation with Cross-Section and Time Series Data," James J. Heckman, Sergio Urzua, and his colleagues made the initial case for System GMM as the optimal estimattion technique for panel data analysis. The authors of this study made the case that system GMM is a more reliable estimator than conventional GMM estimators and that it can be used to estimate models using both cross-sectional and time-series data.

There are many justifications for employing this estimating method. First, by taking into account causality the independent variable, which may come from to the dependent variable and vice versa and may be correlated with the error term, it avoids endogeneity problems. Second, the GMM takes into consideration the relationship between the explanatory variables and the time-invariant individual-specific fixed effects contained in the error term. Another benefit is that it takes into consideration the possibility of autocorrelation brought on by a lagged dependent variable. For panel data with a big N and a short T, GMM is also helpful (Mileva, 2007).

Since then, system GMM has become a widely used estimation technique in panel data analysis. It is particularly popular for estimating models with dynamic effects, where the dependent variable is affected by its own past values. The model is based on the use of multiple instruments to solve endogeniety problems. System Gmm can also control for group effect by including group dummies in the model. Therefore, for the reason mentioned above, system GMM is a better estimation technique for this dataset.

3.5 Causality and Model selection test

3.5.1 Unitroot test for panel data

Determining the direction of causality among our main variables of interest Income inequality and, Human Capital, GDP per capita, Domestic Credit to Private Sector, Inflation Rate, and Population Growth is important. To go further for econometric analysis, it is crucial to check whether the series of data is stationary or not. To check for unitroot, the study used Levin, Lin, & Chu test.

3.5.2 Hausman Specification Test Result

A statistical hypothesis test called the Hausman test is used to compare two distinct parameter estimators. The fixed effects estimator and the random effects estimator are the two estimators that are being compared. To assess whether estimator is more reliable or less likely to be biased, the Hausman test is utilized. A straightforward estimator that can be used to account for time-invariant unobserved heterogeneity is the fixed effects estimator. Although it is a more complicated estimate, the random effects estimator can be used to account for both time-invariant and time-varying unobserved heterogeneity. According to the Hausman test, the individual effects must be uncorrelated with the regressors for the random effects estimator to be

consistent, and only then. The random effects estimator will be biased if the individual effects are associated with the regressors.

3.5.3 Arellano-Bond test for serial correlation

The Arellano-Bond test is a statistical test used to test for the presence of serial correlation in the errors of a generalized method of moments (GMM) model. Serial correlation is a problem in GMM models because it can lead to biased estimates. The Arellano-Bond test is a Lagrange multiplier test that is based on the assumption that the errors in the GMM model are serially uncorrelated. If the Arellano-Bond test is significant, it indicates that there is serial correlation in the errors and that the GMM estimates may be biased. The researcher conducted this test.

3.5.4 Hunsen test

The Hansen test is a statistical test used to test for the validity of over identifying restrictions in a generalized method of moments (GMM) model. Over identifying restrictions are restrictions that are imposed on the model that are not implied by the data. The Hansen test is a Lagrange multiplier test that is based on the assumption that the over identifying restrictions are valid. If the Hansen test is significant, it indicates that the over identifying restrictions are not valid and that the GMM estimates may be biased. The researcher also conducted this test

CHAPTER FOUR

4. RESULTS AND DISCUSSIONS

In this section, the data gathered from different secondary sources will be presented and analyzed in line with the specific objectives that the researcher has aroused. The chapter contains two parts: the first part deals with the descriptive analysis which will focus on issues like Trends of Income Inequality in selected Sub-Saharan Africa, and the trends of explanatory variables in relation with the Income Inequality. The second part contains Econometric analysis of the study that assess variables that affect the Income Inequality in the selected Sub-Sharan counties from year 2010 – 2020. The data was gathered from World Development Indicator, International Wealth Index (IWI) and Subnational HDI Database of the Global Data Lab (GDL).

4.1 Descriptive Analysis of The Variables

4.1.1. Trend of Income Equality (Gini-Coefficient)

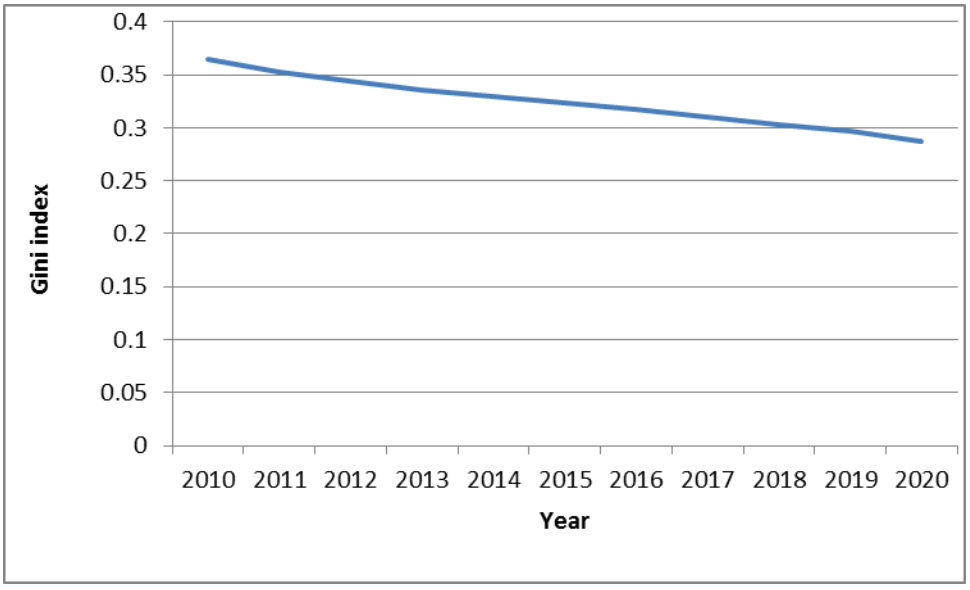

Figure 2 Trends of income Inequality in Sub Saharan Africa

Source: International Wealth Index(IWI).

From the above figure, one can observe that Sub Saharan Africa is experiencing a declining income inequality from 2010 onwards. This could be attributed to the situation that Sub-Saharan Africa has experienced strong economic growth in recent years. This can led to an increase in the incomes of many people in the region and reduce income inequality. According to the African

Development Bank's report, governments in Sub-Saharan Africa have invested heavily in education and healthcare in recent years. This has helped to improve the skills and productivity of the workforce, which has led to higher incomes for most of the people.

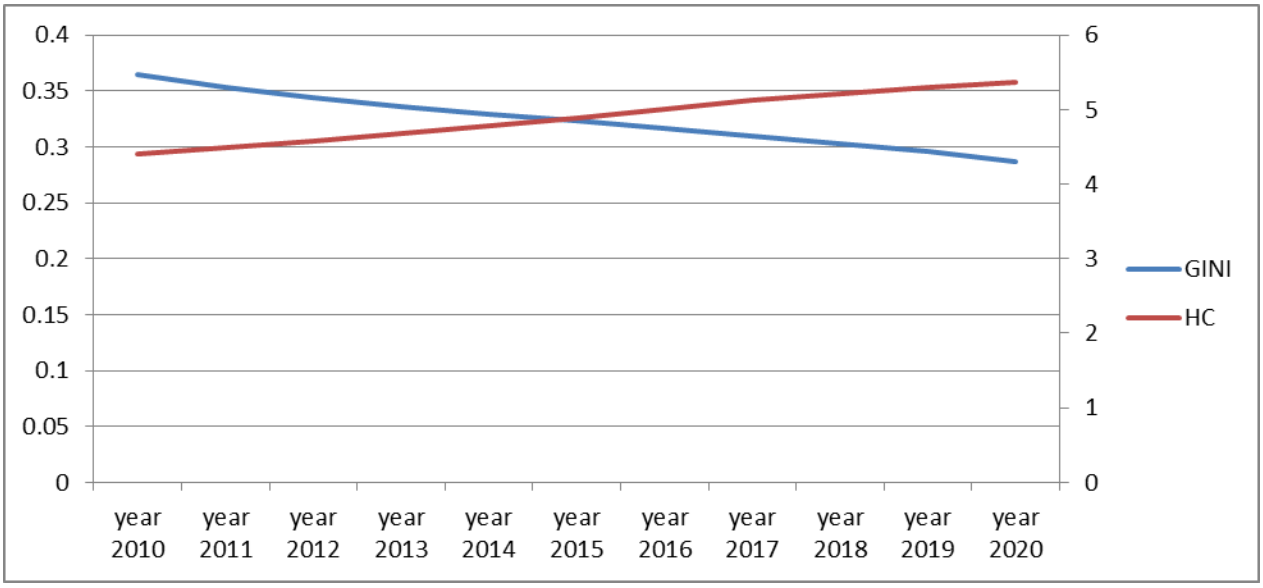

Figure 3 Income inequality and human capital in Sub Saharan Africa

Source: International Wealth Index(IWI) and Subnational HDI Database of the Global Data Lab (GDL).

The interest variable human capital has been getting better since 2010 while income inequality is declining overtime. This suggests that there is an improvement in human capital and income inequality in SSA. This implies that the society is getting a better education. . According to the World Bank report, governments in Sub-Saharan Africa (SSA) are focusing on health and education. Government expenditure on these sectors has significantly increased in recent years. In SSA, for instance, government spending on education increased from 4.3 percentage of GDP in 2000 to 6.3 percentage of GDP in 2016. Similar to this, SSA saw a growth in government spending on health, which increased from 3.4 percentage of GDP in 2000 to 5.2 percentage of GDP in 2016.

Table 1 Values of gini index as compared to the main determining variables

Years	Gini index	Human capital	Domestic credit to private sector	GDP per capita	Inflation	Population growth
2010	0.36	4.40	17.72	1094.17	8.45	2.68
2015	0.32	4.89	20.77	1185.06	5.46	2.46
2020	0.29	5.37	20.08	1200.00	3.99	2.45
(2015-2010)	-11.21	11.28	17.21	8.31	-35.36	-8.28
(2020-2010)	-21.17	22.05	13.31	9.67	-52.77	-8.69

The average values of income inequality as indicated by the Gini index shows a huge reduction between the year 2010 and 2020.The Gini coefficient decreases by 11.21% from the year 2010 to 2015. The value has decreased by 21.17% to reach 0.29 in 2020. Conversely the human capital has also shown a significant growth of 13.31% during the same period and reached 5.37 in 2020.

Domestic credit to private sector has also increased by 17.21% from the year 2010 to 2015 and reached 20.08% of GDP by the year 2020 while income inequality is declining. The huge provision of credit to private sector might be contributing for the reduction of income inequality in the region

The independent variable that experienced a radical change is inflation rate followed by Human Capital and Gini index respectively. Inflation rate has decreased by 35.36% from the year 2010 to 2015 and reached 3.99 by 2020. The change in inflation rate from the year 2010 to 2020 is 52.77%, which is a huge amount. Furthermore, population growth rate has also decreased significantly from 2.68 in 2010 to 2.45 in 2020.

4.1.2 Summary statistics of the variables

Here, the summary statistics of economic and development variables such as income inequality, human capital, domestic credit to private sector, unemployment, GDP per capita, inflation and population growth are considered for those SSA countries.

The table shows that the mean Gini index for the 24 SSA sample countries for the period of 2010–2020 was found to be approximately 0.32, with an overall standard deviation of 0.07 and negligible between- and within-country variations. The least Gini index was found to be 0.13, registered by South Africa in 2020, when it comes to overall changes over the entire sample periods. And the higher Gini index was experienced by Democratic Republic of Congo during 2010.

Data from these SSA countries shows that, the average human capital is 4.89 with a minimal variation between and within deviation. The minimum and maximum human capital was achieved by Mali and South Africa, respectively

Table 2 Summary Statistics of the Variables

Variable	Mean	Std.Dev.	Min	Max	Observations
Gini index					
Overall	.3238636	.0734862	.13	.55	N= 264
Between		.0692791	.1754545	.4654545	n=24
Within		.0279845	.2393182	.4293182	t=11
Human Capital					
Overall	4.892538	1.769337	1.64	9.62	N= 264
Between		1.754695	2.143636	9.38	n=24
Within		.410695	3.837992	6.117992	t=11
Domestic Credit					

Overall	19.75739	22.80224	4.77e-06	128.8384	N= 264
Between		23.05395	5.90e-06	122.5449	n=24
Within		2.94381	6.381917	29.72158	t=11
GDP per capita					
Overall	1175.872	1182.057	263.361	6263.104	N= 264
Between		1201.52	288.1157	6150.003	n=24
Within		92.19887	752.1325	1535.341	t=11
Inflation					
Overall	6.26597	8.016326	-11.87632	60.98697	N= 264
Between		4.87562	.4669499	19.74268	n=24
Within		6.433791	-10.84195	47.51026	t=11

Table 3 Correlation tables of the variables

	Gini	**l.Gini**	**HC**	**Dcp**	**GDPpc**	**Inf**	**PG**
Gini	1.0000						
l.Gini	0.9939	1.000					
HC	-0.3397	-0.3414	1.000				
Dcp	-0.5436	-.5417	0.4853	1.000			
lnGDPpc	-.6703	-.6556	0.4658	.6181	1.000		
INF	0.0325	0.0349	0.2261	-.0794	-.1022	1.000	
PG	0.2956	0.3077	-0.4619	-.4140	-.3243	-.0124	1.000

As it can be seen from the correlation table, the dependent variable Gini coefficient has a strong correlation with its lagged values. This suggests that the current level of income inequality is affected by its past values. There is a negative correlation between both the current and lagged values of income inequality and GDP per capita. The current and the lagged values of income inequality are negatively correlated with Human Capital, Domestic Credit, and GDP per capita. Inflation Rate and Population Growth have a positive correlation with the current and lagged valued of income inequality. Overall there is no significantly higher correlation between the dependent and the explanatory variables and within the explanatory variables.

4.2 Econometric Analysis

4.2.1Panel Unitroot test

Table 4ADF test based on Levin, Lin, and Chu test

Variables	p-value
Gini Index	0.0000
Human Capital	0.0013
Domestic Credit to Private Sector	0.0000
GDP per capita	0.0000
Inflation	0.0000
Population Growth	0.0000

From the above table, one can observe that all the variables are stationary at level. Therefore, we can go for econometric analysis.

4.2.3 The Pooled OLS Estimator

The pooled regression results for a panel data shows that income inequality is significantly affected by a number of factors such as Human Capital, Domestic Credit to Private Sector, GDP per capita, Inflation and Population Growth for the selected 24 Sub Saharan Countries. The result

shows that Human Capital and GDP per capita affects income inequality negatively at a 1% significant level. Human capital significantly affects income inequality negatively implying that a higher average year of education is associated with a lower Gini index. It is expected that when there is an educated society, the income gap will be minimized through increased productivity, and employment.

The other variable that has a significant effect on income inequality is Inflation Rate with a 5% significant level. As inflation rate increases in the economy, it means that the purchasing power of money decreases. This keeps the poor poorer. Domestic Credit to Private Sector and Population Growth do not have a significant effect for the countries under consideration.

It is crucial to remember that the conclusions are supported by a panel dataset, meaning that the same countries are tracked across time. This can help us control for unobserved variables that might have an impact on the independent variables as well as the Gini index. The results, however, could still be biased if any unobserved factors are still present.

A pooled effect regression is a type of regression analysis that is used to analyze data from multiple countries. It assumes that the relationships between the variables are the same across all countries. However, the testparm test shows that there is a country effect in this data. The results suggest that there are some factors that are unique to each country that are affecting the Gini index. This means that the relationships between the variables are not the same across all countries.

The country effect is probably caused by a variety of historical, cultural, political, and economic variables. When creating policies to reduce inequality, it is crucial to take into account the group effect because policies that work in one country may not work for other.

4.2.4 The Within Group Estimator

Table 5 Results of Fixed Effect

Gini index	Coef.	Std.Err.	T	P>|t|
HC	-.0090201	.0039985	-2.26	0.025
Dcp	.000638	.0003696	1.73	0.086
lnGDPpc	-.0353863	.0148471	-2.38	0.018
Inf	.0001075	.0001661	0.65	0.518
PG	-.0032587	.0035435	-0.92	0.359
_cons	.6381797	.1001226	6.37	0.000

The problem was attempted to be solved in the preceding part using the pooled OLS estimation technique. However, the OLS estimation is inaccurate and inconsistent for the reasons mentioned above. Furthermore, the pooled OLS estimator does not take advantage of the panel variation and is unable to benefit from panel data. But because it relies on within-group variance, the fixed effect or within group (WG) estimator outperforms the pooled OLS in terms of benefits from panel data. Additionally, the within groups estimator eliminates the country specific effect.

Fixed effect model have the principal advantage over random effect model in that it is less likely to be biased by omitted time-invariant variables such as culture, geography, history, economic policies, and political system. This is so that any time-invariant variables that are common to all of the sample countries can be controlled for in a fixed effects model, which contains dummy variables for each country.

The random effect regression analysis also allows for the likelihood that the relationships between the variables are different across countries. However, it assumes that the differences between countries are random and do not affect the estimates of the model. This assumption may not be realistic in many cases, as there may be time-invariant factors that are common to some

countries but not others. As a result, a fixed effects model is generally considered to be more reliable than a random effects model when there are time-invariant omitted variables And by doing so, it will be easy to determine the causes of inequality in each nation and create policies that are suited to the demands of each one.

Generally, the decision of whether using a fixed effect model or not is based on the specific data set. If there are time invariant omitted variables that are important, it is advisable to use a fixed effect mode. In this case, the researcher expect that there could be some time invariant factors such as geography, culture, political system, economic policies, demography that can affect the income inequality of sub Saharan countries. Beyond this, there is a statistical test (i.e a Hausman test) to decide on this issue. The test is based on the assumption that the error terms in the two models are not correlated. If the error terms are correlated, then the Hausman test will be biased. The results of this test show that the p-value is 0.0000. This means that the likelihood that the results are due to chance is minimal. Therefore, we can reject the null hypothesis and conclude that the fixed effects model is preferred over the random effects model.

The results of the model indicates that only human capital, Domestic Credit to Private Sector, and GDP per capita have a significant effect on Gini index.

Here we need to determine whether a fixed effect model includes a time effect or not. A time effect is a variable that depicts how the dependent variable has changed generally over time. If a time effect exists, it is crucial to control for it in the model so as to ensure that the results are not due to changes in the dependent variable overtime. The testparm command is used to test for the presence of a time effect in a fixed effect regression model. The results of the test show that there is a significant time effect in the model. This means that the dependent variable is not constant over time, and that the coefficients on the independent variables may be biased if the time effect is not controlled for.

The F-statistic of 12.05 and the p-value of 0.000 indicate that the time effect is significant. This means that there is no way that the results of the test are due to chance. Therefore, the fixed effect regression results which are reported here have controlled for this effect.

We have so far achieved better outcomes using the WG estimates than their OLS counterparts. For the reason which will be explained in the coming section, the use of a more suitable

methodology that can produce parameter estimates that are more accurate while avoiding all potential sources of bias and inconsistency is needed.

4.2.5 The System GMM Estimator

Table 6 Dynamic panel-data estimation, two-step system GMM

Gni index	Coef,	Std,Err	Z	P>|z|	[95% Conf. Interval]	
Gni index L1.	1.043687	.0304466	34.28	0.000	.9840123	1.103361
HC	.0006729	.0003921	1.72	0.086	-.0000957	.0014414
Dcp	.0000207	.0000311	0.67	0.505	-.0000402	.0000816
lnGDPpc	.0001932	.002072	0.09	0.926	-.0038679	.0042542
Inf	-.000095	.0000357	-2.67	0.008	-.0001653	.0000254
PG	-.000489	.0014129	-0.35	0.729	-.0032582	.0022802
_cons	-.024801	.0232018	-1.07	0.285	-.0702758	.0206735
Tests		Z		Pr > z		
Arellano-Bond AR(1)		-3.61		0.000		
Arellano-Bond AR(2)		1.66		0.096		
Tests		chi2(9)		Prob > chi2		
Hansen test		11.35		0.182		

The OLS and WG estimates from the earlier sections are only being used for comparison since these methods only barely address the pre-estimating econometric difficulties. The difference GMM is a first and good attempt that might be able to resolve all the biases and inconsistencies

previously described, by differencing the equation and also producing internal instruments for troublesome regressors. The lag levels of the relevant variable are used to instrument the differenced endogenous variables in this case. This estimator is criticized for the shaky connection between the instrumented regressors and the internally generated instruments, even if it avoids the fixed effect and dynamic panel biases. Furthermore difference GMM model is less robust to autocorrelation and heteroskedasticity than system GMM. Therefore, the system GMM that solves the problem of difference GMM is our chosen estimator.

Here are some reasons why the researcher preferred using system GMM instead of other estimation techniques. The first one is due to the fact that there is endogeneity problem in the dataset. In a panel data analysis, endogeneity occurs when the explanatory variables and the error term are correlated. Numerous factors, including omitted variables, measurement error, or simultaneity, may cause this problem. Furthermore, if the current level of one of the explanatory variable is affected by the lagged value of the dependent variable (i.e, in this case Gini index), then the lagged value of Gini index will be correlated with the error term. It is expected that, for instance, the current level of human capital, is affected by the lagged values of Gini index. This can lead to biased estimates of the effect of human capital on income inequality. Statistically the dependent variable Gini index is highly correlated with its lagged value. Therefore there could be an endogeneity problem in which none of the previous estimation techniques could deal with. System GMM deal with this problem by including instrumental variables which is correlated with the lagged values of the dependent variable but not with error term.

The other problem that make system generalized method of moments (GMM) preferable is that the presence of autocorrelation in the dataset. Autocorrelation is a situation in which the error terms are correlated with each other. A multitude of factors, including time-invariant unobserved heterogeneity, omitted variables, or measurement error, might cause this. Autocorrelation can cause estimates to be unbiased. The correlation matrix of the residuals demonstrates the existence of this correlation. Since the model's errors are not independent, it may be challenging to determine the model parameters with precision.

The residuals' correlation might affect the model in a variety of ways. First of all, it could make it challenging to determine the model parameters with precision. This is due to the possibility that the correlation of residuals can make the model less reliable. Second, residual correlation

may make the model less accurate. This is due to the possibility that the model could be unable to precisely forecast the response variable for new data.

There are a few approaches to determine whether system generalized method of moment (GMM) estimation is robust to autocorrelation. Utilizing the Arellano-Bond test is one option. An ARDL test called the Arellano-Bond test compares the alternative hypothesis of positive autocorrelation with the null hypothesis of no autocorrelation. We can rule out the null hypothesis and declare that there is evidence of positive autocorrelation if the Arellano-Bond test's p-value is less than 0.05.

System generalized method of moment (GMM) estimation can also be tested for autocorrelation robustness using the Hansen test. The Hansen test compares the alternative hypothesis of positive serial correlation with the null hypothesis of no serial correlation. The null hypothesis can be rejected and positive autocorrelation can be inferred if the p-value for the Hansen test is less than 0.05. Depending on this, we can use a system GMM estimator to estimate the model if the Arellano-Bond test or the Hansen test finds evidence of positive autocorrelation. A reliable estimator that is unaffected by positive autocorrelation is the system GMM estimator.

P-value for Arellano-Bond AR(1) test for this analysis is significant showing that there is a first order autocorrelation in the error terms. However, the Arellano-Bond AR(2) fail to reject the null hypothesis of no autocorrelation and conclude that there is no second order autocorrelation.

The Wald chi-squared test of the overall model is significant, indicating that the model fits the data well. The Sargan test of over identifying restrictions is significant, indicating that the instruments are valid. The Hansen test of over identifying restrictions is not significant, indicating that the instruments are not weak.

The coefficient on the Human Capital variable is positive, indicating that a higher level of human capital is associated with a higher income inequality. Contrary to the Pooled and the Fixed Effect model, this model changed the expected sign of human capital. The result shows that human capital has a positive and significant effect on income inequality. The findings were consistent with the result of Moyo, Mishi, and Ncwadi (2022) that explains human capital is related positively to income inequality that indicates unequal opportunities in education and health access. Lam, Finn, and Leibbrandt (2015) has also indicated that the labor composition and returns to education as a primary reason for the positive relationship between human capital and

income inequality. In sub-Saharan Africa, the benefits of human capital improvements are not always evenly provided which can further exacerbate the income inequality. Although the provision of education and health care are growing, the provision lacks equity, not inclusive and unable to maintain the quality. Given the richer gets more access to education and health, the growing investments in the sector fuels the health and education inequality that ultimately raise the income inequality (Ilie & Rose, 2018). Moreover, African education system particularly sub-Saharan Africa pertains low quality and outcome education system, inequitable access to education and poor education systems (Gakusi, 2010; Majgaard & Mingat, 2012). For instance, the tertiary enrolment rate and accesses to health services are about 9% and 42.56% in sub-Saharan Africa, respectively which is very poor as compared to the standard sustainable development goals (SDGs) (Khaled, 2021; Tessema et al., 2022). As a matter of fact for an about more than half of century even though human capital inequality has been reduced, the associated changes in income inequality is sluggish (Castello-Clement & Domenech, 2017).

. According to Obasuyi and Rasiah (2019), all the countries (among they studied) except Zimbabwe have faced massive education inequality for the year 1990 to 2017. Emmanuel Nkonya (2019) also found that education inequality in sub-Saharan Africa is a major obstacle to economic growth and social development. In a 2019 study, he found that the gap in educational attainment between the richest and poorest households in SSA is wider than in any other region of the world.

On the other hand, since the majority of employment in sub-Saharan Africa is in the agricultural sector, the wage of labor is also not education-oriented. The majority of the population has lower levels of literacy and works in less skilled occupations to support livelihoods. Thus, because most industries require little in the way of skill and knowledge advancement, an increase in human capital does not always result in a reduction in the gap between the rich and the poor (Mueller; Sakho-Jimbira & Hathie, 2020; Shimeles, Verdier-Chouchane, & Boly, 2018).

In Sub-Saharan Africa, inequality in access to healthcare and education is mostly a result of poverty. Frequently, poor families are unable to pay for their children's healthcare or send them to school. This can limit their opportunities to improve their lives. Schools and hospitals found far from rural communities in various Sub-Saharan African nations. Due to this, it is challenging for residents in these places to get these services. Even when people have access to healthcare

and education, the quality of these services is often poor. This is brought on by a lack of resources, including facilities, trained teachers, and medical personnel. However, the finding is contrary to the theory of human capital which is developed by Becker, 1964 and Schultz, 1960. The result is also contrary to other findings (Lee and Lee, 2018, Shahpari and Davoudi, 2013, Arabsheibani, Carniro, and Hanley, 2003, Lin,2007).

The other variable that has a significant negative impact on income inequality is inflation rate. The result shows that an increase in the inflation rate is reducing income inequality in Sub Saharan Africa. The result is consistent with the findings of Piketty and Saez (2003). The study found that that a 1% increase in inflation led to a 0.2% decrease in the Gini coefficient, a measure of income inequality. They argued that by redistributing wealth from creditors to debtors, inflation can reduce income inequality. And this redistribution can make the distribution of income better. The other variables which are included in the study do not have a significant effect in Sub Saharan Countries.

CHAPTER FIVE

5. Conclusion and Recommendations

5.1 Conclusion

In recent years, the relationship between income inequality and human capital has been a topic of intense debate. While numerous empirical studies have traditionally supported a negative relationship, some authors, including Moyo, Mishi, and Ncwadi (2022), Lam, Finn, and Leibbrandt (2015), and Ilie & Rose (2018), have presented compelling arguments for a positive association between these two variables. However, the inconclusive results from previous research have prompted the researcher to reexamine the issue, aiming to provide a more thorough analysis.

To assess the impact of human capital on income inequality, the researcher adopts a comprehensive approach encompassing both descriptive and econometric frameworks. The descriptive analysis examines the temporal trends of the dependent variable, the variables of interest, and the dependent variable itself. Furthermore, changes in all variables over time are carefully analyzed.

To ensure accurate and efficient econometric estimation, the researcher employs a more appropriate technique called the system Generalized Method of Moments (system GMM). This advanced approach is well-suited for analyzing the panel dataset covering 24 Sub-Saharan African (SSA) countries over an 11-year period.

The findings from the dataset indicate a positive relationship between income inequality and human capital within the selected SSA countries. These results suggest that the advancements in human capital are not effectively reducing income inequality in these nations. One possible explanation for this positive relationship is that the improvements in human capital, as observed in the descriptive analysis, are not being equitably distributed throughout society. Moreover, the wages of labor may not be strongly influenced by educational attainment, contributing to the persistence of income inequality.

This research provides valuable insights into the complex dynamics between income inequality and human capital in the context of SSA countries. By employing rigorous analytical techniques and considering both descriptive and econometric analyses, the researcher contributed to our understanding of this important issue. However, it is crucial to recognize the limitations of this study, such as the number of countries considered, specific focus on SSA countries and the chosen econometric technique. Further research is needed to corroborate these findings and explore additional factors that may influence the relationship between income inequality and human capital.

5.2 Recommendation

Based on the evidence, there are a number of policy interventions that can be drawn to reduce income inequality in Sub-Saharan Africa. These interventions includes:

- Providing a more inclusive education will help to improve the participation of the population in the labor which can reduce income inequality.
- Since it is impossible to make education inclusive without the intervention of governments, there is a need to intervene in the education system of their respective countries. Those governments need to invest in education infrastructure.
- There is a need to assess the country specific factors which is unique to a specific country and explore further to decide which policy intervention can produce a better outcome.

It is important to note that the effectiveness of these interventions may vary across countries due to specific contextual factors. Therefore, conducting country-specific assessments and evaluations to identify the most suitable policy interventions is crucial for achieving desired outcomes in each Sub-Saharan African country.

REFERENCES

Amparo Castelló-Climent & Rafael Doménech, 2012. "Human Capital and Income Inequality: Some Facts and Some Puzzles," Working Papers 1201, International Economics Institute, University of Valencia.

Appiah, E., & McMahon, W. (2002, April). The Social Outcomes of Education and Feedbacks on Growth in Africa. Journal of Development Studies, 38(4), 27–68. https://doi.org/10.1080/00220380412331322411.

Avom, D., Ntsame Ovono, N. and Ongo Nkoa, E. (2022), "Revisiting the effects of natural resources on income inequality in Sub-Saharan Africa", International Journal of Development Issues

Blotevogel, R., Imamoglu, E., Moriyama, K., & Sarr, B. (2022, June). Income inequality measures and economic growth channels. Journal of Macroeconomics, 72, 103413. https://doi.org/10.1016/j.jmacro.2022.103413.

Castelló-Climent, A., & Doménech, R. (2021, January 14). Human capital and income inequality revisited. EducationEconomics, 29(2),194–212. https://doi.org/10.1080/09645292.2020.1870936

Chancel, L., Cogneau, D., Gethin, A., Myczkowski, A., & Robilliard, A. S. (2023, March). Income inequality in Africa, 1990–2019: Measurement, patterns, determinants. World Development, 163, 106162. https://doi.org/10.1016/j.worlddev.2022.106162

Chani, M. I., Jan, S. A., Pervaiz, Z., & Chaudhary, A. R. (2012, August 11). Human capital inequality and income inequality: testing for causality. Quality & Quantity, 48(1), 149–156. https://doi.org/10.1007/s11135-012-9755-7

Chouchane, & A. Boly (Eds.), Building a Resilient and Sustainable Agriculture in Sub-Saharan Africa (pp. 1-12). Cham: Springer International Publishing.

Cingano, F. (2014), “Trends in Income Inequality and its Impact on Economic Growth”, OECD Social, Employment and Migration Working Papers, No. 163, OECD Publishing. http://dx.doi.org/10.1787/5jxrjncwxv6j-en

Clement Moyo, Syden Mishi & Ronney Ncwadi (2022) Human capital development, poverty and income inequality in the Eastern Cape province, Development Studies Research, 9:1, 36-47, DOI: 10.1080/21665095.2022.2032236

Dabla-Norris, M. E., Kochhar, M. K., Suphaphiphat, M. N., Ricka, M. F., & Tsounta, M. E. (2015). Causes and consequences of income inequality: A global perspective. International Monetary Fund.

Désiré Avom & Nesta Ntsame Ovono & Emmanuel Ongo Nkoa, 2022. "Revisiting the effects of natural resources on income inequality in Sub-Saharan Africa," International Journal of Development Issues, Emerald Group Publishing Limited, vol. 21(3), pages 389-412, June.

Emmanuel Saez and Thomas Piketty (2003), "Inflation and Income Inequality" American Economic Review, Vol. 101, No. 4 (2001), pp. 1187-1214.

Gakusi, A. E. (2010). African education challenges and policy responses: Evaluation of the effectiveness of the African Development Bank's assistance. African Development Review, 22(1), 208-264.

Heckman, James J., Sergio Urzua, Christopher J. Frazer, Whitney K. Newey, and Kenneth L. Judd. "System GMM Estimation with Cross-Section and Time Series Data." Econometrica 67.5 (1999): 1427-1474.

Ilie, S., & Rose, P. (2018). Who benefits from public spending on higher education in South Asia and sub-Saharan Africa? Compare: A Journal of Comparative and International Education, 48(4), 630-647.

Ismail, Rahmah. (2010). Human Capital and Income Distribution in Malaysia: A Case Study. Journal of Economic Cooperation and Development. 31.

Ismail, Rahmah. (2010). Human Capital and Income Distribution in Malaysia: A Case Study. Journal of Economic Cooperation and Development. 31.

Kang-Kook Lee & Trung V. Vu, 2020. "Economic complexity, human capital and income inequality: a cross-country analysis," The Japanese Economic Review, Springer, vol. 71(4), pages 695-718, October.

Khaled, S. (2021). Higher Education in Sub Saharan Africa: Challenges and Prospects. In: Oxford.

Knight, J. B., & Sabot, R. H. (1983). Educational Expansion and the Kuznets Effect. The American Economic Review, 73(5), 1132–1136. http://www.jstor.org/stable/1814679.

Lam, D., Finn, A., & Leibbrandt, M. (2015). Schooling inequality, returns to schooling, and earnings inequality: Evidence from Brazil and South Africa (9292309390). Retrieved from

Lee, H.Y., Kim, J., & Cin, B.C. (2013). Empirical Analysis on the Determinants of Income Inequality in Korea. International Journal of Advanced Science and Technology Vol. 53, April, 2013 Available: https://www.semanticscholar.org/paper/Empirical-Analysis-on-the-Determinants-of-Income-in-Lee-Kim/417525256a417e022101e84d963e59dc356d1bdf

Lee, J.-W. and H. Lee. 2018. Human Capital and Income Inequality. ADBI Working Paper 810. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/human-capital-and-income-inequality.

Lin, CH.A. Education Expansion, Educational Inequality, and Income Inequality: Evidence from Taiwan, 1976–2003. Soc Indic Res 80, 601–615 (2007). https://doi.org/10.1007/s11205-006-0009-8

Majgaard, K., & Mingat, A. (2012). Education in sub-Saharan Africa: A comparative analysis: World Bank Publications.

Matthew Odedokun and Jeffery I. Round, (2001), Determinants of Income Inequality and its Effects on Economic Growth: Evidence from African Countries, No DP2001-103, WIDER Working Paper Series, World Institute for Development Economic Research (UNU-WIDER)

Messy, Martin Ambassa,(2021). Threshold Effect of Corruption on Income Inequality in Sub-Saharan Africa. Journal of Business Studies Quarterly; Antioch Vol. 10, Iss. 3, (Mar 2021): 11-26

Molla, G. G. (2021). Human Capital and Income Inequality Linkage in Sub- Saharan Africa: Panel Data Analysis (1984–2016). JDE (Journal of Developing Economies), 6(2), 186–200. https://doi.org/10.20473/jde.v6i2.22783

Moyo, C., Mishi, S., & Ncwadi, R. (2022, February 4). Human capital development, poverty and income inequality in the Eastern Cape province. Development Studies Research, 9(1), 36–47. https://doi.org/10.1080/21665095.2022.2032236

Ms. Sonia Brunschwig & Mr. Emilio Sacerdoti & Mr. Jon Tang, 1998. "The Impact of Human Capital on Growth: Evidence from West Africa," IMF Working Papers 1998/162, International Monetary Fund.

Mueller, B. A large share of the discourse of rural youth employment in Africa is dominated by a range of common 'perceived truths' or myths. In.

Nkonya, E. (2019). Education inequality in sub-Saharan Africa: A major obstacle to economic growth and social development. International Food Policy Research Institute.

Obasui, T. O., & Rasiah, R. (2019). Addressing education inequality in sub-Saharan Africa. African Journal of Science, Technology, Innovation and Development, 11(5), 629-641. doi:10.1080/20421338.2019.1567655.

Oded Galor & Joseph Zeira, 1993. "Income Distribution and Macroeconomics," Review of Economic Studies, Oxford University Press, vol. 60(1), pages 35-52.

Odedokun, Matthew O.; Round, Jeffery I. (2001) : Determinants of income inequality and its effects on economic growth: Evidence from African countries, WIDER Discussion Paper, No. 2001/103, ISBN 929190029X, The United Nations University World Institute for Development Economics Research (UNU-WIDER), Helsinki.

Okojie, Christiana, and Abebe Shimeles. Inequality in sub-Saharan Africa: a synthesis of recent research on the levels, trends, effects and determinants of inequality in its different dimensions. London: The Inter-Regional Inequality Facility, 2006.

Peterson, E. (2017, December 4). Is Economic Inequality Really a Problem? A Review of the Arguments. Social Sciences, 6(4), 147. https://doi.org/10.3390/socsci6040147

Racha Ramadan, 2021. "Determinants of Income Inequality in Jordan," Working Papers 1513, Economic Research Forum, revised 20 Nov 2021.

Sakho-Jimbira, S., & Hathie, I. (2020). The future of agriculture in Sub-Saharan Africa.

Singh, Lakhwinder and Mengesha, Zemed Degu, Income Inequality, Innovation and Human Capital Nexus: A Comparative Analysis of Asia-Pacific Countries (February 28, 2023). Seoul Journal of Economics, Vol.36, No. 1, 2023, Available at SSRN: https://ssrn.com/abstract=4372451

Stein, C. B., Alderman, H., Fox, K. R., & Gertler, P. J. (2009). Unequal health inequality in sub-Saharan Africa. Health Policy and Planning, 24(6), 467-476. doi:10.1093/heapol/czp021

Shahpari, G., & Davoudi, P. (2014, January). Studying Effects of Human Capital on Income Inequality in Iran. Procedia - Social and Behavioral Sciences, 109, 1386–1389. https://doi.org/10.1016/j.sbspro.2013.12.641

Shimeles, A., Verdier-Chouchane, A., & Boly, A. (2018). Introduction: Understanding the Challenges of the Agricultural Sector in Sub-Saharan Africa. In A. Shimeles, A. Verdier

Teixeira, P.N. Gary Becker's early work on human capital – collaborations and distinctiveness. IZA J Labor Econ 3, 12 (2014). https://doi.org/10.1186/s40172-014-0012-2

Tessema, Z. T., Worku, M. G., Tesema, G. A., Alamneh, T. S., Teshale, A. B., Yeshaw, Y., . . . Liyew, A. M. (2022). Determinants of accessing healthcare in Sub-Saharan Africa: a mixed-effect analysis of recent Demographic and Health Surveys from 36 countries. BMJ Open, 12(1), e054397. doi:10.1136/bmjopen-2021-054397.

T. J. Friderichs, G. Keeton & M. Rogan (2023) Decomposing the impact of human capital on household income inequality in South Africa: Is education a useful measure?, Development Southern Africa, DOI: 10.1080/0376835X.2022.2163228

Van de Walle, Nicolas, The Institutional Origins of Inequality in Sub-Saharan Africa (June 2009).

World Social Report 2020. (2020, February 14). https://doi.org/10.18356/7f5d0efc-en.

Zizzamia, R., David, A. & Leibbrandt, M. (2021). Inequality in sub-Saharan Africa: A review paper. AFD Research Papers, , 1-33. https://www.cairn-int.info/journal--2021-207-page-1.htm.

Appendix 1 Stata Result of Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations	
Country	overall	.	.	.	.	N =	0
	between		.	.	.	n =	0
	within		.	.	.	T =	.
Year	overall	2015	3.168284	2010	2020	N =	264
	between		0	2015	2015	n =	24
	within		3.168284	2010	2020	T =	11
GINI	overall	.3238636	.0734862	.13	.55	N =	264
	between		.0692791	.1754545	.4654545	n =	24
	within		.0279845	.2393182	.4293182	T =	11
HC	overall	4.892538	1.769337	1.64	9.62	N =	264
	between		1.754695	2.143636	9.38	n =	24
	within		.410695	3.837992	6.117992	T =	11
DCp	overall	19.75739	22.80224	4.77e-06	128.8384	N =	264
	between		23.05395	5.90e-06	122.5449	n =	24
	within		2.94381	6.381917	29.72158	T =	11
GDPpc	overall	1175.872	1182.057	263.361	6263.104	N =	264
	between		1201.52	288.1157	6150.003	n =	24
	within		92.19887	752.1325	1535.341	T =	11
Inf	overall	6.26597	8.016326	-11.87632	60.98697	N =	264
	between		4.87562	.4669499	19.74268	n =	24
	within		6.433791	-10.84195	47.51026	T =	11
PG	overall	2.508923	.6590474	-.076949	4.679478	N =	264
	between		.5937195	1.045723	3.364378	n =	24
	within		.308616	1.000399	4.109369	T =	11
country	overall	12.5	6.935334	1	24	N =	264
	between		7.071068	1	24	n =	24
	within		0	12.5	12.5	T =	11
year	overall	6	3.168284	1	11	N =	264
	between		0	6	6	n =	24
	within		3.168284	1	11	T =	11

Appendix 2 Stata Result of Pooled OLS Regression

Source	SS	df	MS		
Model	1.32563994	28	.047344284	Number of obs	= 264
Residual	.09461915	235	.000402635	F(28, 235)	= 117.59
				Prob > F	= 0.0000
Total	1.42025909	263	.005400225	R-squared	= 0.9334
				Adj R-squared	= 0.9254
				Root MSE	= .02007

GINI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
HC	-.0405041	.0032971	-12.28	0.000	-.0469997	-.0340085
DCp	-.0002813	.0004259	-0.66	0.510	-.0011204	.0005577
lnGDPpc	-.0804845	.0169906	-4.74	0.000	-.1139578	-.0470111
Inf	.0004215	.0001949	2.16	0.032	.0000376	.0008054
PG	.0046884	.0041357	1.13	0.258	-.0034594	.0128362
count2	-.053376	.0239886	-2.23	0.027	-.1006361	-.0061158
count3	.1742846	.0133452	13.06	0.000	.1479931	.2005761
count4	.1171401	.0202329	5.79	0.000	.0772791	.1570011
count5	.0523756	.011232	4.66	0.000	.0302473	.0745039
count6	.2364553	.0244138	9.69	0.000	.1883574	.2845531
count7	.0448789	.0131131	3.42	0.001	.0190447	.0707131
count8	-.0513709	.0140061	-3.67	0.000	-.0789644	-.0237774
count9	.0935645	.0152459	6.14	0.000	.0635284	.1236005
count10	.0026434	.0100728	0.26	0.793	-.0172012	.022488
count11	-.0207707	.0134389	-1.55	0.124	-.0472468	.0057055
count12	.178466	.0160672	11.11	0.000	.1468119	.2101201
count13	.0961763	.0147527	6.52	0.000	.0671119	.1252408
count14	.0336638	.0183088	1.84	0.067	-.0024066	.0697342
count15	.0590212	.0232765	2.54	0.012	.013164	.1048783
count16	-.0661851	.0110058	-6.01	0.000	-.0878677	-.0445026
count17	.1097907	.0106688	10.29	0.000	.088772	.1308095
count18	.1940538	.0179903	10.79	0.000	.158611	.2294966
count19	.0706874	.0124718	5.67	0.000	.0461165	.0952582
count20	.0780752	.0137303	5.69	0.000	.0510249	.1051254
count21	-.0366429	.0101349	-3.62	0.000	-.0566096	-.0166761
count22	.0415762	.0142137	2.93	0.004	.0135737	.0695786
count23	.2937216	.0522964	5.62	0.000	.1906919	.3967512
count24	.0149407	.0181188	0.82	0.410	-.0207554	.0506368
_cons	.9900676	.1139604	8.69	0.000	.765553	1.214582

Appendix 3 Stata Result of Random Effect

```
Random-effects GLS regression                   Number of obs      =       264
Group variable: country                         Number of groups   =        24

R-sq:  within  = 0.5362                         Obs per group: min =        11
       between = 0.2947                                        avg =      11.0
       overall = 0.2993                                        max =        11

                                                Wald chi2(5)       =    227.40
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

GINI	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
HC	-.0345327	.0031996	-10.79	0.000	-.0408038	-.0282616
DCp	.0001249	.0003616	0.35	0.730	-.0005839	.0008337
lnGDPpc	-.0599262	.0134407	-4.46	0.000	-.0862696	-.0335828
Inf	.0005222	.0002058	2.54	0.011	.0001189	.0009256
PG	.0036569	.004299	0.85	0.395	-.004769	.0120829
_cons	.8845709	.0865049	10.23	0.000	.7150244	1.054117
sigma_u	.05213521					
sigma_e	.02006576					
rho	.87097997	(fraction of variance due to u_i)				

Appendix 4 Stata Result of Fixed Effect

```
Fixed-effects (within) regression               Number of obs      =       264
Group variable: country                         Number of groups   =        24

R-sq:  within  = 0.5406                         Obs per group: min =        11
       between = 0.3324                                        avg =      11.0
       overall = 0.3302                                        max =        11

                                                F(5,235)           =     55.31
corr(u_i, Xb)  = -0.7870                        Prob > F           =    0.0000
```

GINI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
HC	-.0405041	.0032971	-12.28	0.000	-.0469997	-.0340085
DCp	-.0002813	.0004259	-0.66	0.510	-.0011204	.0005577
lnGDPpc	-.0804845	.0169906	-4.74	0.000	-.1139578	-.0470111
Inf	.0004215	.0001949	2.16	0.032	.0000376	.0008054
PG	.0046884	.0041357	1.13	0.258	-.0034594	.0128362
_cons	1.059366	.1097452	9.65	0.000	.8431562	1.275576
sigma_u	.0943301					
sigma_e	.02006576					
rho	.95670969	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(23, 235) =    72.34             Prob > F = 0.0000
```

Appendix 5 Hausman test

```
. hausman fe re
```

	Coefficients (b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
HC	-.0405041	-.0345327	-.0059714	.0007958
DCp	-.0002813	.0001249	-.0004062	.000225
lnGDPpc	-.0804845	-.0599262	-.0205583	.0103936
Inf	.0004215	.0005222	-.0001008	.
PG	.0046884	.0036569	.0010315	.

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 161.06
Prob>chi2 = 0.0000
(V_b-V_B is not positive definite)

Appendix 6 Fixed Effect Regression with year dummies

```
Fixed-effects (within) regression               Number of obs      =       264
Group variable: country                         Number of groups   =        24

R-sq:  within  = 0.7008                         Obs per group: min =        11
       between = 0.2346                                        avg =      11.0
       overall = 0.2985                                        max =        11

                                                F(15,225)          =     35.14
corr(u_i, Xb)  = 0.0835                         Prob > F           =    0.0000
```

GINI	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
HC	-.0090201	.0039985	-2.26	0.025	-.0168993	-.0011408
DCp	.000638	.0003696	1.73	0.086	-.0000904	.0013664
lnGDPpc	-.0353863	.0148471	-2.38	0.018	-.0646434	-.0061292
Inf	.0001075	.0001661	0.65	0.518	-.0002198	.0004349
PG	-.0032587	.0035435	-0.92	0.359	-.0102413	.003724
Year						
2011	-.0105651	.0048087	-2.20	0.029	-.020041	-.0010892
2012	-.0185193	.0049459	-3.74	0.000	-.0282655	-.0087732
2013	-.0260233	.0051137	-5.09	0.000	-.0361	-.0159465
2014	-.0310164	.0053653	-5.78	0.000	-.0415891	-.0204437
2015	-.0363002	.0055702	-6.52	0.000	-.0472767	-.0253237
2016	-.0413296	.0057482	-7.19	0.000	-.0526569	-.0300024
2017	-.0469199	.0059976	-7.82	0.000	-.0587386	-.0351012
2018	-.0518761	.0062441	-8.31	0.000	-.0641806	-.0395717
2019	-.0572133	.0065171	-8.78	0.000	-.0700557	-.0443709
2020	-.0669025	.0065891	-10.15	0.000	-.0798868	-.0539182
_cons	.6381797	.1001226	6.37	0.000	.4408818	.8354775
sigma_u	.06099291					
sigma_e	.01654916					
rho	.93142866	(fraction of variance due to u_i)				

F test that all u_i=0: F(23, 225) = 91.85 Prob > F = 0.0000

Appendix 7 Twostep system GMM result

Dynamic panel-data estimation, two-step system GMM

Group variable: country		Number of obs	= 240
Time variable : year		Number of groups	= 24
Number of instruments = 15		Obs per group: min	= 10
Wald chi2(6) = 269714.93		avg	= 10.00
Prob > chi2 = 0.000		max	= 10

GINI	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
GINI						
L1.	1.043687	.0304466	34.28	0.000	.9840123	1.103361
HC	.0006729	.0003921	1.72	0.086	-.0000957	.0014414
DCp	.0000207	.0000311	0.67	0.505	-.0000402	.0000816
lnGDPpc	.0001932	.002072	0.09	0.926	-.0038679	.0042542
Inf	-.0000954	.0000357	-2.67	0.008	-.0001653	-.0000254
PG	-.000489	.0014129	-0.35	0.729	-.0032582	.0022802
_cons	-.0248012	.0232018	-1.07	0.285	-.0702758	.0206735

Arellano-Bond test for AR(1) in first differences: z = -3.61 Pr > z = 0.000
Arellano-Bond test for AR(2) in first differences: z = 1.66 Pr > z = 0.096

Sargan test of overid. restrictions: chi2(8) = 29.96 Prob > chi2 = 0.000
(Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(8) = 11.35 Prob > chi2 = 0.182