The impact of oil rents and institutional governance on human development index: evidence from oil exporting Sub-Saharan African countries

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PREFACE AND ACKNOWLEDGEMENTS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

This study aims to empirically verify the impact of oil rents, their transmission mechanisms, and institutional governance on the human development index for 11 oil exporting Sub – Saharan Africa countries from 2000 to 2020. The explanatory variables are oil rents as % to GDP, Foreign direct investment inflow as % to GDP, trade openness as % to GDP, government effectiveness index, income inequality index and the corruption perception index.

Primary investigation was applied, such as central tendency and also bivariate plots between oil rents and human development index. Further investigation was performed employing balanced panel data techniques. Instrumental variable estimation which is a valuable strategy to address endogeneity and strengthen the credibility of the research finding was applied.

The initial analysis reveals that the characteristics of the data set for those countries in the sample are asymmetrical; they are skewed to the right, except for the human development index variable, which has an almost equal distribution. Moreover, the 11 SSA oil-exporting countries remain at low levels of human development index.

The two-way fixed effects model was estimated. However, it is necessary to consider the endogeneity issue. Thus, instrumental variables were employed, supported by diagnostic analysis. The model was improved by correcting for endogeneity; the magnitudes of some estimation coefficients of the explanatory variables changed considerably; and all the coefficients were significant, except foreign direct investment. The results reveal that, the oil rents had no negative impact on the human development index in those countries in the sample, and this is evidence that oil rents are not a curse per se.

Interestingly, the findings show a positive association between government effectiveness and the human development index. This could be because this index is aggregate index consisting of different indicators. As for trade openness, it has a detrimental impact on such nations' human development indices. This is because skilled labour is more likely to benefit from trade openness than unskilled labour.

The findings add to a new line of investigation that addresses a critical gap in our understanding of the resource curse, human development and has policy implications

CHAPTER ONE: INTRODUCTION

This chapter will provide an introduction to the work; it starts by discussing the background to the context, which is followed by the problem statement, the research aim and objectives of the study, research methods and methodology, contribution to knowledge and the significance of the study, then the organization of the research.

1-1 BACKGROUND TO THE RESEARCH

Sub-Saharan Africa (SSA) is experiencing a natural resource boom, with nearly every nation in the region developing crude oil, natural gas, or mineral resources. According to (Janneh and Ping, 2011) and the International Resource Panel (2019), 30% of the world's mineral resources are found in SSA. There have been a lot of resource rents observed in nations that were not previously thought to be resource-rich; for instance, Ghana, Sudan, Chad, and Equatorial Guinea are increasing their oil production and exports, and other countries are predicted to follow suit, which means that more than 80% of SSA will be dependent on natural resources (International Monetary Fund, 2018). These discoveries of natural resources were expected to return billions of dollars to those countries.

Therefore, natural resources present an opportunity to create economic growth and improve wellbeing. They can generate substantial economic rents, which the governments of these countries can put towards public welfare and generational wealth creation. Resource revenues, when managed effectively, can promote development that results in long-term economic prosperity.

When considering natural resource-driven economic growth in SSA, the International Monetary Fund (IMF) issued the first such classification in 2010, with the result that some SSA governments were classified as "resource-rich" developing countries that have either natural resource revenue or exports that are at least 20% of total fiscal revenue and exports; for instance, the natural resource exports increased from $56 billion in 2002 to $288 billion in 2012. A further review was conducted in 2014, and showed that more SSA nations should be categorised as resource-rich developing nations (IMF, 2014). These categories do not differentiate between all types of natural resources, e.g. renewable (like fish or lumber), minerals (like gold or diamonds), or hydrocarbon (like oil or natural gas).

African resource-rich countries grew faster. This suggests that even higher growth is possible in resource-rich countries, and that resources need not be a curse, they can be a great opportunity to escape poverty and achieve development. In principle, according to Karl (2007), hydrocarbon rent especially provides an economy with three benefits. First, the money flow obtained from resource exploitation can raise living standards, which in turn increases levels of both public and private consumption. Second, the exploitation of natural resources can support investment both directly, through income from resources, and indirectly, through borrowing made possible by those revenues. Third, since the majority of the revenue from natural resources goes towards funding the public budget, it can aid in avoiding development hindrances such as a lack of resources.

Therefore, SSA countries' oil revenues are supposed to build up human capital and infrastructure while strengthening institutions and creating markets, to produce effective public services and ensure fair competition for businesses and individuals in order to combat poverty and increase everyone's standard of living. IMF (2010) claims that sub-Saharan Africa is rapidly ascending to a new role in the global economy, with a diverse continent offering natural resources that could lead to inclusive growth and end poverty in the region. However, SSA did not fully take advantage of the opportunities presented by natural resource extraction. SSA nations are among the poorest nations in the world, and the growth pace is unsustainable. The

World Bank report (2018) stated that SSA poverty rate had increased by one percentage; that means 50% of the population live on less than $2 a day, even in countries classified as rich in oil, such as Nigeria. The human development index, at low level as described in Figure 1-1.

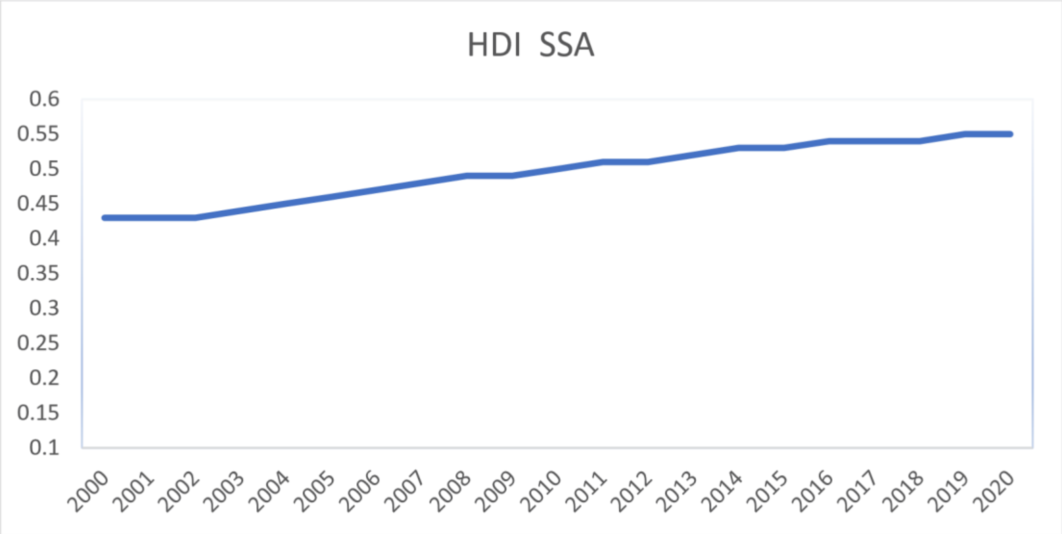

Figure 1-1: Human Development Index for sub-Saharan African countries 2000-2020 Sources of data: author's compilation based on data obtained from the UNDP.

Figure 1-1 illustrates the human development index for SSA in the period 2000-2020. The graph is upward, it ranged between 0.4 and 0.55. That means in general the HDI increased year over year. This increase can be attributed to international aid and cooperation with different international organizations such as United Nations development program which help to improved human development outcomes (UNDP Report, 2018). However, based on UNDP classifications[1], those countries remain at low levels of human development, which is an indication of underdevelopment.

In addition, the data is significantly underwhelming. Figure 1-2 shows the oil rent percentage to GDP for SSA for the period 2000-2020. It can be seen that an early decline between 2000 and 2004 is overshadowed by a period of increase in percentage which peaked in 2008. Another

[1] The human development index lies between zero and one, and countries are ranked according to how close their HDI is to one, dividing them into four levels of human development: less than 0.55 is low, 0.550–0.699 is medium, 0.700–0.799 is high, and 0.800 or greater is very high.

fluctuation is shown for the period 2009-2011; then the contribution percentage decreased sharply to around 2 % in 2020.

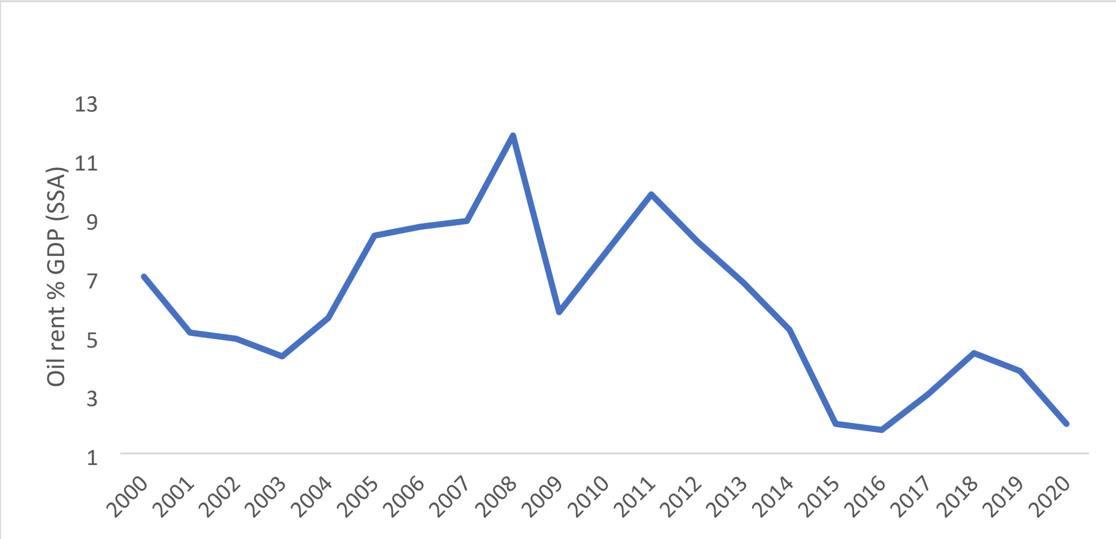

Figure 1-2: Oil rents % to GDP for Sub-Saharan African Countries 2000-2020

Sources of data: author's compilation based on data obtained from the World Bank.

The reason behind that is that oil rent is usually affected by the global oil market which is highly volatile. Sudden drops in prices can significantly impact government budgets, making long-term planning and sustainable development challenging (IMF, 2016), as illustrated in figure (1-2) such as in financial crises in 2008-2009. Another reason is external factors, e.g. changes in global economic conditions, trade policies, geopolitical tensions, and events can also impact the economic performance of oil-exporting countries such as the Covid-19 pandemic in 2020. However, those countries still depended on oil exports, according to Moudjaré and Nourou (2020), data shows that 70% of African nations' exports are made up of oil, and, with regard to some nations, such as Nigeria and Angola, oil accounts for more than 80% of exports.

Although figures 1-1 and 1-2 show a negative relationship between HDI and oil rent, suggesting that as HDI increases, oil rents tend to decrease, this observation is not conclusive for two main reasons:

These figures represent aggregate data for all sub-Saharan African countries, which may obscure variations within individual countries. Each country has its own socio-economic context, policy and development path, potentially affecting the relationship between HDI and oil rents differently. There might be various factors at a broader level that positively link oil rent to HDI, which are not immediately apparent in the graphical analysis. For example, oil revenue might be invested in social services, infrastructure, education, and healthcare, thereby improving HDI over time. Therefore, a more detailed investigation focusing on specific sub-Saharan African countries and considering other underlying variables that influence HDI could yield different outcomes.

1-2 RESEARCH PROBLEM

Despite the wealth generated from natural resources, many oil-exporting sub-Saharan African countries struggle with low human development outcomes. The literature highlights that non-renewable resources like oil, gas, and minerals bring vast profits, impacting national wealth significantly when coupled with good institutions, technology, and knowledge. However, the natural resource curse theory reveals that these resources can have negative impacts, especially in countries with poor institutional quality, leading to economic instability due to the volatility of commodity prices.

Many Sub-Saharan African countries manage their natural wealth through the state government, with revenues from natural resources often going directly to the state government. Where the state asserts control over the extraction, production, and sale of natural resources, including oil, gas, minerals, and timber. SSA countries have adopted a model where the state plays a dominant role in the management of natural resources. Governments often establish regulatory frameworks and state-owned enterprises to oversee the extraction, production processes and marketing. For instance, in Nigeria, the state-owned Nigerian National

Petroleum Corporation (NNPC) manages the country's oil and gas sector, with revenues flowing into government coffers (Oxford Business Group, 2020). Hence, those state governments are responsible for finding the best way to spend that money based on the policy priorities that have been created from the government's own point of view. For instance; in Angola, the government collects significant revenues from the oil sector, which constitute a large portion of the national budget (African Development Bank Group, 2021). Therefore, natural resources are supposed to support the social and spatial transformation of those countries and promote human development and wellbeing, it also poses challenges such as corruption, mismanagement, and lack of transparency (Van Alstine, and De Jong, 2012).

Natural resources potential to influence a country's development and progress has been discussed in a number of different channels. One of these channels is what is known as the "natural resource curse", which holds that natural resources have a detrimental effect on growth, particularly in developing countries. Evidence has been provided by Sachs and Warner (1995, 1997), Gylfason (1999) and Auty (2001).

Volatility of crude oil price is considered to be the other route that affects development, through inducing pro-cyclicality of savings, public spending, and capital flows (Van der Ploeg and Poelhekke, 2011; Lwayemi and Fowowe, 2011; Masan, 2015; Mathew and Ngalawa, 2017). Crude oil prices are highly unpredictable. Since public spending and capital flows rise when the price of the natural resource is high and fall when it is low, this volatility causes issues for nations that strongly rely on them and exacerbates boom and bust cycles (Masan, 2015). Volatility is making development planning difficult, social spending irregular, and foreign investors wary.

In relation to the SSA nations that export oil, they often have very poor-quality institutions and poor government practices (Ross, 2001, 2015). More specifically, corruption can take many forms and it can even have been embedded in cultural tradition; however, it mostly concentrates on the variations related to official government activity. It has been demonstrated (Karl, 1997; Lederman and Maloney, 2007) that countries with natural resources experience substantial economic booms, but this does not appear to have aided in inclusive human development, pointing to inadequate institutional quality as one logical explanation. The role of political institutions also has a negative impact on economic growth and development, through the rise of powerful interest groups (elites) (Martin and Subramanian, 2003; Al-Ubaydi, 2012). People pursue political rents when they attempt to gain advantages for themselves by their power in politics and through the additional revenue from resource rent, which boosts the authority of elites (Leamer et al., 1999; Gylfason and Zoega, 2003; Chang, 2020; Shadabi and Adkisson, 2021; Ertimi et al., 2021). The powerful groups usually take a large portion of these revenues and use it for the benefit of their direct circles rather than investing it to improve infrastructure and sustainable economic development. Therefore, natural resources can be seen as causes of conflict among citizens, politicians, and tribes (Sala-iMartin and Subramanian, 2003; Iimi, 2007), which will harm the economic development and planning in both short and long term.

It has been demonstrated that income inequality is another way that natural resources hinder the accumulation of human capital due to inadequate institutions (Goderis and Malone, 2011; Stiglitz, 2012). Despite the fact that there is no direct or obvious connection between resource reliance and income inequality, it is believed that the resource dependence increases income disparity via weakening governance mechanisms. For instance, the transfer of extra profit from increased prices from consumers to elites can lead to more unequal distribution of income.

1-3 THE RESEARCH AIM AND OBJECTIVES

This study focuses on 11 oil-producing and exporting SSA countries; these countries are classified as oil exporting but they are still underdeveloped and hence home to poor people.

Therefore, to better understand the human development performance in those countries. The aim of this research is to examine the effect of the natural resources in the form of oil rent percentage to GDP with practical emphasis on the transmission mechanism of natural curse and institutional governance on the human development index for 11 oil- exporting sub-Saharan African countries, namely: Angola, Cameron, Chad, Ghana, Gabon, Ivory Coast, Democratic Republic of Congo, Republic of Congo, Equatorial Guinea, Sudan, Nigeria. The research covers the period from 2000 to 2020 on an annual basis.

The objectives of this research are two-fold:

i) Investigate the impact of oil rents on the human development index, which is vital for sustainable development.

ii) Through the natural resources transmission channels, examine the effect of the role of institutional governance e.g. corruption and government effectiveness and policy on the human development index.

1-3-1 **Research hypotheses**

In light of the debate and objectives, the research hypotheses as follow;

The null hypothesis (H0): There are no significant effects between oil rents, the role of institutional governance and policy on the human development index in the 11 oil exporting Sub-Saharan African countries.

The alternative hypothesis (H1): There are significant effects between oil rents, the role of institutional governance and policy on the human development index in the 11 oil exporting Sub-Saharan African countries.

1-4 RESEACH METHOD AND METHODOLOGY

The purpose of this study to investigate the impact of oil rents and its transmission channels e.g. institutional governance on the human development index for 11 oil exporting Sub-Saharan African countries. To accomplish our objective, the study applies quantitative approach which involves advanced statistical analysis. The study utilises balanced panel data of countries over time, which include multiple observations on each country in the sample. Thus the notation in panel data includes (i) for the cross section unit (in this case each country) and (t) for time. Panel data have several advantages which are beneficial for this study. Baltagi (2008) lists some of these advantages. First, it is possible to control for individual heterogeneity, so would eliminate the risk of obtaining biased results. In this case when analysing the effect of oil rent and other explanatory variables on human development index, there may be other variables that are country invariant or time invariant that may affect the human development index. Panel data is able to control for these country and time invariant variables. By combining time series and cross section observations panel data gives more informative data therefore this study will able to take advantage of having information on human development index and explanatory variable on each country over time period.

Selecting between the numerous panel models is a challenging and tricky issue. Therefore, we follow specific analytical procedure to find a proper model for our panel datasets. The statistical tests suggest that the two-way fixed effect model is appropriate. However, it is necessary to consider endogeneity that may result from the connection between the human development index and income inequality index. Thus, IV estimation was applied which enhanced the internal validity of the results and provided more robust foundation for drawing causal inferences. Followed by different diagnostic analysis, for instance, the Wu-Hausman test of endogeneity checks instrument validity, the first stage F-test, and the Wald test are used to for detect weak instruments.

1-5 CONTRIBUTION TO KNOWLEDGE

The empirical resource curse literature attempted to build various models for the SSA economy in order to investigate the driving forces and optimal policies to promote economic growth. These studies seem to be influenced by human development indicators separately. Part of these studies have paid attention to examine the consequences of resource abundance/ dependence that might impact on GDP per capita income. For instance, volatility in commodity price (Nili and Rastad, 2007; Van der Ploeg and Poelhekke ,2000; Keikha et al., 2012; Cavalcanti, 2015); the role of institutions and its consequences (e.g. Leite and Weidmann, 1999; Constantinos et al., 2014); corruption and state stability (Mehlum et al., 2006; Arezki and Bruckner, 2011; Van der Ploeg, 2011; Arezki and Gylfason, 2013); income inequality, which is strictly related to the absence of adequate institutions (Tornell and Lane, 1999; Carmignani, 2013; Veloso, 2015; Parcero and Papyrakis, 2016; Mallaye et al., 2015; Mallaye, 2015; Anyanwu et al., 2016). Other studies examine the nexus between natural resource wealth through government expenditure and human capital accumulation. For instance, public spending and education (Cupta et al., 2002; Baldacci et al., 2003; Thorbecke, 2003; Anyanwu and Erhijakper, 2007; Cockx and Francken, 2015); health and public spending (Cockx and Francken,2014; Karimu 2017). Ibrahim et al., (2018) investigate both health and education and public spending, while Issa and Ouattara, (2005) investigate health expenditure and infant mortality rates. Others investigate human capital accumulation and natural resource dependence (e.g. Philippot, 2010; Kim and Lin, 2017; Karimu et al., 2017).

It is worth noting that this work contributes to both the natural resource curse and human development literature debate for SSA in different ways:

To determine long-term human development, previous studies used the level of GDP per capita as the dependent variable means that it ignored the quality of human life for the SSA countries. Therefore, this study will utilize the Human Development Index (HDI) as an alternative measure, which offers a different perspective compared to the traditional metric, GDP, in evaluating development.

The HDI broadened the evaluation of development to include income per capita, education and life expectancy. In the unique context of Sub-Saharan Africa, where economic challenges and disparities are prevalent, relying solely on GDP per capita as a development indicator may provide an incomplete assessment. According to Hicks and Streeten (1979) and the UNDP (1990) using GDP or GNP per capita, only records monetary transactions and also views natural resources as unlimited and free; additionally, it disregards the significance of free time and ignores how revenue is distributed in society. The use of the Human Development Index (HDI) is more appropriate, as it captures not only economic well-being but also considers crucial non-material dimensions. In SSA, where the goal is not just economic growth but sustainable and holistic development, therefore HDI offers a more comprehensive reflection of the region's progress in improving the overall quality of life for its population.

- The measurement of natural resources in previous studies used either natural resource dependence or natural resource abundance. According to (Sala-i-Martin and Subramanian, 2003, and Shahbaz., et al., 2019), natural resource abundance is defined as the total of natural capital and mineral resources assets in dollars per capita, it means natural resource rents per capita. While the natural resource dependence is mainly based on the share of natural resource rents in real gross domestic product and includes the share of exports of four types of natural resources – fuel, ores, metals, agricultural raw materials and food. Use of these measurements raised debate on the validity of the natural resource curse hypothesis. Recent literature indicates the importance of not pooling commodities when analysing the impact of resources rents on growth (Arezki and Brückner,2009). Therefore, this study will use exclusively oil rents ensuring consistency in the consequences of resource rents on human development. Oil rents are a more appropriate measurement to examine the direct effect of natural resources on human development, theoretically the resource curse hypothesis originally linked with the oil and gas sector and certain minerals than other natural resources (Auty, 1993).

- There are no previous studies focused on how the human development index is affected directly by oil rents exclusively for oil exporting Sub-Saharan African countries (SSA), with particularly emphasis on transmission mechanisms of natural resource curs. The research includes 11 oil exporting sub-Saharan African countries out of 54 countries in Africa and provides a good view of the crude oil-rich countries in which development is supposed to be the most intense namely Angola, Cameroon, Chad, Ghana, Gabon, Ivory Coast, Democratic Republic of Congo, Republic of Congo, Equatorial Guinea, Sudan, Nigeria.
- In addition, this research will extend the period to cover 2000 to 2020; The majority of the literature is based on data gathered from 1963 to 2015, whilst the data set used in this study covers a 20-year period from 2000 to 2020. During this time, SSA experienced policy changes, and, later, the majority of these countries were classified as rich natural resource countries by the International Monetary Fund (IMF), therefore if we go further back some countries were not producing oil and the sample will shrink and get missing data.

1-6 THE SIGNFICANCE OF THE STUDY

This research significantly enhances the existing body of literature by providing a deeper understanding of the complicated relationships between oil rents and the Human Development Index (HDI) in oil-exporting Sub-Saharan African countries. This understanding is crucial for policymakers and stakeholders engaged in sustainable development efforts, as it informs strategies for effective resource management and poverty alleviation.

A key focus of this study is the influence of institutional governance and policy on HDI, considering the broader socio-political context in which development occurs. By examining factors such as corruption and government effectiveness, the research identifies potential barriers or facilitators to human development. This offers insights for improving governance structures and policy frameworks. Thus, the study not only advances theoretical knowledge in development economics but also provides practical recommendations for enhancing governance in resource-rich environments.

The research aligns with global development agendas such as the Sustainable Development Goals (SDGs). By clarifying the factors that influence HDI in the context of oil exporting Sub-Saharan African countries, the study contributes to efforts aimed at achieving SDG targets related to poverty reduction, quality education, good health and well-being, and strong institutions. The research thereby not only advances academic knowledge but also supports global efforts to promote sustainable and equitable development.

Additionally, the empirical findings of this study serve as a valuable resource for future research. By offering evidence-based insights into the determinants of HDI in Sub-Saharan Africa, the study can inform and inspire subsequent research on related topics, thereby contributing to the cumulative knowledge in the field.

In summary, the significance of this study lies in its ability to bridge gaps in existing literature, provide actionable policy insights, and support both regional and global human development objectives.

1-7 ORGANISATION OF THE RESEARCH

This study investigates the impact of natural resources in the form of oil rents percentage of GDP by testing curse theory through its transmission mechanisms and institutional governance on the human development index. Balanced panel data regression techniques were applied, especially procedure and specification tests.

Chapter one has introduced the study context, identified the research aim and objectives have been identified, laid out the value of such research argued, and discussed the study limitations'.

Chapter two aims to understand the development concept and track its rational origins. It has more focus on different human development measures, explaining the intellectual aspects and how they were improved and expanded.

Chapter three reviews the existing literature, e.g. previous studies, in order to highlight the theoretical and empirical literature related to natural resource wealth and its impact on HDI dimensions; it focuses on oil-producing and exporting sub-Saharan Africa countries.

Chapter four presents the theoretical framework, justifies the adoption of a quantitative induction research approach, and discusses the broader research design and also sources of data. In addition, it provides the analysis technique applied to answer the research questions.

Chapter five investigates the direct impact of natural resources in the form of oil rent share in GDP, its transmission channels, and institutional governance on the human development index. Summary statistics analysis is carries out, such as measures of central tendency, and bivariate plot between oil rent and HDI. Balanced panel data and consequences techniques are used to estimate the appropriate model for our data.

Chapter six provides a conclusion summarising the major findings in connection to the aim and objectives of the study. It also discusses the contribution; additionally, it examines the study limitations and suggests opportunities for future investigation.

CHAPTER TWO: EXPLORING HUMAN DEVELOPMENT: INSIGHTS INTO THE HUMAN DEVELOPMENT INDEX, INCOME INEQUALITY, AND GENDER DISPARITIES.

This chapter aims to understand the development concept and track its rational origins. It puts more focus on different human development measures, explaining intellectual aspects and how they were improved and expanded.

2-1 IMPROVING THE DEVELOPMENT CONCEPT

The definition of development in general has been improving over time. Initially, it was built on economic theory to achieve sustained economic development. The form of sustained economic development was concerned with full employment and steady economic growth, which were thought sufficient to solve social problems (Sen, 1999). Hence, the traditional measurement was based on GDP growth (the production factor), it helps in assessing economic growth rates, which are important for understanding how economies are expanding and developing over time (Solow, 1956). In addition, policymakers use GDP data to design and implement economic policies which helps governments assess the effectiveness of their economic strategies and make informed decisions about fiscal and monetary policies (Stiglitz, Sen, and Fitoussi, 2010). However, it has limitation and proved a poor measurement did not reflect the reality of development. The deficiency of traditional development is thought to be its concentration on aggregate national product income and the total supply of specific products instead of on entitlements for people and the capabilities these entitlements generate (Sen, 1984). According to Hicks and Streeten (1979) and the UNDP (1990), using GDP, or GNP per capita, only records monetary transactions and also views natural resources as unlimited and free; additionally, it disregards the significance of free time and ignores how revenue is distributed in society.

Therefore, it became necessary to change development objectives from purely macroeconomic to human objectives. There were grounds for drawing attention to the role of people as promoters of development and progress in early resources, e.g., Adam Smith's, which concentrates on people’s capabilities in some fields that are crucial for the quality of life. The approach focuses on ‘functionings’ that people need for ‘flourishing’ as human beings. The growth theory presented by Solow and Swan (1956) emphasised that human capital (labour) is the main factor promoting economic growth besides capital and technology.

The improvement of the development concept can be traced in the literature through the theory of justice by John Rawls (1971). This started with Atkinson’s poverty article in 1970, which concerned poverty and how to measure it based on the economic theory that led to improve welfare. Then Rawl’s theory argued for a principled reconciliation of liberty and equality that is meant to apply to the basic structure of a well-ordered society. Rawls' two standards of equity are, first, that every individual has an equivalent right to a completely sufficient plan of equivalent fundamental freedoms that is viable with a comparable plan of freedoms for all (Sen, 1992). Rawls' second standard is that social and financial imbalances must fulfil two conditions. In the first place, they should be appended to workplaces and positions open to all under states of reasonable equity of opportunity, and, second, they should be to the best advantage of the least advantaged individuals in society (Sen 1992; Rawls 1971). Further work by Sen and Nussbaum on famine and poverty led to the notation of capabilities based on Rawlsian philosophy (Sen, 1981, 1983 and 1987).

The approach is concerned with what human beings do instead of what they have, moving the discussion away from utility towards capabilities. Sen utilises a further term, ‘’functioning’’ the ability of people to do certain things (such as moving around and being able to read) and to achieve certain types of beings (such as being free from illness and being well nourished), which means capabilities that an individual utilises or participates in. Furthermore, capabilities can have characteristic worth by adding beneficial alternatives or positive opportunities to one's life (Sen, 1999). Nussbaum (2000) recommended a list of 10 capabilities: (1) life; (2) bodily health; (3) bodily integrity; (4) senses, imagination, and thought; (5) emotions; (6) practical reason; (7) affiliation; (8) other species; (9) play; and (10) control over one’s environment. Researchers began to look for alternative measures that included human qualities beyond just economic indicators. The United Nations Research Institute for Social Development (UNRISD) conducted a study in 1966 that measured the "level of living index" in 20 countries, taking into account physical needs (nutrition, shelter, and health), cultural needs (education, leisure, and security), and higher needs measured by income above a certain threshold. UNRISD released a second study in 1972 called the "Development Index", which included nine economic and nine social characteristics (Hicks and Streeten, 1979). In 1975, the United Nations Economic and Social Council ranked 140 countries based on seven indicators: two social (literacy and life expectancy) and five economic (energy, manufacturing share of GDP, manufacturing share of exports, employment outside of agriculture, and number of telephones) (UN-ECOSOC, 1975; Hicks and Streeten,1979).

Morris introduced the Physical Quality of Life Index (PQLI) in 1979 to ensure that the world's most impoverished people could meet minimum human needs. It combines new-born mortality, life expectancy at one year, and basic literacy. (Camp and Speidel's ,1987, cited in Kelley,1989) international human suffering index was an additional attempt to quantify social welfare. Srinivasan (1994) aggregated 10 measurements to create this index, including income, infant mortality, nutrition, adult literacy, and personal freedom.

2-1-1 **Human Development Index (HDI)**

Based on the idea of human capacities as put forth by Sen and Nussbaum as being the fundamental prerequisites for improving human capabilities (Desai, 1991), the Human

Development Index (HDI) was originally produced by the United Nations Development Programme (UNDP) in 1990. The HDI was formed to emphasise that individuals and their abilities should be the definitive model for evaluating the development of a nation, not economic growth alone (Haq, 1995). The Human Development Department defines development as a process of expanding people's options; these options are theoretically limitless and dynamic. But at all stages of development, the three essentials are for people to live a long and healthy life, acquire knowledge, and have access to the resources needed for a decent standard of living. “If these essential choices are not available, many other opportunities remain inaccessible” (UNDP HDR, 1990, p. 10).

Thus, the Human Development Index (HDI) was created using three indicators: life expectancy at birth (health), mean years of schooling for adults and expected years of schooling for children (knowledge), and purchasing power per head (GNI) (standard of living). This emphasises how fundamental these three dimensions are to human development. The GNI component is primarily utilised as a replacement for several significant characteristics of life quality that are left out of calculations for life expectancy and elementary education (Anand and Sen, 2000). Figure 2.1 present the calculation of the human development indexes as described in technical notes 2 in UDHDR.

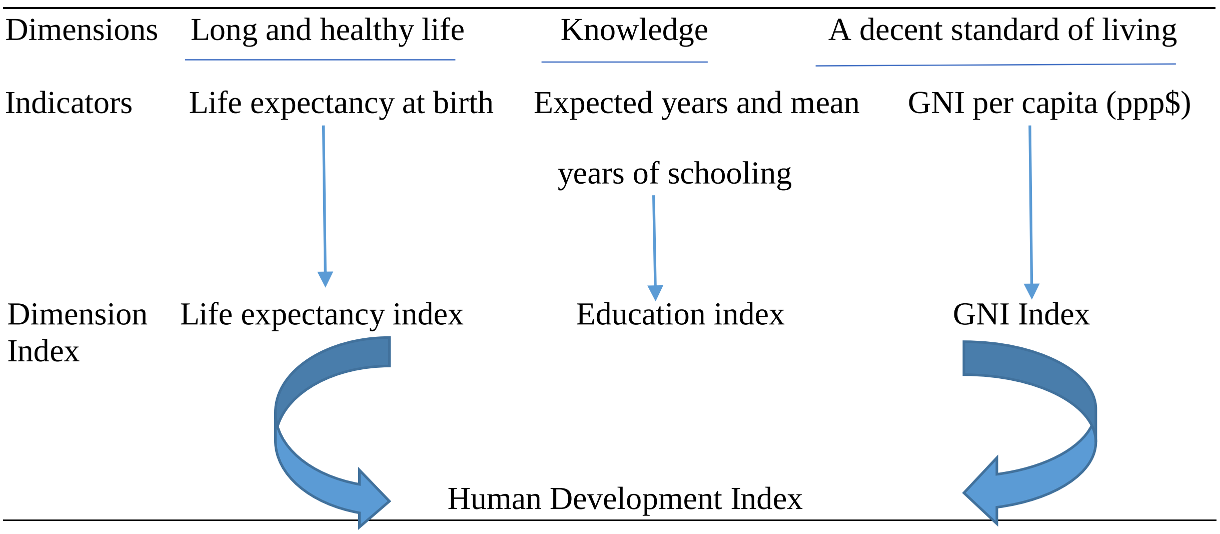

Figure 2-1 calculating the human development index (HDI)

Sources of the graph: author's compilation based on UNHDR.

The HDI ranges from zero to one, and nations are ranked based on how close their HDIs are to one. According to Desai (1991), the HDI can be seen as a first and crucial step in putting general sustainability ideals into action.

Therefore, the documentation of human development includes the concerns of those development initiatives that are unrelated to economic concepts. However, it does not offer the rigorous theorising practises that economists like, such as direct policy concerns about economic level and security that might have a direct impact on human development, as well as distribution issues such as rich/poor, male/female, rural/urban, and issues relating to the distribution of wealth. It can mainly be used to address public policy selections by investigating how two nations with a similar degree of Gross National Income (GNI) per capita can end up with various human improvement results. The divergences in outcomes can stimulate discussion about the need for government programmes. In spite of that, Klasen (2018) stated that the index proved successful for three reasons: first, it connected with a capability approach that gave it a theoretical base and intellectual coherence. Second, it was supported by international organisations, and, third, the HDI's international relations provided it with a wider base of support than measures focused 'only' on developing countries.

The composition of the HDI (in terms of components weights) has been adjusted over time; for example, in the United Nations report (1991), with regard to the educational component, the transformed variable consists of two-thirds of the percentage rate of literate adults among all adults and one-third of the combined first-, second- and third-level educational gross enrolment ratio in per cent. As for the longevity component, it is measured directly by life expectancy at birth in year, while standard of living is represented by real per capita income at purchasing power parity in dollar (PPP$) of country. For each indicator, a maximum and a minimum is defined (Kelly, 1991, cited in Noorbakhash, 1998). Based on that, the old version of the HDI calculation prior to 2010, using linear averaging across the three dimensions, as follows,

$$\frac{(\boldsymbol{helth} + \ \boldsymbol{education} + (\boldsymbol{income})}{\mathbf{3}} \ ,$$

assumed that education, health, and income are perfectly substantial (equal weights) so the absolute value of each component will affect the level of HDI. As a result, estimating HDI with an arithmetic average has been contested in a number of ways, particularly for certain set ranges for its constituents that make it sensitive.

Additionally, it is challenging to compare the component indices between years when they are calculated using minimum and maximum values that vary annually, as stated by Kelley (1991). These factors led a number of writers to publish proposals to alter HDI computation, e.g., Desai (1991), Gormley (1995), Sager and Najam (1998) and Noor Bakhsh (1998a, b).

After that, the method to compute HDI changed based on geometric mean, as follows:

(health x education x income)$^{1/3}$ using D^2 statistics to create a composite index based on the three components' standardised actual values and standardised intended values, by combining the three indices to make HDI more responsive to drops in any one index's value (Sager and Najam 1998). The HDI has undergone significant changes that have altered not only the ranks of the countries, but also the indicator's definition (Martinez, 2012). Since it actually is not about the balance of accomplishments but, rather, the combination of past and present educational policies that affect years of schooling and expected years of schooling, the use of the arithmetic mean seems fair in this situation. The key advantages of the switch are the imperfect substitutability between dimensions and the independence of the ranking to the position of the upper bound, but it is important to note that the empirical significance of this difference between the geometric mean and the arithmetic mean is only marginal (Klugman et al., 2011). Also, the UNDP did a historical update; all the figures are comparable in a new definition.

Although HDI as a measurement of development has significantly contributed to changing the field of international development, the index has been criticised by scholars and professionals because of its concentration of the complications of human development into just three components, the absence of a distribution of capabilities among each nation, such as gender based inequality and income inequality, Furthermore, the HDI has also been criticised for the lack of an environmental or natural resource depletion dimension, and political liberties (Desai, 1993; Noorbakhsh. 1998). More specifically, HDI fails to account for other welfare-relevant effects of income inequality, as well as for welfare-relevant effects of inequalities in the distribution of health and education outcomes themselves. For example, inequalities in all three components of HDI may have corrosive effects on human well-being through their association with decreasing social cohesion, increasing violence, or increasing environmental degradation. Moreover, many, if not all, people place an intrinsic value on equality as an end in itself. The lack of such data as a justification for eliminating measures of inequality (UNDP, 1990) would appear somewhat myopic for several elements of distribution, particularly gender-based inequality and income disparity.

2-2 ADDITIONAL EVALUATIONS OF HUMAN DEVELOPMENT

As discussed earlier, measures of inequality were excluded from HDI for no other reason than a lack of data (UNDP, 1990). Over the years, the UNDP has improved its stance on the purpose of HDI, ensuring that disparities are a major concern in human development analysis; as a result, numerous different indicators of poverty and inequality have achieved a permanent place in the narratives of the human development reports and their statistical appendices. Some of these different indicators are detailed below.

2-2-1 **Income inequality**

Income inequality greatly impacts on health, education, and income, the three essential dimensions of human development. Nearly 60% of births in underdeveloped nations happen without a medical professional present, and 20% or more of the population in one-third of all countries lacks even the most basic literacy (UNDP, 2005).

The HDI, similar to GDP, is based on national averages; but it considers a larger range of wellbeing indices. The practice of correlating averages with national well-being ignores potential trade-offs in social welfare between rising averages and falling distributional inequality. Early Human development reports (HDRs) recognised the significance of dispersion to human development explicitly: presenting average data for each nation hides a number of significant inequalities, including those between urban and rural areas, rich and poor, male and female, as well as between ethnic groups and other locations; the HDI should represent how people actually live (UNDP 1992). But the HDI is a measure of national average and does not integrate inequality.

In fact, a measure of income inequality, either the Gini coefficient or income shares by quintile, has been reported by the majority of human development reports. For instance, in early report (1990), it discussion in text with sample of HDI’s sensitivity to income distribution, Quintile ratios and GINI which presented in tables. This version also included a technical note for female and male using GDP per capita as their income measurement.

The calculation of GINI is defined as A/ (A+B), where A is the area between the line of perfect equality while B is the area under the Lorenz curve. In some cases, the entire Lorenz curve is unknown, and only data at specific intervals are presented. In this situation, the Lorenz curve's missing data can be interpolated using a variety of techniques to estimate the GINI coefficient. The fundamental benefit of the Gini coefficient is that it measures inequality through ratio analysis as opposed to using a quantity that is not representative of most of the population, like per capita income or gross domestic product. In addition, it is easy to compare and understand across nations because it is sufficiently straightforward, such as it shows how income has changed for the rich and the poor. Moreover, it also can be used to show how the income distribution has changed over time within a nation, allowing one to determine whether inequality is rising or falling (Stewart and Langer, 2008). The main disadvantage in using the GINI coefficient is in measuring a large economically diverse country, which will generally result in a much higher coefficient than each of its regions has individually.

Early reports also included an "income-distribution-sensitive HDI" that adjusted the HDI's income component according to a formula utilising the Gini coefficient for income for each country (Stewart and Langer, 2008). This measure was initially mentioned in human development reports 1990 to 1994, but it has not been reported since. The majority of assessments of inequality and poverty place a strong emphasis on the person: they are concerned with the numbers of individuals in poverty in the world as a whole, not with who they are, or where they live (Stewart and Langer, 2008). Therefore, what are called horizontal inequalities have been represented using comparative HDIs measured for certain regions or racial/ethnic groupings within countries. For instance, the HDI is disaggregated by race and gender: whites, blacks and Latinos, and so on.

2-2-2 **Gender inequality**

In attempting to eliminate gender discrimination in the three HDI indicators and to improve the situation of women, in 1995, the UNDP developed two composite indices of gender equality: The Gender-related Development Index (GDI) and the Gender Empowerment Measure (GEM); both indexes drew attention to the gender inequality issue in international policy debates.

2-2-2-1 **The Gender-related Development Index (GDI)**

The GDI is intended to measure relative well-being, similar to the HDI, considering the disparities between men and women. It consists of the adjusted variables, i.e., education (2/3 literacy and 1/3 primary, secondary, and tertiary school enrolments), income, and health (life expectancy), and it then the average determined by the level of gender inequality.

The process of calculating GDI values involves four steps. The first step is to estimate the earned earnings of men and women by dividing the total wage bill by their respective percentages. In step two, the indicators are normalised (the indicators, which are in different units, are first converted into indices to provide the female and male HDI values, the dimension indices for each sex are then combined by taking the geometric mean. The HDI's goalposts are utilised to convert the indicators into indices that range from 0 to 1, with the exception of life expectancy at birth, which is modified to account for the typical five-year biological advantage that women have over males). Then, in step three, the female and male human development index values are computed; while the last step is comparing the female and male HDI values (UN technical note 3, 2022).

The GDI categories are based on the (GDI’s 100). |GDI-1| is absolute divergence from gender parity. Countries having an absolute deviation from gender parity of 2.5% or less are categorised as group 1 countries, because they have high gender equality in HDI achievements.

Group 2 countries are those with an absolute divergence from gender parity of 2.5–5%, and they are thought to have a medium-high level of equality between women's and men's HDI achievements. In terms of women's and men's HDI achievements, nations with an absolute divergence from gender parity of 5-7.5% are categorised in group 3 as having medium equality (UN technical note 3, 2022).

Group 4 countries are those with medium-low equality in HDI achievements between women and men, defined as those with an absolute divergence from gender parity of 7.5–10%, while countries having an absolute divergence from gender parity of more than 10% are categorised as group 5 countries and are thought to have low HDI accomplishment equality between women and men (Technical note 3, 2022). In other words, the more significant the gender inequalities, the closer the GDI is to zero (Gaëlle, 2010). As a result, when men's and women's levels of development decline simultaneously, a country's GDI declines, both when the gender development gap increases, and when it does not. The greater the differences between men and women in terms of basic capabilities, the smaller the GDI in a country is, compared to its HDI. Thus, the GDI is just the HDI with gender disparities weighted (Gaëlle, 2010). Graph 2.2 illustrates the calculation of the Gender related Development Index (GDI) as described in technical note 3 in the UNPD.

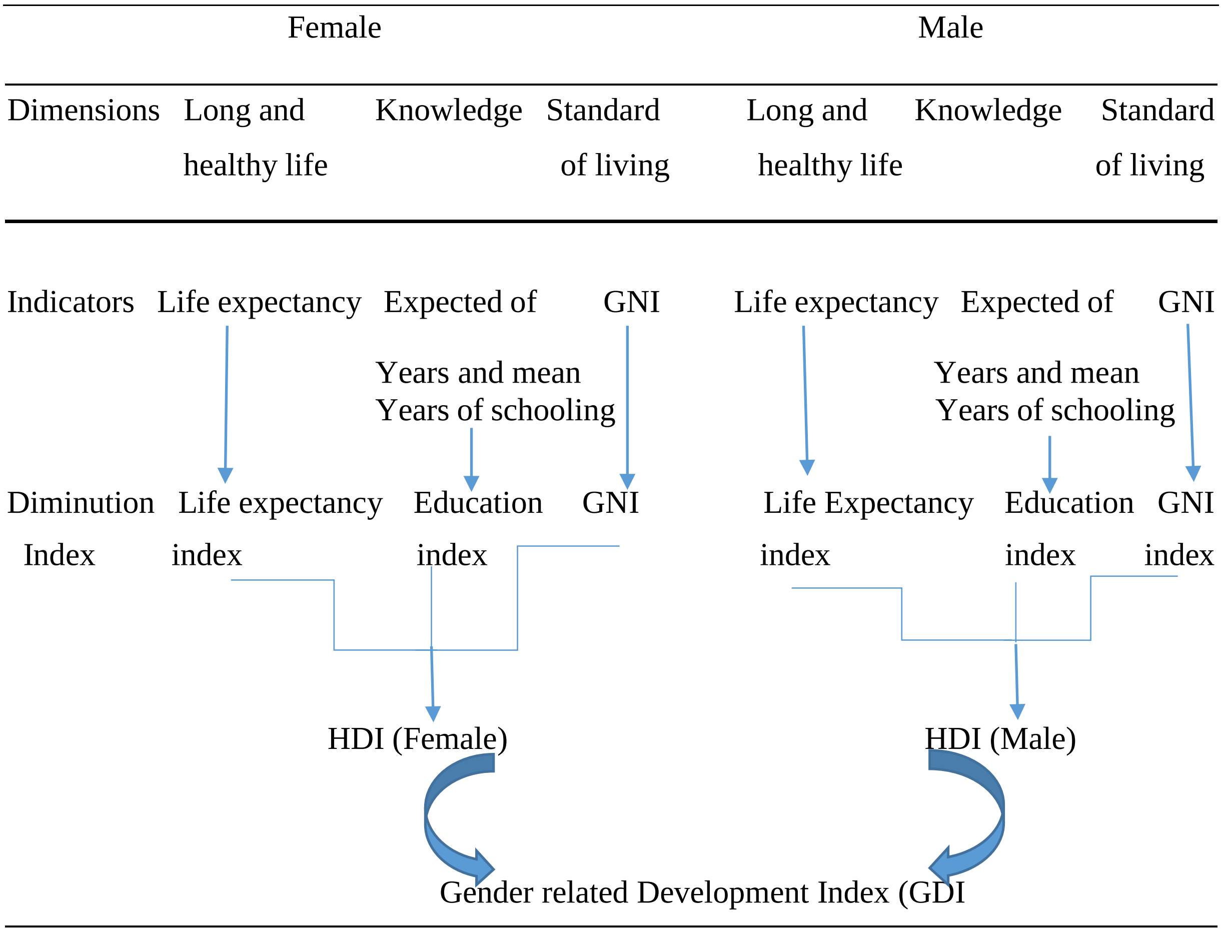

Figure 2-2 the calculation of Gender related Development Index(GDI)

Source of the graph: author's compilation based on UNHDR

2-2-2-2 **The Gender Empowerment Measure (GEM)**

To contrast to GDI, the GEM is meant to be a measure of gender inequality in political power, professional, and economic participation. The index includes the quota of women in government, the share of women in technical, professional, and management positions, and also unadjusted income. The same "aversion to inequality" utilised in the GDI is then applied to penalise gender gaps, aiming for 50/50 shares across all three components (Bardhan and Klasen, 1999 cited in Gaëlle, 2010). Both indexes have since been reported yearly in human development reports (Dijkstra, 2002 cited in Gaëlle, 2010).

But, it is important to note that a measure like the GDI, which is based on data that is separated out for males and females, is nevertheless aggregative in this way due to the lack of information regarding the disparities within the population between males and females. This kind of practice is hence "group-based". It is effectively an approach that shows the disparities in opportunity between men and women in a nation. However, it does not, by definition, address inequities that may result from other demographic factors, so it is still at base an aggregative and not a distributional index (Hicks, 1997). In other words, GDI as currently formulated fails to provide a common-sense measurement of gender disparity in human development. It lacks transparency, has covert prejudices, and makes heroic assumptions while adding up inequalities between men and women (Martınez, 2011).

Several scholars have addressed some issues related to GDI and GEM, e.g. Dijkstra and Hanmer (2000), (Bardhan and Klasen ,1999 cited in Gaëlle, 2010); the GDI and the GEM are not regarded as measures of gender equality since they compute a combination of absolute levels of accomplishment and a penalty for inequity. This suggests that they cannot be employed to determine how gender equality and economic performance are related. Because of this, the UNDP gender indicators are unable to evaluate the needs of women in poor nations or establish a priority list for addressing gender inequality.

In 2000, 189 nations adopted the United Nations Millennium Declaration, which represents an extraordinary commitment from both wealthy and developing nations to pursue enhanced human development. Eight Millennium Development Goals (MDGs) that include targets for gender equality, environmental sustainability, poverty reduction, and promoting global partnerships are a condensed version of this initiative (UNDP, 2003). This emphasis on the

MDGs has substantially challenged both concerns about the lack of trustworthy and readily available data to monitor the MDGs' development and the choice of policy solutions to achieve them. The choice of policy alternatives to achieve the MDGs and worries about the absence of reliable and accessible data to track the MDGs' progress have both been seriously contested by this focus on the MDGs. The MDGs focused on education and included two significant points:

first, all children should complete primary school, and, second, all nations should achieve gender equality at all levels of education. There is more concentration on African governments to promote gender equality and the empowerment of women as effective ways to combat poverty, hunger, and disease and to motivate development that is truly sustainable to develop and implement strategies that give young people everywhere a real chance to find decent and productive work (MDGS, 2000).

Therefore, an alternative gender inequality index was constructed by Dijkstra (2002); it is known as the Standardised Index of Gender Equality (SIGE). This index attempts to avoid the methodological limitations of GDI and GEM and to provide a broader vision including Eight Millennium Development Goals (EMDGs). Thus, it aims to satisfy the following three criteria: i) all relevant aspects of gender equality should be considered in the index; ii) it ought to be a comparative measure; iii) it should be properly weighed (Dijkstra, 2002). In this manner, Dijkstra (2002) outlines the types of gender imbalance that ought to be taken into account by gender sensitive indexes. The key aspects of gender disparity that should be considered while developing a new measure, as well as a comparison of nations: for instance: access to social resources, such as healthcare and education; gender identity, which describes how socialisation and education have shaped gender roles; political power; access to land, housing, and credit, a job and income; and body autonomy (Gaëlle, 2010).

To avoid the limitation of unintended weighting in previous gender inequality indexes, the SIGE used a standardised method by subtracting the mean then dividing by the standard deviation (Dijkstra, 2002). The variables are assumed to have a normal distribution in this methodology. However, Dijkstra (2002) does not reveal the distribution or the normalisation of the data, which results in a lack of transparency and significantly increases the measure's ambiguity (Klasen and Schuler, 2009 cited in Gaëlle, 2010). In fact, the SIGE index is not authorised or used by the UNDP.

2-2-2-3 **Gender Inequality Index**

Accordingly, the Gender Inequality Index (GII), developed by the UNDP in 2010 as the new gender index, replaced GEM. The GII, which consists of five indicators across three dimensions, is used to evaluate the negative effects gender inequality has had on human development in the areas of "reproductive health", "empowerment", and "labor market" (UNDP, 2010).

The indicators for "empowerment" are "female and male shares of parliamentary seats" and "population with at least secondary education (% ages 25 and older)"; the indicator for "labor market" is "labor force participation rate". The indicators for the aspect of "reproductive health" are "maternal mortality ratio" and "adolescent fertility rate". In fact, the GII covers a limited number of indicators, but covers as many dimensions of gender equality as possible, which allows comparisons between countries.

As discussed above, the GII comprises three components: political empowerment, reproductive health, and labour market; the four stages listed below are used to determine the GII after the individual dimensions have been determined.

Step 1 uses the geometric mean to aggregate across the dimensions for each gender group. Then utilises the harmonic mean to combine data from different gender groups. This demonstrates disparities and permits a connection between the dimensions. In Step 3: for each dimension, determine the geometric mean of the arithmetic mean. The last step is: determine the GII.

The gender inequality index ranking ranges between 0 and 1; the closer the value is to 0, that means men and women are treated fairly (no inequality), while 1 means one gender does the worst across all measurable dimensions (complete inequality) (Technical note 4, 2022). Therefore, the higher the value of the GII, the greater the disparity between males and females and vice versa.

One hundred and seventy nations are ranked by the GII as it is given in the Human Development Report. In general, nations with high levels of human development have GII values that are close to zero based on their Human Development Index (HDI) scores. In comparison, the GII values for the nations with lower HDI ratings are closer to 1.

2-3 MULTIDIMENSIONAL POVERTY INDEX (MPI)

The Capability Poverty Measure (CPM) was first introduced by the UNDP in the Human Development Report of 1996; it is a composite measure of three basic capabilities: being well nourished and healthy (the percentage of underweight children under five); capability for healthy reproduction (the percentage of births that are not attended by a qualified medical practitioner); and education (female illiteracy). The CPM was created to provide special attention to the deprivation of women because of how crucial they are to the human development of families and society (UNDP, 1996).

Then, the Human Poverty Index (HPI) was introduced, taking the place of CPM, which measured: longevity (the proportion of those who will die before they turn 40); knowledge (adult illiteracy); and living standards (the proportion of people with access to health care, the proportion of people with access to clean water, and the proportion of children under five who are underweight). The UNDP (1997) provided an explanation for the need for HPI by stating that, unlike HDI, which adopts a perspective in which everyone's well-being – rich and poor – counts, HPI concentrates primarily on the least well-off. In the Human Development Report of 1998, the UNDP renamed HPI and it is now known as HPI-1, which was intended only for use in measuring poverty in developing nations. And it added HPI-2 as a measure of poverty in industrialised countries because a community's social and economic conditions affect human deprivation in different ways.

Different measures of longevity are included in HPI-2 (the percentage of people expected to die before age 60); knowledge (a higher standard of literacy than what was required for HPI-1); and living standards (the proportion of individuals with disposable incomes that are lower than 50% of the median); and it adds a measure of social inclusion (the percentage of persistent unemployment).

Then, the Multidimensional Poverty Index (MPI) was introduced in 2010 by Alkire and Santos in collaboration with the UNDP's Human Development Report Office (HDRO). It measures several deprivations at the household level in terms of standard of living, health, and education. It uses micro data from household surveys, and, unlike the Inequality-adjusted Human Development Index, all the indicators required to create the measure must come from the same survey. It uses the same indicators as HDI (health, education, and standard of living) but include 10 dimensions; for instance, health includes nutrition and child mortality, education includes both years of schooling and school attendance; while the living standards comprise cooking fuel, sanitation, drinking water, electricity, housing, and assets (Alkire and Jahan, 2018). Figure 2-3 show the calculation of Multidimensional Poverty Index (MPI).

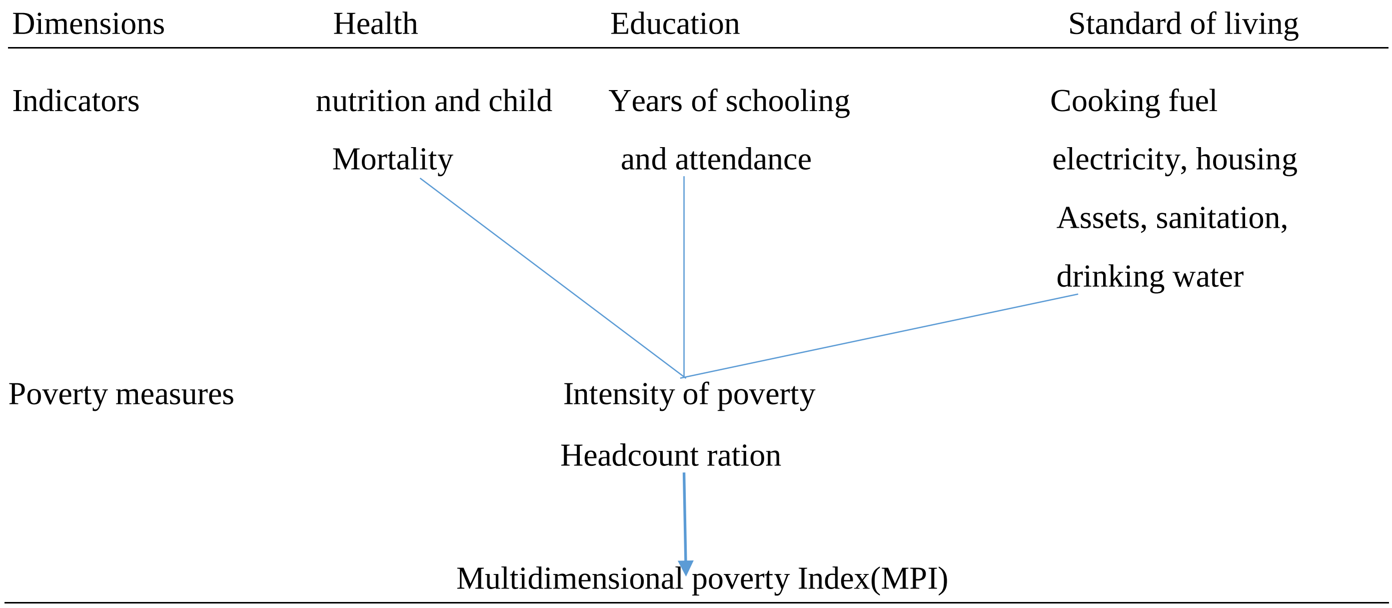

Figure 2-3 the calculation of Multidimensional Poverty Index (MPI)

Sources. of the graph: author's compilation based on UNHDR

The MPI was created for each person's deprivation profile, which identifies which of the 10 dimensions they are deprived in relation to; for instance, each household member's level of deprivation in terms of health and education can be determined based on the information that is known about the other household members. The deprivation score for each individual is then calculated by averaging their deprivations across all categories. The indicators have a nested weight structure, with identical weights applied to each indicator inside a dimension as well as across all dimensions (UN technical note 5, 2022).

The highest deprivation score in each dimension is 33.3%, or, more precisely, 1/3, as the maximum deprivation score for all dimensions is 100%. Each of the two indicators for the health and education dimensions is weighted at 1/6, while each of the six indicators that make up the standard of living dimension is weighted at 1/18 (UN technical note 5, 2022).

The household deprivation score is calculated by adding up the deprivation scores for each indication in order to identify persons who are multidimensionality poor. To differentiate between poor and non-poor people, a cut-off of 1/3 is applied. A household is deemed multidimensionality poor people if the deprivation score is at least 1/3 for all members of the household. People are regarded as being vulnerable to multidimensional poverty if their deprivation score is 1/5 or higher but less than 1/3. People are categorised as being in severe multidimensional poverty if they have a deprivation score of 1/2 or above (UN technical note5, 2022). The multidimensional poverty headcount ratio[2] and the intensity of poverty[3] are the two measurements that combine to provide the MPI value. A country's deprivation structure can be shown by calculating each dimension's contribution to multidimensional poverty, which can also aid in policy targeting.

[2] The headcount ratio is the proportion of multidimensionality poor people in the population.

[3] The average percentage of the weighted component indicators that multidimensionality poor people are deprived of determines the intensity of poverty.

2-4 INEQUALITY ADJUSTED HUMAN DEVELOPMENT INDEX (IHDI)

Although the income inequality has been considered through the Gini coefficient, unequal distribution in health and education can cause socioeconomic inequality. For instance, as indicated in the literature, there is a relationship between individual health and individual income; increased income improves heath and then redistribution of income would change the average level of health (Marmot, 2002). The same reasoning holds true for education: individual income and education are inversely correlated or concave; as a result, average education is higher when income is more equally distributed. The loss in HDI caused by inequality is approximately 23% on average worldwide, ranging from 5% (Czech Republic) to 43.5% (Namibia) (Alkire and Foster, 2010). Following South Asia and the Arab States, people in sub-Saharan Africa experience the greatest losses as a result of inequality in all three categories. While South Asia and the Arab States suffer significant losses as a result of unequal distribution in education, sub-Saharan Africa experiences the highest levels of health disparity.

Accordingly, it is essential to modify the human development index for inequality that not only changes the rankings of the countries, but also the meaning of the indicator. In 2010, the UNDP updated the human development index; the major modification was related to the calculation of HDI, as explained earlier, by replacing geometric mean as the aggregation formula instead of arithmetic mean. In addition, the mean years of schooling and expected years of schooling replaced the adult literacy rate and gross enrolment ratio, and the measures of inequality in the health, education, and income distribution were added to the index.

In other words, the Inequality Adjusted Human Development Index (IHDI) considers not only the average successes of a country in terms of health, education, and income, but also how those achievements are distributed among its population by "discounting" the average value of each dimension in accordance with the degree of inequality (Alkire and Foster, 2010).

Figure 2-4 illustrates the calculation of IHDI as described in technical note 2 in the UNPD.

Dimensions	Long and healthy life	Knowledge	A decent standard of living
Indicators	Life expectancy at birth	Expected years and Mean years of schooling	GNI per capita ($PPP)
Dimension Index	Life expectancy	Years of schooling	Income/consumption
Inequality Adjusted Index	Inequality-adjusted life expectancy index	Inequality adjusted education index	Inequality-adjusted income index

Inequality-adjusted Human Development Index (IHDI)

Figure 2-4 the calculation of IHDI

Sources of the graph: author's compilation based on UNHDR.

The IHDI computing method is based on a family of inequality measures developed by Atkinson (1970) and Foster, Lopez-Calva and Szekely (2005) that are distribution-sensitive composite indices. It is calculated as the geometric mean of the dimension indices taking into account inequality. The inequality in each dimension is estimated using the Atkinson inequality measure, which is based on the assumption that society as a whole has some degree of antipathy to inequality (Alkire and Foster, 2010).

Accordingly, the natural measure of the aggregate inequalities in a society across all achievements can be defined as follows:

$$A_\varepsilon = (H_0 - H_\varepsilon)/H_0 \quad \text{Eq. (2.1)}$$

Equation (2.1) measures both H_0 and H_ε

H_ε measures the level of achievement for the entire society in terms of human development.; it is the level of per capita achievement that, if equally distributed, would produce the same level of human development as in the actual distribution. In contrast, H_0 is the actual distribution's per capita achievement level. The inequality measure A_ε is the portion of per capita accomplishment that is lost due to disparities in the allocation of accomplishments. (Alkire and Foster, 2010). The above expression for A_ε can be stated equivalently as:

$$H_\varepsilon = H_0(1-A_\varepsilon) \qquad \text{Eq.(2.2)}$$

In other words, the IHDI is the HDI adjusted for achievement distribution inequality as determined by the Atkinson inequality metric. For example, in the case of $\varepsilon = 1$, the inequality measure is $A_1 = 1 - g/\mu$, where g is the geometric mean (or actual human development) and μ is the arithmetic mean (or the highest potential human development) associated with the achievement matrix, and the associated IHDI can be expressed as $H_1 = H_0(1-A_1)$. In what follows, we focus on H_1 as a key example of the IHDI class, and also one that has particularly useful interpretations and properties (Alkire and Foster, 2010). Be aware that the 2010 Human Development Report has an additional adjustment, which creates an index that is related to the HDI by applying the ratio H_1/H_1 to the 2010 HDI. The geometric mean of normalised indices for health, education, and the log of income are combined to create the 2010 HDI (Alkire and Foster, 2010).

The IHDI's key disadvantage is that it does not detect overlapping inequalities. For instance, the distributional inequality of the HDI dimensions is captured by the IHDI. The fact that it is not association sensitive means that it does not take into consideration overlapping disparities or the fact that the same individuals may be subjected to various forms of deprivation (Alkire and Foster, 2010).

Additionally, given that some indicators, such as income, have individual values that are zero or even negative, they have all been uniformly adjusted to non-negative non-zero values. For the measure association to be sensitive, all the data for each individual must be available from a single survey source, which is currently not feasible for a lot of countries (UN technical notes 2, HDR 2011). Therefore, Alkire and Foster (2010) stated that there are challenges related to implementing the IHDI for a large set of countries, due to data constraints Choices must be made between imperfect alternatives by combining empirical research and normative reasoning. The goal is to apply the measurement technique in a way that is as precise as possible and as little as practical distorted by data constraints (Alkire and Foster, 2010).

Overall, over the past few decades, the development concept has made substantial progress in terms of definition. Prior to that, it was built on economic theory; hence, the traditional measurement of development was based on GDP growth, which proved a poor measurement and did not reflect the reality of development. It became necessary to change development objectives from purely macroeconomic to human objectives. Hence, several attempts were made to draw attention to the role of people as promoters of development. The early attempts were by various authors e.g., Adam Smith, Solow (1956) and Rawls (1971). Then, Morris introduced the Physical Quality of Life Index (PQLI) in 1979, and, after that, in 1990, human development indexes were produced by the United Nations Development Programme. They included three essential dimensions: for people to live a long and healthy life, acquire knowledge, and have access to resources related to a decent standard of living.

Additional evaluations of human development were produced for inclusion in the human development report, such as income inequality (GINI), gender inequality (e.g., GDI and GEM, which latter become GII), and the multidimensional poverty index.

Even though income inequality has been considered through the GINI index, inequality in distribution in health and education causes socioeconomic inequality and a loss in HDI. Therefore, the human development index was modified in 2010 to an inequality-adjusted human development index, which is based on Atkinson (1970) and Foster, Foster et al (2005), which are distribution sensitive composite indexes. In other words, the IHDI evaluates the degree of human development after taking inequality into consideration. When there is no disparity in the achievement levels of persons in society, the IHDI and HDI are equal, but, as disparity increases, the IHDI drops below the HDI. The difference between the HDI and IHDI, represented as a percentage, is the loss in potential human growth caused by inequality.

Since 2010, the United Nations development department has documented all these indexes – HDI, IHDI, GDI, GII, and MPI – in the Human Development Report, which reflect disparities in every single dimension. which also can be utilised by governments as a roadmap to better understand the disparities among populations and how they contribute to the overall decline in inequality, which shapes the prospects of people even in the future.

2-5 HUMAN DEVELOPMENT IN SUB–SAHARAN AFRICA COUNTRIES COMPREHENSIVE OVERVIEW.

Human development in Sub-Saharan Africa is a multifaceted and dynamic topic influenced by a wide range of factors, including economic, social, political, and environmental dimensions. This region is characterized by diverse cultures, languages, and histories, and its development landscape varies significantly across countries. This section provides an overview of human development in SSA, exploring key dimensions such as health, education, and well-being.

2-5-1 **Health indicators**

The health indicators in SSA reflect a complex interplay of factors including disease burden, access to healthcare, and public health interventions. Noteworthy trends include:

2-5-1-1 **Life expectancy and infant mortality**

The two most widely used indicators of population health are life expectancy and infant mortality. Life expectancy effectively reflects the health impact of the disease environment since premature death is the most significant and notable impact of disease. On the other hand, infant mortality is an indicator of the state of the health care system and can signal the need for improved health care services (UNDP, 1995).

Since late 20th century, the world experienced more significant improvements in life expectancy and reductions in infant mortality than in any other period in global history (World bank, 2017). However, the distribution of these gains across world regions have been uneven (Chewe and Hangoma, 2020).

There were remarkable improvements in health indicators in sub Saharan Africa, particularly child and infant mortality, which fell by over 50 per cent between 2000 and 2020 as shown in figure 2-5. Similarly, life expectancy at birth went from 51 years in 2000 to 61 years in 2020 (see figure 2-5).

While these successes in improving health outcomes indicate that the region is on the path towards better health outcomes, the improvements are slower than other regions of the world due to fact that the region was affected by HIV/AIDS, tuberculosis (TB), and malaria (the three together termed as ATM) (World Health Organization, 2018). Therefore, the development of African households, communities, and nations is threatened by the concurrent distribution of ATM, which is acknowledged to be most lethal and widespread in the setting of significant social and economic challenges (World Health Organization, 2018).

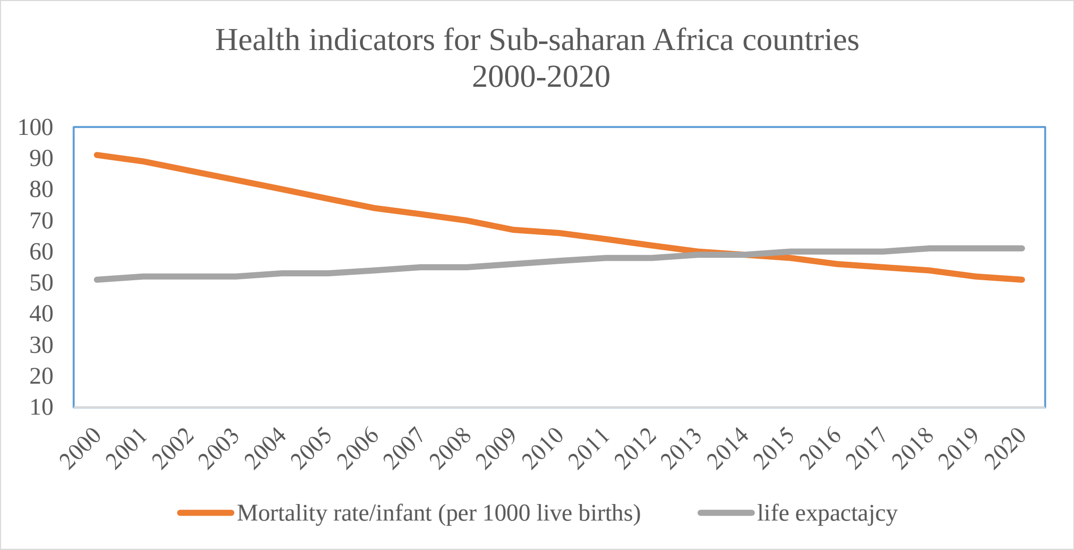

Figure 2-5 Health indicators for sub-Saharan Africa countries

Sources of the figures: author's compilation based on data obtained from the World Bank.

Health care access is another issue of the health sector across SSA. Significant challenges are characterized by a range of issues such as limited infrastructure with inadequate numbers of hospitals and healthcare centres. Insufficient healthcare facilities, a shortage of professionals including doctors and nurses which lead to a high patient-to-doctor ratio. Another issue connected with the health sector is financial barriers, many individuals in Sub-Saharan Africa face financial barriers to accessing healthcare, including out-of-pocket expenses and a lack of health insurance coverage (Su and Kouyaté, 2015).

For policymakers and actors in global health according to Chewe and Hangoma, (2020) to adequately design policies and interventions to accelerate improvements in life expectancy and infant mortality, they must acquire a comprehensive understanding of the influence of various macro level determinants of health on these health indicators. Understanding the effects of macro-level determinants could provide policymakers with the evidence that they need to design targeted interventions and policies to rapidly improve health outcomes in the population.

2-5-2 **Education and literacy**

Sub-Saharan African nations, like the majority of nations globally, are working to develop their human capital in order to compete for investments and jobs in a world that is becoming more interconnected. The region is home to the greatest number of nations that have not yet achieved universal primary education. Therefore, education and literacy in sub-Saharan Africa have been areas of concern and focus for several decades.

2-5-2-1 **School enrolment**

School enrolment refers to the number of students officially registered or attending a particular level of education, such as primary or secondary within a specified time frame. It is a key indicator used to assess the extent to which children and young people are participating in the formal education system as defined by UN development department.

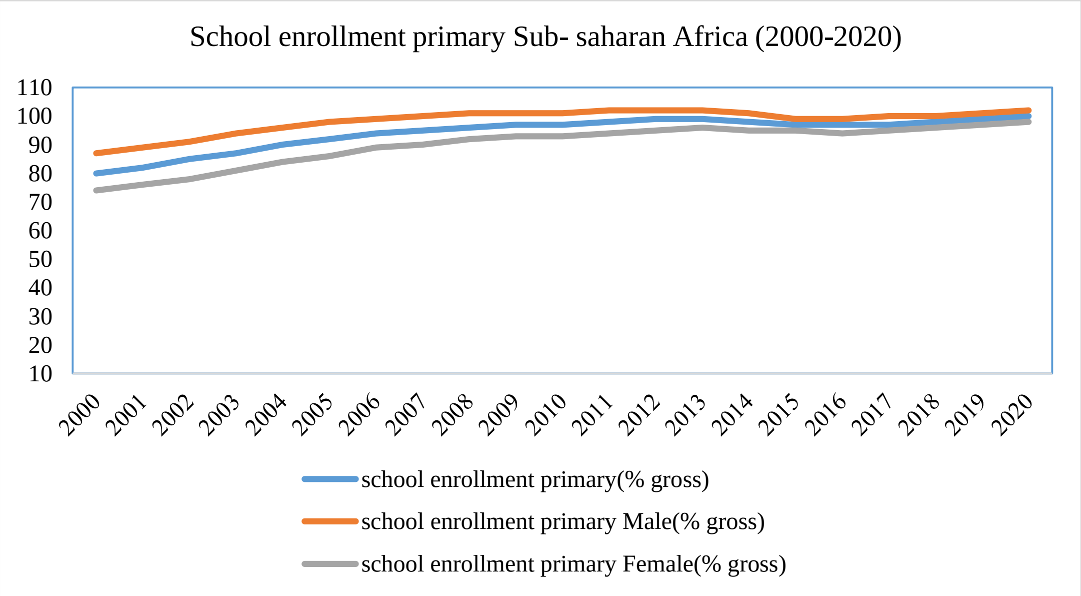

Figure 2-6 School enrolment, primary for Sub- Saharan Africa

Sources of the figures: author’s compilation based on data obtained from the World Bank.

As shown in figure 2-6 Sub-Saharan Africa has made progress in improving primary school enrolment gross[4] rate over the years increased from 80% in 2000 to 98% in 2020. However, gender disparities persist in sub-Saharan African countries, with girls facing greater challenges in accessing education as described in figure (2.6). UNESCO's Global Education Monitoring Report (2020) highlighted that sub-Saharan Africa has the highest out-of-school rates globally, with over 32 million children of primary school age out of school. Referred that to conflicts and political instability have disrupted educational systems, leading to displacement, destruction of schools, and a decline in education quality, moreover poverty and cultural norms (Global Education Monitoring Report, 2020).

2-5-2-2 **Literacy rates**

Literacy rate is the another measure for education, and it is defined as the percentage of people ages 15 and above who can both read and write with understanding a short simple statement about their everyday life (UNDP, 1995).

There have been improvements in literacy rates in sub-Saharan Africa was 67.27% in 2019 increased by a 70.21% in 2020 as described in figure (2-7). However, sub Saharan Africa still lags behind other regions (World bank, 2019).

[4] Please note that enrolment rate expressed as gross enrolment rates which include students of the official age group as a percentage of the total population of that age group as defined by World Bank.

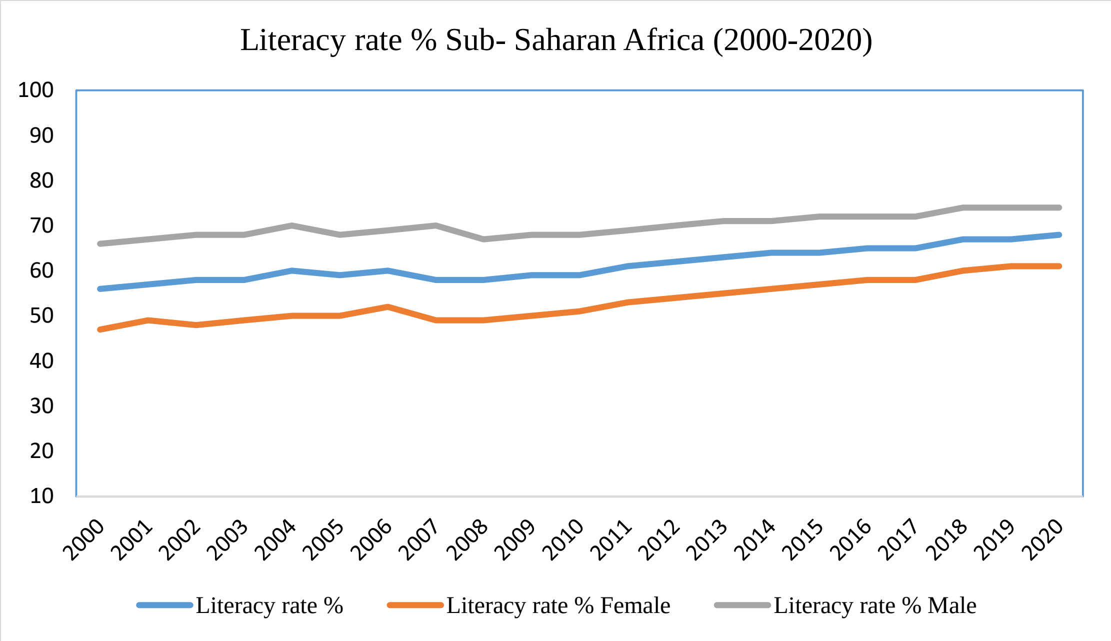

Figure 2-7 Literacy rate % for Sub- Saharan Africa

Sources of the figures: author's compilation based on data obtained from the World Bank.

Gender disparities in literacy rates persisted in Sub Saharan Africa, with females often having lower literacy rates than males, in 2020 the percentage of literate females was 61%, compared to 74 percent of males as illustrated in figure 2-7.

In general, the region's literate population has been gradually increasing, with a significant gender disparity being prevalent.

2-5-3 **Standard of living**

Standard of living is one of the main dimensions in the human development index is represented by Gross National Income (GNI) per capita, which takes into account the economic dimension of human development. Figure 2-8 illustrates the Gross National Income per capita in US dollars for Sub-Saharan Africa during the period 2000-2020.

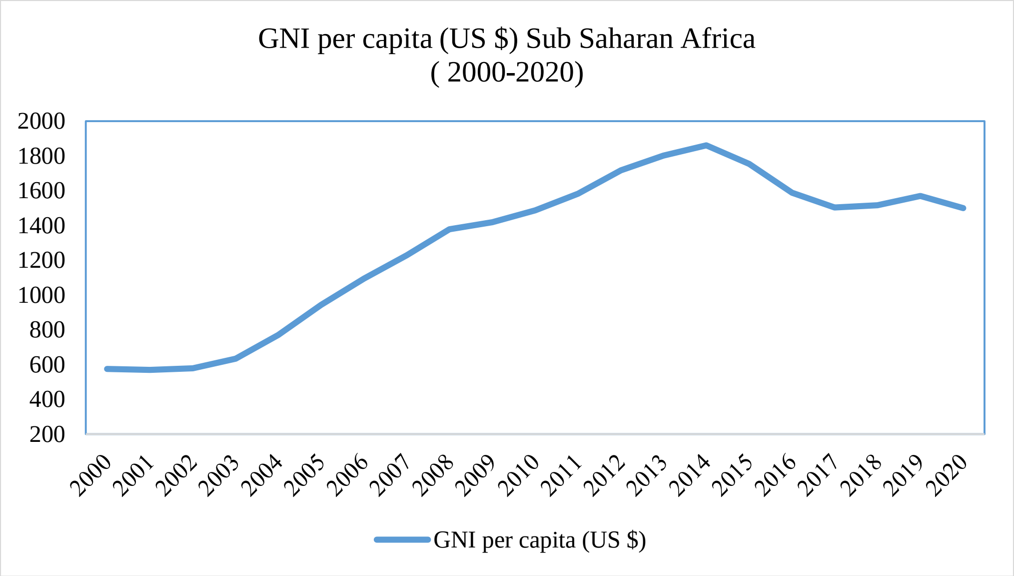

Figure 2-8 Gross National Income (GNI) per capita for Sub- Saharan Africa

Sources of the figures: author’s compilation based on data obtained from the World Bank.

As clearly seen in figure 2-8, the GNI per capita has been increasing over the time. The range of GNI per capita within the SSA was $575 in 2000 to reach to the maximum at $1861 in 2014, then declined to $1500 in 2020. However, still those countries have low level of GNI compared with the world average GNI per capita which is around $17,500 (World Bank, 2020).

The low gross national income per capita can be attributed to a combination of factors. For instance, colonial legacy; many Sub Saharan Africa countries has had long lasting economic effect colonial power often exploited resources without investing in infrastructure or human capita development (Collier, 2007).

Economic structure is a key factor attributed to low GNI in those countries, several economics in Sub Saharan Africa are characterized by heavy reliance on primary sectors such as an agriculture, mining and extraction of natural resources as crude oil. Dependency on a few key industries can make countries vulnerable to commodity price fluctuation and hinder the development of more diverse and resilient (African Development Bank, 2019).

Political instability, corruption and weak governance structure have been challenges in most Sub Saharan Africa countries. These factors can deter foreign investment, hinder economic development and contribute to inefficient resource allocation (World Bank, 2018).

Overall, human development in SSA is a dynamic process influenced by a myriad of factors. While marginal progress has been achieved, persistent challenges necessitate continuous efforts and innovative approaches to ensure sustainable development for all.

CHAPTER THREE: LITERATURE REVIEW

This chapter seeks to review previous studies, in order to highlight the theoretical and empirical literature related to natural resource wealth and its impact on Human Development Index (HDI) dimensions, focusing on oil producing and exporting sub-Saharan Africa countries.

3-1 INCOME PER CAPITA

Gross national income per capita (GNI) is the significant component of human development index, which is required for decent living; it is perhaps the most important factor toward human development, especially for individual. It reflects the variety of capabilities that individuals value intensely and which are not addressed adequately in figures of both life expectancy and education (Anand and Sen, 2000). According to Arisman (2018), theoretically, one factor that can accelerate the HDI is the increase in per capita income. Hasan (2013) and Eren et al. (2014) claim that GDP per capita affects the level of development, and this improvement will increase the purchasing power of people and in the end will improve the quality of education and health. Anyanwu (2017) states that one of the most important driving forces for reducing poverty, especially in the region (SSA) is higher economic development (per capita income).

However, natural resources income is a function of several factors which might have significant impact on government spending, thus human development, such as volatility in commodity prices. In this regard, Nili and Rastad (2007) state that oil economies[5] have experienced a fall in average per capita income by 29% over the period 1975 to 2000. This compares to the rest of the world, whose average per capita income increased by 34% over the same twenty-five-year period. In their comparative study between oil economies[6] and non-oil countries[7] they

[5] Oil economics: are those oil exports that constitute more than 10% of their GDP and 40% of total exports.

[6] Algeria, Brunei, Congo Rep., Gabon, Iran, Kuwait, Nigeria, Oman, Saudi Arabia, Trinidad and Tobago, United Arab Emirates and Venezuela.

[7] Including 132 non-oil countries and in some cases, is restricted to 78 developing countries.

investigated the causal relationship between financial development and economic growth. The study considers the indicators of financial intermediary development variables as a share of GDP, in addition per capita GDP growth rates, the index of rule of law (related to the quality of institutions) and the investment rates. The generalized method of moments (GMM) is constructed to estimate dynamic panel models. A weak correlation between investment and financial indicators was found in oil exporting countries compared with non-oil countries, which referred to these countries that are usually subject to considerable commodity price volatility and suffer from a high degree of macroeconomic instability, which sequentially might have negative effects for their GDP per capita (Nili and Rastad, 2007). Plus, the lack of financial development associated with a weakened role of government contributed to the poor economic growth and caused the low level of GDP per capita and crowded out foreign direct investment.

The study conducted by Van der Ploeg and Poelhekke (2009), included cross-country data from 1970 to 2003 using maximum likelihood (ML) fixed-effects panel techniques. The study presented evidence that volatility of unanticipated GDP per capita growth has a significant negative impact on economic growth, which is caused by the high volatility of international prices in countries that depend heavily on them. They found that ‘countries with share of natural exports to GDP greater than 19% have a standard deviation of output growth of 7.3% compared to standard division of only 2.83% for countries with resource export/GDP ratio of less than 5%’, but the effect depends on a country’s level of financial development. The authors claim that effective financial systems can reduce the impact of sudden fluctuations in resource income, and in addition, openness and physical access to world trade can also help to reduce the level of volatility and boost development. However, the study utilized unanticipated output growth variable, which was caused by factors that are not directly linked to natural resources abundance and are probably endogenous.

Keikha et al. (2012) investigated the impacts of oil prices on economic growth in 32 oil-rich countries covering the period from 1975 to 2010. The dependent variable is economic growth of oil exporting countries, and the independent variables are ratio of investment to domestic gross product, commercial independence or openness, oil price and index of institutional quality use as control variable by applying panel co-integration and an error correction model. They found that high institutional quality combined with trade openness helps countries avoid the negative impacts of oil price fluctuations and would have a significant effect on economic growth. In addition, if oil-exporting countries have poor institutional quality, they will have significant challenges in long-term economic growth.

Cavalcanti (2015) investigated whether volatility of commodity terms of trade (CToT) has a negative effect on GDP per capita growth in primary commodity abundant countries, using data that covered the period from 1970 to 2007 on real GDP per capita and CToT index based on the prices of 32 primary commodities. Both systems generalized methods of moments (GMM) approach and the dynamic common correlated effects pooled mean group estimator were applied. The result shows that the higher volatility of CToT harms GDP for primary commodity exports, the channels through which this effect operates, notably physical and human capital accumulation, which consider volatility as a fundamental barrier of economic prosperity. The finding also illustrates that, on the contrary, for countries with a more diversified export basket, CToT volatility is not significantly related to GDP per capita growth. Therefore, effective policy is to play a role to capture the transmission of volatility to growth. For instance, through managing resource rents from commodity export windfalls by investing in human and physical capital and insulating against external shocks by conducting structural reforms, which can greatly benefit from natural resources in the long run.

3-1-1 **Income inequality**

The poverty rate, which affects living quality; in SSA has increased by 1% (World Bank report, 2018). According to Bicaba et al. (2017) poverty will not be eliminated in SSA by 2030, but it can be reduced to low levels through high growth and income redistribution towards the poor segments of society. This means, even if natural resources do not affect per capita income directly, the negative impact on income distribution or inequality will still lead to a curse on human development.

In September 2015, the agenda for sustainable development and its 17 Sustainable Development Goals (SDGs) drew a great deal of attention to income inequality in sub-Saharan Africa (SSA), to achieve the goal of ‘no one left behind’ by 2030 (Corina etal., 2017). The United Nations Development Programme (UNDP) Regional Bureau for African needs to properly document the income inequality levels, trends, determinants and outcomes of the region. The UNDP considers the 2030 agenda to be an integrated indivisible agenda. It is important to understand that addressing the challenges of justice will accelerate progress towards the achievement of the SDGs. However, several countries in sub-Saharan Africa still show the characteristics of non-egalitarian societies. Following Latin America, the region has the world’s second-highest income inequality, even though the average unweighted Gini coefficient between 1991 and 2014 fell by 3.4% points (UNDP, 2017) it stands at about 0.58, so sub-Saharan Africa is considered a home of ten out of nineteen most unequal countries in the world (UNDP, 2017).

As a consequence, a high level of income inequality puts pressure on the economy over the years. Income inequality can be a signal of a lower level of mobility and lack of opportunities, reflecting a permanent disadvantage to certain segments of society. In addition, it has significant implications for growth and macroeconomic stability, thus raises crisis risk, e.g. conflict (Corak, 2013).

High and sustained levels of income inequality have an adverse effect that undermines the opportunities to access quality education and efficient health care services. It can significantly undermine individuals' educational and occupational choices and health status, affecting consumption of food and preventive and therapeutic medical consumption, due to disproportionately low incomes for poor households (Birdsall et al., 1995; Subramanian and Kawachi, 2004; Torre and Myrskyla, 2011). It also has the tendency to reduce life expectancy, even beyond its absolute value, due to extremely poor health outcomes in SSA, which is still far from achieving the Sustainable Development Goals' (SDGs) targets, especially in reducing child mortality (United Nations, 2017b). It makes a greater proportion of the population vulnerable to poverty.

The causes of income inequality on an individual basis can be attached to the variations that are related to their income and other socio-economic issues. These involve differences in human capital, skills, employment, and so forth. These differences can be seen on a national scale, which determines income inequality (Corina etal., 2017).

However, generally in Africa it can be traced back to different standard traditional explanations; for instance, access to land rights. There are many reasons to believe income inequality observed in a handful countries are linked to a significant community of settler farms there before independence in Africa. Settler colonialism, such as in South Africa and Zimbabwe, Kenya, Namibia, has contributed to serious rural inequality, resulting in a very small number of Europeans owning a very disproportionate share of arable land (Manji, 2001). Land struggles have intensified significantly in recent years as population pressures and ecosystem declines have increased. In addition, geographical locations between cities and villages, and poor infrastructure contributed more to uneven access to economic and other resources that worsened income inequality in Africa.

Another explanation was based on Kuznets curve (1955), which argues that inequality initially increases with increasing income, but then declines again in an inverted U shape with higher income levels (Fallers, 1964: cited in Van de Walle, 2009). It may also be possible as a result of structural changes in the economy at various stages of development (higher levels of inequality at intermediate levels of GDP per head when the economy begins to industrialize) (Parcero and Papyrakis, 2016). That means inequality was unlikely to happen in an economy where there is almost no accumulation of capitalists (Hyden, 1983; cited in Van de Walle, 2009). Based on this argument, Africa’s poorest and least-developed countries were expected to show low inequality.

Indeed, Kuznets curve has been criticized, e.g. according to Banya (1995), Kuznets inverted U curve is not a theory, rather a pattern of development. Thus, the inverted U pattern does not explain income inequality. Acemoglu and Robinson (2002) said that the experimental legitimacy of Kuznet’s discoveries has been totally explored, however, the proof is blended. One of the issues with Kuznets curve is the way that information came from a small sample (included few countries that had the availability of long time series data). That means, it would cause a problem of extrapolation as the findings cannot be fully applied to less-developed countries.

The other traditional explanation responsible for high levels of income inequality in developing countries can be referred to globalization and trade openness (Monfort and Nicolini, 2000; Paluzie, 2001). Market integration aggravates income inequality due to the fact that an upward thrust in worldwide exchange consequences, results in a growth in profits of rich owners of factors of production, and decreases the profits of the proprietors of scarce factors. Manufacturing in most developed countries, is coupled with the supply of skilled workers, which is capital intensive. Market integration through trading is more likely to be more beneficial to skilled labour than unskilled workers, thereby increasing inequality. Moreover, in developing countries the income inequality characterized by labour intensive production and trading is expected to worsen (Gimba et al., 2021). According to Ukpere (2011), statistics show that globalization is influential in widening Africa's income inequality. The opening of borders for the free movement of goods, capital and other services has created prosperity. However, cheap labour and the availability of natural resources have led to marginalization by foreigners and multinationals, reflected in the high level of income inequality that exists.

However, there is an argument about the association between income inequality and market integration; it may be positive (Ezcurra and Rodríguez-Pose, 2013; Rodríguez-Pose, 2012) or negative (Asteriou et al., 2014; Zhou et al., 2011), depending on the spatial effect of trade integration (i.e. the pattern of internal dispersion or aggregation of economic activity and comparative advantage).

Trade openness may also be associated with reporting behaviour at the national level; some countries that are open for trade have no incentive to disclose income inequality information to business partners if high-income inequality is likely to act as an obstacle to foreign investment. For example, income inequality is usually associated with rising crime rates and political uncertainty. Richer economies, on the other hand, are more likely to have better equipped administrations and statistical agencies to collect and report statistics on a regular basis on inequality, as well as other variables (Williams, 2011 cited in Langnel et al., 2021).

In terms of natural resources and the link with rise of income inequality, Odusola et al. (2017) consider unequal distribution of national resources as an important factor driving income inequality, due to weak resource governance bodies that lead to the classic case of the resources curse.

Income inequality is a critical consideration in the context of natural resource governance, as unequal distribution of national resources can exacerbate disparities in wealth and opportunity within a society. Weak governance structures, as highlighted by Tornell and Lane (1999), can perpetuate a cycle of inequality by fostering rent-seeking behaviour and corruption, particularly in countries with low institutional quality. This "voracity effect" can lead to wastage of resource revenues and hinder inclusive development efforts (Tornell and Lane, 1999, p. 22). From a political economy perspective, Collier and Hoeffler (2009) argue that because resource rents are not created through taxation, citizens in resource rich economies frequently have little or no desire for accountability from their governments. As a result, governments are under less pressure to use revenues effectively. A study conducted by Veloso (2015) investigates the link between windfall and the standard of living in both the short and long term for 130 countries, for all continents with more concentration on 28 sub-Saharan African countries from 1963 to 2007. Panel data sets for welfare index, which include GDP, income inequality (Gini coefficient) and life expectancy and resources windfall index[8] were used. The empirical evidence shows that SSA countries have not only poor economic performance but also poor income distribution and health conditions, resulting from weaknesses in management, both natural resource rents and macroeconomic effects. In addition, poor governance in some SSA countries seem to have played an important role in inclusive development.

Furthermore, the management of resource wealth plays a pivotal role in determining the impact of oil rents on income inequality. Extractive institutions, as described by Acemoglu and Robinson (2012), prioritize the interests of the ruling elite over broader societal well-being, contributing to higher levels of income inequality and hindered human development. Weak governance can also lead to elite capture of resources, further exacerbating disparities in wealth distribution.

The interconnectedness between income inequality and key indicators of human development, such as education and healthcare, underscores the importance of addressing inequality for

[8] The index consists of average of various commodity prices weighted by exports of each commodity for a given country.

promoting inclusive development. High levels of inequality can limit social mobility, perpetuate poverty traps, and impede efforts to improve living standards for the entire population (White, 2017). According to the (World Inequality Report, 2022), persistent income disparities can hinder progress towards achieving key human development indicators, such as reducing child mortality rates, improving literacy rates, and promoting gender equality.

In principle, oil rents can be associated with low-income inequality if the revenues are significantly redistributed and is potentially targeting the low-income group. But Gylfason and Zoega (2003) argue that natural-resources wealth can be positively correlated with income inequality if the distribution of natural capital is more unequal compared to other forms of capital in the economy.

Discoveries of natural resources lead to weakened institutions given political capture of rents (Esther and Hauk, 2011). Natural resources are thought to increase income inequality in three ways. First, it can affect the quality of the system and reduce the availability of publicly funded medical and educational facilities. Because, for those who most benefit from this publicly funded supply, this reduction in supply will disproportionately reduce the health, education, and subsequent income of the poor and increase income inequality.

Second, this higher inequality amplifies the negative impact of resource dependence on the quality of the system. As Li et al., (1998) and Auty (2001) argue, the rich can make better use of their political power to redirect scarce public funds for the purpose of benefiting them and further increases income inequality, compared with lower health educational or social relocation of funds that benefits the poor.

Third, natural resources concentrate in the few hands (elite) that own or invest income extracted sectors compared to sectors with a large distribution of ownership, such as the manufacturing industry. Increasing income inequality reduces the accumulation of human capital by increasing the liquidity constraints of those at the lower end of income distribution. So, the poor may not be able to borrow for health or education, even if it would offer them a high rate of return. Moreover, Leamer et al. (1999) argue that workers in resource-rich economies are unprepared for the advent of human capital-intensive manufacturing, because resource exploitation does not require much human capital. As a result, these economies may experience greater income inequality than resource-poor economies for longer periods of time.

Indeed, a handful of studies precisely look at the association between resource abundance and income inequality. In contributing to the debate over whether economic growth exacerbates income inequality or reduces the equal distribution of income, Gylfason and Zoega (2003) claim that resource dependence leads to both lower growth and increased income inequality and that could clarify the opposite association among growth and natural resources income in cross-country data for 74 countries. They regress the Gini index on initial per-capita income (linear and squared) and the share of natural capital in total capital. The finding shows that the estimated coefficient of the natural capital share is 0.30, with a t-ratio of 2.84, which means that natural resources significantly increase income inequality. Adinde (2017) examines whether economic growth effect on income inequality follows Kuznets inverted U hypothesis in Nigeria, in addition to identifying the relationship between income inequality and economic growth. A quadratic model was applied, and the result confirms that the Kuznets inverted U curve does not hold for Nigeria; the finding shows also that GDP growth derives income inequality. Moreover, the multiple regression analysis confirms that income inequality in Nigeria is determined by GDP, CPI, population growth and education.

To explore the nature of association between natural resources and income inequality, Parcero and Papyrakis (2016) investigate the relationship between oil dependence/ abundance and income inequality for cross-country using standardized world income inequality data base with more attention to the tendency of oil rich nations to under-report relevant data. To validate the tendency of oil-rich countries to under-report and correct for any bias that may develop as a result of this, Heckman selection models were used. The finding illustrates that oil resources nations are associated with greater income inequality, especially countries that are extremely dependent on oil exports.

Mallaye et al. (2015) conducted a study to investigate the effect of oil rents on income inequality, which included 52 developed and developing oil economic countries covering the period from 1984 to 2008 and applied the GMM technique. They point out that the relationship between oil rents and income inequality is non-linear, and also concluded that the effect of oil rents on income inequality is conditional to quality of governance. A similar study by Mallaye (2015) included 40 developing nations to examine the effect of oil rent on income inequality over the period from 1996 to 2008, applied dynamic panel data methods. The outcome illustrates that non-linear relationships between oil rent and income inequality have been spotted, more explicitly, in the short run, oil rents decline with income inequality as the oil incomes increase. The study also documented that the fall in income inequality as a result of increase in oil rents due to increasing corruption. However, those studies generally do not clearly show the empirical mechanisms of the connection.

In regard to the issue of political institutional efficacy, Hartwell et al., (2019) investigate how democratic institutions impact the relationship between natural resources and income inequality, with the hypothesis that democracy can help to mitigate the effects of resources on income inequality. The study applied a cross-country regression analysis during the period from 1980 to 2009 for less development countries. The finding implies that, there is no relationship between resource rents and income inequality unless one takes into account political institutions.

In particular, it appears that democracies tend to minimize resource-related inequality relative to more authoritarian states. Lee (2005) conducted a study that combines and evaluates different ideas for how the size of the public sector and democracy affect income inequality.

The study included 64 developed and development countries, covered the period from 1970 to 1994, and used unbalanced panel data. The finding illustrates that, as a result of successful targeted redistribution, fully institutionalized democracy has lower income inequality. In contrast, in more authoritarian regimes, government may use the civic sector and monetary sector with particular industries and lobby groups with vested interests in government policies. There was an interesting study conducted by Carmignani (2012) to understand resource abundance influences on human development. The author tests two hypotheses, (i) whether resources abundance raises inequality of income distribution and (ii) if increased income inequality would lower human development. By applying an estimation of system equations, using cross-sectional data for the period 1970 to 2010 it shows that, there is strong evidence that natural resources directly and indirectly affect human development through income inequality because of the lack of quality of the institutions. This amplifies the negative impact of resources on both inequality and human development, however, this effect is minimal in terms of magnitude.

In assessing the effect of some factors on income distribution, a recent a study by Gimba et al., (2021) investigated the factors behind the rising of income inequality in SSA for the period 2000 to 2017. Applying bootstrap cointegration to test the long-run relationship and ARDL technique, the study included economic growth, population growth, trade globalization, corruption and unemployment rate as independent variables, with the Gini index which measures the income inequality as a dependent variable. The finding illustrates that in the long run economic growth promotes income inequality; likewise, reducing corruption across SSA will help equalize income. While trade globalization deteriorates the income distribution of the SSA countries, on the contrary for central and east African countries trade globalization reduce the problem of unequal distribution income. It has also been empirically confirmed that rising unemployment is supporting rising income inequality in SSA and its sub- region. The result also confirmed that population growth rate is a key driver of income inequality. Xu., et al. (2020) used panel data from 2000 to 2015 and the generalized method of moment (GMM) technique, investigating the relationship between trade openness, foreign direct investment (FDI), and income inequality in sub-Saharan Africa. The data reveals that FDI has a statistically significant negative association with income inequality, implying that if FDI and per capita income rise, the level of income inequality decreases. On the other hand, trade openness, education, political stability, corruption, and the rule of law, have a significant positive correlation with income inequality. The study recommended adopting policies to attract more foreign investors, which will contribute to the creation of jobs in the region. In addition, more infrastructure is needed to provide high-quality education. Implementing an effective policy to encourage local production will help to create jobs and create a robust anti-corruption institution.

Bekele (2020) examines the impact of macroeconomic indicators such as economic growth, inflation, unemployment, foreign direct investment, financial sector development, population growth rate, political instability, regulatory quality and corruption on income inequality for selected SSA countries. The results show that in the short run, a positive relationship between economic growth and income inequality exists; on the contrary, in the long run, a negative association has been found. This means that inequality tends to increase at early growth levels but decreases in the long run. As for foreign direct funding, this has been found to aid decreasing the capacity on income inequality, while unemployment, population growth rate, and corruption were found to have an increasing impact on income inequality.

In contrast to several studies that consider income inequality as a dependent variable and corruption as an independent variable, Sulemana and Kpienbaareh (2018) assume that income inequality may affect corruption. Using unbalanced panel data for 48 SSA countries, they found that rising inequality is linked to lower levels of corruption – their results also oppose the findings from developed countries. Kunawotor et al. (2020) employed a dynamic GMM regression to investigate the impact of institutional quality on income inequality in Africa and found that institutions have no important role in driving income inequality. However, enforcing the rule of law is critical to fostering equitable income distribution in Africa.

Adams and Klobodu (2016) use the pooled mean group estimator to examine the role of financial development and corruption management on income distribution in SSA. Their results have come to the conclusion that financial development aggravates the unequal distribution of income. However, managing corruption and transparency has been shown to reduce the incidence of income inequality. In a case study, Anyanwu et al. (2016) assessed the key drivers of income inequality in West Africa and applied the dynamic GMM estimation technique. Their contribution is to show why income inequality is important, to empirically verify internal and external factors for income inequality, and to use a broad dataset on net income inequality in West Africa. The finding confirms the Kuznets hypothesis. It also shows that income inequality will decline with access to secondary education, age dependency and democracy. However, trade openness, population density, foreign direct investment, natural resources, civil unrest, domestic investment, and government consumption can worsen the unequal income distribution. In another study, Anyanwu (2016) investigates the primary drivers of income inequality in Southern Africa. Anyanwu (2016) finds that past levels of income inequality are connected to the present level of inequality. An increase in population growth rate also increases income inequality, whereas access to secondary education and availability of natural resources reduces the incidence of income inequality. To determine whether rising income inequality is caused by trade openness or financial globalization,

Jaumotte et al. (2008) look at both high- and low-income nations using cross-country analysis. They found that technological advancement and globalization is thought to have a greater impact on income inequality – both boost the returns on human capital. In addition, trade openness and export growth are associated with lower income inequality, whereas foreign direct investment has been shown to aggravate income inequality.

3-2 EDUCATION AND HEALTH COMPONENTS

The United Nations Human Development Index (HDI) provides a comprehensive measure of human development, integrating economic indicators, education, and health. This section explores the intricate connections between these dimensions and their relevance to understanding the impact of oil rents on human development in Sub-Saharan Africa (SSA).

Relying solely on per capita income as a measure of human development can be misleading. The HDI incorporates education, measured by expected years of schooling for children and mean years of schooling for adults, and health, measured by life expectancy at birth, to provide a more comprehensive view of development (UNDP, 1995). These components influence income, poverty, and inequality, aligning with our research goal of examining the interplay between oil rents and HDI components.

In fact, the role of human capital in promoting economic development is well documented in the literature, early theoretical foundations have been concerned about human development. Adam Smith emphasized the importance of human abilities for improving quality of life, while Solow and Swan (1956) highlighted the role of human capital in their growth theory. Hartwick (1977) suggested that rental income from non-renewable resources should be reinvested in physical or renewable capital. Thus, these theories widely assumed there are associations between resources wealth and human capital accumulation.

Empirical studies offer diverse perspectives on the relationship between natural resource wealth and investments in education and health.

The most popular input measure on education and health is government expenditure, which is considered as the main key to promote human development. The reasoning for government spending on human capital has various impacts: it may improve human quality (Sachs and Warner 1997; Robinson et al., 2006; Cabrales and Hauk 2010; Arezki and Gylfason 2013; Devarajan;1995, 2019); boost the economic growth process (Barro and Salai-i-Martin, 1995; Barro,1996); reduce poverty (Squire, 1993; Schultz, 1999; Nazar and Tabar, 2013), or contribute to development and aid natural resources countries' escape from the resource curse (Atkinson and Hamilton, 2003).

In fact, the role of human capital in promoting economic development is well documented in the literature, for instance, Adam Smith's approach focuses on human abilities in some areas that are important to quality of life. Solow and Swan (1956) proposed a growth theory that emphasized human capital (labour) as the most important factor in promoting economic growth, alongside capital and technology. Therefore, human capital has received a great deal of attention in the empirical literature of economic growth, particularly in the context of the endogenous growth theory.

From the perspective of economic development, human capital accumulation that accompanies mineral activities should be positive. Hence, it is argued that rental income from non-renewable resources of should be invested in the development of physical capital (Hartwick, 1977) or generating renewable natural capital. Thus, it is widely assumed in the literature there are associations between natural resources wealth and human capital accumulation.

The literature provided various studies related to the linkage between natural resources (in different forms) and education or health separately, while few studies introduced both education and health, as they considered both health and education are measures of public investment.

The most popular input measure on education and health is government expenditure, which is considered as the main key to promote human development. The reasoning for government spending on human capital has various impacts: it may improve human quality (Sachs and Warner 1997; Robinson et al., 2006; Cabrales and Hauk 2010; Arezki and Gylfason 2013; Devarajan;1995, 2019); boost the economic growth process (Barro and Salai-i-Martin, 1995; Barro,1996); reduce poverty (Squire, 1993; Schultz, 1999; Nazar and Tabar, 2013), or contribute to development and aid natural resources countries' escape from the resource curse (Atkinson and Hamilton, 2003).

A crucial result regarding public spending on education was found by Cupta et al. (2002) and Baldacci et al. (2003). Both studies found an association between government spending on education and improving accomplishment in schools. Anyanwu and Erhijakper (2007) used panel data over the period from 1990 to 2002 to investigate the relationship between government expenditure on education enrolments for Nigeria and SANE[9] countries. The paper found that other policy interventions, such as consolidating and sustaining democracy, accelerating national income, and the international community fulfilling its aid promises to Africa, could help those countries in moving toward Millennium Development Goals (MDGs). However, increasing spending alone is not enough to achieve the MDGs or increase the quantity and quality of human capital.

Karimu et al. (2017) examine the key features of the connection between public investment (health and education) and resource rents in SSA countries and whether natural resources play any significant role in scaling-up public investment. Using panel data, applying the fixed effect model and pooled OLS estimator, covering the period 1990 to 2013. The variables under investigation were, resource rents, real GDP growth, investment aid, trade openness and institutional variables, e.g. polity index and institutional index. The empirical results show that

[9] It includes 4 countries, South Africa, Algeria, Nigeria and Egypt.

resource rents have a positive impact on public investment. Regardless of the measure employed to count public capital spending (public investment rate or public capital stock), the positive effect persists. Evidence also suggests that resource rents, investment aid, external debt stock, trade openness, political institutions, and the relationship between political institutions and resource rents are all important drivers of public investment, albeit with varying magnitudes of influence. Furthermore, the finding shows that public investment has a positive impact on economic growth, with the magnitude of the benefit varying depending on the level of resource rents. Ibrahim et al. (2018) investigated whether natural resource rents are important for augmenting expenditures on education and health to enhance the inclusion of human capital for inclusive growth process. The study included 18 SSA countries and covered the period from 1995 to 2014, by the estimating panel model. It was found that augmenting health spending with natural resources, on the other hand, appears to be more important for ensuring that the growth process is inclusive. In particular, they found that increasing government expenditure on health increases GDP per capita growth in these countries but this says nothing about whether this growth is inclusive.

In contrast, other authors find that public expenditure has a negative impact on education and health. Issa and Ouattara (2005) disaggregate health expenditure into private and public and divide the countries into two groups according to their level of development (income). Using panel data of 160 countries, their results show a strong negative relation between health expenditure and infant mortality rates. Similarly, Cockx and Francken (2014) used a panel data set of world countries covering the period from 1991 to 2009 to investigate whether and via which transmission channels natural resource wealth influences social spending. They investigate the relationship between natural resource wealth and public health spending. The findings imply that robust significant adverse link between public health spending and resource abundance over time. Even after accounting of state autonomy, volatility, and other variables, the effect is still quite substantial. In another study, Cockx and Francken (2015) explore the relationship between natural resource dependence and public education spending for 140 countries (SSA included) over the period 1995 to 2009; they found that resource rents, particularly from point source resources[10], crowd-out public expenditure on education. This result is consistent with Philippot (2010) who investigates the nexus between natural resources and human capital accumulation for 208 countries (SSA included) during the period from 1990 to 2003, using country-fixed effects. The result illustrates that the share of resource rents in GDP is adversely related to public education spending and enrolment rates; additionally, he discovers that point resources[11] have a greater detrimental impact than diffuse resources[12]. However, the use of public education expenditures is an imperfect representative of national commitment, as some societies prioritize private education over others. While Kim and Lin (2017) found mixed results, they examine the long-run relationship of natural resource dependence with human capital (education and heath), applying a dynamic heterogeneous panel cointegration estimator, including 55 developing and advanced countries for the period 1970 to 2011. The result shows that the positive effects of resource dependence on national education are more pronounced in the later stages of economic development, better legal quality, greater democratization, less corruption, and more homogeneous societies increase. On the other hand, the adverse health effects of resource dependence are more pronounced in countries with opposite characteristics**.** The study suggests that policies for better economic and political institutions and reduction of ethnic tensions or conflicts will help resource-rich countries to accumulate more education and health capital.

However, Gylfason (2001) argues that the dependency on natural resources capital for government expenditures may affect government policy and planning, due to volatility of

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[10] Hydrocarbon, mining products, plantation crops.
[11] E.g. Oil and Minerals.
[12] E.g. agricultural products.

natural commodity price and international market uncertainty. In addition, as the extraction of natural resource is considered capital intensive, they may be pushed into supporting capital accumulation rat the expense of public spending on education and health. For instance, Bloom and Sacha (1998) argued that sub-Saharan Africa countries are vulnerable to volatility of commodity prices, as it depends on natural resources income; therefore, may affect the real exchange rate that hence cause failing in investment in both physical capital and learning.

Despite literacy rates having improved lately in sub-Saharan Africa, in an early study, (by Gylfason et al., 1999; Gylfason, 2001) discussed that dependency on natural capitals may reduce people's motivation to accumulate human capital due to high levels of non-wage income or resource-based wages. He provides evidence that school enrolment for 90 resource-rich developing countries at all stages have an inverse correlation to natural resource dependence. Similarly, Birdsall et al. (2001) argued that schooling may turn into consumption good, instead of investment good, since the characteristic of the natural resource sector is providing few occupations which require exceptionally taught workers, and those jobs are usually allocated to members of the elite. Therefore, outsiders may find it hard to find such jobs; even if they get adequate skills in this situation, young people may find that investing in education would have little impact on their hopes in the labour market and as a consequence education will be inefficient.

In terms of the income distribution's influence on health and educational outcomes, it has been noted that high income inequality has a negative impact on access to quality education and effective health care services, especially for low-income people and marginalized ethnic groups (African Development Bank, 2015). Sub-Saharan Africa has long been regarded as the world's most unequal region, second only to Latin America (Cord et al., 2013 cited in Getaye Molla, 2021), Although the average unweighted Gini for SSA declined by 3.4% points between 1991 and 2011, according to the human capital report that was presented by World Economic

Forum's 2019; whereas the global average human capital gap is 38%, SSA's is 47% implying that the region is leveraging less than half of its human resources. Scholars attributed that to poor institutions, poor infrastructure, and policy failures (Oyinlola et al., 2020, p. 88). Additionally, high income inequality made sub-Saharan Africa a home of ten out of nineteen most unequal countries in the world (UNDP, 2017).

Human capital in terms of education is emphasized in the literature as one of the main elements impacting the degree of income disparity. Although higher education investment is frequently justified by policymakers as a highly effective instrument for reducing income disparity. The theoretical literature indicates that the relationship between education and income inequality is not clear (Johansen, 2014).

A study by Checchi (2004) uses an unbalanced panel of 108 countries from 1960 to 1995 to examine the link between income inequality and human capital in terms of education. His key finding is that there is a negative link between income disparity and secondary school enrolment. A recent study conducted by Getaye Molla (2021), investigates the relationship between income inequality and human capital. The study uses fixed effect panel data analysis with least square dummy variable for 25 nations in sub-Saharan Africa, covering the period from 1984 to 2016. The empirical findings show that human capital has a negative impact on income disparity in terms of secondary school enrolment rate. The study also discovered a U-shaped association between real gross domestic product per capita and income inequality, contradicting the Kuznets curve theory. In contrast, Johansen (2014) examines and analyses the impact of human capital on income inequality for the period including 123 countries. The study considers educational attainment as a proxy for human capital to investigate its effect. A two-stage least squares estimator is utilized to solve the problem of endogeneity using parents' education as an instrument. The results of the instrumental variable estimation show that the nexus between income inequality and education is still a puzzle, i.e. are people more educated as a result of their greater income or do people have a high income because they have higher education?

Overall, this section reveals a substantial body of work linking human capital accumulation to human development, emphasizing the positive role of education and health. Notably, studies argue that government expenditure on education and health serves as a key driver of human development. As we explore the intersection of public investment, resource rents, and economic growth, our focus directly aligns with the goal of understanding how these factors contribute to or hinder human development.

Crucially, examine the impact of resource rents on education and health spending finds resonance in studies by Cupta et al. (2002), Baldacci et al. (2003), Jung and Thorbecke (2003), Anyanwu and Erhijakper (2007), Karimu et al. (2017), and Ibrahim et al. (2018). These works provide valuable insights into the associations between resource rents, public investment, and economic growth, forming a vital part of our investigation. However, contrasting views, such as those presented by Issa and Ouattara (2005), Cockx and Francken (2014, 2015), and Gylfason (2001), also add complexity to the narrative. These studies highlight potential negative impacts of public expenditure on education and health, introducing a nuanced perspective that aligns with our aim to capture the multifaceted relationships within the context of resource-dependent economies.

Moreover, the inquiry into income distribution's influence on health and education outcomes corresponds with the documented challenges of high income inequality in Sub-Saharan Africa. High income inequality exacerbates disparities in access to quality education and health services, negatively impacting human development (African Development Bank, 2015). Studies indicate a negative relationship between income inequality and educational attainment: Checchi (2004); Getaye Molla (2021); Johansen (2014). As a consequence, the explored literature, which spans the nexus between natural resources, education, health, and income distribution, directly supports our central research objective of comprehending the intricate dynamics shaping the human development index in oil-exporting Sub-Saharan African countries. This examination sheds light on both positive and potential adverse consequences of resource-related factors offering a comprehensive view of their impact on human development.

3-3 THE INTERACTIONS BETWEEN INSTITUTIONAL GOVERNANCE, OIL RENTS AND HUMAN DEVELOPMENT.

The concept of institutional governance is still characterized by ambiguity, however is plays a pivotal role in determining how a country manages its resource rents. This include establishing framework for extracting, setting taxation policies and creating mechanisms for revenue distribution. Bhattacharyya and Hodler (2015) highlight the importance of institutional quality in determining the developmental impact of natural resource abundance. Countries with effective governance structures are better positioned to attach oil revenues for sustainable human development. Transparent and accountable management of oil revenues is essential for ensuring that resource wealth contributes to human capital development.

Strong regulatory frameworks, fiscal transparency measures, and public oversight mechanisms are necessary to prevent corruption, mismanagement, and elite capture of resources (Acemoglu and Robinson, 2012). When institutions are well-governed, there is a reduced likelihood of rent-seeking behaviour, misappropriation, and other corrupt practices associated with the exploitation of natural resources. Clear policies, robust oversight mechanisms, and adherence to the rule of law create an environment that discourages corrupt activities (Smith, 2015; Kaufmann et al., 2010). Conversely, weak institutional governance is often associated with an escalation of corruption in the extraction and distribution of natural resources (Bauhr and Nasiritousi, 2012). Inadequate management and poorly defined regulations create an environment conducive to rent-seeking behaviour and embezzlement, diverting resource benefits away from the broader population (Bardhan, 1997; Robinson et al., 2006). Therefore, the relationship between institutional governance and corruption in this research underscores how the quality of governance structures can either mitigate or exacerbate corrupt practices in the management of natural resources, influencing the overall outcomes related to human development and income inequality (Dreher and Herzfeld, 2005; Mungiu-Pippidi, 2006).

Several studies addressed the connection between institutions governance and resource rents, and political systems that have been extensively explored in the literature for their implications on corruption and human development (Smith, 2019; Jones etal., 2020). Leite and Weidmann (1999) investigated the factors that influence corruption, with a focus on the function of natural resource abundance and its effect on economic growth. They established a robust statistical relationship between countries' exports of oil relative to the GNP, and the level of corruption for a sample of 72 countries in 1970. The finding illustrates that countries dependent on crude oil are often characterized by corruption, poor governance, and a culture of rent seeking.

In the same vein, Constantinos et al. (2014) investigated the role of institutions on economic growth in one of the natural resources developing countries, Sudan, and applied an autoregressive distributed lag model. They found that investment, trade openness and political freedom index as a measure of institutional quality all have negative effects on the GDP growth of Sudan over the period 1972 to 2008; they also found that only population growth played a positive role.

Arezki and Bruckner (2011) investigated the causal effect of oil rents on corruption and state stability for 30 oil-exporting countries[13] (the list included some of SSA) covering the period from 1992 to 2005, using fixed effects panel regressions. The findings proved that corruption

[13] Algeria, Angola, Azerbaijan, Bahrain, Brunei, Cameron, Chad, Congo, Ecuador, Equatorial Guinea, Gabon, Indonesia, Iran, Kazakhstan, Kuwait, Libya, Mexico, Russia, Nigeria, Norway, Oman, Qatar, Saudi Arabia, Sudan, Syria, Trinidad and Tobago, UAE, Venezuela, Yemen.

would be greater when oil rents increase as a consequence of decreases in political rights; however, this does not necessarily threaten the state's stability. Remarkably, the study also reported that countries with a high share of government involvement in oil production experience more corruption, while no such link exists in countries where government participation in oil production is low.

Mehlum et al. (2006) estimated rent seeking model and claimed that an entrepreneur chooses between rent-seeking and productive activities, which depend on institutions' quality such as the rule of law and bureaucratic efficiency. Using data set from Sachs and Warner (1997a, b), which included 87 countries[14] (including SSA), covered the period 1965 to 1990, the dependent variable is GDP growth and exploratory variables are initial income level, resource abundance (share of exports of primary products in Gross National Product (GNP), gross domestic investment to GDP, openness and institutional quality index[15]. By estimating various regression equations, the results show that with an interaction term of natural resources and a rule of law, the institutional quality index has a significantly positive effect on income growth. The study concluded that the resource curse applies in countries with low institutional quality, which motivates apportion of entrepreneurs to be rent-seekers, consequently natural resources, in turn, lower national income, and thus would affect development planning and human quality. While in the case of high quality of institutions, all entrepreneurs seemed to be active producers. However, the study estimates may be biased through the problem of causality effect between the measure of growth and the measure of natural resource abundance. Similarly, Arezki and Gylfason (2013) conducted a study taking into account the importance of political systems and institutions which connected with natural resources rents. The study included 29 sub-Saharan

[14] Bolivia, Haiti, Salvador, Bangladesh, Thailand, Guatemala, Ghana, Philippines, Uganda, Brazil, Israel, Niger, Nigeria, Mali, Zaire, Syria, Peru, Honduras, Indonesia, Congo, Somalia, Egypt, Jordan, Pakistan, India, China, Japan, Argentina, Zambia, Morocco, Sri Lanka, Algeria, Jamaica, Greece etc.

[15] The institutional quality index is an unweighted average of five indexes based on data from Political Risk Services: a rule of law index, a bureaucratic quality index, a corruption in government index, a risk of expropriation index and a government repudiation of contracts index.

African countries and covered the period from 1985 to 2007, using GMM estimators and time effects. The authors claim that good institutions provide the right environment for optimum operational performance and vice versa. Interestingly, their study also finds that increasing the natural resources rents in less democratic countries faced with civil war – the authors referred that to the ability of political elites in those countries to more effectively suppress the people through redistribution of resources rents to the public. Indeed, their results contradict Van Der Ploeg (2011), who finds that resource booms reinforce rent grabbing and civil conflict, especially if institutions are bad, inducing corruption, particularly in undemocratic countries.

Accordingly, rent-seeking and corruption thrive in oil-exporting and producing countries due to the concentration of wealth and power in the hands of a few elites, facilitated by the rentier nature of oil revenues. Oil rents often create a rentier state dynamic where the government becomes the primary source of wealth, leading to intense competition among elites to capture and control access to oil rents. Institutions responsible for oversight, accountability, and enforcement of regulations are often underdeveloped and susceptible to capture by powerful interest groups. This enables elites to manipulate rules, regulations, and decision-making processes to their advantage, diverting oil revenues for personal gain rather than public welfare (Ross, 2001).

3-4 THEORIES OF NATURAL RESOURCES EFFECT

There are different types of natural resource wealth, for example Humphreys et al. (2007) identified oil, gas and mineral as non-renewable resources unlike other natural resources such as forests, water and fertile land. The non-renewable resources do not need to produced, instead they are extracted, and this can occur relatively independently of other economic processes.

These non-renewable resources can bring vast profits; however, do little to create employment e.g. in oil and gas sector. Therefore, the direct impact of employment may be limited; this sector creates few jobs per unit of capital invested, and these jobs require well-qualified and educated people, which may not fit the profile of an underdeveloped country's unemployment. On the other hand, this industry plays a vital role in stimulating broader economic development and job growth indirectly through manufacturing, transport, and services.

It's been argued that natural resources may are one of the major elements of national wealth for several countries when there is combination of good institution, intensive technology and knowledge (Mehlum et al.,2006; Lizuka and Soete,2011; Manzono,2012 cited in Labra et al.,2016), it is supposed to be a key determinant of their growth and advance their human development profile.

Karl (2007) argues that from an economic viewpoint, in principle, three advantages might be offered from these natural resources for an economy; initially, the income flow gained from natural resource extraction can increase living standards, which grow both levels of public and private consumption. Second, the extraction of natural resources can feed the investment directly from resource income and indirectly from borrowing, which is made possible by that income. Third, given that the natural resources income mostly accumulates into the public budget, it can help to avoid barriers to development such as deficiency of fiscal funds required to support public services and infrastructure (Karl, 2007).

In practice, most of the studies in the literature are focused on non-renewable natural resources or depleted sources, especially crude oil, in an attempt to discuss the reasons for natural resources countries experiencing failure in development rather than suggesting it would be better off without them.

Though, it has been noticed that the ownership of natural resources is neither required nor sufficient to confer economic prosperity. For instance, some countries are rich in oil and other natural resources, and yet their people continue to suffer low per capita income and a poor standards of living. Mahbub ul Haq (1999: 4) says that '*we have begun to acknowledge still with reluctance that in many societies GNP increase while human lives shrivel'*. Conversely, countries with few natural resources have experienced remarkable changes in their economic structure that have led to enormous increases in the standard of living of their population as Southeast Asian tigers (Singapore, Taiwan, and South Korea) and similarly for many European countries (Beny and Cook, 2009).

Based on the literature review, various streams have been addressed through which natural resources may affect growth and the development path of a country. One of these is to recognize as the 'natural resource curse', that natural resources have negative impact on growth, especially in developing countries – early evidence has been provided (Sachs and Warner 1995, 1997; Gylfason, 1999; and Auty, 2001). More especially, the natural resource curse is more likely occur for certain types of natural resources, such as crude oil (Auty, 2001; Isham, Woolcock, Pritchett, and Busby, 2005).

This natural resources curse is known as 'Dutch disease', and it operates through two different ways: the resource movement effect and the spending effect. The former happens when the booming sector draws capital and drives labour away from other sectors; while the spending effect occurs when additional revenue resulting from the booming resource rents is spent on domestic goods and services (Corden, 1984; Limi, 2007). Natural resource booms have been found to crowd out other important sectors (Papyrakis and Gerlagh, 2004; Frankel, 2010; Dartey-Baah et al., 2012). In such cases, the economy becomes resource-dependent and deeply exposed to the instability of commodity prices.

The other route is volatility of commodity prices, which often induces pro-cyclicality of savings, public spending and capital flows (Van der Ploeg and Poelhekke, 2011; Lwayemi and Fowowe, 2011; Masan, 2015; Mathew and Ngalawa, 2017). The prices of crude oil, natural gas, gold and other commodities are extremely volatile. Such volatility creates problems for countries which depend heavily on natural resources, aggravating boom and boost cycles, as public spending and capital flows increase when the price of the natural resource is elevated and decrease when it is low (Masan, 2015). Price volatility is harmful because the influences for the duration of booms do not compensate for the losses during a price boost, and behaviour during booms may spread the sources for trouble during busts. Sachs and Stiglitz (2007) argue that volatility has many adverse effects, making development planning difficult, social spending irregular, and foreign investors wary.

In the last decade, institutional theory of economic growth has emerged, with more specific trends; corruption can take many forms and it can even have been embedded in cultural tradition, but generally it focuses on the variants associated with government activities. It has been demonstrated (Karl, 1997; Lederman and Maloney, 2007) that natural resources countries have enormous economic booms but this seems not to have helped inclusive human development, suggesting that one rational suspect is poor institutional quality. Mehlum, Moene and Torvik (2007) emphasize that the natural resources curse happens only with countries that have low institutional quality (Boschini, Pettersson, and Roine, 2007). Several studies explored the role of institutional quality (Arezki and van der Ploeg, 2007; Boschini et al., 2007; Hooshmand et al., 2013; Lundgren et al., 2013; Horvath and Zeynalov, 2014) and concluded that the natural resource curse can be avoided if institutional quality is sufficient. And also, if there is a transparent management approach transferring natural resource revenues to productive investments, which contribute to sustain economic growth performance and promote development.

As for the role of political institutions, it has been explored that oil and minerals have a negative impact on economic growth, through the rise of powerful interest groups (elites) (Martin and Subramanian, 2003; Al-Ubaydi, 2012). People seek political rents when they try to get benefits for themselves via their political influence (Gylfason, 2001; Iimi, 2007) and through the bonus of resource revenues, which increases the power of elites, (Leamer et al., 1999; Gylfason and Zoega, 2003). The powerful groups usually take a large portion of these revenues and use it for the benefit of their direct circles rather than investing it to improve infrastructure and sustainable economic development. Andersen and Aslaksen (2008) demonstrate that the effect of natural resources is conditional upon electoral rule, estimating that the negative growth effect of resource rents may turn positive in countries with greater economic freedom. Furthermore, Acemoglu et al. (2004) find that higher resource rents make it easier for dictators to buy off political challengers. Hodler (2006) claims that institutional quality is formed by ethnic fractionalization during the rent-seeking process, thereby pointing to ethnicity as a significance source of the curse. Therefore, natural resources can be seen as causes of conflict among citizens, politicians and tribes (Sala-iMartin and Subramanian, 2003; Iimi, 2007), which will harm the economic growth and development planning in both short and long term. Ross et al. (2011), find that for any given five-year period, the chance of a civil war in an African country ranges from less than 1% in countries without resource wealth to nearly 25% in those countries with it. However, Vesco and Carraro (2020) highlight that the mechanism behind the resources conflict connection remains poorly understood and researchers do not agree about both the magnitude and direction of this relationship.

As a result of inadequate institutions, recently it has been shown that another channel where natural resources affect human capital accumulation is income inequality (Goderis and Malone, 2011; Stiglitz, 2012). Although, no direct or clear link exists between resource dependence and income inequality, the resource dependence is thought to raise income inequality through weak governance mechanisms that pose serious challenges to efficient delivery and administration. For instance, excess profit from higher prices transferred from consumers to elites, resulting in inequitable distribution of income. Consequently, lowering the supply of publicly funded health and education outcomes and subsequent earnings led to raising income inequality.

Overall, the natural resource curse theory provides a conceptual framework for understanding the adverse effects of resource abundance on development, particularly in developing countries. Numerous empirical studies have provided evidence supporting the existence of a resource curse phenomenon, highlighting the negative impact of resource dependency on various socio-economic indicators. The theory offers valuable insights for policymakers by emphasizing the importance of transparent resource governance and institutional reforms to mitigate the adverse effects of resource dependency.

However, the natural resource curse theory may oversimplify the complexities of resource-dependent economies and overlooks heterogeneity among resource-rich countries. The effects of resource abundance can vary significantly depending on contextual factors such as governance quality, institutional capacity, and economic diversification. Furthermore, establishing a clear causal relationship between resource abundance and economic stagnation is challenging due to the presence of confounding variables and endogeneity issues in empirical studies.

In terms of the relationship between natural resources, political systems, and economic outcomes remains subject to ongoing debate and uncertainty in academic research. While some studies align with the theory, others present conflicting findings or emphasize the need for further research to unravel the complexities involved. Methodological differences, data availability, and evolving political and economic landscapes contribute to varied conclusions. As politics and economies evolve, the effects of natural resources may change over time, adding layers of complexity to the analysis and challenging the theory's universal applicability and predictive power.

The examination of the natural resource curse theory within the context of 11 oil-exporting sub-Saharan African countries necessitates precise analysis of various socio-economic factors, each contributing to the understanding of the relationship between resource dependence and human development outcomes

Firstly, focusing on the 11 oil-exporting Sub-Saharan African countries, which depend on oil extraction for their development, requires examining the impact of oil wealth on social development indicators such as the Human Development Index (HDI), which includes education, healthcare, and standard of living. This involves assessing whether resource revenues have been effectively channelled towards enhancing human development outcomes.

Secondly, an assessment of governance and corruption issues is important in understanding the management of oil resources. Considering their implications for equitable resource distribution and development outcomes.

Furthermore, analysing the impact of inequalities in the distribution of oil revenues on human development within these countries is crucial. Examining income inequality offers insights into the distributional impacts of oil wealth on human development, allowing us to understand the socioeconomic dynamics that influence social inclusivity and development trajectories.

Additionally, considering the vulnerability of oil-exporting countries to external shocks, such as fluctuations in global oil prices, is necessary. Assessing the resilience of these countries' economies to external shocks provides insights into their adaptive capacity and policy responses, such as economic diversification. Evaluating the extent to which countries have utilized their oil wealth to attract foreign investment and encourage trade diversification is crucial.

Based on a thorough review of existing literature, identify key theories and empirical study's findings that shed light on the relationship between oil dependence and human development in sub-Saharan African countries. Therefore, it necessary to formulate hypotheses that express the expected relationships between the key variables. These hypotheses should be clear, specific, and testable, and they should reflect the theoretical understanding of how oil dependence may impact human development in sub-Saharan African countries.

3-4-1 **Research hypotheses;**

Null Hypothesis (H0): There are no significant effects between oil rents, institutional governance, and policy on the human development index in the 11 oil-exporting Sub-Saharan African countries.

Alternative Hypothesis (H1): There are significant effects between oil rents, institutional governance, and policy on the human development index in the 11 oil-exporting Sub-Saharan African countries.

This hypothesis is formulated based on the evidence that oil rents, institutional governance, and policy play crucial roles in shaping human development outcomes in oil-exporting Sub-Saharan African countries. The hypothesis suggests that these factors collectively influence the human development index, reflecting the overall socio-economic well-being of the population.

- Oil rents: Oil rents represent a substantial source of revenue for many Sub-Saharan African countries. However, the impact of oil wealth on human development is contingent upon how effectively these rents are managed and utilized. Previous studies have highlighted both positive and negative effects of oil rents on human development, including improvements in infrastructure, healthcare, and education, as well as challenges such as corruption, resource mismanagement, and environmental degradation.

- Institutional governance**:** The quality of institutional governance plays a critical role in determining the extent to which oil revenues contribute to human development. Weak institutional governance structures are often associated with corruption, rent-seeking behaviour, and ineffective resource management, which can undermine the potential benefits of oil wealth for socio-economic development.

- Policy interventions: The formulation and implementation of appropriate policies are essential for harnessing the potential benefits of oil revenues for human development. Effective policies in areas such as education, healthcare, poverty alleviation, and infrastructure development can help mitigate the adverse effects of oil dependence and promote inclusive growth. Conversely, inadequate or misaligned policies may exacerbate inequalities, perpetuate resource dependency, and hinder human development progress.

By examining these relationships, the study aims to provide insights into the key determinants of human development in these countries and inform evidence-based policy recommendations for fostering sustainable development.

CHAPTER FOUR: RESEARCH METHODOLOGY AND DESIGN

This chapter focuses on data, research method and analytical procedures. It provides a comprehensive view of the research structure and analysis applied to answer the research questions.

4-1 THE DATA

This study aims to examine the effect of the natural resources in the form of oil rents with practical emphasis on the transmission mechanism of natural curse and institutional governance on the human development index for 11 oil exporting sub-Saharan African countries, namely: Angola, Cameron, Chad, Ghana, Gabon, Ivory Coast, Democratic Republic of Congo, Republic of Congo, Equatorial Guinea, Sudan, Nigeria.

The choice of these 11 sub- Saharan Africa oil countries is guided by several strategic considerations. Firstly, these countries represent a diverse range of socio-economic and political contexts, offering a comprehensive view of the region. By including oil-rich economies, such as Nigeria and Angola, and those with a more diversified economic base, such as Gabon and Ghana, we aim to capture a nuanced understanding of the impact of oil rents on human development across different development trajectories. In addition, exploring whether it translates into improved living standards and well-being for the population.

Secondly, these nations are homogeneous in terms of race, but they belong to several tribes, and they speak various official and native languages, some are francophone, while others are Anglophones. There are many distinct faiths practiced in each country. The selected countries reflect linguistic and cultural diversity, allowing for the exploration of how these factors interact with oil wealth and human development outcomes. In addition, geographical spread is considered to ensure a representative sample of the Sub-Saharan African region. Including countries from different sub-regions helps account for regional variations in economic, social, and political contexts.

Thirdly, some of the selected countries may be significant players in global energy markets such as Nigeria, Angola and Gabon. Studying their experiences provides not only insights into regional dynamics but also contributes to a broader understanding of the global implications of oil wealth on human development. This thoughtful selection ensures that the study's findings are meaningful, relevant, and contribute to a comprehensive understanding of the relationship between oil rents and human development in Sub-Saharan Africa.

In addition, these oil-exporting Sub-Saharan African countries have attached lower Human Development Index (HDI) which should indeed be acknowledged as a significant aspect of development discussion. Despite the presence of valuable natural resources, including oil, they still struggle with comparatively lower HDI scores. This phenomenon highlights a critical divergence between economic wealth, often derived from resource extraction industries like oil, and the overall well-being and development indicators of these nations.

The low Human Development Index (HDI) in these countries is largely due to a number of problems in the provision of quality education, health care and living standards.

One of the main reasons for the low HDI in these oil-rich SSA countries is the persistent problem of low income. Despite the substantial revenues from oil exports, the wealth generated often does not translate into improved living standards for the majority of the population. Effective management of natural resources is crucial for transforming resource wealth into broad-based economic development. Nevertheless, many sub-Saharan African countries are struggling with resource mismanagement and corruption. Transparency International’s Corruption Perceptions Index consistently ranks many sub-Saharan African countries as the most corrupt countries in the world. In 2020, Sub-Saharan Africa had an average score of 32 out of 100, indicating a high level of perceived corruption (Transparency International, 2020). Corruption diverts resources away from key services and infrastructure, exacerbating the challenges of achieving higher HDI scores.

These governance problems lead to a concentration of wealth among the elite and limited reinvestment in public goods such as education and healthcare (Auty, 2001).

Accordingly, quality education remains a significant challenge in these countries. The allocation of resources to education is often inadequate, and when funds are available, they are not always efficiently utilized. Studies have shown that increased government expenditure on education can significantly enhance educational outcomes (Cupta et al., 2002; Baldacci et al., 2003). However, in many SSA countries, oil revenues are frequently diverted towards short-term political gains rather than long-term human capital development. In the same vein, healthcare services in these countries also suffer due to similar reasons. The healthcare infrastructure is often underfunded and poorly managed, leading to insignificant health outcomes. For instance, despite oil revenues, Nigeria still grapples with high infant mortality rates and low life expectancy (Issa and Ouattara, 2005). This emphasises the importance of efficient and transparent management of oil revenues to ensure that funds are directed towards enhancing public health services. Living standards in oil-exporting SSA countries are also affected by high levels of income inequality. The wealth generated from oil often benefits a small elite while the broader population remains poor. This income disparity further hinders access to quality education and healthcare, preserving low HDI scores (African Development Bank, 2015).

The interplay between low income, poor education, inadequate healthcare, substandard living conditions, and governance issues highlights the need for integrated and strategic approaches. As a consequences Sub-Saharan African countries can achieve significant advancements in human development.

To update the literature review, this research extends the period to be included from 2000 to 2020; previous studies covered up to 2015. This time frame allows us to capture specific periods of interest, such as a policy implementation phase or a period of economic fluctuations. During this period, most of these countries were considered rich in natural resources and classified as oil-exporting nations by the International Monetary Fund (IMF). As a consequence, there have been changes in policy in Sub-Saharan Africa (SSA); e.g., collaboration with international organizations such as the United Nations has become a key aspect of policy frameworks. Those countries engaged in partnerships to leverage expertise, attract investments, and implement sustainable development initiatives. For example, attempts to improve social services, including education and healthcare, were implemented to address the needs of growing populations and improve the quality of life for their citizens.

As for data availability and reliability, the amount of data required for analysis can vary depending on the specific context and the complexity of the analysis. However, a common rule of thumb is that more data is generally better for the analysis. Having a larger dataset can help capture the underlying patterns, trends, and seasonality of the data (if exist) and make more accurate forecasts. Therefore, 20 years of data can provide a reasonable period for econometric analysis (if we go further back some countries were not producing oil and then the sample will produce missing data); it allows us to observe the evolution of variables over a substantial period and capture gradual changes in the economic phenomena of interest. In particular, our dataset is consistent, and covers the relevant variables under consideration for the analysis. Moreover, in this research, we use panel data (observations on multiple entities over time); 20 years of data can be quite valuable. Panel data allows for the control of unobserved heterogeneity and the capture of individual-specific effects (more details in technical framework).

The study utilizes a diverse data set sourced from reputable international organizations. The majority of the dataset was collected from World Bank open databases such as FDI inflow to GDP, oil rents (% of GDP), Trade Openness (% of GDP) and government effectiveness index; while Human Development Index and Income Inequality Index data were gathered from the United Nations development programme department; and the corruption perception index was taken from Transparency International. The consistent use of these indicators aligns with international standards and enhances the comprehensiveness of the research. The data set's reliability is further strengthened by its longitudinal nature, spanning multiple years, Therefore, the potential for good results and reliable findings is underscored by the credibility of the data set.

As indicated in the literature review, previous studies have ignored the association between natural resources in the form of oil rents and human development. Most SSA countries have managed their natural wealth through state government; for example, revenues from natural resources go directly to the government. Hence, it is responsible for finding the best way to spend that money based on the policy priorities that have been created from its own point of view. Therefore, natural resources are supposed to support the social and spatial transformation of the country and promote human development and well-being, but it appears that these countries have not exploited well the opportunity from the extraction of natural resources. To better understand the development performance in those countries, (which does not appear to have been fully investigated), the research presents two objectives:

i) Investigate the impact of oil rents on human development in those countries during the period of study.

ii) Through the natural resources transmission channels, examine the effect of the role of institutional governance and policy on the human development index. Accordingly, this study derived a number of control variables to be included in the empirical model on the basis of the natural resource theoretical frameworks described in the literature review. The six explanatory variables are retained to control for omitted variables bias in our model.

- Market characteristics: as suggested in the literature, oil wealth considers the key macroeconomic variable. The importance of the oil rents arises from the fact that they are a significant source of the government's expenditure, which suppose supplies social and economic needs. Oil rents are a more appropriate measurement to examine the effect of natural resources on human development. Theoretically, the resource curse hypothesis was originally linked with the oil and gas sector and certain minerals than other natural resources (Auty, 1993). In this regard, this work will use oil rents as % of GDP as input, which represents the relative net profits from oil exporting. Based on the World Bank, it is estimated as follows: natural resource rent estimates are derived as the difference between the price of a commodity and its average cost of production. This is accomplished by determining the price of individual commodity units and deducting estimates of typical unit extraction costs. These unit rents are then multiplied by the actual amounts extracted by nations to get the rents for each item as a proportion of GDP. The effect of oil rents on human development index especially for oil-exporting SSA is not investigated in the literature. However, a reverse association has been documented between dependence on natural sources and growth. In our model, we expect a significant relationship between oil rents and human development index, for those nations under investigation. oil rent supposed to provide citizens with basic social services. These include providing access to healthcare and educational opportunities, and creating jobs that reduce social inequalities.

- Policy variables are changeable at any given period because they are under the effect of policymakers. It is vital to manage the microeconomic instability of natural resources through effective policies, which are supposed to have a positive impact on all forms of capital. This study considered both foreign direct investment inflows and trade openness as effective policies. Oil-exporting countries need to fill the foreign exchange gap; most SSA countries lack sufficient foreign investment that would be used to finance goods and services and also bring technology and skills. According to Majeed and Ahmed (2008), foreign direct investment and human development were considered the key drivers of economic growth in both developed and developing countries. Each one has an individual effect on growth; however, they also reinforce each other through complementary effects. Therefore, this research will use foreign direct investment net inflows as % of GDP as an input. Based on the World Bank database, the FDI is defined as follows: "foreign direct investment is the net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. This data displays net inflows (new investment inflows less disinvestment) of foreign capital into the reporting economy divided by GDP".

- Trade openness is another policy factor that is considered as one of the key factors of growth. This study will use trade as % of GDP as an input. The World Bank database calculates trade as the sum of exports and imports of goods and services measured as a share of gross domestic product.

Trade and FDI can play role in poverty reduction by creating job opportunities and improve income distribution. Attracting responsible FDI can contribute to achieving multiple sustainable development goals (United Nations, 2015). The relationship between trade, FDI and human development in SSA can vary (positive or negative) based on multiple factors such as quality of governance and institutions. Davis and Lee (2018) emphasized the role of strong governance structures in translating trade benefits into improved human development outcomes. We expect significant relationship to be associated to these variables, as this research considered only 11 oil-exporting SSA countries. The underlying assumption is that foreign investment and trade play a pivotal role in fostering development by generating employment opportunities, promoting the development of human capital, and facilitating the transfer of technology.

- The role of institutional quality: several studies (e.g., Mehlum et al., 2006; and Boschini et al., 2007) argue that while natural resources may not inherently be detrimental, their impact on growth is contingent upon the quality of institutional governance. Institutions in African nations are often fragile and weak; the World Bank and the IMF have enforced structural adjustment programmes (SAPs) for many African economies, which include privatising state-owned enterprises (SOEs). However, economic reform could have negative effects if institutions are inadequate and could lead to bad outcomes, in the sense that there are strong causal relationships between good governance and development outcomes such as higher per capita income, low infant mortality, and higher literacy (Kaufmann et al., 1999). Thus, the Government Effectiveness Index (GE) will be used as an input in this study. As defined by the World Bank, "it assesses the quality of public government services, the extent to which it's free from political pressure", the quality of policy formulation and execution, as well as the credibility of the government's dedication to such policies. One hundred and ninety-three nations are included in this index, which ranges in effectiveness from -2.5 (less effectiveness) to 2.5 (more effectiveness). The data comes from two different sources, polls (surveys) of experts and cross-national surveys of residents. The government effectiveness index cannot be used to identify individual issues facing a nation or to analyse specific remedies because it is an aggregate measurement. But it is a valuable tool to make general comparisons between nations, or measure a country's progress. A positive sign is expected to be associated to this variable.
- Apart from that, corruption is considered as the main issue in African countries; it is systemic and involves high-level political leadership (Gyimah-Brempong, 2002). The

literature emphasises that the resource curse applies in countries with low institutional quality, which motivates to rent seekers. Consequently, natural resources in turn lower national income and thus would affect development planning and human quality (Leite and Werdmann, 1999; Mehlum et al., 2006; Arezki and Bruckner, 2011). Therefore, the Corruption Perceptions index will be used as an input; this index rates countries according to their perceived levels of public sector corruption, as judged by expert judgments and opinion surveys. Corruption is defined by the CPI as "abuse of entrusted power for private gain." The perceived amount of public sector corruption in a nation is measured on a scale from 0 to 100, where 0 represents severely corrupt and 100 represents extremely clean. We expect a positive sign, an increase of CPI in value which is close to 100; that means those nations have less corruption and thus enhance human development.

- Income inequality: based on natural resource theories, income inequality is a conditional variable strictly linked with quality of governance. Reducing income inequality is not only helpful but essential; high income inequality, according to Wilkinson and Pickett (2010, p. 195), is “divisive and socially corrosive”. So, this research will use the Gini coefficient index as an input, which is often used to measure income inequality. The possible range of the Gini Index is 0-100, with a value of zero meaning perfect equality. The United Nations classification divides countries into different groups of income inequality based on their Gini coefficient as follows: very low income inequality (0–0.3999), low income inequality (0.4 to 0.4999), middle income inequality (0.5 to 0.5299), high income inequality (0.53 to 0.5999) and very high income inequality is >0.6. A higher value is thus expected to be associated with this variable; an increase in the value of income inequality that means those nations have more gap in income inequality, which reflects negatively on human development.

- As for the dependent variable, the majority of previous studies used the level of GDP per capita as the dependent variable, probably because it is the most well-known and is used as an absolute economic indicator of progress. It may not fully capture the complexities of development in oil-exporting Sub-Saharan African countries, ignore the quality of human life in the SSA countries, for instance, and it not account for inequality in income distribution or address non-economic aspects of development such as health and education. Nations with high GDP per capita might still face significant inequalities and poor social indicators. According to (Stiglitz etal., 2010) argue that GDP overlooks essential aspects of well-being and social progress, thus providing a narrow view of development. In terms of inequality, GDP per capita averages income across a population, masking income inequalities. For instance, a country with a high GDP per capita could have a substantial portion of its wealth concentrated in the hands of a few, with the majority living in poverty. Piketty (2014) highlights that income inequality has been rising globally, and GDP per capita fails to capture this trend, making it an inadequate measure of true economic welfare.

  In addition, oil-exporting countries often experience significant fluctuations in GDP per capita due to volatility in oil prices and production levels. This can result in misleading assessments of economic well-being, as GDP per capita may temporarily rise during periods of high oil revenues without necessarily translating into sustainable development or improved living standards for the population (Ross, 2012). The other reason is that oil-dependent economies often face challenges related to the sustainability of development and the need for economic diversification. Relying solely on GDP per capita may overlook the importance of investments in human capital, infrastructure, and non-oil sectors for long-term sustainable development (Kalu, 2015).

Accordingly, this study will use the human development index, which provides a more comprehensive measure by incorporating indicators of health and education alongside income, thus offering insights into the overall well-being of the population.

The human development index broadens the evaluation of development, emphasising that individuals and their abilities should be a definitive model for evaluating the development of a nation, not economic growth alone. According to Desai (1991), the HDI can be seen as a first and crucial step in integrating general sustainability themes into development measurements. In general, the three necessities are for people to live long, healthy lives, to learn, and to have access to the resources they need to live comfortably. Numerous other chances remain unreachable if these fundamental options are not available (UNDP 1990, p. 10). It was therefore created using four indicators: life expectancy at birth (health), mean years of schooling for adults and expected years of schooling for children (knowledge), and purchasing power per head (GNI) (standard of living), which emphasise how important and fundamental these three dimensions are for human development. According to Anand and Sen (2000), the GNI component is primarily used as a stand-in for some essential aspects of life quality that are overlooked in life expectancy and basic education.

Using the Human Development Index (HDI) as a dependent can offer a multifaceted analysis of socio-economic development. It offers insights that are relevant for policy-making beyond just economic growth. For oil-exporting countries, which often deal with issues like resource curse, governance, and social development, the HDI can inform policies aimed at diversification, improving public services, and reducing poverty (UNCTAD, 2017). And also, it allows for comparisons not only across different oil-exporting countries but also with global development trends. This facilitates benchmarking, identifying areas for improvement, and learning from best practices in other countries (UNDP, 2020).

In terms of data availability and transparency, HDI data is readily available and regularly updated by credible sources like the United Nations Development Programme (UNDP), ensuring transparency and comparability across countries (UNDP, 2020).

The human development index ranges from zero to one, and countries are categorised into four categories of human development based on how close their HDIs are to one: less than 0.55 is low, 0.550–0.699 is medium, 0.700–0.799 is high, and 0.800 or more is extremely high. The formula used to determine the HDI value has evolved over time. For example, in a 1991 UN report, the transformed variable for the educational component was changed to include two thirds of the proportion of adults who are literate among all adults and one-third of the overall combined ratio of first-, second-, and third-level educational gross enrolment in percent. The life expectancy at birth in years serves as a direct measure of longevity, whereas real per capita income and purchasing power parity in dollars (PPP$) are indicators of a country's level of living. For each indicator, a maximum and a minimum is defined (Kelly, 1991; cited in Noorbakhsh, 1998). Based on this, the old HDI calculation before 2010 used linear averaging across the three dimensions and was as follows: (health+education+income)/ 3. This method assumes that education, health, and income are perfectly substantial (equal weights), so the level of HDI will be affected by the absolute value of each component. Because it is sensitive, computing HDI via an arithmetic average has been contested in numerous ways, notably for certain fixed ranges for its components. For these reasons, several authors, including Desai (1991), Gormley (1995), Sager and Najam (1998), and Noor Bakhsh (1998a, b), presented methods to alter HDI computation. Following that, the formula to calculate HDI was modified based on the geometric mean and is now (health x education x income)1/3.

Since the mix of past and present educational policies that influence years of schooling and expected years of schooling is more important than the balance of achievements, the use of the arithmetic mean seems justified in this situation. The main benefits of the change are the imperfect substitutability of the dimensions and the independence of the ranking from the location of the upper bound, but it's important to note that the empirical significance of this difference between the geometric mean and the arithmetic mean is relatively small (Klugman et al., 2011). Additionally, the UNDP updated its historical data, making all the results comparable under the new definition.

In light of the debate and research objectives, the research hypotheses as follow;

The null hypothesis (H0): There are no significant effects between oil rents, the role of institutional governance and policy on the human development index in the 11 oil exporting Sub-Saharan African countries.

The alternative hypothesis (H1): There are significant effects between oil rents, the role of institutional governance and policy on the human development index in the 11 oil exporting Sub-Saharan African countries.

The empirical panel version turns out to be as per the following:

$HDI_{it} = b_{0} + b_1$ oil rents % of GDP_{it} + b_2 Government Effectiveness Index $_{it}$ + b_3 Corruption Perceptions $index_{it}$ + b_4 income $inequality_{it}$ + b_5 foreign direct investment net inflows % of GDP $_{it}$ + b_6 Trade openness % of GDP $_{it}$ + ε_{ti}……………………………………………………………….... Eq. (4.1)

Where, the Human Development Index is denoted as HDI, for (i) country and (t) time.

Oil rents as a percentage of GDP is denoted as OR, for (i) country and (t) time.

Corruption Perceptions index is denoted as CPI, for (i) country and (t) time.

Government Effectiveness Index is denoted as GE, for (i) country and (t) time.

Income Inequality Index is denoted as GINI, for (i) country and (t) time.

Foreign direct investment net inflows as a percentage to GDP is denoted as FDI, for (i) country and(t) time.

Trade openness as a percentage to GDP is denoted as TO, for (i) country and (t) time.

b_0 is a constant in all individuals in all time periods.

b_1 to b_6 coefficients of parameters for each explanatory variable, and ε_{ti} is the error term or composite error term, while i denotes the cross-sectional units (i=1……,11) and t denotes the time series (t = 2000, …, 2020).

There are no missing values in the dataset except the income inequality index variable has approximately 63 figures that were missed. Therefore, it is necessary to handle the missing values and replace them with actual ones, which is where data imputation comes into play.

4-1-1 **Imputation data**

Observations missing from the sample data are a regular occurrence in applied research. For instance, time series data may include gaps in the dataset due to special circumstances and data that is unavailable or kept secret for strategic purposes. In cross-sectional data, especially when the data derives from questionnaire-type surveys, information on some variables for some individuals is often missing. Additionally, in panel data, some participants leave the study or do not answer all the questions, which results in missing data (Baltagi, 2001).

Missing data is always seen as a problem which decreases our confidence related to the outcomes. It happens once we have no information about that data point in the dataset due to lack of information. According to Baltagi (2001), in the case of missing data that are independent of the available observations, we can just utilise the data we have and ignore the missing observations; most statistical software programmers perform this automatically.

However, the sample size is reduced and the regression coefficients may not be possible to estimate precisely; thus, it is better to impute the missing data to avoid dispersion (i.e. variance of the estimates would be too large, hence impeding hypotheses testing) regression coefficients. Imputation is especially crucial when dealing with real-world datasets where missing data is common. It helps researchers and analysts address the challenges associated with incomplete information. By imputing missing values, researchers can improve the statistical power of their analyses, leading to more reliable and generalizable results (Schafer, 1997).

In this regard, data availability is the main problem with most modelling studies of developing countries. The problems in these countries include short time series data, a lack of monthly, quarterly and annually data, missing observations and variables, and the imposition of secrecy on some data and information. In addition, some of indicators have been created recently, hence cover only a few years.

This study encountered missing data for the income inequality index (GINI) variable; approximately 63 numbers were missing. For instance, our sample over some years suffers from missing data as some countries may fail to report their accounts for certain years. Therefore, it is necessary to handle missing values in data analysis, replace the null values with actual ones; which is where data imputation comes into play.

The easy way to do that is by using the mean method where, essentially, for each of the features we just take the average and then replace all of the null values with that given mean. The mean method is actually easy and simple; it also will not affect the overall mean within that given feature. The other imputation method is the median; it is a good method when there are a lot of outliers with the dataset and so, if all the missing values are replaced with a given median, this could help spruce up the data a little bit more. However, both of these methods are good for numerical-type data but are not suitable for categorical-type data or even strings. This is because they do not really take into consideration the relationships among the other independent features and also they are limited as to what data they can use. And also, these methods assume that the data is missing completely at random and may not be suitable for skewed income distributions.

The important thing one should take into account when working with lack of observations or values that have missing we should not remove them because this often leads to poor results. Removing data from the data set is actually hampering the true values within the overall data. Although this research is dealing with numerical data and it is easy to apply one of the above described methods (median or mean), it is better to apply advanced practice to ensure we choose the appropriate imputation method for our data set. Therefore, the researchers used a multiple imputation approach to handle missing data. Multiple Imputation involves creating multiple plausible imputed data sets to account for the uncertainty associated with missing data, Rubin's rules are commonly used to combine results from analyses on each imputed dataset. According to (Young and Johnson,2015), there are advantages of using multiple imputation, such as preserving the temporal structure of the data, capturing variability, and producing more accurate and reliable results compared to simpler imputation methods.

A study by (Chen and Fu, 2015), used multiple imputation method to handle the bias resulting from missing data. They utilized a multiple imputation approach combined with an inverse Mills ratio to impute the missing income data for China. In their study case they found that, the Gini indices based on the imputed complete data more appropriately capture income inequality in China. Suggesting that the imputation process with the extended model improved the accuracy of the results (Chen and Fu, 2015). Recent study by (Sotiropoulou and et al., 2021) about exploring relationships among financial development, economic growth, income inequality, and other economic variables in the context of 27 European Union countries over the period 2000-2017. The focus was on handling missing observations in the data set through multiple imputation, the study utilizes the statistical package Amelia II and the EMB for multiple imputation.

The multiple imputation process generated five fully imputed data sets. This indicates that the researchers didn't rely on a single imputation but rather considered the uncertainty associated with missing values by creating multiple imputed data sets.

Accordingly, more advanced technique for imputing the data set is using the [16]MICE package. The MICE package in R program is a powerful tool for multiple imputation, a technique used to handle missing data by creating several imputed data sets with plausible values. The package uses a method called "Chained Equations" to impute missing values in a step-by-step manner. Each variable with missing data is imputed in turn, using the observed data and imputed values from other variables, which is based on the procedure proposed by Rubin (1976). This method has the ability to handle both categorical- and numerical-type features. The primary features of MICE are that this method executes multiple imputations instead of single imputations, thereby maintaining some form of a relationship among the features. The really neat thing about MICE is that this technique provides a statistical uncertainty measurement to imputation, whereas for median or mean imputation there is no uncertainty measurement, which can lead to biased data (Kropko et al., 2014). The MICE imputation process takes into account the temporal structure of panel data, preserving the time-series relationships among observations. This is crucial for maintaining the integrity of panel data and ensuring that imputed values align with the underlying patterns in the dataset (Van Buuren, 2018). Moreover, by considering missing data patterns through the MICE package, we systematically account for the various ways data may be missing across observations. This approach allows us to capture the complexity of missing data scenarios and impute values that align with the observed patterns, enhancing the reliability of our panel data analysis (Graham et al., 2007).

[16] Multivariate Imputation by Chained Equations

MICE can provide us with information about how many numbers of nulls to working with to be imputing; this is called the missing data pattern. After executing the command pattern, we have 1323 data set in total and there are 63 missing values. In general, the rule of thumb when working with imputation is that it is heavily recommended that the missing data should present no more than 5% of the entire data set. In this case, we can impute these nulls and replace them with values after choosing the best method through MICE.

To impute the missing values in our data set by using MICE, the following procedure were applied;

First, we have to check out what type of method we can actually utilise. MICE package supports various imputation methods, such as "pmm" (Predictive Mean Matching), "logreg" (Logistic Regression), "rf" (Random Forest), etc. Specifying the method for each variable is a crucial step (Van Buuren, 2018). Therefore, the MICE provides a list of different of these imputing methods (for more details, please see Appendix I), the outcome suggested that predictive mean matching is more appropriate imputation method in our data set.

Then, specify the number of imputed data sets we want to generate. In our case, the number of imputed data sets is five, the default value is m=5 (for more details, see Appendix I), this indicate that we want to create 5 imputed data sets. Each of these data sets contains imputed values for missing observations, generated based on the observed data and the specified imputation methods (Van Buuren, 2018).

Having multiple imputed data sets allows you to account for the uncertainty introduced by the imputation process. Instead of relying on a single imputed data set, you can analyse multiple data set and pool the results using Rubin's rules or other methods to obtain more robust estimates of parameters and standard errors. By repeating the process for “m” cycles once the number of cycles is completed we can check the imputed values place holder values for each feature is set back to the original value (for more details, see Appendix I). As a result, there is no more missing data and our data set is ready to use. Thus, the data are constructed as balanced panel data.

4-1-2 **Outliers data**

Outliers are data points that deviate significantly from the overall pattern or distribution of a data set. They are observations that are notably different from the majority of the data and may influence the statistical analyses. According to (Tukey, 1977), outliers are defined as observations that lie an abnormal distance away from other values in a dataset, it may be introducing a level of irregularity in statistical analyses.

Outliers can result from measurement errors, data entry mistakes, or genuine extreme values in the phenomenon being studied (Hawkins, 1980). Therefore, in the context of robust statistics, outliers are considered influential data points that may significantly impact the results of statistical analysis (Hampel et al., 1986). However, (Cleveland, 1993) pointed out that, outliers can be indicative of rare events, anomalies, or unique phenomena within a dataset, offering researchers an opportunity to gain insights into exceptional occurrences. They may represent genuine variability and should be examined in the context of the specific research question and domain knowledge (Cox, 1993).

Detecting outliers involves using various statistical methods and visualizations, for instance the sample way is visual inspection; such as boxplot which provide a visual representation of the distribution of data, enabling the identification of potential outliers beyond the whiskers (Tukey, 1977). While scatter plots allow for the visual inspection of data points, revealing potential outliers and their relationships with other variables (Chambers et al., 1983). Part from that statistical methods can be used to deduct the outliers such as Grubbs' test, Modified Z-

Score Test, Rosner's test, Percentiles method and Tukey's Fences, the choice depends on the characteristics of the data however, it's often recommended to use a combination of methods for a more comprehensive outlier analysis (Chambers et al., 1983).

Accordingly, it is suggested that there might be outliers present in the data set. In order to ensure the integrity of our analysis and draw accurate conclusions, we conduct a detailed check for outliers using appropriate statistical methods. This step is crucial for understanding the potential impact of extreme values on our results and making informed decisions regarding their treatment in our analysis.

To identify and manage outliers, we will combine two statistical methods e.g., box plots, and Grubbs' test. Additionally, we will consider domain knowledge and the context of our data to determine whether outliers are valid data points carrying important information or if they should be treated differently. Our commitment to robust data analysis includes addressing outliers appropriately to ensure the reliability and validity of the results.

4-1-2-1 Boxplot

Boxplot is also known as box and whisker plot is widely used as a method for graphing depicting groups of numerical data through their quartiles. It used to analyse the range and distribution of data, so it provides a good graphical image of constructing the data as well as the kind of symmetry in the data. The objective of the boxplot is to highlight how the data is spread out as well as the central value. According to (Tukey, 1977cited in Wooldridge, 2014) box plots offer a concise representation of the central tendency and spread of a dataset, with the box indicating the interquartile range (IQR) and the median line dividing the data evenly.

The 'whiskers' extending from the box in a box plot show the range of the data within a certain factor of the IQR, providing insights into the data's variability. Outliers in a box plot are typically identified as individual data points beyond the whiskers, which may be further explored to understand their significance (Tukey, 1977, cited in Wooldridge, 2014).

Figure 4-1 illustrate that the boxplot for all the dataset for the variables under investigation. As can be seen the interquartile range (IQR) is shown as a box in the plot, it includes the middle 50% of the information. The median, or middle value after the data is sorted, is the x symbol that appears inside the box, it offers a central tendency measurement. Within a specific factor of the IQR, the 'whiskers' extend from the box to the minimum and maximum values. They provide indication of how most data are distributed, and the data points that extend beyond the whiskers are regarded as possible outliers, they are shown as distinct points.

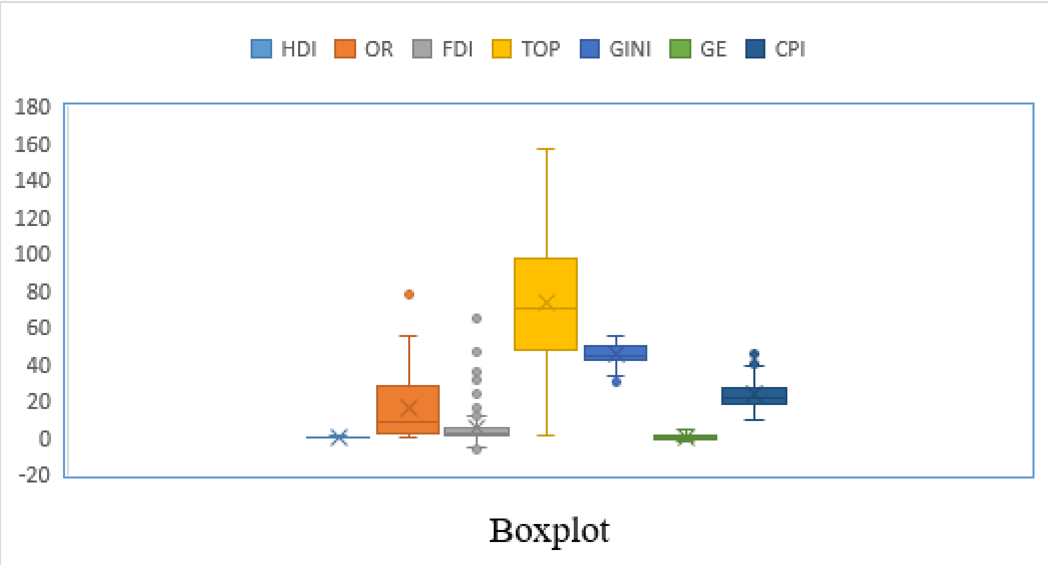

Figure 4-1 boxplot for the dataset

The boxplot suggests that. the Foreign Direct Investment (FDI) variable displays outliers, signifying potential extreme values or variations in investment patterns. Conversely, the variable for Oil Rents has only one outlier, indicating relative stability in this economic aspect, with occasional exceptional values.

The GINI coefficient, representing income inequality, displays a single outlier, that may be resulting from policy change that resulted in a drastic shift in income distribution. The

Corruption Perception Index (CPI), reflecting perceptions of corruption, shows only two outliers, which may be indicative of significant fluctuations influenced by governance changes, legal reforms, or other factors affecting corruption perceptions.

On the other hand, Government effectiveness (GE) and Trade Openness (TOP) exhibit no outliers, indicating stability in these variables. The Human Development Index (HDI) variable also shows no outliers, reflecting a relatively stable distribution of human development across observed entities.

Additional statistical method is required to confirm the persistence and validity of these identified outliers. Therefore, a Grubbs test will be conducted to further examine the robustness of the outlier detection process.

4-1- 2-2 Grubbs' test

Grubbs' test is a statistical test used to detect outliers in a univariate dataset. The test identifies whether a data point significantly differs from the others. It focuses on detecting extreme values that significantly deviate from the mean of the data. Grubbs' test formulates a hypothesis regarding the presence of an outlier.

The null hypothesis (H_0): assumes that there are no outliers.

Alternative hypothesis (H_{1}); suggests the existence of an outlier.

The test calculates a test statistic to assess the validity of the null hypothesis. The test employs critical values to determine the significance of the calculated test statistic and. If the test statistic exceeds the critical value at a chosen significance level (for instance 0.05), the null hypothesis is rejected, indicating the presence of an outlier (Grubbs,1969 cited in Montgomery, 2012). The table 4 .1 shows the Grubbs test outcomes.

Table 4-1 Grubbs test outcomes

Variables	G (Test statistic)	U (Critical value)	P-value
HDI	2.48822	0.97296	1
OR	3.70336	0.94011	0.0199
FDI	6.94909	0.78913	2.182e-11
TOP	2.43160	0.97418	1
GINI	3.01077	0.96042	0.2752
GE	2.7945	0.9659	0.5622
CPI	3.24689	0.95396	0.1192

As described in table 4-1, these data set HDI, CPI, GINI, TOP and GE have P-values are greater than the typical significant level at 0.05, therefore there are no evidence to reject the null hypothesis suggesting that these datasets not have outliers.

The Grubbs test results indicate that the value of 78 in oil rents (OR) for Equatorial Guinea in 2001 is identified as an outlier, signifying a substantial departure from the typical values for that year. Similarly, the test reveals statistical significance in the FDI variable, with a data point of 64.4 considered as an outlier for Equatorial Guinea in 2001. The low p-value associated with the FDI outlier provides robust evidence to reject the null hypothesis, suggesting that the presence of this outlier.

The outliers observed in Equatorial Guinea in 2001 can be justified by the substantial expansion of oil output during the period 1998-2002, which played a dominant role in shaping the country's economic landscape. According to (IMF report, 2003), this period witnessed a remarkable surge in oil production, escalating from approximately 60,000 barrels per day in

1997 to about 250,000 barrels per day in 2002. This robust growth in oil production significantly contributed to the economic development across various sectors.

The economic impact of this oil boom was profound, reflected in the surge in oil revenue was equally noteworthy, with an average annual increase of 50 percent during the same period. This period of remarkable economic transformation resulted in a notable accumulation of net foreign assets in the banking system. The government, benefiting from increased oil revenue, accumulated deposits both at the Bank of Central African States and in domestic commercial banks, along with rising balances held in accounts abroad (IMF report, 2003).

In light of these economic dynamics, the outliers in variables oil rents (OR) and Foreign Direct Investment (FDI) during this period can be considered legitimate reflections of the extraordinary economic conditions in Equatorial Guinea. Including these outliers in the analysis allows for a more nuanced understanding of the impact of the oil boom on various economic indicators, providing valuable insights into the unique and exceptional economic circumstances during the specified timeframe. Accordingly, the outliers observed in the dataset, particularly in the variable FDI and OR, are not errors but rather indicative of real and exceptional economic events in Equatorial Guinea.

The robustness of our data is supported by its origin from reliable sources the World Bank and these extreme values align with known economic phenomena as explained above, and our analysis takes into consideration the unique circumstances that may lead to such outliers. This approach is consistent with the literature on outlier analysis in economic datasets, emphasizing the importance of considering outliers as valuable pieces of information rather than dismissing them as errors. According to (Rousseeuw, and Hubert, 2018), long-term economic trends and structural changes can contribute to outliers, analysing these extreme values may provide insights into evolving economic landscapes and identify critical turning points. So, outliers are often reflective of real-world variations and phenomena, inclusion of outliers allows the analysis to capture the full spectrum of variability present in real-world phenomena (Rousseeuw, and Hubert, 2018).

In this study, data was collected from reputable source, the World Bank, this organization employ robust methodologies for data collection, which often involve rigorous surveys, on-site assessments, and cross-verification from multiple reliable sources. The dataset is constructed as balanced panel data, according to (Wooldridge, 2002), panel data analysis is recognized for its ability to account for time-invariant individual heterogeneity (e.g. fixed effect model), making it particularly suitable for economic data sets with varying country-specific characteristics. Fixed-effect models are robust against outliers, especially when implemented at the individual or time level, these models effectively control for unobserved heterogeneity, reducing the impact of extreme values on overall model estimates (Wooldridge, 2002). Therefore, fixed effects regressions are robust in handling outliers and yield reliable estimates of model parameters.

4-2 EMPIRICAL FRAMEWORK

In order to address the research objectives, the study employs a positivistic paradigm and also known as positivism. Positivism asserts that knowledge should be based on observable, measurable facts and that scientific inquiry should be conducted in a systematic and objective manner.

This paradigm is closely associated with the development of the natural sciences, particularly physics, and it has also influenced social sciences, such as sociology and psychology (Babbie, 2020). The Key characteristics of the positivistic paradigm include that the use of empirical observation and experimentation to gather data about the natural and social world. This involves systematic observation and measurement of phenomena to generate objective evidence. Positivism stresses the importance of objectivity in research, aiming to minimize bias and subjective interpretation to maintain neutrality and detachment from the phenomena being studied (Babbie, 2020).

Positivism favours quantitative methods which involves advanced statistical analysis (Hussey and Hussey, 1997). These methods allow researchers to quantify variables and test hypotheses rigorously, allowing researchers to draw reliable conclusions from the patterns and relationships within the data. It allows to explore causal relationships between variables in panel data. By controlling for potential confounding factors and using appropriate statistical techniques, researchers can identify the effects of independent variables on dependent variables over time (Wooldridge, 2010). Quantitative method provides a systematic and robust framework for analysing panel data, enabling researchers to uncover patterns, relationships, and trends that contribute to a deeper understanding of the phenomena under investigation.

Several empirical resource curse literatures build numerous models for the SSA countries, in order to understand the driving forces and optimal policies to promote economic growth by applying different types of panel data techniques. One of the pioneering works in the resource curse literature, Sachs and Warner (1995), the study used cross-country regressions and panel data analysis to establish a negative correlation between resource abundance and growth in SSA.

Eregha and Mesagan (2020) used a heterogeneous panel approach; Xu., et al. (2020), Cavalcanti, (2015), Veloso (2015) and Gylfason (2013) adopted the Generalised Method of Moments (GMM) approach and time effects; Carmignani (2012) used system equations; while Arezki and Bruckner (2011) used panel fixed effects regression and instrumental variables model. By employing panel data techniques, researchers obtain more robust and reliable estimates of the relationships between natural resources and economic growth, considering the dynamic and heterogeneous nature of the data across countries and time. These methods contribute to a more nuanced understanding of the resource curse phenomenon in Sub-Saharan Africa and other regions.

Accordingly, this study adopted panel data technique which allows to explore causal relationships between variables and get robust outcome. Panel data techniques offer a powerful analytical framework help to obtain more accurate and nuanced insights into the relationship between oil rent and human development index, while considering the diverse contexts of individual countries. The relationship between oil rent and human development index can be plagued by endogeneity and simultaneity issues. So, the panel data techniques provide tools to address endogeneity concerns, such as instrumental variable approaches or dynamic panel models, which explicitly account for feedback loops between oil rent and human development index.

The use of panel data has the advantage of providing more observations for the analysis, which increases the possibility of efficiency of estimation. However, the main benefit is enabling the researchers to examine causal relationships by using before and after observations; in the same vein, the stability between dependent and independent variable can be examined. Another couple of important motivations for applying panel data are that it enables us to explore the dynamic variation of the relationship and reduces the omitted variable bias (Wooldridge, 2006). This is especially true for so-called error components models, e.g. the fixed effects model, which has the ability to eliminate time invariance unobserved errors specific to each observation; therefore, as a result providing more statistically robust estimations (Hsiao, 2003).

It is important, though, to be mindful of the completeness of the panel data structure; for instance, all data observations are completely listed chronologically for each individual or unit.

This type of data is called balanced panel data. In other words, balanced panel data have an equal number of observations for each firm for the entire period (Baltagi, 2001). In contrast, unbalanced panel data is when the number of observations is not the same for all subjects; for instance, firm one has two observations while firm two has three observations. It is necessary to be careful when utilising unbalanced panel data because it might encounter a problem of inconsistent and unbiased parameter estimates if the right assumptions are not made. The panel data may be short (micro panel); this indicates that the number of individuals or units is more than the number of periods. In contrast, long panel or macro panel is the case when the number of periods exceeds the number of individuals or units (Baltagi, 2001).

Panel data approaches are broadly classified into two types:

- Homogeneous or pooled panel data models, which presume that the model parameters are the same for all individuals.
- Heterogeneous models, which allow for some or all of the model parameters to differ within the individual; for example, fixed and random effects model.

The assumptions created regarding the variation of the model between individuals are the main reason for which model to select within these categories. For instance, let us consider the following simple linear regression model:

$$y_{it} = \alpha + \beta x_{it} + \mu_{it} \qquad \text{Eq. (4.3)}$$

Where y is dependent variable

α is the constant

β the coefficient and x is explanatory variable

μ_{it} is error term

Equation (4.3) represents a homogenous model; in this case, the main assumptions are: the constant α and the coefficient β are both constant and the same within group and time. Any differences between groups are only introduced into the model via the error term μ_{it}. Alternatively, we could assume that groups have common coefficients on regressors but differ in their intercepts, as is captured in the fixed effects or least squares dummy variable (LSDV) model as show in Equation (4.4):

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it} \quad \text{Eq (4.4)}$$

Where y is dependent variable

α is the constant

β the coefficient and x is explanatory variable

μ_{it} is error term

Accordingly, equation (4.4) represent heterogeneous model due to the fact that α_i are group specific constants such as fixed effects model. In the case of random effects, the alternative assumption made by the coefficients models is that they fluctuate randomly around a common average. The following methods are typically used to evaluate the assumptions regarding parameters and error terms and choose the best estimation: These methods are called pooling tests to check poolability. (Croissant and Millo, 2008).

As discussion above, we have balanced panel data, the number of years is 20 years and the number of units are 11 SSA countries (for more details, see Appendix I). Considering the aim of this research, which investigates the causal effect between oil rent and its transmission channel on the human development index for-oil producing SSA countries, this research will use a panel data technique. Thus, it is better to follow an appropriate procedure to ensure that the estimation model is valid and to obtain robust results. Accordingly, an appropriate analytical procedure was applied; please note that all the empirical analyses have been done by R program. This program was created to make the estimation and other analysis straightforward. It includes different types of packages, such as PLM (linear model for panel data), and then the researcher can apply suitable formulas and arguments that are invoked with the model or the test they need to execute.

4-3 ANALYTICAL PROCEDURE

Selecting between the numerous panel models is a challenging and tricky issue. Panel data sets can exhibit diverse characteristics, including heterogeneity across entities, time dynamics, and potential endogeneity. Choosing the most suitable model requires understanding how different models handle these complexities. It needs to align the chosen model with the specific characteristics of the data set and research question. Therefore, it is important to navigate these challenges by conducting specific procedures as recommended by experts (Wooldridge, 2010; Baltagi, 2001) and conducting diagnostic tests, and sensitivity analyses to enhance the robustness and reliability of the finding. Accordingly, the following producers and steps have been considered to choose apporiporate paned data model.

4-3-1 **Poolability Test**

Poolability test is used to justify our panel datasets, whether it is pooled OLS or it requires panel effects; in other words, it is an *F* test of stability for the coefficients of a panel model that will help us to avoid unnecessary tests and ensure that we get a valid model. The simplest poolability test has as null hypothesis that the same intercept applies to each individual, that means pooled OLS model as following;

$Y_{it} = \alpha + \beta_1 X_{it} + \mu_{it}$ .... Eq. (4.5) where Y_{it} is the dependent variable; X_{it} is the explanatory variable; μ_{it} is the error/disturbance term; α is the common intercept; β_1 is the structural parameters. Note that the coefficients α and β_1 are the same for all units (do not have i or t subscript).

The alternative hypothesis is; the same intercept does not apply to each individual. That means pooled OLS is unstable; in this case, the dataset may be better represented by a fixed effects model. In a fixed effects model, individual-specific intercepts αi are introduced, but the slope coefficients β remain constant for all individuals as it is;

$$Y_{it} = \alpha_i + \beta X_{it} + \mu_{it} \quad \text{......} \text{Eq. (4.6)}$$

where Y_{it} is the dependent variable; X_{it} is the explanatory variable; μ_{it} is the error/disturbance term; α_i is the individual-specific intercept; β is the structural parameters. Note that the coefficients α_i and β are the difference for all units in other words, we test for the presence of individual effects.

The outcome from the poolability test associated with the F statistic based on the construction principle is as described in Equation (4.7).

$$F = (ESSR - ESSU) / (N - 1) \; ESSU / ((T - 1) N - K) \quad \text{......} \text{Eq. (4.7)}$$

Under the null hypotheses, the statistic F is distributed as F with (N − 1, (TN − N − K) degrees of freedom, the ESSR and ESSU are the residual sum of squares resulting from the pooled OLS and fixed effects estimation respectively.

The test statistics corresponding with the p-value can be used to determine whether the null hypothesis can be rejected or not. There is no need to specify a panel model if the statistic is still insignificant because all the individuals are sufficiently homogeneous. However, most empirical panels generally reject their null hypothesis (Baltagi, 2003), as in our panel data.

4-3-2 **Lagrange multiplier test**

Once our panel specification is found to need panel effects, the next step was to run the three essential options, individual, time and two-way effects, using Lagrange multiplier or LM test to decide what effects we have.

Breusch-Pagan test (BP test) is used to detect both individual effects and time effects. It is the most well-known test for detecting unobserved heterogeneity. It has the most practical characteristic test as a Lagrange Multiplier test, which needs simple computing of the parameter estimates under the null, i.e., under the null of no unobserved heterogeneity (Breusch-Pagan, 1980 cited in Baltagi, 2021). Since there is no unobserved heterogeneity under the null, the computational issue is eliminated. Two-way effects are performed through Gourieroux and Holly and Monfort; these tests are also under the Lagrange Multiplier type of

tests.

The outcomes from those tests illustrate that our panel data has two-way effects, which means it includes both individual and time effects. Therefore, in the next step we have to estimate both two-way fixed effects and random model effects.

4-3-3 **Testing of two-way fixed effects model**

The two-way fixed effects model is a regression model that considers not only the influence of individual but also the influence of time effects. The validity of the two-way fixed effects model is based on two important assumptions: previous independent variable values have no direct influence on the present outcome, and past outcomes have no effect on the present independent variable values (Imai and Kim, 2019). Thus, the estimation equation which represents our model is as follows:

$Yit = \alpha i + \beta_1 Xit + \mu_{it}$………………………………………………………. ………...Eq. (4.8)

Where Y is the dependent variable (HDI), i is a unit or individual represented with time t, for i=1, 2,3……. N and t= 1, 2, 3…. T.

The assumption of disturbance is $\mu_{it} = \mu i + T_t + ʎ_{it}$.. Eq. (4.9)

Alpha (αi) is individual or cross-sectional effect and T_t is time-specific effect that is not included in the regression; it could be a disruption in oil supply such as what happened in Nigeria (Delta) due to a strike. And, $ʎ_{it}$ is the remaining error term.

β_i is the unknown coefficient of our independent variable X for each unit country i, with time t. The presence of unit or cross-sectional and time fixed effects accounts for both unit-specific (but time-invariant) and time-specific (but unit-invariant) unobserved confounders in a flexible way. These specific unit and specific time effects are usually caused by the outcome and control variables; therefore, the interaction between these two types of unobserved confounders is assumed to be absent or zero (Imai and Kim, 2019).

Accordingly, to eliminate the two effects in the estimation of the linear least squares model, we assumed both α_i and γ_t are fixed parameters and the disturbance term is considered to be independent; $e_{it} \sim$ IID (0, σ2e). In this case, we can say that the above equation (4.9) represents the two-way fixed effects.

The mechanism behind the estimation of the two-way effects model is to create a matrix of dummy variables for both the time periods and the groups which producing many of dummies create very large matrices (which are quite sparse since they contain a lot of zeroes); as a result, this takes up a lot of computer memory that slows down the estimation. Therefore, instead, a within-group estimator is used to estimate two-way models, which eliminates variance for both the time periods and the group, which requires the explanatory variables to be strictly exogenous but does not impose any restriction upon the relationship between α_i and X_{it}. By using the R through plm packages, under this method we are calculating the fixed effects estimator. This way is more computationally efficient, especially as our model is more complex.

4-3-4 **Testing of two-way random effects model**

The random effects model is a linear regression model applied to panel data. The advantage of using the random effects model is to eliminate heteroscedasticity. Every level in a random effect can be viewed as a random variable drawn from an underlying process or distribution. The estimation of random effects offers insight into the precise levels as well as population level data and, consequently, absence levels. The idea that the given levels in a random effect are not separate and independent is frequently referred to as exchangeability (Wooldridge, 2002; Baltagi, 2021).

The main assumption is that α_i are random factors, independently and identically distributed over individuals. Thus, the random effects model can be described as follows:

$Y_{it} = \beta_0 + \beta X_{it} + \alpha_i + \mu_{it}$ ....Eq. (4.10)

$\mu_{it} \sim HD(0, \sigma^2), \alpha_i \sim HD(0, \sigma^2)$ ....Eq. (4.11)

where Y_{it} is the dependent variable for entity i at time t; β_0 is the intercept; β is the slope coefficient for the explanatory variable X_{it}... α_i is the individual-specific effect (random effect) that is assumed to be constant over time for entity *i*.

μ_{it} is the remainder error term for entity i at time *t*, which includes both individual-specific and time-specific variations.

All the correlation of the error terms over time is attributed to the individual effects α_i, it is assumed that αi and μ_{it} are mutually independent and independent of X_{it} (Wooldridge, 2002). This implies that the GLS estimator for β_0 and β is unbiased and consistent.

In the case of two-way random effects, that means the model allows the presence of both time specific effects and individual-specific effects, as described in Equation (4.12).

$Yit = \beta_0 + \beta\, Xit + \alpha i + \lambda_t + \mu_{it}$ .... Eq. (4.12) where Y_{it} is the dependent variable; X_{it} is the explanatory variable; β_0 is the intercept; β is the structural parameters, μ_{it} is the error term.

Where, αi capture any unobservable individual,

λ_t refer to time-specific effects; it clear that the individual-specific effects do not vary with time, while the time-specific effects do not vary across individuals.

The estimations will be inaccurate, and the t-statistics and related standard errors will be biased. Therefore, the random effects model differs from the fixed effects model in estimation technique, as it does not use the conventional least squares principle but rather the maximisation of likelihood or feasible generalised least squares principle (Wooldridge, 2002;
Baltagi, 2021).

After testing both two-way fixed and random effects models, then we can run a Hausman test to decide which model is the right one and only estimate it for our panel data set.

4-3-5 **Hausman specification test**

Selection of a model for balanced panel data regression, i.e. fixed effects model or random effects model, according to Baltagi (2001), Greene (2003) and Wooldridge (2006) is not easy; it depends on unobserved heterogeneity, whether it is independent of the explanatory variables or not. In order to determine the statistical significance of the changes in the coefficients on the time-varying explanatory variables, many researchers estimate both random effects and fixed effects, then the Hausman specification test is typically used to select between fixed and random effects models (Greene, 2003).

The Hausman test contrasts fixed and random effects under the null hypothesis is: no correlation between individual specific effects and independent variables. Under the Null FE and RE coefficients are not significantly different from each other.

The alternative hypothesis is that, there is correlation between individual specific effects and independent variables; FE and RE coefficients are significantly different from each other (Baltagi, 2001; Greene, 2003). If the null hypothesis is not rejected, the random effects model is used because it results in more accurate estimators.

In contrast, if the null hypothesis is rejected, the fixed effects model is used. In order to test these hypotheses, we would calculate the difference in random effects and the fixed effects coefficients, for instance the difference in RE and FE coefficients (β_{RE} - β_{FE}). In order to evaluate the significance of this difference, we need its covariance's matrix. Therefore, estimation of the covariance between them is required. Then we can compute the Hausman test statistic as follows:

$E_H = (FE - \hat{\beta}_{RE}) \{\hat{V} (\hat{\beta}_{FE\}} - \hat{V}(\hat{\beta}_{RE})\}^{-1} ((\hat{\beta}_{FE} - \hat{\beta}_{RE})$ ………………………………… Eq. (4.13)

Where the $\hat{V}s$ denote estimates of the true covariance matrices. Under the null hypothesis, the difference between these estimator's ($\hat{\beta}_{FE}$ - $\hat{\beta}_{RE}$) approaches zero in probability limits, but is ($\hat{\beta}_{FE}$ - $\hat{\beta}_{RE}$) nonzero under the alternative. The variance of this difference is equal to the difference in variances, because the covariance would be equal to zero under the null hypothesis and E_H has an asymptotic chi-squared distribution with k degree of freedom where k is the number of estimates in β (Baltagi, 2008).

Accordingly, the Hausman test evaluates the consistency of an RE estimator against the FE estimator that is known to be consistent; the individual specific effects are typically correlated with the independent variables, making the FE estimator more appropriate.

As discussed above, a Hausman specification test was applied with two-way time specification (based on the outcome of BP test) to check whether the two-way random effects model or two way fixed effects model is more appropriate for our dataset. The outcome illustrates that the two-way fixed effects model is more appropriate for our dataset.

4-4 TWO-WAY FIXED EFFECTS MODEL INSTRUMENTAL VARIABLE ESTIMATION

As explained above, we estimated two-way fixed effects as an appropriate model for our datasets using the least-squares method, which assumed that the error terms were contemporaneously uncorrelated with explanatory variables or even that they were independent of all explanatory variables (Baltagi, 2001). Since the explanatory variables are suspect of being correlated with the equation's error term, in this case, the OLS estimator could be biased and inconsistent.

There are different reasons may we argue that error terms are contemporaneously correlated with one or more of the explanatory variables; these may include omitted variable bias, which arises if a relevant explanatory variable is correlated with the included regressors, so it is omitted from the model (Baltagi, 2001). Omitted variable bias arises if there are unobservable omitted factors in the model that happen to be correlated with one or more of the explanatory variables. This bias is of particular concern when attaching a causal interpretation to our model coefficients, in which includes all other factors that have an impact on the outcome variable Y_{it} whether observed or unobserved. So, in the case of the situation in which the equation contains an unobserved element that may be connected with the observed regressors, it is referred to as unobserved heterogeneity. It means that the observational units differ in many other respects than is observable for a researcher; the problem is that OLS does not control for these differences and may therefore attach the wrong importance to differences in the observed explanatory variables (Baltagi, 2001). This issue is said to be endogenous; those uncorrelated ones are called exogenous; therefore, endogeneity of regressors is a concern, and OLS results are susceptible to endogeneity.

There is another form of the endogeneity problem, which is reverse causality. It refers to the possibility that not only does X_i have an impact on Y_t but at the same time Y_i has an impact on one or more elements of X_i, say X_{2i}. This reverse causality arises when the dependent variable and explanatory variable are simultaneously determined, which results in inconsistent estimates and inaccurate inferences, leading to misleading findings and incorrect theoretical interpretations. Such a bias can sometimes result in coefficients with incorrect signs (Zaefarian et al., 2017).

Accordingly, this issue has been spotted, as the literature highlights that natural resources greatly widens the income inequality, which has an impact on human development. As an illustration, Mallaye et al. (2015) point out the connections between oil rents and income inequality. Strong evidence is provided by Carmignani (2012) that wealth disparity and natural resources both directly and indirectly affect human development. Consequently, this nexus may cause an endogeneity issue. In our model, the human development index (HDI) is considered the dependent variable (Y_{it}), while the income inequality index (GINI) is used as an independent variable (X_{it}), so the justification could be that, since the GINI is used to determine how income is distributed and cross-national income per capita (GNI) is one of the HDI components, if income changes along with how it is distributed (i.e., income growth has an impact on how it is distributed while at the same time, the distribution of income affects its growth), in this case, endogeneity arises when the dependent variable (HDI) is simultaneously determined with the GINI. In other words, when the causal relationship between one (or more) explanatory variables is co-determined and they have an impact on each other concurrently, simultaneity bias develops (Wooldridge, 2002).

Being more specific, our two-way fixed effect linear model is;

$Yit = \alpha i + \gamma t + \beta_1 Xit + \mu it$… ………………………………. ……………………….. Eq. (4.14)

where Y_{it} is the dependent variable; X_{it} is the explanatory variable; β_1 is the structural parameters. The necessary conditions for consistency require to consider that:

$E(\mu it, Xit) = 0$ ……………………………………………………………………… Eq (4.15)

Where the µit includes all unobservable factors that affect GINI, including things like households, state location, and also other unobserved characteristic for other independent variables. In this case, OLS is consistently estimating the conditional expected value for HDI among other things but not consistently estimating the causal effect of GINI.

However, if these assumptions are relaxed, the model no longer corresponds to the conditional expectation of y_{it} given x_{1t} and $x_{2t.}$; thus, the OLS method produces a biased and inconsistent estimator for our parameters in the model. Without using the proper econometric methods to account for endogeneity, “spurious correlations" between the explanatory variables and the dependent variable result. In addition to providing wrong coefficient estimates, it could lead to misguided policy suggestions and uncertain directions for future study.

Hence, it is necessary to look for an alternative estimation model to derive a consistent estimator and make sure that our model is statistically identified. Accordingly, we need to implement a superior estimation technique that offers reliable estimations; for instance, an instrumental variable estimate (IV) which deals with endogeneity. This has the capacity to regulate a number of sources of endogeneity, including reverse causality, simultaneous bias, measurement error, and the presence of unmeasured confounding effects (Stock, 2001). However, improper usage of IVs can make problems worse by producing coefficients and interpretations that are inconsistent.

In this regard, we need to impose additional assumptions; otherwise, the model is not identified and any estimator is necessarily inconsistent (Murray, 2006, cited in Zaefarian et al., 2017). Referring to Equation (3.15), this condition in terms of expectations (moments) that are implied by the model is sufficient to identify the unknown parameters in the model. However, as soon as the condition is violated, the condition fails, making it impossible to solve for the parameters. Given this, we need at least one additional momentary condition, which typically derives from the availability of an instrument.

IVs are variables that are uncorrelated with the error term, but correlated with the endogenous explanatory variable (Murray, 2006; Baltagi, 2001).

In this case the condition can be replaced by:

$E\ (Y_i - x_{1i}\ \beta_1 - x_{2i}\ \beta_2)\ Iv_{2i}) = 0$ …………………………………………………………. Eq. (4.16)

An instrument that is uncorrelated with the equation's error term, is referred to as exogenous provided the moment condition in the equation (4.16) is not a combination of the other ones (iv_{2i} is not a linear combination of x_{1i}) this is sufficient to identify the parameters β_1 and β_2 (Baltagi, 2001). The typical economic perception related to IVs-based estimation splits observed variations in independent variables into an exogenous and endogenous part. In order to separate exogenous variation, IVs use additional regression known as 'first-stage regression.' Finding a strong instrument is the key challenge when applying IVs; doing so results in different estimates, even when endogeneity bias is absent (Murray, 2006). The literature has established that the best method for doing so, is to rely on theory and there have been numerous attempts to define how to choose a decent instrument. In principle, it can identify instrument variables that are either within the unit of analysis as the lagged variable or that are outside the unit of analysis but nevertheless affect it (Murray, 2006).

An IV may satisfy the exogenous condition if it is discovered outside of the unit analysis, but it is less likely to satisfy the relevance criteria. However, finding an IV within the unit of analysis enhances the likelihood that the relevance requirement will be satisfied and is extremely unlikely to satisfy the exogenous condition. In order to determine if the selected instruments are strong or weak, it is vital to confirm that they are both exogenous and relevant.

In our model, within the unit of analysis, a lagged variable was chosen, oil rents to GDP % (OR), and income inequality index (GINI), while lag (OR,1) and lag (GINI,1) were used as the instruments. These selected lagged variables are required to be relevant, which means the degree of correlation between the instrument and the endogenous variables, as well as the extent to which the chosen instrument and the disturbance terms are uncorrelated.

Then we can estimate the two-way effects within the model's instrumental variable by R packages, where we expected the efficiency of standard OLS will increase. That implies the presumed endogenous variables are revealed to be exogenous; in this case, endogeneity is not a cause for concern. But it is essential to ensure that the IV estimation is correct and works because, when the relationship between the IVs and the endogenous variable is not sufficiently strong, IV estimators do not correctly identify causal effects. There are a number of tests that can be performed to determine an instrument's explanatory power; they are called weak instrument tests.

4-4-1 **Testing validity and weak instruments**

The instrument validity is a test used to evaluate the degree of the correlation between the additionally included IVs and the endogenous variables. Different tests are used to deduce the validity of instruments.

As explained previously, there are two conditions to have a valid instrument: first, the instrument must be relevant, meaning that it must be correlated with the endogenous independent variable. The other condition is that it also must be exogenous, meaning that it is not correlated with the model's error term.

An instrument is valid if it is:

Relevant: corr (iv, x) $\neq$ 0

Exogenous: corr (iv, μ) = 0

Where iv is the instrumental variable, x is the endogenous independent variable, and μ is the error term.

The Wu-Hausman test is also known as Durbin-Wu-Hausman test. The purpose of these tests is to obtain the estimation lagged variables (OR) and (GINI) Wu-Hausman tests separately to check whether both variables are endogenous.

The idea behind these tests is based on the null hypothesis as a repressor being exogenous, so we have an efficient estimator under the null hypothesis yet inconsistent under the alternative hypothesis. And we also have a consistent estimator under both null and alternative (iv estimator) estimators. We can re-form this as follows:

H0: Cov (x, μ) = 0; OLS preferred

H1: Cov (x, μ) $\neq$ 0; IV preferred

More precisely, Wu-Hausman test will estimate both OLS and IV regressions and then compute the difference between the estimated coefficient of β OLS and β iv and standard error for each one. In this test, the IV estimator and the OLS estimate are compared; if they are similar, the OLS estimator is fine (fail to reject the null that the OLS is consistent, or that the variable is exogenous). If the difference between the estimated coefficients is large, an IV estimator is required; however, this reduces our efficiency somewhat.

The instruments used in this test are likewise presumed to be exogenous. The Hausman statistic test has degrees of freedom equal to the number of endogenous regressors instrumented in the IV model and follows a chi squared distribution (Baltagi, 2001, 2008).

Then, we need to check whether the instruments are sufficiently correlated with the endogenous variable, i.e. whether they are weak instruments. A weak instrument indicates that the properties of the IV estimator can be very poor and the estimator can be severely biased if the instruments exhibit only weak correlation with the endogenous regressors (Baltagi, 2001, 2008). There is a variety of evidence that suggests that, if the instruments we have selected are not sufficiently strongly related to the endogenous independent variable, then we may still have bias, and perhaps it may be even larger than before.

More specifically, weak instruments have only a weak relationship with endogenous independent variables; if the instruments are weak, then the two-stage least squares estimator is biased. This, of course, raises a concern because the whole purpose of introducing the instrumental variable two-stage least squares strategy is to eliminate the bias that was present in ordinary least squares. Therefore, it is suggested that, if the instruments that we have selected are not sufficiently strongly related to the endogenous independent variable, then we may still have bias; and perhaps it is an even larger bias than before. In these cases, the normal distribution provides a very poor approximation to the distribution of the IV estimator even if the sample size is large. As a result, the standard IV estimation is biased, its standard errors are misleading and hypothesis tests are unreliable.

For instance, the IV estimator regressors is;

if xi = x_i - x …………………………………………………………………. Eq. (4.17)

which denote the regressors' values in deviation from the sample mean. Similarly, for y_i and z_i

, then the IV estimator can be written as $\widehat{\beta 2}$ iv $= \frac{\left(\frac{i}{n}\right)\sum_{i=1}^{n} \bar{y}\text{i} \;\; \bar{z}\text{i}}{\left(\frac{i}{n}\right)\sum_{i=1}^{n} \bar{y}\text{i} \;\; \bar{z}\text{i}}$ ………………Eq. (4.18)

Accordingly, if the instrument is valid and under weak regularity conditions, the instrumental variable estimator is consistent and can be expressed as the sample covariance between z and y divided by the sample covariance+ between z and x as exhibited in Equation (4.19):

$\widehat{\beta 2}$iv $= \frac{Cov\ (zi-yi)}{cov(xi-yi)}$……...Eq (4.19)

However, if the instrument is not correlated with the regressors, the denominator of this expression is zero. In this case, the iv estimator is inconsistent and the asymptotic distribution of (β_2)̂iv deviates substantially from a normal distribution. The instrument is weak if there is some correlation between zi and xi but not enough to make the asymptotic normal distribution provide a good approximation in a finite, potentially very large sample (Baltagi, 2008). To figure out whether we have a weak instrument, it is useful to examine the reduced form regression and evaluate the explanatory power of the additional instruments that are not included in the equation of interest. The value of the F statistic is a measure of the information content contained in the instrument (Baltagi, 2008). In the interests of simplicity, rules of thumb have been identified. First, to estimate the first stage, which means we regress the endogenous independent variable on all of the instruments. Then, we test that the null hypothesis coefficients are equal to zero and, if we have more than one instrument, we would generally use the F statistic to check whether the F statistic is less than 10 or not.

Staiger and Stock (1997) formalised the relevant asymptotic theory and advised using the "rule of-thumb" measurement to test for weak instruments using a partial F-test. The partial F-test can be performed in the presence of clustering and heteroscedasticity, too. The typical rule of thumb for identifying weak instruments is based on estimating the first stage, which means we regress the endogenous independent variable on all of the instruments and then test the null hypothesis. If only one instrument is considered, the F-statistic is equivalent to the square of the t-statistic of the instrument coefficient in the first stage.

Certain tests such as Wald and WU-Hausman tests can be used to determine whether we have a weak instrument problem. When we have more than one instrument, as in our case, the F-statistic is used to check the value of the F- statistic.

It turns out that the difference between the IV estimate for beta (β) and its true value relative to the difference between the OLS estimate for beta and its true value is approximately equal to 1 divided by the F statistic that we get from regressing x on z and then test the hypotheses that the coefficient on z is zero.

The criteria and the threshold are: the higher the F statistic, the more strongly we reject the null hypothesis that the instrument has no effect on x, which means instruments are likely to be relevant. However, if this F statistic's value is less than 10 we expect that our instrumental variable estimator would have finite sample bias, thus the instruments are weak and we should therefore be concerned about the coefficient estimation being biased. According to Cameron and Trivedi (2005), if we have many instrument variables, it may be a good strategy to use the most relevant subset and drop the weak one. And also try to mitigate it by collecting more data and increase our sample size, and then holding the R-squared constant; this is because, as the n gets bigger, the variance of our IV estimator is going to decline.

Overall, this chapter has focused on the research methodology that will be applied, data collection and research design. It has presented the overall steps involved in the research process and given rational reasons for adopting this analytical process. The analysis based on balanced panel data includes two-way fixed model and subsequent analysis which has been explained. Finally, to make a comprehensive relationship portfolio, we emphasise fixed effects specifications that relate within-country variations in oil rents to those in the human development index. As a result, we are able to avoid a significant endogeneity bias that results from unobserved cross-country heterogeneity by using instrumental variable technique.

CHAPTER FIVE: ESTIMATION AND MODEL SELECTION RESULTS

This chapter investigates the impact of oil rents share in GDP, its transmission channels e.g. institutional governance and income inequality on the human development index. The explanatory variables are net foreign direct investment as a percentage of GDP, trade openness to GDP, Government Effectiveness, Corruption Perception Index, and Income Inequality Index. The study included 11 oil-exporting sub-Saharan African countries (Angola, Cameroon, Chad, D R of Congo, Congo Rep, Ivory Coast, Equatorial Guinea, Gabon, Ghana, Nigeria, and Sudan). Primary investigation has been applied, such as measures of central tendency, which provide an overview and highlight the characteristics of the data, and also bivariate plot between oil rent and HDI has considered which allows us to observe the movement of oil rents and the human development index in a slightly different way.

Further investigation is needed to choose an appropriate model for our data set. Therefore, balanced panel data regression techniques were applied, such as the fixed effects model and random effects model, and subsequent analysis was performed through the estimation modelling steps. The statistical tests suggest that the two-way fixed effect model is appropriate. However, it is necessary to consider endogeneity that may result from the connection between the human development index and the oil rents (OR) and income inequality index(GINI). Thus, instrumental variables were employed, a common technique for dealing with endogeneity problems, followed by further analysis. For instance, the Wu-Hausman test of endogeneity checks instrument validity, the first stage F-test, and the Wald test are used to for detect Weak instruments.

5-1 DESCRIPTIVE STATISTICS

It is necessary to perform a descriptive analysis of the database of variables in this study, observed over a period of 20 years (from 2000 to 2020). Descriptive data analysis summarises and organises the characteristics of a data set; it gives a primary indication for each variable individually. This analysis is performed through the characteristics of the central tendencies such as the mean value of the variables, the median, and another informative characteristic such as minimum and maximum values. Table (5-1) presents the summary statistics for all variables included in the empirical study, for 11 oil-producing sub-Saharan Africa countries.

Table (5-1) Descriptive variables

Variables	Minimum	Maximum	Median	Mean
Human Development Index (HDI)	0.293	0.69	0.501	0.503
Oil rents % to GDP (OR)	0.000	78.00	9.20	15.98
NET Foreign Direct investment % GDP (FDI)	-6.400	64.400	2.700	5.119
Trade Openness to % GDP (TOP)	1.000	157.00	68.00	72.07
Government Effectiveness (GE)	-1.880	0.160	-1.11	-1.064
Corruption Perception Index (CPI)	10.000	48.00	22.00	23.95
Income Inequality Index (GINI)	30.600	55.6	43.4	45.6

As can be readily seen from this data, the human development index for the 11 oil-producing sub-Saharan Africa countries has almost same median and mean with 0.501 and 0.503 respectively, that indicate the HDI has almost zero skewness. While the range recorded minimum value at 0.293, and a maximum at 0.69 accordingly, based on UNDP classifications, those countries remain at low levels of human development, which is an indication of underdevelopment.

In terms of oil rents % of GDP, the data reveals a substantial range between the minimum and maximum values across countries, spanning from zero to a striking 78.0 percentage points. The exceptional outlier of 78.0% in Equatorial Guinea in 2001 is largely attributable to the pivotal role of the oil sector in the country's economy, as explained in chapter Four. This outlier has a notable impact on statistical measures, particularly the mean, potentially skewing its value. The mean, at 15.98 percentage points, surpasses the median, which stands at 9.20 percentage points. This disparity between the mean and median points to a non-symmetric and unequal distribution of the data. The concentration of data on the left side, coupled with lengthened tail to the right, signifies an asymmetry in the distribution of oil rents % of GDP across the observed countries. This asymmetry is revealing of the significant influence of outlier value, suggesting Equatorial Guinea, is driving the overall distribution towards higher value.

Similarly, government effectiveness data set has un equal distribution, had negative median and mean values; -1.11, -1.064 points, respectively and it ranged between a minimum of -1.880 points and a maximum of 0.160 points. It is notable in table (5.1) that those countries scored low on the corruption perception index (CPI)[17], with a minimum score of 10 and 48 index points as a maximum. While the median and mean value logged at 22.00 and 23.95 index points respectively that means the distribution of the CPI data is non-symmetric and it slightly skewed to the right.

While the GINI index is a vital measure for assessing within-country income inequality, it's crucial to note the presence of imputed data, with around 63 figures being imputed to address

[17] The perceived amount of public sector corruption in a nation is measured on a scale from 0 to 100, where 0 represents severely corrupt and 100 represents extremely clean.

missing values. Imputation is a standard practice employed to enhance the completeness of the analysis, but its potential impact on results should be acknowledged.

According to the United Nations Development Department(UNDP) classification of income inequality, countries are classified into different groups of income inequality according to their Gini coefficient as follows: very low income inequality (0– 0.3999), low income inequality (0.4 to 0.4999), middle income inequality (0.5 to 0.5299), high income inequality (0.53 to 0.5999) and very high income inequality is >0.6 (UNDP report, 2017). However, the imputed data introduces a degree of uncertainty, which may influence the precision of GINI coefficients and subsequently impact the classification of countries into income inequality groups.

As shown in Table (5.1), the average Gini index for the 11 oil-exporting nations is 45.6 index points and the median is 43.4 index points, despite the imputation process, the majority of these nations still fall within the category of low income inequality, emphasizing the prevailing trend. While the upper bound of those countries is 55.6 index points and the lower bound is 30.6 index points, this wide range, extending from very low to high income inequality, underscores the heterogeneity within the sampled nations. However, it is important to be aware of the inherent uncertainties associated with imputed values in our assessment of income inequality across these oil-exporting nations.

Profitable investment and trade openness are crucial for economic development; typically, they are supposed to make a positive significant contribution to economic development. The analysis of net foreign direct investment across all countries in the sample, as presented in table (5.1), reveals distinct characteristics. Notably, Equatorial Guinea in 2001 stands out with an outlier value of 64.400 percentage points, significantly deviating from the rest of the data set. This outlier emphasises the unique economic circumstances in Equatorial Guinea during that specific period. Examining the overall statistics for net foreign direct investment % GDP, the mean and median are intended at 5.119 and 2.70 percentage points, respectively.

This disparity between the mean and median suggests an uneven distribution, indicative of the influence of the outlier. The data set's range is noteworthy, spanning from a minimum of -6.40 percentage points to a maximum of 64.40 percentage points. The negative minimum value implies instances of investment outflows, further emphasizing the diversity in investment trends observed across the sample. It's crucial to recognize the impact of outliers, such as the exceptionally high FDI recorded for Equatorial Guinea. While this outlier contributes to the unequal distribution of the data, it also provides valuable insights into the specific economic dynamics of certain countries, particularly during extraordinary periods. Meanwhile the trade openness % to GDP exhibited notable variations, ranging from a minimum of 1.000 percentage points to GDP to a maximum of 157.00 percentage points. This broad range suggests diverse levels of openness in trade, possibly contributing to the overall economic development of these countries. the median trade openness % to GDP is recorded at 68.00, while the mean stands at 72.07. This implies that, on average, the trade openness is relatively high among the SSA oil-exporting nations. These figures shed light on the degree of economic engagement and integration with the global market, reflecting the importance of trade in shaping the economic landscape of these countries.

5-2 BIVARIATE PLOT

It is useful to consider the movement of oil rent as % to GDP and the human development index together over time in order to have a primary indication of the relationship between them. Thus, the two main variables were plotted as a double Y-axis against time. This time series analysis allows us to observe the co-movement of oil rents and the human development index in a slightly different way.

Figures 5-1, 5-2, 5-3, 5-4 and 5-5 illustrate the time series of oil rents as % to GDP and human development index during the sample period (2000-2020) for each country.

It can be clearly seen that the percentage of GDP derived from oil rents shows significant fluctuations across all countries, reflecting the volatility of global oil prices and production levels. While, the HDI growth in these countries is relatively slow and remain at low levels based on UNDP classification, indicating that oil wealth is not effectively translating into broader socio-economic development

It is important to note that each country has unique circumstances and the implications of observed trends vary. For instance, Angola, Nigeria and Republic of Congo, oil rents as a percentages of GDP show significance fluctuation with periods of high dependency impacting overall economic stability, while HDI gradual improvement. These countries need to diversify their economies to reduce reliance on oil. Diversification would mitigate the impacts of oil price fluctuations and foster sustainable development (Gelb,2010).

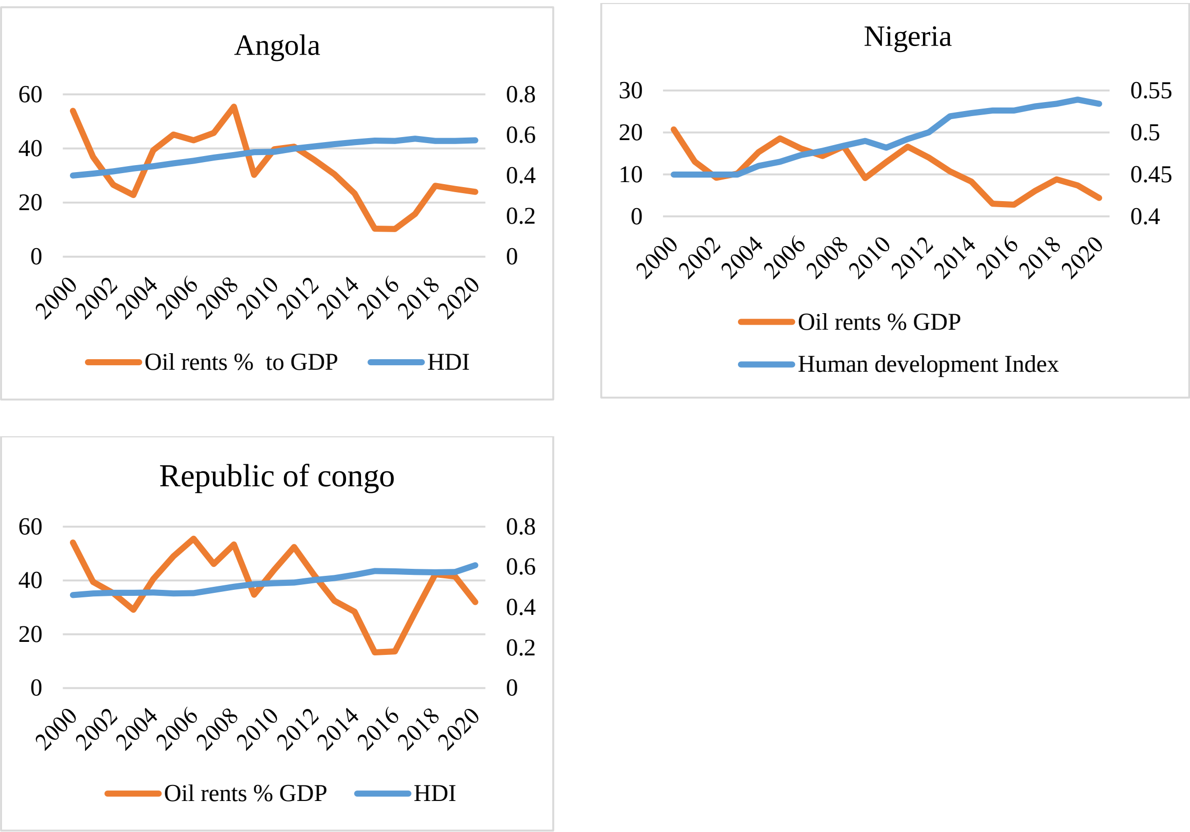

Figure 5-1 Time series plot of oil rents % GDP and HDI for Angola, Nigeria and Republic of Congo.

Sources of the figures: author's compilation based on data obtained from the World Bank and UNDP.

Countries like Chad, Sudan and the Democratic Republic of Congo show low and volatile oil rents with minimal human development index improvement. Reflecting sever socioeconomic and challenges and limited impact of oil revenues on development due to persistent conflict and poor governance (Fearon and Laitin,2003).

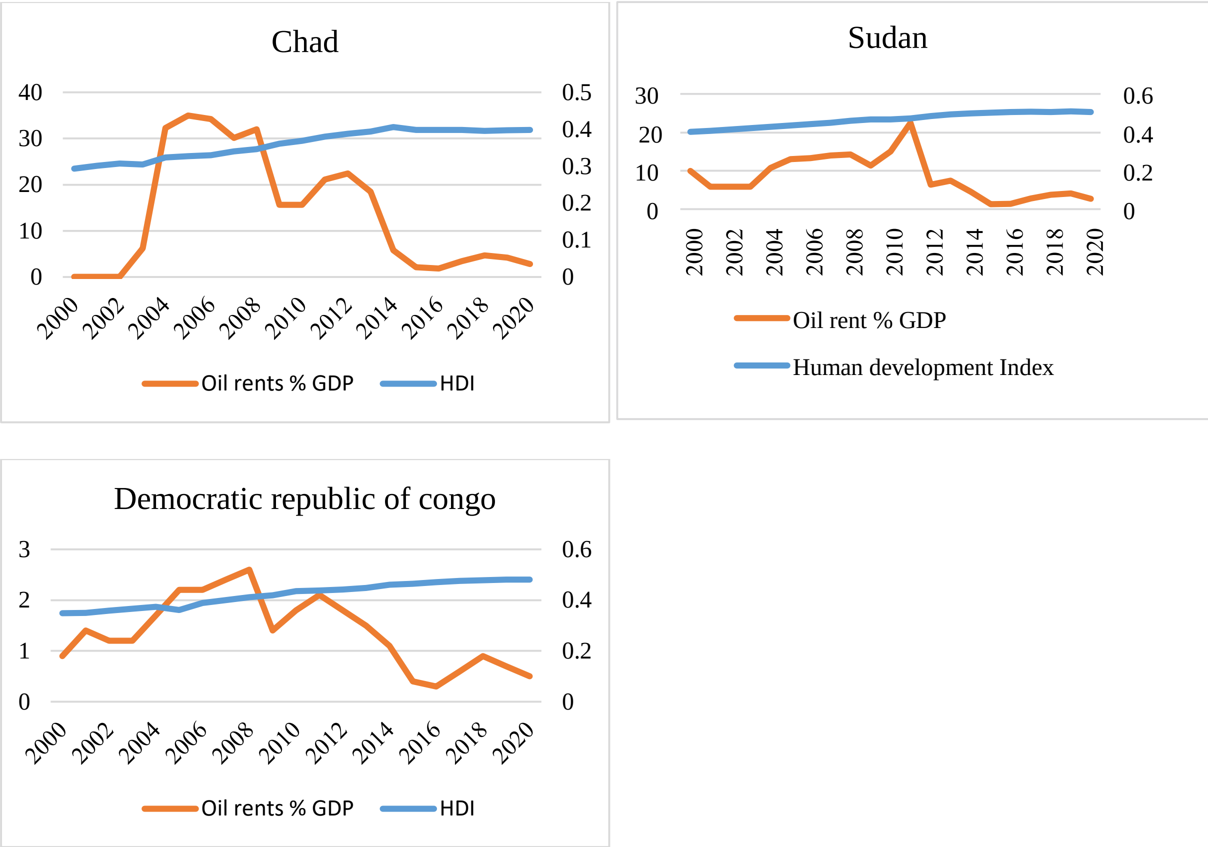

Figure 5-2 Time series plot of oil rents % GDP and HDI for Chad, Sudan and the Democratic Republic of Congo.

Sources of the figures: author's compilation based on data obtained from the World Bank and UNDP.

As for Equatorial Guinea and Gabon both show extremely high oil rents with varied HDI Outcomes. The HDI for Equatorial Guinea has shown a general upward trend, although it has been characterized by significant volatility, increasing from 0.52 in 2000 to around 0.58 in 2020. While Gabon exhibits improvement in HDI moving from around 0.62 in 2000 to 0.69 in 2016. The relatively steady increase in HDI suggests a degree of resilience and possibly better resource management compared to Equatorial Guinea.

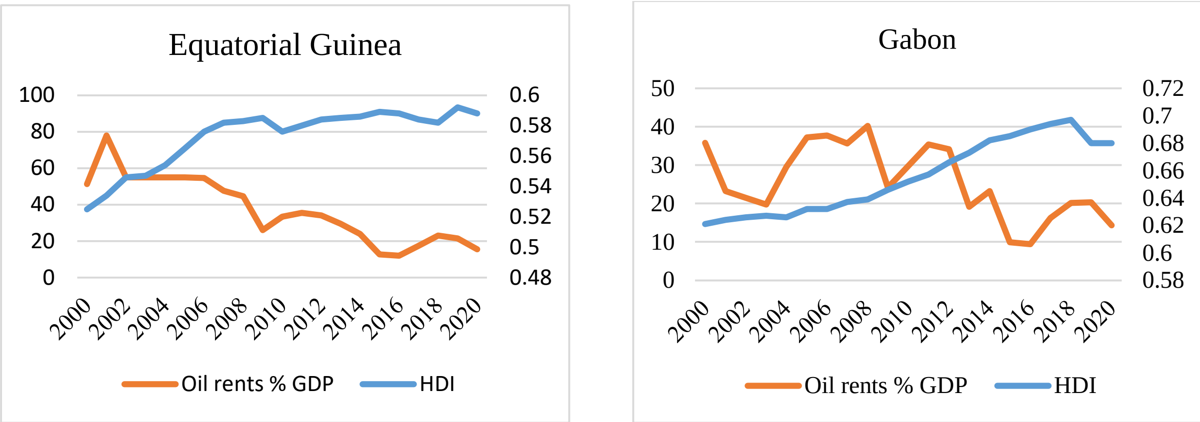

Figure 5-3 Time series plot of oil rents % GDP and HDI for Equatorial Guinea and Gabon.

Sources of the figures: author's compilation based on data obtained from the World Bank and UNDP.

Ivory Coast and Cameroon's oil rents exhibit moderate and relatively stable levels, combined with steady improvements in their Human Development Index (HDI).

Ivory Coast's oil rents as a percentage of GDP have remained stable, reflecting moderate reliance on oil revenues. Similarly, Cameroon has maintained a moderate dependence on oil, contributing to its economic stability and HDI improvements. This moderate dependence on oil revenues can be seen as a relative advantage, as it may reduce vulnerability to global oil price shocks compared to more heavily oil-dependent economies (Gelb,2010).

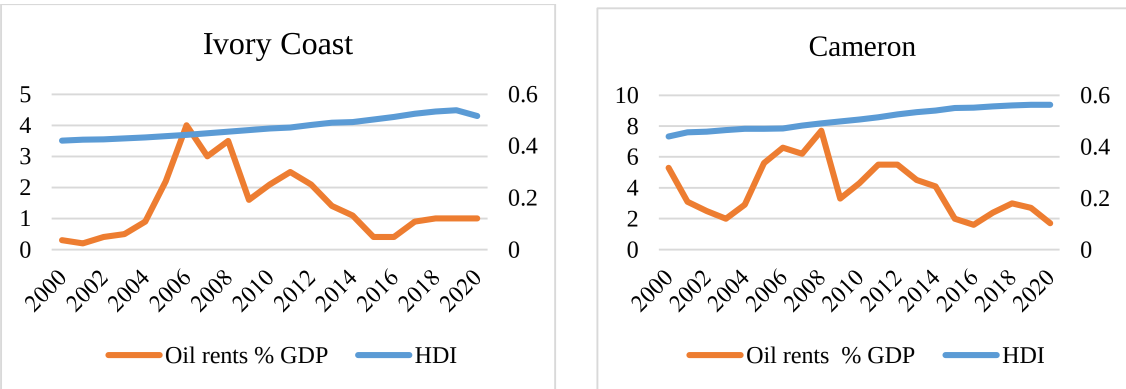

Figure 5-4 Time series plot of oil rents % GDP for Ivory Coast and Cameroon.

Sources of the figures: author's compilation based on data obtained from the World Bank and UNDP.

It is remarkable that Ghana's oil rent is relatively low compared to other countries, yet it has shown a steady improvement in its Human Development Index. This may be attributed to a diversified economy, effective resource management, and strong governance.

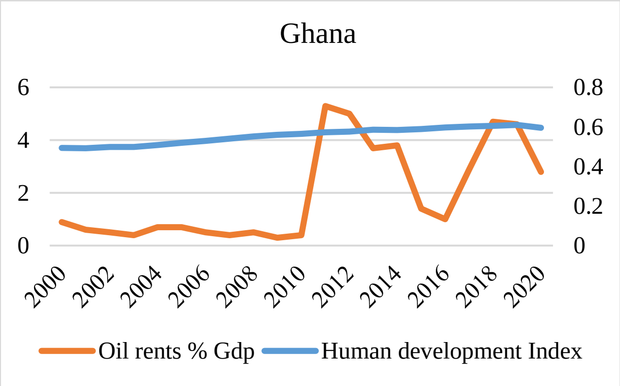

Figure 5-5 Time series plot of oil rents % GDP and HDI for Ghana.

Sources of the figures: author's compilation based on data obtained from the World Bank and UNDP.

Overall, the trends observed across these countries emphasise the complex relationship between oil wealth and human development index, highlighting common challenges in governance, economic management, and political stability.

To sum up this section, the primary results suggest that, the characterises of the data set for those countries in the sample is un symmetric, it skewed to the right except for human development index variable which almost has equal distribution. Moreover, while there is a relationship between oil rents and HDI over time, the nature of this relationship is complex, and additional factors may be influencing the observed patterns such as the distributional aspects of oil wealth, governance issues, or other socio-economic factors that may be influencing development outcomes. Therefore, further analysis and exploration of potential drivers behind the observed trends could provide valuable insights into the relationship between oil rents and human development in these countries.

5-3 ESTIMATION AND MODEL SELECTION

A panel data contains both time series and cross-sectional dimensions, where the same unit cross section is observed at various times. The panel is called balanced when the amount of time (year) used for each panel (state) is the same or constant for each individual. Alternatively, one has an unbalanced panel when the amount of time observations varies for each individual. Panel data is a data structure that is used for regression analysis. Typically, the Ordinary Least Squares (OLS) method is used to estimate the parameters in the regression analysis with cross sectional data (Baltagi, 2001; Greene, 2003).

Using panel data allows the researcher to take into account characteristics that are difficult to detect or quantify, such as cultural aspects, as well as those that vary over time but not between different entities e.g., international agreements According to Hsiao (2003) and Klevmarken (1989), panel data has several benefits, e.g., controlling for individual heterogeneity, individuals, businesses, states, or countries may be heterogeneous.

Studies using time-series data alone or cross-sectional data that do not account for this heterogeneity run the risk of producing biased outcomes. In addition, panel data can examine more complicated behavioural models; for instance, it can handle issue like economies of scale and technological change better than pure cross-sectional or pure time series data. Moreover, they encompass the ability to effectively handle outliers, manage missing data, and capture the evolving nature of entities over time. These attributes make panel data a valuable tool for researchers seeking a deeper insight into the dynamic relationships within their study subjects. In this regard, panel data provides more efficient estimation that is more varied, more useful, has more degrees of freedom and is less collinear with other variables and generates noticeably superior results (Hsiao, 2003).

However, it does have some drawbacks, e.g., data collecting problems (such as sampling design and coverage), non-response in the case of micro panels, or cross-country dependence in the case of macro panels (such as correlation between nations).

The formulations of the three basic forms of panel data models (i.e., estimators) are: pooled ordinary least square model (OLS); fixed effects model (FEM) and random effects model (REM).

Each model has special characteristics, e.g. the Pooled OLS (Ordinary Least Squares) model handles a dataset as if it were any other cross-sectional data, disregarding the fact that it contains temporal and individual dimensions. As a result, the assumptions are comparable to those of standard linear regression. In panel data, a pooled OLS model can be used to derive unbiased and consistent estimates of parameters even when time constant attributes are present. When applying pooled OLS, it is necessary to assume that the composite error term is not correlated with the explanatory variable (Wooldridge, 2006).

While a fixed effects model is used in analysing the impact of variables that vary over time, it is designed to study the causes of changes 'within' an entity a time invariant characteristic.

When using a fixed effects model, we assume that something 'within' the individual may impact or bias the independent variables and we need to control for this; this is the rationale behind the assumption of the correlation between error term and independent variables. The fixed effects model removes those time-invariant characteristics, by applying one of these methods: time-demeaning model, the least squares model with dummy variables (practical when the individual dimension is not too big), and the first-difference model. Thus, we can assess the net effect of independent variables on the dependent one.

Regarding the random effects model, also known as the error components model, the rationale is that the variation across entities is assumed to be random and uncorrelated with the independent variables included in the model. The random effects model assumes that the entity error term is not correlated with the independent variables, which allows for time-invariant variables to play a role as independent variables. The intercepts of all the selected entities are different and due to the randomness of the sample, unlike the fixed effects model, which assumes the difference is due to different factors such as capital, production, etc. (Wooldridge, 2006). There are two methods used to estimate the variance structure; the generalised least squares method is used when the variance structure among groups is known. On the other hand, the feasible generalised least squares method is appropriate to estimate the variance structure if the variance structure is unknown.

Accordingly, for panel data we must justify our model choice from among the three – pooled OLS, random effects model and fixed effects model – by applying a poolability test. This is a test to determine the data set's poolability, which essentially examines the stability of the parameters. The test's objective is to determine whether the same coefficients hold true across all subjects and periods of time. If this is the case pooled OLS produces unbiased estimates. If not some of the panel estimation methods (i.e. FEs or REs) is needed.

5-3-1 **Lagrange multiplier test (lm)**

Lagrange multiplier is a test of individual and or time effects for panel models. These three essential time effects provide information on whether a panel model or a pooled model (OLS) is required. Individual effects mean individual-specific but time-invariant random variables, while two-way effects mean both individual and time effects specifications. By using the R program, both individual effects and time effects are executed separately through a Breusch-Pagan test.

On the other hand, two-way effects are performed through Gourieroux and Holly and Monfort; these tests are under the Lagrange Multiplier test.

5-3-2 **Individual effect**

Table (5-2) reports the outcome of the Breusch-Pagan test for balanced panel data with individual effect. It can be seen that chi-square is statistically significant at less than 5% confidence level, the p- value = 2.2e-16; therefore, the test is significant. This rejects the data poolability and hence a panel estimation is needed.

Table (5-2) LM test individual effect

Chi-sq	Df	p-value
268.84	1	<2.2e-16

5-3-3 **Time effect**

Then the panel data is estimated with the time effect by applying the Breusch-Pagan test. As represented in Table (5-3), the p-value is significant at less than % 5 confidence level; thus, the test is significant time effects.

Table (5-3) LM test time effect

Chi-sq	Df	p-value
14.073	1	0.0001759

5-3-4 **Two-way effect**

The last test is to estimate two-way effects using Gourieroux and Holly and Monfort for balanced panel data.

Table (5-4) Two-way effects

Chisq	df0	df1	df2	W0	W1	W2	p-value
282.91	0.00	1.00	2.00	0.25	0.50	0.25	<2.2e-16

As presented in Table (5-4), the p-value is close to zero; it is less than 5%. Therefore, we can reject the null hypothesis and accept the alternative, that means we cannot reject neither individual nor time effects, this suggest that both (i.e. two way effects) are needed

Thus, the next step is to estimate both random effects model and fixed effects model with two-way specification to choose the proper model for our data set.

5-4 SELECTION METHOD FOR BALANCED PANEL DATA REGRESSION

According to Baltagi (2001), Greene (2003) and Wooldridge (2006), the choice between fixed effects model and random effects models is not easy; it depends on unobserved heterogeneity, whether it is independent of the explanatory variables or not. In order to determine the statistical significance of the changes in the coefficients on the time-varying explanatory variables, many researchers estimate both random effects and fixed effects, then the Hausman specification test is typically used to select between fixed and random effects models (Greene, 2003). The Hausman test contrasts fixed and random effects under the null hypothesis that an individual effect is independent of the other explanatory variables in the model. If the null hypothesis is not rejected, the random effects model is used because it results in more accurate estimators.

In contrast, if the null hypothesis is rejected, the fixed effects model is used (Baltagi, 2001; Greene, 2003).

As discussed above, to check whether the random effects model or fixed effects model is more appropriate for our data set, a Hausman specification test was applied with two-way time specification based on the result in table (5.4), after estimating random and fixed effects models individually. Accordingly:

the hypothesis of the Hausman test is that the random effects model is more appropriate than the fixed effects model. It basically tests whether the unique errors (ei) are correlated with the regressors; the null hypothesis is that they are not.

The null hypothesis, H0: the appropriate model is random effects. There is no correlation between the error term and the independent variables in the panel data model, i.e., the covariance between the error term and the covariates is zero.

Cov e (αi, Xit) = 0. In other words, if $p > 0.05$ then select the random effects model, otherwise the alternative hypothesis.

Alternative hypothesis, H1: the appropriate model is fixed effects. The correlation between the error term and the independent variables in the panel data model is statistically significant, i.e., the covariance between the error term and the covariates is different from zero, Cov e (αi, Xit) $\neq$o. That means if $p < 0.05$ then select the fixed effects model.

After estimating both fixed and random with two time effects and saving them, we run a Hausman specification test. The table (5-5) shows the Hausman Test outcome.

Table (5-5) Hausman test

Chi-sq	Df	p-value
13.357	6	0.037

The Hausman chi-square test statistic is statistically significant at the 5% level of significance (Prob =0.03771 < 0.05). Since the p-value is less than 5%, then the null hypothesis is rejected in favour of the alternative hypothesis. To be specific, the Hausman chi-square test outcome shows that the two-ways fixed effects model is the appropriate one; therefore, we focus on it in the next empirical analysis.

5-4-1 **Estimation of two-way fixed effects models**

Based on the outcome of the Hausman test, the two-ways fixed-effects estimator is applied through the R program. Actually, the approach is widely assumed to establish causal effects (Baltagi, 2010). Thus, this study investigates the causal effect between the dependent variable, which represents the measuring of economic development using human development index (HDI), and the independent variables, which are oil rents % GDP, net foreign direct investment % GDP, trade openness to % GDP, government effectiveness, corruption perception index and income inequality index, respectively. The validity of the two-way fixed effect model is based on two important assumptions: previous independent variable values have no direct influence on the present outcome, and past outcomes have no effect on the present independent variable values (Imai and Kim, 2019). Since our balanced panel data set includes both time effect and individual or cross-sectional effect, thus, the estimation equation which represents our model is as follows: $Y_{it} = \alpha_i + \gamma_t + \beta_1 X_{it} + \mu_{it}$……………………………………..…...Eq (5-1)

Where Y is the dependent variable (HDI), i is a unit or individual represented with time t, for i=1, 2,3……. N and t= 1, 2, 3…. T. Alpha (αi) are country fixed effects that capture unobservable time invariant country characteristics, and (γt) are year fixed effects that capture shocks or unobservable time specific heterogeneity common to all countries that are not included in the regression; it could be a disruption in oil supply such as what happened in Nigeria (Delta) due to a strike or fluctuation in international oil prices. The parameter estimate β is the unknown coefficient, refers to the marginal effect that a country specific change in independent variables X have a country specific change in human development index. and μit is the unobservable term or idiosyncratic error term.

The presence of unit or cross-sectional and time fixed effects accounts for both unit-specific (but time-invariant) and time-specific (but unit-invariant) unobserved confounders in a flexible way. These specific unit and specific time effects are usually caused by the outcome and control variables; therefore, the interaction between these two types of unobserved confounders is assumed to be absent or zero (Imai and Kim, 2019).

Accordingly, to eliminate the two effects in the estimation of the linear least squares model, we assumed both αi and γt are fixed parameters and the disturbance term is considered to be independent; $\mu it \sim$ IID (0, $\sigma 2e$). In this case, we can say the above equation (5-1) represents the two-way fixed effects.

The mechanism behind the estimation of the two-way effects model is to create a matrix of dummy variables for both the time periods and the groups which producing many of dummies create very large matrices (which are quite sparse since they contain a lot of zero) as a result takes up a lot of computer memory that slows down the estimation, causing a large reduction in degree of freedom. Therefore, instead, a within-group estimator is used to estimate two-way models which eliminates variance for both the time periods and the group. The inclusion of country and time fixed effects in the two-way model helps mitigate the influence of outliers, providing a more stable estimation of the underlying relationships (Wooldridge, 2010). And also, the two-way model, with its inherent flexibility, accommodates the complexities introduced by imputation, ensuring that the estimation process remains robust and informative. Accordingly, the two-way effects model not only rationalises the computational challenges associated with large matrices but also exhibits resilience in the face of outliers and imputed data. These features make it a valuable tool for researchers aiming to extract meaningful insights from panel data sets while navigating the intricacies of computational efficiency and data completeness.

By using the R program through (plm packages), under this method we are calculating the fixed effects estimator. This way is more computationally efficient, especially as our model is more complex. The regression outcomes of the estimation of the two-way fixed effects model include: an overview of model estimation some of the fit measures, e.g., sum squared and F-test.

The outcome in Table (5-6) describes the estimation model; it includes the coefficient estimation, standard error, absolute value of t- test and the p- values of the estimation coefficients for all the independent variables. The reported P- values can be used to assess the significance of the estimated (regression) coefficients; in other words, to measure the quality of the statistical model. Typically, we check whether the P - value is significantly different from zero at the 5% level of significance. To do this, all we need to do is check whether the reported Pr(>|t|) value is less than 0.05 confidence level. If it is, then it suggests that the null hypothesis that the population coefficient value is zero must be rejected. If the reverse is true, that the P- value is an excess of 0.05, it indicates that the null hypothesis that the population coefficient is zero cannot be rejected.

Table (5-6) Two way fixed model effects estimation result

Variables	Coefficients Estimate	Std.Error	t-value	Pr(>|t|)
Oil rents % GDP	4.4973e-04	1.3122e-04	3.4273	0.0007443 ***
NET FDI % GDP	-1.1933e-04	1.2186e-04	-0.9792	0.3287068
TOP	-1.3733e-04	6.7895e-05	-2.0227	0.0444788 *
GINI	-7.8654e-04	2.4076e-04	- 3.2669	0.0012857 **
GE	1.7899e-02	4.5978e-03	3.8930	0.0001361 ***
CPI	-9.7025e-04	2.6501e-04	-3.6612	0.0003237 ***

***, ** and * denote the 1%, 5% and 10% levels of significance.

As described in Table (5-6), all the coefficients have passed the zero restriction test at the 5% or 1% confidence level, and also the absolute values of the t-test are higher than 1.96 combined with low standards errors. The combination of low standard errors and high t-values across variables generally suggests a robust relationship, even in the presence of outliers and imputed values, as the estimate is statistically reliable, the coefficient estimates are precise and statistically significant model. The robust standard errors contribute to this reliability, helping mitigate the potential impact of heteroscedasticity and outliers on the estimated coefficients. Except for FDI, the relatively low standard errors suggest a precise estimate for the coefficient of FDI. However, the t-value being close to zero indicates that the coefficient is not statistically significant. The low t-value suggests that the impact of outliers may be less pronounced, as the coefficient lacks statistical significance.

To be specific, all the variables have a significant influence and relevance to the human development index, except for the net foreign direct investment % GDP (FDI) variable. It has a p-value = 0.3287068 and, since this value is greater than the 0.05 confidence level, therefore FDI does not exert a statistically significant affecting the human development index in the model, at least for those countries under investigation.

The R-square and F-test reported below in table (5-7). It illustrates that R-squared which represents the amount of variance of dependent variable explained by independent variables is equal 0.19845, which means only 19% of the variation in the dependent variable can be explained by the independent variables. But the low R^2 does not cause a problem since the model is not for generating predictions that are relatively precise (narrow prediction intervals); a low R^2 can be a showstopper.

Table (5-7) Sum of squares and F –statistic outcomes

R-squared	Adj. R-squared	F-statistic	DF	p-value
0.19845	0.049708	8.00516	On 6 149	9.9578e-08

As for the F-Statistics: is used to determine the statistical significance of the simultaneous effect of the predictor variable to the responder variable. If the value of p is less than the critical limit, i.e., 0.05, then accepting alternative hypothesis (H1), that means simultaneous influence of predictor variable to the response variable proved statistically significant. Conversely, if the p value exceeds the threshold, accept the null hypothesis (H0), which denotes that the simultaneous impact of the predictor variables on the response variable has not been demonstrated to be statistically significant. As can be clearly seen, the p-value is < 0.05; then the model is valid. In conclusion, we can say that the two-way fixed effects model is adequate, accordingly, we accept it to present our data set.

Returning to the results of the estimation model in Table (5-6) which suggest an increase in the human development index associated with a higher share of oil rents in GDP for the countries in the sample. The observed relationship between oil rents and HDI in this study appears to be nuanced and ambiguous. While our findings suggest a significant association between the share of oil rents in GDP and the human development index, it's essential to note the complexity of this relationship. The ambiguity arises from the interplay of various factors and contextual considerations that shape the impact of oil rents on human development. The significant correlation observed in our results may indicate that, under certain circumstances and institutional frameworks, oil rents can contribute positively to human development.

This contradicts the conventional notion of the resource curse, which often depicts oil wealth as a hindrance to development. However, it is crucial to approach this relationship cautiously and acknowledge the multifaceted nature of the interactions involved. Several potential explanations for this ambiguity should be considered. Firstly, the quality of governance and institutional structures in each country may play a pivotal role in determining whether oil rents lead to positive or negative outcomes for human development. Additionally, the effective utilization of oil revenue for investments in education, healthcare, and infrastructure is paramount in shaping the impact on human development indicators. Our results are in line with several studies (e.g., Mehlum et al., 2006; Snyder, 2006; Hodler, 2006; Boschini et al., 2007; Alexeev and Conrad, 2009) which provide evidence that natural resources are not a curse per se, but that their effect is conditional on the quality of underlying institutions.

The findings from Table (5-6) underscore the prevalent issue of income inequality in the countries under examination, indicating a persistent disadvantage for certain societal segments. This inequality, measured by the Gini coefficient, is portrayed as a lasting obstacle that diminishes overall human development quality in these nations. The research expected a significant negative sign in the Gini coefficient's estimation, anticipating that an increases in income inequality would correspond to a reduction in the human development index. The data aligns with this expectation, revealing that a one-point increase in the Gini coefficient is associated with a substantial decrease in the human development index—specifically, a decline of at least 0.0007864 points. This outcome underlines income inequality as a channel through which the impact of oil rents on the human development index. In simpler terms, heightened income inequality tends to lead to a decrease in the quality of human development. This adverse effect is magnified in the context of constraints on accessing quality education and efficient healthcare, with potentially severe consequences for the ongoing battle against poverty in these countries. Furthermore, the observed income inequality and its consequences on human development imply that these countries are still far from achieving the targets set by the Sustainable Development Goals (SDGs). The persistently high levels of income inequality pose a substantial challenge to realizing these developmental objectives in the examined countries.

Our result is in accordance with Carmignani (2012), who provided empirical evidence that natural resources directly and indirectly affect human development through income inequality, but this effect is small and the negative relationship is not robust but still results in the human development curse. Most of the previous studies (e.g., Odusola et al., 2017; Owusu and Asumadu, 2016; Parcero and Papyrakis, 2016; Mallaye et al., 2015; Mallaye, 2015) hold the view that unequal distribution of natural resources can explain the income inequality in SSA as a whole. According to Nikuman and Boyce (2012), Schuber (2006) and Gary and Karl (2003), oil rents have done little to improve the living conditions of the poor, especially in African countries, where almost 50% of the population live on less than $2 a day. For instance, Nigeria’s oil production is huge, but it has extremely unequal income distribution that raises income inequality and thus the poverty rate, which affects living quality. Additionally, Jonathan et al. (2021) and Xu et al., (2020) report that corruption, trade globalisation, foreign direct investment, poor government and population rate are likely promoting the income inequality in SSA. In addition, it might be because developing countries face rising income inequality at the initial stage of development.

Moving on to the other controls, we examine the corruption perception index (CPI), which can take different forms but we generally focus on the variant associated with government activities in those countries. The negative relationship observed between the Corruption Perception Index (CPI) and HDI indicates that higher perceived corruption is associated with lower human development. This supports the resource curse theory, as a 'grabber-friendly' environment linked to poor institutions impedes development. The evidence in our sample affirms the validation of the oil rent transmission channel via corruption, aligning with earlier empirical findings. According to van der Ploeg (2011), resource booms reinforce rent grabbing and civil conflict, especially if institutions are bad, inducing corruption, particularly in undemocratic countries. This finding is in accordance with several studies in the literature which provided empirical evidence that the natural resource curse happens only with countries that have low institutional quality (e.g., Mehlum et al., 2006; Boschini, Pettersson, and Roine, 2007; Mehlum et al., 2007; Arezki and van der Ploeg, 2007; van der Ploeg, 2011; Hooshmand et al., 2013; Lundgren et al., 2013; Horvath and Zeynalov, 2014).

In contrast to the CPI, the government effectiveness (GE) is significantly correlated to the human development index. The estimation coefficient of GE as verified in Table (5.6), demonstrated that a one-point increase of GE is associated with an increase of the human development index by 0. 017899.

The apparent contradiction emphasizing the mechanisms through which corruption and government effectiveness impact governance and human development. For instance, corruption often leads to the misallocation of resources diverting funds away from essential public services hindering economic and social development, high levels of corruption erode public trust in government institutions. While high government effectiveness ensures efficient delivery of public services, including education and healthcare. Effective governance is associated with successful policy implementation. Furthermore, government effectiveness is aggregate index consisting of different sets of indexes such as voice and accountability, political stability, regulatory quality, rule of law. These indicators collectively provide a comprehensive picture of overall governance environment, therefore, it does not allow us to identify the specific problem.

Unexpectedly, trade openness shows a significantly inverse impact on HDI. An increase in trade openness corresponds to a decline in the human development index. This finding contrasts with conventional expectations and highlights the complex dynamics of market integration, suggesting that in certain contexts, trade openness may have adverse effects on human development. Our results are in line with a number of authors (e.g., Asteriou et al., 2014; Zhou et al., 2011 Monfort and Nicolini, 2000; Paluzie, 2001; Gimba et al., 2021). The traditional explanation is that, due to the strict connection to the income inequality, market integration through trading is more likely to be beneficial to skilled labourers rather than to unskilled workers. Thereby, it increases income inequality, especially in developing countries where the income inequality is characterised by labour-intensive production and trading is expected to worsen.

In summary, the findings uncover a complex relationship between oil rents and the human development index in 11 Sub-Saharan African oil-exporting countries. The outcomes, derived from a meticulous analysis of panel data from 2000 to 2020, challenge existing paradigms and bring to light the nuanced dynamics inherent in the resource curse phenomenon.

The regression outputs present an interesting revelation a positive correlation between the share of oil rents in GDP and the HDI. This unexpected association prompts a re-evaluation of the conventional understanding of oil rents as a detriment to human development. However, the depth of our interpretation reveals a more intricate narrative. Contrary to the anticipated direct negative impact on the HDI, our results emphasize that oil rents, in isolation, do not wield a curse. The true challenge lies in the secondary effects – the appropriation of oil revenue appears to foster corruption, while the uneven distribution of natural resources heightens income inequality. These, are the critical transmission channels that truly impede human development. This connection becomes tangible when examining the socio-economic ramifications. A one-point increase in the Gini coefficient, symbolizing a rise in income inequality, manifests as a substantial reduction in the HDI. This underscores income inequality as a pivotal transmission channel for the influence of oil rents on human development. The consequences are profound limited access to quality education, efficient healthcare, and a setback in the ongoing battle against poverty, highlighting a significant shortfall in achieving Sustainable Development Goal (SDG) targets. Conversely, the positive correlation between government effectiveness (GE) and the HDI presents a hopeful aspect. A one-point increase in GE correlates with a substantial rise in the HDI, underscoring the significance of good governance in policy implementation. However, the broad nature of the GE index necessitates a more granular exploration into specific governance indicators to identify precise areas for improvement.

In an unexpected variation, the negative impact of trade openness on the HDI challenges conventional understanding. The analysis indicates that, contrary to expectations, an increase in trade openness leads to a decline in the HDI. This surprising finding prompts a re-evaluation of the presumed benefits of trade, especially in SSA, where skilled labor seems to disproportionately benefit.

Overall, the analysis provides robust evidence on the relationship between human development and oil rents, government effectiveness, corruption, trade openness, and income inequality in 11 oil exporting SSA. However, to strengthen the conclusiveness of our findings, a more thorough examination of potential confounding variables and a robust sensitivity analysis are warranted. This will enhance the robustness of our conclusions by accounting for potential variations in the coefficients of the variables and the presence of endogeneity. Therefore, addressing concerns related to endogeneity, particularly regarding oil rents, is paramount. Acknowledging potential endogeneity and discussing our model's attempts to mitigate this concern adds nuance to the interpretation, such as explore instrumental variable techniques to further enhance the reliability of our estimates.

5-5 TWOWAYS FIXED EFFECTS MODEL INSTRUMENTAL VARIABLE ESTIMATION

The literature suggests that the relationship between natural resources, income inequality, and human development is complicated and varies across different contexts. While it is commonly acknowledged that the abundance of natural resources can contribute to increased income inequality, leading to potential adverse effects on human development. For instance, Mallaye et al. (2015) identify the relationships between oil rents and income inequality have been spotted. Carmignani (2012) provides strong evidence that natural resources have an impact on human development both directly and indirectly through wealth disparity. Consequently, this nexus may cause an endogeneity issue. Three common sources of endogeneity are emphasized: simultaneity, omitted variables, and revers causality (Zaefarian et al., 2017). Endogeneity bias can result in inconsistent estimates and inaccurate inferences, leading to misleading findings and incorrect theoretical interpretations. Such a bias can sometimes result in coefficients with incorrect signs (Zaefarian et al., 2017).

In our model, the human development index(HDI) is considered the dependent variable, while the income inequality index (GINI) is used as an independent variable, so the justification could be that since the GINI is used to determine how income is distributed and cross-national income per capita(GNI) is one of the HDI components if income changes along with how it is distributed (i.e., income growth has an impact on how it is distributed while at the same time, the distribution of income affects its growth); in this case, endogeneity arises when the dependent variable (HDI) is simultaneously determined with the GINI. Therefore, conducting instrumental variable (IV) estimation is indeed a practical approach to address endogeneity concerns in our model. IV estimation helps isolate the exogenous variation in the independent variable (in this case, GINI) by identifying a suitable instrument that is correlated with the endogenous variable but not directly related to the dependent variable (HDI).

It has the ability to control several sources of endogeneity, such as reverse causality, simultaneous bias, measurement error, or the presence of unmeasured confounding effects (Stock,2011). However, inappropriate use of IVs may exacerbate issues, resulting in inconsistent coefficients and interpretations.

IVs are variables that are uncorrelated with the error term but are correlated with the endogenous explanatory variable, even though they originally serve as explanatory variables regression model (Murray, 2006; cited in Zaefarian et al., 2017). The typical economic perception related to IVs-based estimation splits observed variations in independent variables into an exogenous and endogenous part. In order to separate exogenous variation, IVs use additional regression known as' first stage regression' and using additional variables refer to an IV.

The main issue in applying IVs is to find a good instrument; using invalid or weak instruments leads to different estimates, even when there is no endogeneity bias (Rossi, 2014). Numerous attempts have been made to outline how to choose a good instrument, and the literature has documented that the best way to do so is to rely on theory. In principle, it can find instrument variables outside the unit of analysis but still have an impact on it, or within the unit of analysis as the lagged variable (Rossi, 2014). If the IV is found outside the unit analysis, it may meet the exogenous condition; such an IV has a lower chance of fulfilling the relevance condition. On the other hand, finding IV within the unit of analysis increases the probable fulfilment of the relevance condition, and is highly unlikely to meet the exogenous condition. Therefore, it is necessary to verify that, the selected instruments are both exogenous and relevant (which means that the instrument is strong or weak).

In our model, within the unit of analysis, a lagged variable was chosen, oil rents to GDP % (OR), and income inequality index (GINI). While lag (OR,1) and lag(GINI,1) were used as the instruments. Table (5-8) reports twoways effects within instrumental variables estimates.

Table (5-8) Twoways effects within model instrumental variable estimation.

Variables	Estimation coefficient	Std. Error	z-value	Pr(>|z|)
OR	8.6048e-04	1.8494e-04	4.6527	3.277e-06 ***
FDI	-1.5459e-04	1.2446e-04	-1.2421	0.2142133
TOP	-1.4269e-04	7.4292e-05	-1.9206	0.0547802.
GINI	-5.8913e-04	2.5188e-04	2.3390	0.0193376 *
GE	1.7201e-02	4.7643e-03	3.6104	0.0003057 ***
CPI	-1.0646e-03	2.7452e-04	-3.8779	0.0001054 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

As described above in table (5-8) the magnitudes of some estimation coefficients of the explanatory variables change considerably. For example, for oil rents (OR), income inequality index (GINI), and corruption perception index (CPI), the magnitude of the coefficients increased significantly compared with the results reported in table (5-6). All the coefficients remain significant except foreign direct investment (FDI), similar to the outcomes reported in table (5-8).

Overall, the inclusion of an instrumental variable has enhanced the performance of the model. Nevertheless, it is crucial to validate the accuracy and effectiveness of the instrumental variable estimation. Because if the connection between the instrumental variables and the endogenous variable lacks sufficient strength, instrumental variable estimators may fail to accurately identify causal effects. Therefore, the next step is to testing validity of the instrumental variable.

5-5-1 **Testing validity and weak instruments**

The instrument's validity was tested by comparing the estimates with and without the instruments. If significant, instruments change the estimates, which implies endogeneity in the first place. Different tests are used to deduce the validity of instruments, for example, the Wu-Hausman test. Thus, it is better to check whether both variables are endogenous. The purpose of these tests is to obtain the OR and GINI Wu-Hausman tests separately. Table (5-9) display the outcomes of the instrumental variables validity tests.

Table (5-9) Tests of endogeneity

	Model 1 (OR) is endogenous				Model 2 (OR) and (GINI) are endogenous				Model 3 (GINI) is endogenous			
Instruments	Df1	Df2	statistic	P value	Df1	Df2	statistic	P value	Df1	Df2	statistic	P value
Weak instruments (OR)	1	185	197.639	< 2e-16	2	185	116.65	<2e-16				
Weak instruments (GINI)					2	185	12.84	5.98e-06	1	185	14.15	0.00022
Wu – Hausman	1	184	4.518		2	183	7.49	0.00074	1	184	10.82	0.00120

The results indicate that the null hypothesis can be rejected, and the p-value is less than 0.05 both when the instrumental variables are tested individually and together. Thus, we can conclude that both instruments in this case are identifiable via their first lags. The Wu Hausman test checks that whether OLS model estimates are similar to instrumental variables regression. In this case, the p-value is less than 5%, which means the tests are statistically significant; hence, we can reject the null hypothesis that assumes an exogeneity in the model, which suggests that instrumental variables estimation coefficients are quite different from the fixed effects model and therefore, we have valid instruments.

However, we still need to check whether the instruments are sufficiently correlated with the endogenous variable, i.e. whether they are weak instruments.

Weak instrument indicates that the instrument has a weak relationship with the endogenous independent variable. There is a variety of evidence suggests that, if the instruments that we have selected are not sufficiently strongly related to the endogenous independent variable, then we may still have bias, perhaps it is even larger than before (Stock and Yogo,2002).

The literature provides different methods for testing the weakness of IVs, which test the joint significance of the instrument coefficients. Staiger and Stock (1997) formalized the relevant asymptotic theory and advised using the "rule-of-thumb" measurement to test for weak instruments using a partial F-test. The partial F-test can be performed in the presence of clustering and heteroscedasticity too. The typical rule of thumb for identifying weak instruments is based on estimating the first stage, which means we regress the endogenous independent variable on all of the instruments and then test the null hypothesis. If only one instrument is considered, the F-statistic is equivalent to the square of the t-statistic of the instrument coefficient in the first stage. If we have more than one instrument, as in our case, use the F statistic by checking the value of the F- statistic.

The criteria and the threshold are: If the F- statistic value is less than 10, then the instruments are weak, and we should therefore be concerned about the coefficient estimation being biased. However, instruments are likely to be strong (relevant) if the F-statistic is greater than 10. Table (5-10) illustrates the first and second stages of our model. The first stage tests are for weak instruments, they test the significance of the instrument in the first stage and need to be highly significant. The Second stage tests are tests for validity of instruments

These tests either whether the effects of the instruments (the fitted values from the first stage) are significant in the second stage (as in the F and Wald tests) or whether the estimates for the endogenous variables are sufficiently different from that of the non IV mode (as in the Wu-Hausman test. If the latter condition hold, the instruments are valid.

As reported below in the table (5-10), the outcomes of the partial F-test (first and second stage), Wald test, and Wu-Hausman test in the presence of clustering. The null hypothesis of the F-test is that the instrument is weak, so here we can reject the null hypothesis in favor of alternative hypothesis, which means the instrument is sufficiently strong.

The second stage F- test and Wald test have similar interpretations to the WU_Hausman one (they test the significance of the instruments in the second stage). Thus everything seems to be in order. Hence, the model is therefore valid in terms of quality. Therefore, second stage and IV only is the same (as it should be) so one set is not needed at all.

Table (5-10) The outcomes of F-test, Wald test and WU-Hausman test

F-test (1st stage) (OR)	123.0	P= < 2.2e-16 , on 2 and 195 DoF
F-test (1st stage)	13.5	p = 3.121e-6 , on 2 and 195 DoF
F-test(2nd stage)	19.7	p = 1.613e-8, on 2 and 195 DoF.
F-test (IV only)	19.7	p = 1.613e-8, on 2 and 195 DoF.
Wald (1st stage) (OR)	184.6	p = 2.2e-16, on 2 and 195 DoF, VCOV: Clustered (ID).
Wald (1st stage) GINI	12.8	p = 6.008e-6, on 2 and 195 DoF, VCOV: Clustered (ID).
Wald(2nd stage)	41.4	p = 1.029e-15, on 2 and 195 DoF, VCOV: Clustered (ID).
Wald (IV only)	41.4	p = 1.029e-15, on 2 and 195 DoF, VCOV: Clustered (ID)
Wu-Hausman	7.49822	p = 7.415e-4 , on 2 and 183 DoF.

In summary, this section deals with the endogeneity problem raised by the indirect nexus between the dependent variable (HDI) and independent variable (GINI). This endogeneity bias can lead to inconsistent estimates and inaccurate theoretical explanations. Furthermore, this can sometimes result in coefficients with incorrect signs. Therefore, the endogenous instrumental variable(IVs) technique was applied. IVs can control for several sources of endogeneity, such as reverse causality, simultaneous bias, measurement error, or the presence of unmeasured confounding effects. However, inappropriate use of IVs may exacerbate issues, resulting in inconsistent coefficients and interpretations. Thus, instruments should have a particular set of properties to be valid. They must be both exogenous in the sense that their only impact on the outcome variable is due to their influence on the endogenous variable. They have to be relevant in that they must be determinate of endogenous variables.

It can find instrument variables outside the unit of analysis but still have an impact on it, or within the unit of analysis as the lagged variable. In our model, within the unit of analysis, a lagged variable was chosen, oil rents to GDP % (OR), and income inequality index (GINI) as endogenous. Lag (OR,1) and lag(GINI,1) were used as the instruments. The IV regression outcome shows that the model was improved by adding an instrumental variable, assuming that we are confident in the validity of our instruments. However further tests have been applied e.g. Wu- Husmann test and partial F-test. The outcome of both tests has proved the validity of the instrument variable, and thus, they are sufficiently strong.

CHAPTER SIX: CONCLUSION

The aim of this chapter is to conclude the study; it provides a summary of the major findings in relation to the aim and objectives and also discusses the contribution. Besides too that it examines the study limitations and suggest opportunities for future work.

6-1 SUMMARY OF THE OUTCOMES AND CONTRIBUTIONS

The main aim of this study is to verify the direct impact of natural resources in the form of oil rent percentage of GDP by testing curse theory through its transmission mechanisms and institutional governance on the human development index. This work contributes to both the natural resource curse and human development literature debates for SSA in five ways.

The research focus on 11[18] oil-producing and exporting countries in sub-Saharan Africa out of 54 countries in Africa provides a good view of the crude oil-rich countries in which development is supposed to be the most intense. Previous studies either focused on all sub Saharan African countries, mixed countries from different continents, or individual oil producing countries.

A great bulk of literature is based on data collected from 1963 to 2015; therefore, to obtain results with more updated trends in the nexus and policy implications, the data set in this study covers 20 years, from 2000 to 2020. During this period, SSA experienced shifts in policy and, later, most SSA countries were considered rich natural resource countries as classified by the International Monetary Fund (IMF).

The measurement of natural resources in previous studies used either natural resource dependence or natural resource abundance. According to Sala-i-Martin and Subramanian (2003) and Shahbaz et al. (2019), natural resource abundance is defined as the total of natural

[18] Angola, Cameroon, Chad, Ghana, Gabon, Ivory Coast, Democratic Republic of Congo, Republic of Congo, Equatorial Guinea, Sudan, Nigeria

capital and mineral resources assets in dollars per capita; it means natural resource rents per capita. In contrast, the natural resource dependence is mainly based on the share of natural resource rents in real gross domestic product and includes the share of exports of five types of natural resources – fuel, ores, metals, agricultural raw materials, and food. Use of these measurements raised debate on the validity of the natural resource curse hypothesis. Some literature indicates the importance of not pooling commodities when analysing the impact of resources rents on growth (Arezki and Brückner, 2009). Therefore, this study exclusively used oil rent, ensuring methodological consistency in the consequences of resource rents on human development. Oil rent is a more appropriate measurement to examine the direct effect of natural resources on human development; theoretically, the resource curse hypothesis was originally linked with the oil and gas sector and certain minerals rather than other natural resources.

Previous research has overlooked the wellbeing in SSA nations by using the level of GDP per capita as the dependent variable to measure long-term development. As a result, the Human Development Index (HDI) is used in this study, which has replaced the traditional measurement, i.e. GDP indicator. The HDI expanded the definition of development to include factors like per capita income, life expectancy, and educational attainment.

The empirical resource curse literature attempted to develop a number of models for the SSA economy in order to investigate the factors that influence economic growth and optimal policies to implement. These studies seem clear that deeply influenced by human development indicators individually. Parts of these studies have paid attention to examining the consequences of resource abundance/dependence that might impact on GDP per capita income.

For instance, volatility in commodity price (Nili and Rastad, 2007; Van der Ploeg and Poelhekke, 2000; Keikha et al., 2012; Cavalcanti, 2015); the role of institutions and the consequences (e.g. Leite and Weidmann, 1999; Constantinos et al., 2014); corruption and state stability (Mehlum et al., 2006; Arezki and Bruckner, 2011; Van der Ploeg, 2011; Arezki and Gylfason, 2013); and income inequality, which is strictly related to the absence of adequate institutions (Tornell and Lane, 1999; Carmignani, 2013; Veloso, 2015; Parcero and Papyrakis, 2016; Mallaye et al., 2015; Mallaye, 2015; Anyanwu et al., 2016). Additionally, a number of researchers (e.g. Philippot, 2010; Kim and Lin, 2017; Karimu et al., 2017) investigate human capital accumulation and natural resource dependence. Other studies look at the relationship between government spending on natural resource wealth and the development of human capital. For instance, public spending and education (Cupta et al., 2002; Baldacci et al., 2003; Thorbecke, 2003; Anyanwu and Erhijakper, 2007; Cockx and Francken, 2015); and health and public spending (Cockx and Francken, 2014; Karimu 2017). Ibrahim et al. (2018) investigate both health and education and public spending, while Issa and Ouattara (2005) investigate health expenditure and infant mortality rates.

Accordingly, this research considered the Human Development Index (HDI) as the dependent variable to examine the fundamental form of the relationship between a number of independent ones, which are oil rent percentage to GDP, FDI inflow percentage to GDP, trade openness percentage to GDP, government effectiveness index (GE), income inequality index (GINI) and corruption perception index(CPI).

A range of statistical analyses were applied to clarify the relationship between oil rents and human development index (HDI). Measures of central tendency provided an overview of the data, revealing its unsymmetrical nature, skewed to the right, except for the HDI variable, which showed a nearly equal distribution. Bivariate plots between oil rents and HDI indicated an apparent long-run co-movement but suggested an inverse relationship in some instances, prompting further investigation.

To comprehensively analyse this relationship, Balanced panel data regression techniques, guided by diagnostic tests such as the Hausman test, indicated that the two-way fixed effects model was the most appropriate. This model effectively controlled for variances across time periods and countries, revealing that oil rents did not have a negative impact on HDI. Instead, oil rents can contribute to human development when managed effectively.

The regression outputs provide significant insights. The coefficient for oil rents (% GDP) was 0.00044973 with a p-value of 0.0007443, indicating a highly significant positive relationship at the 1% level. This suggests that higher oil rents are associated with increased HDI, highlighting the potential benefits of oil wealth when properly managed. Conversely, the coefficient for net FDI (% GDP) was -0.00011933 with a p-value of 0.3287068, indicating an insignificant relationship. This suggests that FDI does not directly enhance human development, possibly due to its volatility and conditional nature.

Trade openness (TOP) showed a coefficient of -0.00013733 with a p-value of 0.0444788, suggesting a significant negative relationship at the 5% level. This implies that trade openness may negatively impact HDI, likely benefiting skilled labor more and exacerbating income inequality, particularly in labour-intensive economies. The Gini coefficient (GINI) had a coefficient of -0.00078654 with a p-value of 0.0012857, demonstrating a highly significant negative impact at the 1% level. This emphasises how income inequality hampers human development, reinforcing the need for equitable resource distribution.

Government effectiveness (GE) was found to have a coefficient of 0.017899 with a p-value of 0.0001361, indicating a highly significant positive relationship at the 1% level. This highlights the critical role of effective governance in enhancing HDI and leveraging natural resources for development. On the other hand, the Corruption Perceptions Index (CPI) showed a coefficient of -0.00097025 with a p-value of 0.0003237, indicating a highly significant negative relationship at the 1% level. This suggests that higher corruption levels correlate with lower HDI, indicating that corruption undermines the positive effects of oil rents on human development.

To address potential endogeneity, the study employed instrumental variable (IV) estimation, using lagged variables of oil rents and Gini coefficient as instruments. The outcome shows that the model was improved by adding an instrumental variable.

The validity of these instruments was confirmed through the Wu-Hausman and partial F-tests, ensuring robust and unbiased estimates. These tests demonstrated the strength and appropriateness of the instruments, reinforcing reliability of the regression results.

Accordingly, the actual impact of the findings can be negotiated as follows: those countries, although rich in oil, are still suffering from poverty, and, based on UNDP classifications, they remain at low levels of human development, which is an indication of underdevelopment. The outcomes indicated several reasons; for instance, corruption, which is considered to be the main problem; it is notable that those countries scored low on the corruption perception index (CPI) with a minimum score of 10 and 48 index points as a maximum due to lack of accountability.

Unequal distribution of wealth and openness to trading increase the gap in income inequality. In order to improve wellbeing, policymakers should be rethink different solutions, such as the development of a financial system that has the ability to generate resources for other industries (not only the oil and gas sector), the development of domestic market, encourage private enterprise and improve the infrastructure – all of these combined with good institutions.

Particularly, the results showed that the oil rent had no detrimental effects on human development.

6-2 THE LIMITATIONS OF THE STUDY

This research is not without limitations, research limitations are often based on practical considerations such as time constraints, methodology, confounding variables, data availability or lack of generalisation, which may impact the findings. Therefore, it's crucial to discuss the limitations of this study, which may lay the foundation for future research.

Consideration should have been given to the important macroeconomic shocks, for example, the international financial crisis in 2008 and the pandemic in 2019. uncontrolled confounding variables can affect the relationship between the independent and dependent variables. The macroeconomic instability has economic impact, the financial crisis led to a decline in oil prices and reduced demand for oil Sub-Saharan African countries which heavily dependent on oil exports. Thus experienced economic challenges, affecting their revenue and ability to fund development projects.

The pandemic as well caused a severe economic contraction globally, leading to reduced economic activities, decreased oil demand, and plummeting oil prices. This had a direct impact on the oil-dependent economies of Sub-Saharan Africa, affecting their revenue streams.

Therefore, the detection of structural breaks, or the so-called change point problem, is important. A structural break in refers to a sudden and significant change in the relationship between variables. When considering the relationship between oil rent, explanatory variables and human development in Sub-Saharan African countries, a structural break could have several implications for the econometric model: it leads to a significant change in the parameter estimates of the relationship between oil rent and human development. For example, before the break, the relationship might be positive, indicating that oil rents contribute to human development. After the break, the relationship may become negative or weaker due to changing economic conditions. And also the occurrence of a structural break could result in a shift in the causal relationship between oil rent and human development. Before the break, it might be the case that higher oil rents lead to increased funding for human development projects. After the break, economic, political, or external factors may alter this causal link. Detecting and properly identifying structural breaks is crucial.

Understanding the occurrence of a structural break can have important policy implications. Governments and policymakers need to be aware of changes in the relationship between oil rent and human development to make informed decisions about resource allocation, economic diversification, and development strategies.

In addition, the findings from this study cannot necessarily be generalised to other oil exporting countries.

6-3 FUTURE WORK

This study has investigated the direct impact of oil rent, its transmission mechanisms, and institutional governance on the human development index for 11 SSA oil exporting counties; there was a restriction on the number of countries that were explored. Therefore, examining additional oil-exporting countries in Africa, such as Libya and Algeria (North Africa) these countries have experienced varying degree of success in managing their oil resources. Facing different challenges and adopting diverse policy responses this diversity would provide more information and allow to conduct comparative analysis and identify best practices and pitfalls in the relationship between oil rent and human development. Additionally, it could be better to study all SSA African countries and compare and contrast oil-rich countries with non-oil-rich countries.

Future investigations may explore additional channel via which the extraction of natural resources in those countries that can impact the human development, among these is the political instability and conflict.

Resource extraction can contribute to political instability and conflict, as competing groups vie for control over lucrative resources. This instability can undermine human development by disrupting essential services, displacing populations, and diverting resources away from education and healthcare (Ross, 2004).

More variables i.e., (macroeconomic variables) could be added as well to provide more comprehensive understanding of the relationship between oil rents and the Human Development Index. These variables should be chosen based on their potential influence on human development indicators and their relevance to the broader economic context, such as infrastructure, and social services will provide insights into the direct impact of resource management on human development or measuring the level of economic diversification in each country can help assess the extent to which these economies are dependent on oil.

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APPENDIX I

Please note that all the operation used by R program;

1) DATA SET

country	ID	YEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
Angola	1	2000	0.4	53.9	9.6	153	50.1	-1.46	17
Angola	1	2001	0.41	36.9	24	150	50.1	-1.24	17
Angola	1	2002	0.42	26.6	11.4	105	50	-1.24	17
Angola	1	2003	0.435	22.8	20.1	104	50	-1.16	18
Angola	1	2004	0.446	39.4	9.3	104	49.9	-1.31	19
Angola	1	2005	0.46	45.2	-3.5	107	49.9	-1.14	20
Angola	1	2006	0.473	43	-0.1	95	49.7	-1.37	22
Angola	1	2007	0.489	45.8	-1.4	108	49.5	-1.21	22
Angola	1	2008	0.501	55.4	1.9	151	49.4	-1.06	19
Angola	1	2009	0.515	30.3	3.1	122	49.3	-0.96	19
Angola	1	2010	0.517	39.7	-3.9	104	49.4	-1.12	29
Angola	1	2011	0.533	40.7	-2.7	100	49.5	-1.15	27
Angola	1	2012	0.544	35.8	-1.1	92	49.5	-0.99	22
Angola	1	2013	0.555	30.5	-5.2	87	49.6	-1.12	23
Angola	1	2014	0.565	23.4	2.5	79	49.6	-1.12	19
Angola	1	2015	0.572	10.4	8.6	63	49.7	-1	15
Angola	1	2016	0.571	10.3	-0.2	53	49.7	-1.04	18
Angola	1	2017	0.582	15.8	-6.1	52	49.8	-1.03	19
Angola	1	2018	0.571	26.2	-6.4	66	49.8	-1.05	19
Angola	1	2019	0.571	25	-4.6	64	51.3	-1.12	26
Angola	1	2020	0.574	24	-3.6	67	na	-1.18	27
Cameroon	2	2000	0.44	5.3	1.5	48	44.2	-0.75	20

Cameroon	2	2001	0.456	3.1	-0.1	52	44.2	-0.85	20
Cameroon	2	2002	0.458	2.5	4.1	48	44.2	-0.85	22
Cameroon	2	2003	0.464	2	2.1	40	44.3	-0.7	18
Cameroon	2	2004	0.469	2.9	0.4	42	44.3	-0.7	21
Cameroon	2	2005	0.47	5.6	-3.5	45	44.4	-0.91	22
Cameroon	2	2006	0.471	6.6	1.2	47	44.4	-0.95	23
Cameroon	2	2007	0.482	6.2	0.3	53	44.5	-0.84	24
Cameroon	2	2008	0.49	7.7	0.8	57	44.5	-0.81	23
Cameroon	2	2009	0.498	3.3	0.1	42	44.6	-0.84	22
Cameroon	2	2010	0.505	4.3	2.7	47	44.7	-0.89	27
Cameroon	2	2011	0.514	5.5	2.1	52	44.7	-0.89	25
Cameroon	2	2012	0.525	5.5	1.7	50	44.8	-0.9	26
Cameroon	2	2013	0.534	4.5	1.6	50	44.8	-0.92	25
Cameroon	2	2014	0.54	4.1	2	51	44.9	-0.79	27
Cameroon	2	2015	0.55	2	2.2	46	na	-0.78	27

Country	ID	YEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
Cameroon	2	2016	0.552	1.6	2	41	na	-0.76	26
Cameroon	2	2017	0.557	2.4	2.3	39	na	-0.81	25
Cameroon	2	2018	0.56	3	1.9	41	na	-0.8	25
Cameroon	2	2019	0.563	2.7	2.6	43	na	-0.81	25
Cameroon	2	2020	0.563	1.7	1.8	33	na	-0.88	25
Chad	3	2000	0.293	0	8.3	52	41.6	-0.7	15
Chad	3	2001	0.301	0	26.9	64	41.6	-0.85	15
Chad	3	2002	0.307	0	46.3	126	41.7	-0.85	15
Chad	3	2003	0.305	6.2	26	83	41.7	-1.05	15
Chad	3	2004	0.324	32.3	10.6	102	41.8	-1.17	16
Chad	3	2005	0.327	35	-1.5	86	41.9	-1.38	17
Chad	3	2006	0.33	34.2	-3.7	96	42	-1.48	20
Chad	3	2007	0.34	30.1	-3.7	85	42.1	-1.63	18

Chad	3	2008	0.346	32	4.5	80	42.1	-1.58	16
Chad	3	2009	0.361	15.6	4	77	42.2	-1.45	16
Chad	3	2010	0.369	15.6	2.9	80	42.3	-1.47	20
Chad	3	2011	0.38	21.1	2.3	81	42.5	-1.37	20
Chad	3	2012	0.388	22.4	4.7	81	42.5	-1.49	19
Chad	3	2013	0.394	18.5	4	73	42.5	-1.39	19
Chad	3	2014	0.406	5.8	-4.8	77	42.5	-1.5	22
Chad	3	2015	0.398	2.1	5.1	67	na	-1.46	22
Chad	3	2016	0.398	1.8	2.4	63	na	-1.51	20
Chad	3	2017	0.398	3.4	3.6	74	na	-1.46	20
Chad	3	2018	0.396	4.7	4.1	74	na	-1.52	19
Chad	3	2019	0.397	4.2	5	75	na	-1.57	20
Chad	3	2020	0.398	2.8	5.1	68	na	-1.46	21
D R of Congo	4	2000	0.349	0.9	0.5	27	na	-1.88	18
D R of Congo	4	2001	0.35	1.4	1.4	25	na	-1.69	18
D R of Congo	4	2002	0.358	1.2	2.1	29	na	-1.69	18
D R of Congo	4	2003	0.366	1.2	4.4	54	42.1	-1.53	19
D R of Congo	4	2004	0.374	1.7	4	49	42.1	-1.45	20
D R of Congo	4	2005	0.361	2.2	1.5	52	43.4	-1.57	21
D R of Congo	4	2006	0.389	2.2	1.8	48	43.4	-1.62	20
D R of Congo	4	2007	0.4	2.4	10.8	80	43.4	-1.75	19
D R of Congo	4	2008	0.412	2.6	8.7	84	43.4	-1.67	17
D R of Congo	4	2009	0.419	1.4	-1.3	63	43.4	-1.69	19
D R of Congo	4	2010	0.435	1.8	12.7	91	47.6	-1.74	19
D R of Congo	4	2011	0.438	2.1	6.2	85	47.8	-1.68	20
D R of Congo	4	2012	0.442	1.8	9.9	68	47.7	-1.65	21
D R of Congo	4	2013	0.448	1.5	5.2	77	47.7	-1.48	22
D R of Congo	4	2014	0.46	1.1	4.2	79	na	-1.56	22
D R of Congo	4	2015	0.464	0.4	3.1	61	na	-1.63	22
D R of Congo	4	2016	0.471	0.3	2.5	72	na	-1.51	21

COUNTRY	ID	YEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
D R of Congo	4	2017	0.475	0.6	2.8	65	na	-1.63	21
D R of Congo	4	2018	0.478	0.9	3	72	na	-1.55	20
D R of Congo	4	2019	0.48	0.7	2.7	57	42.1	-1.63	18

D R of Congo	4	2020	0.48	0.5	3.1	58	42.1	-1.69	18
Congo, Rep	5	2000	0.461	54.1	-3	124	na	-1.26	18
Congo, Rep	5	2001	0.468	39.4	-4.8	131	na	-1.25	20
Congo, Rep	5	2002	0.471	35.2	6.6	135	na	-1.25	20
Congo, Rep	5	2003	0.471	29	6.3	157	47	-1.23	22
Congo, Rep	5	2004	0.473	40.5	1.9	131	47	-1.09	22
Congo, Rep	5	2005	0.469	48.9	12	120	47.1	-1.27	23
Congo, Rep	5	2006	0.47	55.5	18.4	126	47.2	-1.26	22
Congo ,Rep	5	2007	0.486	46.1	16.2	149	47.3	-1.32	21
Congo, Rep	5	2008	0.501	53.3	16.7	133	47.4	-1.22	19
Congo, Rep	5	2009	0.514	34.6	12.2	136	47.5	-1.23	19
Congo ,Rep	5	2010	0.52	43.9	11.6	124	43.4	-1.23	21
Congo, Rep	5	2011	0.522	52.4	1.9	125	43.4	-1.2	22
Congo, Rep	5	2012	0.535	41.9	-0.4	97	43.4	-1.17	26
Congo, Rep	5	2013	0.545	32.4	10.5	93	na	-1.16	22
Congo, Rep	5	2014	0.56	28.4	16.1	104	na	-1.11	23
Congo, Rep	5	2015	0.58	13.2	36	123	na	-1.02	23
Congo, Rep	5	2016	0.578	13.6	0.5	131	na	-1.1	20
Congo, Rep	5	2017	0.574	28.1	39.8	113	na	-1.2	21
Congo, Rep	5	2018	0.573	42.3	31.6	120	na	-1.21	19
Congo, Rep	5	2019	0.574	41.5	36.4	127	na	-1.39	19
Congo, Rep	5	2020	0.608	31.9	39.4	110	48.9	-1.43	19
Ivory Coast	6	2000	0.421	0.3	1.4	55	49.8	-0.75	27
Ivory Coast	6	2001	0.424	0.2	1.6	53	50.7	-0.85	24
Ivory Coast	6	2002	0.426	0.4	1.2	56	51.5	-0.85	27
Ivory Coast	6	2003	0.429	0.5	0.8	53	51.8	-0.7	21
Ivory Coast	6	2004	0.433	0.9	1.2	58	52.1	-0.7	20
Ivory Coast	6	2005	0.438	2.2	1.5	63	52.4	-0.91	19
Ivory Coast	6	2006	0.443	4	1.4	64	52.8	-0.95	21
Ivory Coast	6	2007	0.449	3	1.5	61	53.1	-0.84	21
Ivory Coast	6	2008	0.455	3.5	1.4	62	53.5	-0.81	20
Ivory Coast	6	2009	0.462	1.6	1.2	67	53.8	-0.84	21
Ivory Coast	6	2010	0.468	2.1	1	67	54.1	-1.29	36
Ivory Coast	6	2011	0.472	2.5	0.8	65	54.4	-1.16	22
Ivory Coast	6	2012	0.482	2.1	0.9	70	54.7	-1.1	29

Ivory Coast	6	2013	0.49	1.4	1	58	55	-0.93	27
Ivory Coast	6	2014	0.492	1.1	0.9	54	55.3	-0.83	32
Ivory Coast	6	2015	0.503	0.4	1.1	53	55.6	-0.69	32
Ivory Coast	6	2016	0.513	0.4	1.2	48	55.6	-0.67	34
Ivory Coast	6	2017	0.525	0.9	1.9	49	55.6	-0.76	36

COUNTRY	ID	YEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
Ivory Coast	6	2018	0.534	1	1.1	46	na	-0.57	35
Ivory Coast	6	2019	0.538	1	1.5	46	na	-0.48	35
Ivory Coast	6	2020	0.516	1	0.8	42	na	-0.48	36
Equatorial Guinea	7	2000	0.525	51.3	14.8	55.6	na	-1.51	19
Equatorial Guinea	7	2001	0.534	78	64.4	53	na	-1.34	19
Equatorial Guinea	7	2002	0.546	55	17.9	54.4	na	-1.34	19
Equatorial Guinea	7	2003	0.547	55	27.8	44.5	na	-1.24	19
Equatorial Guinea	7	2004	0.554	55	7.7	131	na	-1.44	19
Equatorial Guinea	7	2005	0.565	55	9.4	131	na	-1.43	19
Equatorial Guinea	7	2006	0.576	54.6	4.7	119	na	-1.58	21
Equatorial Guinea	7	2007	0.582	47.7	9.5	134	na	-1.67	19
Equatorial Guinea	7	2008	0.583	44.6	4.5	129	na	-1.67	17
Equatorial Guinea	7	2009	0.585	26	4	122	39	-1.7	18
Equatorial Guinea	7	2010	0.576	33.5	16.8	145	39	-1.68	17
Equatorial Guinea	7	2011	0.58	35.5	9.2	114	39	-1.63	19
Equatorial Guinea	7	2012	0.584	34.2	4.4	117	39	-1.61	20
Equatorial Guinea	7	2013	0.585	29.5	2.7	107	39	-1.54	19
Equatorial Guinea	7	2014	0.586	23.9	0.8	104	34	-1.51	25
Equatorial Guinea	7	2015	0.589	12.7	1.8	99	34	-1.42	25

Equatorial Guinea	7	2016	0.588	12.1	0.5	93	na	-1.41	27
Equatorial Guinea	7	2017	0.584	17.4	2.5	102	na	-1.44	27
Equatorial Guinea	7	2018	0.582	23	3	104	30.6	-1.46	28
Equatorial Guinea	7	2019	0.592	21.5	4	95	30.6	-1.34	29
Equatorial Guinea	7	2020	0.588	15.6	5.3	90	na	-1.47	28
Gabon	8	2000	0.621	35.8	5.5	102	na	-0.57	28
Gabon	8	2001	0.624	23.2	-2	84	na	-0.34	30
Gabon	8	2002	0.626	21.5	0	85	na	-0.34	30

COUNTRY	ID	TEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
Gabon	8	2003	0.627	19.7	1.5	80	na	-0.44	32
Gabon	8	2004	0.626	29.5	4	82	40.8	-0.78	33
Gabon	8	2005	0.632	37.2	3.4	84	40.8	-0.81	29
Gabon	8	2006	0.632	37.7	2.6	89	40.7	-0.78	30
Gabon	8	2007	0.637	35.6	5.3	85	40.7	-0.79	33
Gabon	8	2008	0.639	40.2	4.5	89	40.7	-0.82	31
Gabon	8	2009	0.646	24.1	5.2	84	40.7	-0.74	29
Gabon	8	2010	0.652	29.8	3.6	89	40.7	-0.77	31
Gabon	8	2011	0.657	35.4	6.2	90	40.7	-0.8	30
Gabon	8	2012	0.666	34.1	3.9	92	40.7	-0.9	42
Gabon	8	2013	0.673	19.1	1.8	91	40.7	-0.83	34
Gabon	8	2014	0.682	23.2	6.9	74	40.7	-0.64	37
Gabon	8	2015	0.685	9.9	0.3	74	40.6	-0.73	34
Gabon	8	2016	0.69	9.4	8.9	70	40.5	-0.79	35
Gabon	8	2017	0.694	16.2	8.8	75	38	-0.92	32
Gabon	8	2018	0.697	20.1	8.2	77	na	-0.81	31
Gabon	8	2019	0.68	20.3	9.2	73	na	-0.9	31
Gabon	8	2020	0.68	14.3	11.2	70	na	-0.91	30
Ghana	9	2000	0.494	0.9	3.3	116	41.4	0.07	35
Ghana	9	2001	0.493	0.6	1.7	110	41.6	-0.1	34
Ghana	9	2002	0.5	0.5	1	97	41.8	-0.1	42
Ghana	9	2003	0.5	0.4	1.8	97	42.1	-0.2	33

Ghana	9	2004	0.509	0.7	1.6	100	42.2	-0.2	36
Ghana	9	2005	0.52	0.7	1.3	98	42.4	-0.19	33
Ghana	9	2006	0.53	0.5	3.1	66	42.5	0.16	37
Ghana	9	2007	0.541	0.4	5.6	65	42.7	0.13	37
Ghana	9	2008	0.553	0.5	9.5	70	42.8	0.03	39
Ghana	9	2009	0.56	0.3	9.1	72	42.9	-0.05	39
Ghana	9	2010	0.565	0.4	7.8	75	43	-0.04	43
Ghana	9	2011	0.574	5.3	8.3	86	43.1	-0.05	39
Ghana	9	2012	0.577	5	8	93	43.2	-0.05	35
Ghana	9	2013	0.586	3.7	5.1	61	43.3	-0.1	46
Ghana	9	2014	0.585	3.8	6.1	64	43.3	-0.28	48
Ghana	9	2015	0.59	1.4	6.5	77	43.4	-0.22	47
Ghana	9	2016	0.598	1	6.2	68	43.4	-0.17	43
Ghana	9	2017	0.602	2.9	5.4	71	na	-0.11	40
Ghana	9	2018	0.606	4.7	4.4	68	na	-0.21	41
Ghana	9	2019	0.611	4.6	5.7	77	na	-0.21	41
Ghana	9	2020	0.596	2.8	2.7	68	43.5	-0.15	43
Nigeria	10	2000	0.45	20.7	1.6	49	43.4	-0.96	12
Nigeria	10	2001	0.45	13	1.6	50	43.3	-1.03	10
Nigeria	10	2002	0.45	9.2	2	40	43.2	-1.03	16
Nigeria	10	2003	0.45	10.2	1.9	49	43.1	-0.96	14
COUNTRY	ID	YEARS	HDI	OR	FDI	TOP	GINI	GE	CPI
Nigeria	10	2004	0.46	15.3	1.4	32	43.1	-0.94	18
Nigeria	10	2005	0.465	18.6	2.8	33	43.1	-0.89	19
Nigeria	10	2006	0.473	16.1	2.1	43	43.1	-0.97	22
Nigeria	10	2007	0.478	14.4	2.2	39	43.1	-1.04	22
Nigeria	10	2008	0.484	16.7	2.4	41	43.1	-0.98	27
Nigeria	10	2009	0.49	9.1	2.9	36	43.1	-1.21	25
Nigeria	10	2010	0.482	12.9	1.7	43	43.1	-1.17	24
Nigeria	10	2011	0.492	16.6	2.2	53	43	-1.1	24
Nigeria	10	2012	0.5	14	1.6	45	42.9	-1	27
Nigeria	10	2013	0.519	10.7	1.1	31	42.8	0.99	25
Nigeria	10	2014	0.523	8.3	0.9	31	42.7	-1.19	27
Nigeria	10	2015	0.526	3	0.6	21	42.5	-0.96	26
Nigeria	10	2016	0.526	2.8	0.9	21	42.4	-1.09	28

Nigeria	10	2017	0.531	6.1	0.6	26	42.3	-1.01	27
Nigeria	10	2018	0.534	8.8	0.2	33	42.2	-1.02	27
Nigeria	10	2019	0.539	7.4	0.5	34	na	-1.09	26
Nigeria	10	2020	0.534	4.4	0.6	25	na	-1.03	25
Sudan	11	2000	0.403	10	3.2	29	51.7	-1.17	21
Sudan	11	2001	0.409	5.9	3.7	22	51.8	-1.17	21
Sudan	11	2002	0.415	5.9	3.9	26	52	-1.11	22
Sudan	11	2003	0.422	5.9	6.3	27	52.2	-1.25	23
Sudan	11	2004	0.43	10.8	5.7	31	52.4	-1.22	22
Sudan	11	2005	0.437	13.1	4.4	36	52.6	-1.4	21
Sudan	11	2006	0.443	13.4	4.1	36	52.7	-1.14	20
Sudan	11	2007	0.45	14.1	2.5	35	52.9	-1.1	18
Sudan	11	2008	0.461	14.3	2.5	38	53.1	-1.27	16
Sudan	11	2009	0.468	11.4	3.3	44	53.3	-1.25	15
Sudan	11	2010	0.469	15.1	3.5	44	53.2	-1.34	20
Sudan	11	2011	0.474	22.5	3.2	30	53.2	-1.38	16
Sudan	11	2012	0.486	6.5	6.1	28	53.1	-1.42	13
Sudan	11	2013	0.494	7.5	3.9	26	53.1	-1.49	11
Sudan	11	2014	0.499	4.6	2.5	1	53	-1.53	11
Sudan	11	2015	0.504	1.4	3.3	2	53	-1.48	12
Sudan	11	2016	0.507	1.5	2.5	1	na	-1.52	14
Sudan	11	2017	0.509	2.9	2.6	1	na	-1.43	16
Sudan	11	2018	0.506	3.8	3.7	1	na	-1.61	16
Sudan	11	2019	0.51	4.2	3.2	1	na	-1.62	16
Sudan	11	2020	0.507	2.8	3.4	1	na	-1.49	16

2) Imputed data set using MICE

```
> methods(mice)
 [1] mice.impute.2l.bin              mice. impute.2l. lmer
 [3] mice. impute.2l. norm           mice.impute.2l.pan
 [5] mice. impute. 2lonly.mean       mice. impute. 2lonly.norm
 [7] mice.impute.2lonly.pmm          mice. impute. cart
 [9] mice. impute. jomoImpute        mice. impute. lasso. logreg
[11] mice. impute. lasso. norm       mice. impute. Lasso. select. Logreg
[13] mice.impute.lasso.select.norm   mice.impute.lda
[15] mice.impute.logreg              mice.impute.logreg.boot
[17] mice.impute.mean                mice.impute.midastouch
[19] mice.impute.mnar.logreg         mice.impute.mnar.norm
[21] mice.impute.norm                mice.impute.norm.boot
[23] mice.impute.norm.nob            mice. impute. norm. Predict
[25] mice.impute.panImpute           mice.impute.passive
[27] mice.impute.pmm                 mice. impute. polr
[29] mice.impute.polyreg             mice.impute.quadratic
[31] mice. impute.rf                 mice.impute.ri
[33] mice. impute. Sample            mice. mids
[35] mice. theme
>tempData1$imp$GINI
```

	1	2	3	4	5
21	52.4	43.1	55.6	47.8	47
37	44.2	50	47.7	52.9	42.9
38	53.1	39	44.4	44.6	42.7
39	42.1	55.6	53.2	42.1	54.7
40	53	34	47.7	49.7	51.3
41	53.1	39	44.5	42.5	43.1
42	53	49.7	42.1	43.4	44.7
58	43.1	39	54.4	43.2	42.5
59	43.3	52.4	43.4	53.1	47.8
60	53	50	49.7	43.1	43.1
61	53	42.4	49.7	42.1	54.4
62	53	49.5	42.1	43.1	47.7
63	43 3	34	53.1	53.1	44.5
64	43.4	47.7	53.1	53.3	49.7
65	51.8	47.6	53.1	43.2	52.1
66	49.8	49.6	53	52.4	42.1
78	43.4	49.9	44.2	44.3	43.1
79	53	39	53.1	42.1	49.6
80	53	43	53.3	53.1	43.1
81	53.1	42.7	52.4	43.3	52.9

82	53	42.2	53.3	53.1	54.4
85	53.1	53	53.1	53	53.1
86	39	42.5	44.9	44.4	51.7
87	40.7	39	43.1	49.9	49.5
98	50	30.6	42.2	41.7	47.5
99	30.6	40.7	42.7	55.3	54.1
100	40.5	47.2	43.1	42.7	40.7
101	53	41.7	47.8	53.1	43.1
102	40.7	43.3	43.3	47.1	40.7
103	40.8	42.9	40.7	43.4	40.7
104	47.1	43.4	43.3	42.5	47.1
124	42.7	47.3	42.1	55	40.7
125	42.2	40.8	49.5	39	42.7
126	50	40.7	30.6	42	40.7
127	43.4	55.6	47.1	43.4	49.5
128	43.3	40.7	40.7	40.7	42.2
129	43.3	42.2	43.4	43.4	41.7
130	40.7	47.1	43.3	42.8	40.7
131	48.9	39	40.5	42.9	55.3
132	40.7	42.4	40.5	34	49.5
133	42.9	47	40.7	49.9	49.5

134	40.8	42.1	43.2	43	42.9
135	49.7	49.5	49.4	42.1	53.2
143	51.8	30.6	49.5	51.8	55.6
144	52.6	41.7	42.1	53.2	50
147	55	42.7	55.6	43.4	41.6
148	43.4	41.4	40.7	40.6	38
149	48.9	49.5	39	55.6	41.7
150	40.7	49.4	30.6	39	50.1
151	43.4	43.2	50.1	39	47.4
166	43.4	40.8	47.1	54.7	40.8
167	54.1	41.8	41.8	43	47.3
168	43.1	41.8	40.5	34	43.2
186	41.8	43	43.5	43.1	42.2
187	42.9	43.3	48.9	39	43.3
188	40.7	43.3	43.4	47	43.3
209	53.1	41.6	43	53.1	52.4
210	43.4	42.4	43.1	53	39 227 53 52.7 43.3 53 53.1
228	43.3	39	42.1	53.1	53.1
229	53	51.3	43.2	53.1	43.3
230	53	34	52.4	53	53.1

231	53	42.3	49.7	53.1	53.1

APENDIX II

1) DESCRPTIVE DATA

> summary(data)

Variables	Minimum	Maximum	Median	Mean
Human Development Index (HDI)	0.293	0.69	0.501	0.503
Oil rents % to GDP (OR)	0.000	78.00	9.20	15.98
NET Foreign Direct investment % GDP (FDI)	-6.400	64.400	2.700	5.119
Trade Openness to % GDP (TOP)	1.000	157.00	68.00	72.07
Government Effectiveness (GE)	-1.880	0.99	-1.11	-1.056
Corruption Perception Index (CPI)	10.000	48.00	22.00	23.95
Income Inequality Index (GINI)	30.600	55.6	43.4	45.6

1) ESTIMATION INDIVIDUAL, TIME AND TWO WAYS EFFECTS

>plmtest (HDI~OR+FDI+TOP+GINI+GE+CPI, data=panel, index=c("ID","YRS"), effect="individual", type="bp").

Lagrange Multiplier Test - (Breusch-Pagan) for balanced panels

data: HDI ~ OR + FDI + TOP + GINI + GE + CPI
chisq = 390.62, df = 1, p-value < 2.2e-16 alternative
hypothesis: significant effects

>plmtest (HDI~OR+FDI+TOP+GINI+GE+CPI, data=panel, index=c("ID","YRS"), effect="time", type="bp")

Lagrange Multiplier Test - time effects (Breusch-Pagan) for balanced panels

data: HDI ~ OR + FDI + TOP + GINI + GE + CPI chisq = 46.824, df = 1,

p-value = 7.765e-12 alternative hypothesis: significant effects

>plmtest (HDI~OR+FDI+TOP+GINI+GE+CPI, data=panel, index=c("ID","YRS"), effect="twoways", type="ghm")

Lagrange Multiplier Test - two-ways effects (Gourieroux, Holly and Monfort) for balanced panels

data: HDI ~ OR + FDI + TOP + GINI + GE + CPI

chibarsq = 437.44, df0 = 0.00, df1 = 1.00, df2 = 2.00, w0 = 0.25, w1= 0.50, w2 = 0.25, p-value < 2.2e-16

alternative hypothesis: significant effects

3) FIXED MODEL VS. RANDOM MODEL (TWO WAY EFFECTS)

Estimate two ways fixed model

> fe<-plm (HDI~OR+FDI+TOP+GINI+GE+CPI, data=imputed data, index=c("ID","YRS"), effect="twoways", model="within")

> summary(fe)

Twoways effects Within Model Balanced

Panel: n = 11, T = 21, N = 231

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.04172241	-0.00571224	-0.00049741	0.00647517	0.04144021

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)	
OR	4.4973e-04	1.3122e-04	3.4273	0.0007443	***
FDI	-1.1933e-04	1.2186e-04	-0.9792	0.3287068	
TOP	-1.3733e-04	6.7895e-05	-2.0227	0.0444788	*
GINI	- 7.8654e-04	2.4076e-04	-3.2669	0.0012857	**
GE	1.7899e-02	4.5978e-03	3.8930	0.0001361	***
CPI	-9.7025e-04	2.6501e-04	-3.6612	0.0003237	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 0.037529

Residual Sum of Squares: 0.030081

R-Squared: 0.19845

Adj. R-Squared: 0.049708

F-statistic: 8.00516 on 6 and 194 DF, p-value: 9.9578e-08

<u>Estimate two ways random effect model</u> summary(re)

Twoways effects Random Effect Model

(Swamy-Arora's transformation)

Balanced Panel: n = 11, T = 21, N = 231

Effects: var std.dev share

Idiosyncratic 0.0001551 0.0124523 0.081

individual 0.0015210 0.0390005 0.799 time

0.0002278 0.0150934 0.120 theta: 0.9305 (id)

0.7586 (time) 0.756 (total)

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.05338214	-0.00843056	0.00022998	0.01085529	0.05457298

Coefficients:

	Estimate	Std. Error	z-value	Pr(>|z|)
(Intercept)	4.9899e-01	2.3880e-02	20.8956	< 2e-16 *** OR
2.8472e-04	1.6387e-04	1.7375	0.08229.	
FDI	-5.2136e-05	1.5574e-04	-0.3348	0.73780
TOP	-1.8307e-04	8.5677e-05	-2.1367	0.03262 *
GINI	8.3519e-04	3.0690e-04	2.7214	0.00650 **
GE	1.4951e-02	5.8200e-03	2.5689	0.01020 *
CPI	-3.8206e-04	3.3329e-04	-1.1463	0.25167

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 0.062734

Residual Sum of Squares: 0.057355

R-Squared: 0.085751

Adj. R-Squared: 0.061262
Chisq: 21.0098 on 6 DF, p-value: 0.0018272

To decide between fixed or random affects a Hausman test was performed.

H0: Random effects model is consistent

H1: Fixed effects model is consistent

If p-value of the test is >0.05 we accept null hypotheses, random is consistent and efficient and vicaversa. By using R package phtest (fe, re)

4) <u>Hausman Test outcomes</u> chisq = 13.357, df =

6, p-value = 0.03771 alternative hypothesis: one

model is inconsistent

As a result, we reject the null hypotheses and accept alternative, so the nodal is two way fixed model is consistent.

Therefore, the preferred model is twoways fixed effects model

<u>Estimation twoways within effects model</u> Call:

Plm (formula = HDI ~ OR + FDI + TOP + GINI + GE + CPI, data = imputed data, effect = "twoways", model = "within", index = c("ID", "YRS"))

Balanced Panel: n = 11, T = 21, N = 231 Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.04172241	-0.00571224	-0.00049741	0.00647517	0.04144021

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
OR	4.4973e-04	1.3122e-04	3.4273	0.0007443 ***
FDI	-1.1933e-04	1.2186e-04	-0.9792	0.3287068
TOP	-1.3733e-04	6.7895e-05	-2.0227	0.0444788 *
GINI	-7.8654e-04	2.4076e-04	-3.2669	0.0012857 **
GE	1.7899e-02	4.5978e-03	3.8930	0.0001361 ***
CPI	-9.7025e-04	2.6501e-04	-3.6612	0.0003237 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 0.037529

Residual Sum of Squares: 0.030081

R-Squared: 0.19845

Adj. R-Squared: 0.049708

F-statistic: 8.00516 on 6 and 194 DF, p-value: 9.9578e-08

5) Two ways within model instrumental variable estimation.

iv_01<-plm (HDI~OR+FDI+TOP+GINI+GE+CPI|. -OR+lag(OR,1)+-GINI+lag(GINI,1)+CPI+lag(CPI,1),data=m2,model="within",effect="twoways",index=c("ID","YRS"))

> summary(iv_01)

Twoways effects Within Model, Instrumental variable estimation

Balanced Panel: n = 11, T = 20, N = 220

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.03605367	-0.00611554	-0.00027949	0.00627669	0.04147035

Coefficients:

	Estimate	Std. Error	z-value	Pr(>|z|)
OR	8.6307e-04	1.8498e-04	4.6658	3.074e-06 ***
FDI	-1.5493e-04	1.2450e-04	-1.2445	0.2133318
TOP	-1.4295e-04	7.4314e-05	-1.9236	0.0544063.
GINI	-5.8814e-04	2.5195e-04	2.3343	0.0195787 *
GE	1 .7209e-02	4.7657e-03	3.6111	0.0003049 ***
CPI	-1.0654e-03	2.7460e-04	-3.8798	0.0001045 ***

---Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 0.033461

Residual Sum of Squares: 0.028169

R-Squared: 0.17955

Adj. R-Squared: 0.023491

Chisq: 52.0246 on 6 DF, p-value: 1.8437e-09

6) Wu-Hausman Test of endogeneity

	Model 1 (OR) is endogenous				Model 2 (OR) and (GINI) are endogenous				Model 3 (GINI) is endogenous			
Instruments	Df 1	Df2	statistic	P value	Df1	Df2	statistic	P value	Df 1	Df2	statistic	P value
Weak instruments (OR)	1	185	197.63 9	< 2e-16	2	185	116.65	<2e-16				
Weak instruments (GINI)					2	185	12.84	5.98e-06	1	185	14.15	0.0002 2
Wu – Hausman	1	184	4.518		2	183	7.49	0.000742	1	184	10.82	0.0012 0

7) A combined or partial F—test for weak instruments.

These test whether the instruments are sufficiently correlated with the endogenous variable(s). the proper IV tests (taking into account both panel effects and clustering the covariance).

F-test (1st stage), OR : stat = 123.0 , p < 2.2e-16 , on 2 and 195 DoF.
F-test (1st stage), GINI: stat = 13.5 , p = 3.121e-6 , on 2 and 195 DoF.
-test (2nd stage): stat = 19.7 , p = 1.613e-8 , on 2 and 195 DoF.
F-test (IV only): stat = 19.7 , p = 1.613e-8 , on 2 and 195 DoF.
Wald (1st stage), OR : stat = 184.6 , p < 2.2e-16 , on 2 and 195 DoF, VCOV: Clustered (ID).
Wald (1st stage), GINI : stat = 12.8 , p = 6.008e-6 , on 2 and 195 DoF, VCOV: Clustered (ID).
Wald (2nd stage): stat = 41.4, p = 1.029e-15, on 2 and 195 DoF, VCOV: Clustered (ID).
Wald (IV only): stat = 41.4, p = 1.029e-15, on 2 and 195 DoF, VCOV: Clustered (ID).
Wu-Hausman: stat = 7.49822, p = 7.415e-4, on 2 and 183 DoF.
The second stage F and wald test have similar interpretation to the WU_Hausman one (they test the significance of the instruments in the second stage).