MEASURING YOUTH POVERTY IN NAMIBIA: AN APPLICATION OF A MULTIDIMENSIONAL, MULTILEVEL MODELLING APPROACH

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ABSTRACT

Officially, poverty in Namibia is measured by means of monetary thresholds, using the World Bank's Cost of Basic Needs (CBN) approach. Poverty cannot, however, be solely defined by the lack of monetary resources. Rather, it is a combination of a range of non-monetary factors which act as constraints on individuals' abilities to reach their capabilities. Adopting the Oxford Poverty and Human Development Initiative (OPHI)'s Multidimensional Poverty Index (MPI), an index that captures acute deprivations that a person faces simultaneously, this study assessed multidimensional poverty rates amongst the youth (15-34 years) in Namibia. It examined the incidence and intensity levels, as well as the determinants impelling the level of youth poverty at individual, household and regional levels.

The results from this study indicate that the prevalence of youth multidimensional poverty in Namibia stands at 31.4 percent. Across demographic groups, the results show that multidimensional poverty was high amongst females (32.2 percent), the younger youth aged 15-19 years (43.1 percent), those who resided in rural areas (42.8 percent), as well as those who lived in households that were headed by females (33.7 percent). The disaggregation of multidimensional poverty measures by regions indicates that the three regions with the highest rates were Kunene (56.1 percent), Kavango West (53.3 percent) and Kavango East (50.4 percent). The intensity levels further showed that the regions with the most deprived youth also had the most severe poverty. The study found significant determinants of the prevalence and intensity of youth multidimensional poverty not only at the individual level, but also at household and regional levels. In addressing youth multidimensional poverty, the study recommends an integrated approach that takes into account the hierarchical socio-economic effects on the livelihood of the youth, strengthening female's integration into the labor market with equal access to social protection and equalizing rural and urban opportunities in the labor, health and education sectors.

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ABBREVIATIONS AND ACRONYMS

AF	Alkire-Foster
AIC	Akaike Information Criterion
AU	African Union
CA	Capability Approach
CBN	Cost of Basic Needs
GDP	Gross Domestic Product
GLM	Generalized Linear Models
GNI	Gross National Income
HDI	Human Development Index
HH	Head of Household
IAOS	International Association for Official Statistics
ICT	Information and Communications Technology
IMF	International Monetary Fund
MDG	Millennium Development Goals
MENA	Middle East and North Africa
MLM	Multilevel Models
MPI	Multidimensional Poverty Index

MSYNS	Ministry of Sports, Youth and National Services
NCBS	National Central Bureau of Statistics
NDP	National Development Plan
NEET	Not in Education and Not in Training
NHIES	Namibia Household Income and Expenditure Survey
NIDS	Namibia Inter-censal Demographic Survey
NLFS	Namibia Labor Force Survey
NPC	National Planning Commission
NSA	Namibia Statistics Agency
OECD	Economic Co-operation and Development
OLS	Ordinary Least Squares
OPHI	Oxford Poverty and Human Development Initiative
SDG	Sustainable Development Goals
SSRN	Social Science Research Network
UN	United Nations
UNDP	United Nations Development Programme
UNECA	United Nations Economic Commission for Africa
UNSD	United Nations Statistics Division

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DEDICATIONS

I dedicate this report to my nephews and nieces; Ruben, Pandu, Pameni, M'tangeni, Pomwene, Shali, Pombili, Glory, Tuli, Puna, Pamwe, Megameno, Mewiliko, Meutho, Gamena, Yambeka, Bonita, Twapewa and those that are still on their way. At least one of you must grow up to be a Statistician someday. Aunty loves you all so much.

DECLARATION

I, Selma Ngula Megameno Shifotoka, hereby declare that this is my own work and is a true reflection of my research, and that this work has not been submitted for a degree at any other institution.

I, Selma Ngula Megameno Shifotoka, grant The University of Namibia the right to reproduce this thesis in whole or in part, in any manner or format, which The University of Namibia may deem fit.

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1. CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Like many developing countries, Namibia continues to battle various socio-economic impacts of poverty that compromises the country's progress towards the realization of its Vision 2030 goals. The fight against poverty is a government priority, called for in the first thematic area of the country's Vision 2030 framework. According to the Monitoring and Evaluation Plan for Vision 2030 by National Planning Commission (NPC) (2016a), the vision is that poverty will be reduced to the minimum and all citizens will be able to realize their full potential. The effectiveness of government interventions in eradicating poverty will require comprehensive definitions, clear measurements and informed Monitoring and Evaluation (M&E) programs.

The United Nation's 2030 agenda for sustainable development defines poverty as having multiple forms. There is now a global recognition of the importance of having a comprehensive measure of multidimensional poverty that captures the multiple deprivations faced by the poor and provides information related to the intensity and composition of poverty. To measure multidimensional poverty, The United Nations Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI) have developed the Multidimensional Poverty Index (MPI). The MPI measure is based on the Alkire-Foster (AF) method, which is a way of measuring multidimensional poverty developed by OPHI's Sabina Alkire and James Foster, and involves counting the different types of deprivation that individuals experience at the same time, and then constructing a multidimensional index of poverty that identifies individuals as poor on non-poor.

In order to identify the poor, the AF method counts the overlapping or simultaneous deprivations that a person or household experiences in different weighted indicators of poverty (Alkire & Santos, 2010). Individuals are then classified as multidimensionally poor if the weighted sum of their deprivations is greater than or equal to a poverty cut off or threshold.

The MPI approach differs from the classical World Bank's Cost of Basic Needs (CBN) measure of poverty. With the CBN, the cost of basic human needs such as food, housing, education and health in a society are computed based on household's consumption expenditure and the total cost of basic needs is used to determine a monetary threshold for poverty status. Under the CBN approach, NPC (2015) described in its report which was aimed at studying the root causes of poverty in Namibia, that the poverty line as being set by first computing the cost of a food basket that enables households/individuals to meet a minimum nutritional requirement and then adding an allowance for the consumption of basic non-food items (such as housing, education and health). Households/individuals whose total consumption expenditure equates or exceeds this total cost of basic needs are considered non-poor, while households/individuals whose total consumption expenditure falls below the total cost of basic needs are considered poor.

Since 2003, poverty in Namibia is officially measured through the Cost of Basic Needs (CBN) approach, as stated by the NSA in the 2015/16 Namibia Household Income and Expenditure Survey report. (NSA, 2018). The CBN as a national measure of poverty replaced the approach that was used in the country since 1990, which was based on a relative food consumption ratio. Using data from the 1993/4 Namibia Household Income and Expenditure Survey (NHIES), the National Central Bureau of Statistics (NCBS) defined the official poverty line using the relative share of food expenditure to the total expenditure of households. This way, the 1993/4 NHIES report showed that a household was considered “poor” if food expenditure made up 60 percent or more of total expenditure, while a household was classified as “severely poor” if food expenditure made up 80 percent or more of total expenditure (NCBS, 1996). In 2003/2004, Namibia shifted from using the conventional food consumption ratio by replacing it with the CBN approach as the official measure of poverty in Namibia (NSA, 2018).

In addressing poverty, Namibia’s fifth National Development Plan (NDP) that was launched by NPC (2017) states that the government of the Republic of Namibia is striving towards building a Namibia where there are no structural poverty traps. The fifth NDP has four main pillars; Economic progression, Social transformation, Environmental sustainability and Good governance. As a strategy in eradicating poverty, the pillar of social transformation focuses on youth empowerment, which aims at strengthening youth skills and promoting youth’s health and wellbeing.

In the 2020-2030 National Youth Policy by The Ministry of Sport, Youth and National Service (2021), the youth in Namibia were defined as individuals aged 15-34 years. Demographically, the 2016 Inter-censal Demographic Survey (NIDS) report showed that the youth made up about 37 percent of Namibia’s population, with a literacy rate of 94 percent. Despite this, the youth still faces the socio-economic challenge of a high unemployment rate reported at 46.1 percent in the 2018 Namibia Labor Force Report by NSA(2019), and this setback may limit the youth from participating in economic activities and draw or keep them into multidimensional poverty.

In order to properly monitor and evaluate progress of poverty alleviation programs amongst the youth, it is imperative that comprehensive research is carried out to measure the rate and the depth of youth multidimensional poverty in the country. The CBN approach used to measure poverty in Namibia since 2003 is limited only to a monetary dimension, thus classifies individuals as poor or non-poor, depending on whether or not their income or consumption expenditure falls below a monetary threshold (NSA, 2018). This one-dimensional nature of the CBN approach implies that it excludes other forms of deprivations that are directly linked to human development, such as the inability to read/write, food insecurity, inadequate housing, to mention a few. This raises a concern that the CBN approach might not be comprehensive enough to inform youth poverty-eradication strategies, given that these deprivations can still exist for those that are above the monetary poverty line.

In order to inform policies aimed at eradicating poverty while specifically acknowledging the prominent role that the youth play in shaping economic trajectory as indicated by Ozdamar and Giovanis (2019), this study profiled multidimensional poverty amongst spatial subgroups of the youth (aged 15-34) in Namibia. To be precise, this study sought to assess the multidimensional poverty rates of youth in Namibia, assessing not only the incidence and intensity levels, but also the determinants driving the prevalence of youth poverty across different demographic groups of the youth population in the country.

1.2. Statement of the problem

Many youths in Namibia continue to be faced with multiple deprivations. Of the total population considered as monetary poor in Namibia, the 2015/16 NHIES report showed that the youth made up about 32 percent (NSA, 2018), while the youth unemployment rate computed from the 2018 Annual Labor Force Survey (LFS) stood at 46.1 percent, which is higher than the national rate of 33.4 percent, according to the NSA's 2018 Namibia Labor Force Report (NSA, 2019). Youth unemployment in the country shows an increasing trend over the years, reported at 34.5%, 36.7%, 29.6%, and 34.0 percent in 1997, 2004, 2013, and 2016 respectively as stated in the 2018 NLFS report by NSA(2019). In addition, the Demographic Dividend Study report by NPC (2016b) stated that lack of access to productive assets, capital, land and skills compromise progress in youth empowerment. Furthermore, common monetary-based definitions of poverty do not give a comprehensive picture of the youth's living standards, as argued by Sandel (2012) that many aspects of well-being cannot be properly priced or monetarily valued, such as the ability to read and write, longevity and good health, security, political freedoms, social acceptance and the ability to move about and connect. These aspects are therefore still not properly understood, and cannot be improved until capability-based, non-monetary approaches of poverty are used to define youth multidimensional poverty.

Furthermore, Ozdamar and Giovanis (2019) assert that unidimensional poverty measures such as the CBN approach used in Namibia, do not constitute or adequately represent human wellbeing and deprivation that is needed to tackle poverty to the full extent. In addition, these measures do not indicate the specific deprivations being experienced by the poor, which policy makers need to tackle in order to eradicate poverty. As a result, the effectiveness of interventions that are based on a one-dimensional poverty measures are often compromised.

Moreover, poverty analysis that do not consider multilevel effects lacks crucial information that allows for better interventions suitable at different levels of geography and demography. (Smith & Shively, 2019). While there is a good collection of data fit to assess socio-economic deprivations for the youth in the country (such as education, labour participation and social welfare indicators which are all collected by the NSA), there is limited evidence to guide the poverty eradication efforts, that considers individual, household and regional random effects on a multidimensional level. Likewise, there is inadequate coordination of poverty eradication efforts across multiple levels of the population on a multidimensional level.

1.3. Objectives of the study

The main objective of the study was to create a youth Multidimensional Poverty Index for the youth (aged 15-34 years) in Namibia, and use it to model the prevalence and multilevel determinants of youth multidimensional poverty rates in Namibia. The specific objectives were to:

1) Apply the Alkire-Foster method to determine the level of youth multidimensional poverty in Namibia
2) Assess the disparity in the intensity of youth multidimensional poverty in Namibia
3) Examine the hierarchical socioeconomic and demographic factors affecting the prevalence of youth multidimensional poverty in Namibia

1.4. Significance of the study

The findings from this study can contribute to the literature on the multiple deprivations faced by the youth in Namibia. The study further identifies empirical evidence on the disparities in intensity of multidimensional poverty amongst the youth. Additionally, the results can provide information on the socioeconomic and demographic factors affecting the prevalence of multidimensional poverty amongst the youth, while the study's hierarchical analysis approach can enrich literature aimed at enabling targeted planning and implementation of poverty eradication efforts.

1.5. Limitations of the study

Firstly, the study used multiple data sources to obtain regional indicators, namely; the 2015/16 Namibia Household Income and Expenditure Survey (NHIES), the 2016 Namibia Inter-censal Demographic Survey (NIDS) and the 2016 Namibia Labor Force Survey (NLFS). This may have affected the estimations, given that the three (3) surveys used different methodologies and were conducted at different periods. While the 2015/16 NHIES and the 2016 NIDS surveys are the latest versions at the moment, the most recent LFS was conducted in 2018. However, the researcher decided to use the 2016 LFS as it's time period was close enough to the other surveys being used for the study, therefore the indicators from all three surveys were computed from a relatively similar population.

Secondly, the data sources used for analysis lack constituency level variables that would have provided information at the constituency level for better targeted planning.

1.6. Delimitations of the study

There are various challenges facing the youth in Namibia, despite government's efforts towards empowering the youth. Amongst these challenges are high unemployment rate, high monetary poverty rate, as well as exclusion from education and training. These challenges are discussed in detail in section 2.5 of this study. In order to contribute to the efforts of eradicating these challenges, the analysis of multidimensional poverty in this study was limited to the youth, aged 15-34 years.

2. CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

This chapter begins with a theoretical framework on poverty definitions. This is followed by a review of common methodologies of poverty measurement, looking not only at their structures, but also at their applications globally, continentally and nationally. The chapter further looks into how multivariate Generalized Linear Models (GLMs) have been previously applied to poverty measurement. The chapter concludes with a review of the importance of investing in the youth, which motivated the researcher to limit the analysis of the study only to the youth aged 15-34 years.

2.2. Poverty definitions

The concept of poverty has always been recognized throughout human history, which explains the existence of the broad variety of definitions and measurement approaches. The definitions of poverty found in literature tend to vary widely, with diverse perspectives such as primary, secondary, absolute, relative, subjective, extreme, transient and chronic poverty (Ozdamar & Giovanis, 2019). To be poor in a developing country might be different from being poor in a developed one, and the way that the poor see their own condition might be different from the view of a policymaker or a researcher. Sen (2018) points out that despite the difficulties in finding a common definition of poverty, to look for this consensual definition is an important task, not only theoretically or empirically, but also practically, considering that this definition is meant to guide public policies that are designed to fight poverty or to ameliorate the conditions of people considered as poor.

This sub-section reviews two common approaches of defining poverty, namely, poverty as economic circumstances and poverty of lack of capabilities.

2.2.1. Poverty as economic circumstances

Wisor (2012) noted that the most widely used and dominant measures of poverty are monetary-based. These approaches assess the shortage of income or inadequate consumption expenditure, which suggests eradication of poverty by ensuring economic growth. Monetary measures are often based on income, but consumption expenditure is also considered as a common measure. Researchers argue that consumption-based indicators of welfare are more descriptive of poverty than income-based indicators. Using consumption in welfare measurement is preferred because unlike income, consumption is not closely tied to short-term fluctuations, and that it is smoother and less-variable over time (Deaton & Zaidi, 1990). Taking current income can be a misleading because income is often underreported and it is sensitive to short-term lifestyle changes such as seasonal fluctuations and temporary job losses, while consumption is much more stable in an individual's life (Sabanovic, 2017).

The definition of poverty proposed by Joseph Rowntree in the early 20th century understood primary poverty as "earnings that are insufficient to obtain the minimum necessaries for the maintenance of merely physical efficiency", while during the 1970s, Adam Smith also defined poverty as "the inability to purchase necessities required by nature or custom" (Davis & Sanchez-Martinez, 2014). Since 1990, The World Bank has been using monetary measures such as income and consumption expenditure to define poverty. According to World Bank (2018a) poverty is the inability to attain a minimal standard of living. The bank uses monetary thresholds, commonly known as poverty lines, to reflect the amount below which a person's basic need such as education, nutritional, clothing, and shelter needs cannot be afforded.

United Nations Economic Commission for Africa (UNECA) (2013) also acknowledged the importance of considering income in defining poverty by stating that it allows people to satisfy their needs and pursue many other goals that they deem important, and as such, those with low incomes typically have restricted capacities to consume the goods and services they need to participate fully in the society in which they live. Additionally, James (2019) also defined poverty as a state or condition in which a person or community lacks the financial resources and essentials for a minimum standard of living.

Despite the common use of this approach, however, it has received a lot of criticism. Ozdamar and Giovanis (2019) assert that monetary measures of poverty do not adequately represent human wellbeing and deprivation that is needed to understand tackle poverty to the full extent. The measures do not indicate the specific deprivations being experienced by the poor, which policy makers need to tackle in order to eradicate poverty. As a result, the effectiveness of interventions that are based on one-dimensional poverty measures are often compromised. Similarly, Knecht (2012) agreed that income only represents the capability of purchasing goods on markets, but does not say anything about what can be accomplished with the purchased goods.

Another notable criticism is by Davis and Sanchez-Martinez (2014) who argued that the monetary approach defines poverty narrowly in terms of consumption that is derived from current income by assuming that individuals are identical in terms of needs or preferences and abstracts from the potential benefits of community, social goods and social interaction by taking a purely individualistic standpoint. Furthermore, OPHI (2020) argued that using income only as an indicator of well-being is not sufficient because individuals have different capacities converting income into functionings.

Using income can be misleading, because low incomes do not necessarily imply low standards of living. UNECA (2013) argues that a household with a low income may be able to enjoy higher living standards by using savings or taking on debt (based on expectations of higher income in the future), or on high levels of wealth, which are typically not taken in account in monetary poverty indicators.

2.2.2. Poverty as a lack of capabilities

Economist and philosopher Amartya Sen initially defined the Capability Approach (CA) in poverty analysis during the 1980s, focusing on the notion of functionings and capabilities. Sen (1981) argued that the right focus of poverty is neither upon commodities, nor in personal characteristics, or even in the concept of utility, but in the real freedoms that people actually have to realize what they want. According to the CA, social arrangements should primarily be evaluated according to the extent of freedom people have to promote or achieve the plural functionings they value. It therefore follows that the CA views poverty as a deprivation of valuable freedoms and evaluates multidimensional poverty according to capabilities (Alkire and Foster, 2007).

Sen (1981) further explained that a person's well-being can be conceived in terms of the ways that a person can function, which is, the various doings and beings that can be assessed as functionings. According to Mendosa Dos Santos (2018), the approach places the definitions of functionings and capabilities as activities (eating, reading, seeing) or states of existence or being, from the elementary ones (being well nourished, being free from avoidable diseases) to more complex ones (not being ashamed of his/her own clothing, taking part in the life of the community, having self-respect).

One notable criticism of this approach is the absence of a definite list of capabilities that are to be considered as basic ones, or more valuable amongst others, to measure welfare. However, unlike Nussbaum (2000) who made a proposition of a standard list of which capabilities are relevant to poverty analysis, Sen(1981) emphasized that there is, and there should not be a fixed universal list of functionings in the perspective of the capability approach. According to Alkire et al (2010), Sen explained that insisting on a fixed list of capabilities would deny the possibility of progress in social understanding and also go against the productive role of public discussion, social agitation and open debates. As such, his approach leaves the selection of considerable capabilities in the hands of researchers based on their own context.

By contrast, Nussbaum (2000) argued that it is essential to specify a list of valued capabilities and has specified a list of ten (10) central human capabilities that emerge from her Aristotelian analysis of human flourishing and the requirements necessary to secure human dignity. These capabilities are: life; bodily health; bodily integrity; senses, imagination, and thought; emotions; practical reason; affiliation; other species; play; and control over one's environment. Nussbaum (2011) stressed that these capabilities should provide the basis for "constitutional principles that should be respected and implemented by the governments of all nations". Similarly, Alkire & Santos (2010) pointed out that analysis of the dimensions selected by various authors shows emergence of 'areas of consensus'. However, as OPHI (2011a) highlighted, Sen (1981) maintains that the approach is deliberately incomplete, and it has to be operationalized differently in different contexts.

Another criticism of the capability approach is it's focus on individual functionings rather than relative deprivations. According to Alkire & Foster (2007), critics argue that prospective analyses and recommendations that do not carefully scrutinize the role of collective actions, institutions, and other social structures in creating individual capabilities, will be deeply flawed. Hick (2012) explained how Economist Peter Townsend criticized the nature of the capability approach, arguing that the concept of poverty must reflect both material and social needs, and that these could only be considered relative to the societies in which people live because people's needs were socially determined.

A clear summary of the Townsend-Sen debate is put forward by Mendosa Dos Santos (2018). Townsend highlighted that the approach does not adequately represent the concept of relative deprivations, and it's focus only on the functionings of an individual basis poverty more in terms of individual motivation, than in terms of social organization. However, Sen described his concerns with relative measurement of poverty, that may conceive that poverty simply cannot be eliminated, because in every society there will always be some people that will not have what others have and that people will be, relatively speaking, poor, even if they have the minimal conditions necessary to have a modest life. He further emphasized that poverty is not just a matter of being relatively poorer than others in the society, but of an individual not having certain minimum 'capabilities'.

Given the limitations of the monetary definition of poverty highlighted above, this study followed the capability approach to define youth poverty. This was done through the application of the multidimensional poverty index, which, together with other methodologies of measuring poverty, are discussed in the next sub-section.

2.3. Methodologies of measuring poverty

Measuring poverty not only equips us with information about those who are suffering and the extent of their plights but it also enhances the formulation and implementation of government policies (World Bank, 2018a). Poverty measures typically will involve the identification of poor based on a poverty threshold. Specifically, the World Bank (2018a) outlined that a given poverty measure first defines an indicator of welfare, then secondly establishes a minimum acceptable standard of that indicator to separate the poor from the non-poor (the poverty line), and lastly generates a summary statistic to aggregate the information from the distribution of this welfare indicator relative to the poverty line. This section discusses the structure and applications of three methodologies of measuring poverty, namely; The Cost of Basic Needs (CBN), the Human Development Index (HDI) and the Multidimensional Poverty Index (MPI).

2.3.1. Cost of Basic Needs (CBN)

The CBN approach is based on the understanding that poverty means a lack of command over 'basic consumption needs', and the poverty line to be the cost of those needs. The measure is therefore fundamentally based on the economic-related definition of poverty discussed in section 2.2.1 above. Dissatisfaction with purely monetary measures of poverty led to the development of the CBN approach during the 1970s (Watson, 2014).

Watson (2014) noted that the main foundation of the CBN approach is a consequentialist ethic that argues that a good society is one in which all people will be able to meet their basic needs. A person is said to be poor if he or she is unable to meet his or her basic needs. According to World Bank (2018a), the consumption bundle includes goods that a person consumes (i) to be adequately nourished and (ii) to fully participate in the society he/she lives in. In addition, a non-food component is added, consistent with the spending patterns of the poor. Together they provide an estimate for an absolute poverty line—explicitly fixed at a specific level of welfare—allowing for poverty comparisons across individuals. As such, the CBN approach stipulates a consumption bundle that is deemed to be adequate, with both food and non-food components and then estimates the cost of the bundle for each subgroup. An individual is considered to be poor if they cannot afford the cost of the determined consumption bundle.

The CBN method is widely applied and broadly accepted as a guidepost to best practice in estimating absolute poverty line (Arndt, Mahrt & Tarp, 2016). The World Bank uses this approach to monitor global poverty. Ferreira, Mitchell and Prydz (2015) noted that the World Bank has been assessing the extent of extreme poverty across the world since 1979 and more systematically since the World Development Report 1990, which introduced the dollar-a-day international poverty line.

According to the Poverty and Shared Prosperity report by World Bank (2018b), the number of people living below the international poverty line of $1.90 decreased from 1.9 billion in 1990 to 741 million in 2015. The report further indicated that the number of people living in extreme poverty remained unacceptably high, and there were several reasons to believe that the target of reducing the share of people living in extreme poverty to below 3 percent by 2030 would not be achieved. Sub-Saharan Africa showed the slowest pace of poverty reduction compared to other regions, in line with the forecast that extreme poverty will be a predominantly African phenomenon in the coming decade (Beegle and Christiaensen 2019; World Bank 2018b). While poverty was higher for rural based households across African countries, the rural poverty rates in Western and Southern Africa declined about 40 percent between 1996 and 2012 (Beegle et. Al., 2016).

At national level, the application of the CBN approach in Namibia indicated that poverty was reducing. According to the 2015/16 report by NSA (2018), 17.4 percent of the population in Namibia were considered poor using the upper bound poverty line (N$ 520.8). This indicated a decline in the national poverty levels in 2009/2010 (28.8 percent) and 2003/2004 (37.5 percent). The report further shows that in Namibia, poverty was higher for rural, female-headed households. Beegle et. al., (2016). In an investigation of how accessibility to financial services was linked to poverty alleviation in rural areas of Namibia, Shaninga (2018) indicated that inadequate financial institutions were some of the determinants of poverty in Namibia.

Although widely applied, the CBN approach has also been criticized. Hick (2012) noted that while income has the potential to expand people's choices, monetary measures may be an imperfect guide to the human development successes of a given country or region. OPHI (2011a) argued that many countries, for example, have high levels of income per capita but low levels of other human development indicators (and vice versa). Ozdamar and Giovanis (2019) also argued that uni-dimensional poverty measures such as monetary poverty lines do not adequately represent deprivation needed to tackle poverty fully. Salecker, Ahmadav and Karimli (2020) noted that using only monetary measures results in significant downward bias in terms of estimating poverty rates and trends, adding that capability-based measures can be better suited to accurately account for the complex—compound and variegated—nature of poverty than standard monetary measures. Many aspects of well-being cannot be properly priced or monetarily valued (Sandel, 2012), such as the ability to read and write, longevity and good health, security, political freedoms, social acceptance and the ability to move about and connect. Due to these limitations of the CBN approach, the HDI, which is based on the Capability Approach (CA), was developed.

2.3.2. Human Development Index (HDI)

The use of income as a measure of welfare was gradually accepted shortly before the mid twentieth century especially after the Second World War. With a focus on the welfare of growing populations, institutions like World Bank and International Monetary Fund (IMF) were created to rebuild the economies affected by the war and assist developing countries world-wide to come out of poverty. Klasen (2018) described that emphasis was on restoring economic growth, the primary metric of development at the time. However, Shokunbi (2017) noted that it later became evident that income growth does not result in increased welfare since production and distribution continuously constrain household income. As a result, researchers begun to contemplate on additional potential approaches of analyzing welfare, globally. OPHI (2011a) explained that the Human Development Index (HDI) was introduced as an alternative to conventional measures of national development such as income per capita and the rate of economic growth. The first version of the HDI was reported in 1990 in the UNDP’s Human Development Report. This measure is fundamentally based on the capability-related definition of poverty as discussed in section 2.2.2 above.

Amartya Sen's Capability Approach (CA) contributed to the launch of the HDI, within the context of which poverty is defined as the lack of opportunities in the areas of education, health and command over resources, as well as for participation in the democratic processes. Different authors have acknowledged how the CA was very critical to the creation of the HDI. Shonkunbi (2017) stated that the indicators employed by the HDI evidence the result of increasing/decreasing the functionings of people in different societies. In its report explaining the concepts of measuring poverty, UNDP (2016) explained that the HDI was premised on the fundamental idea that wellbeing is multidimensional and encompasses multiple aspects of human life, including how people interact with each other and with our physical environment.

The HDI is a summary measure of achievements in three key dimensions of human development: a long and healthy life, access to knowledge and a decent standard of living. (UNDP, 2019). Shokunbi (2017) outlined how these dimensions are measured by life expectancy, years of schooling and Gross National Income (GNI), respectively. The HDI is calculated as the geometric mean (equally-weighted) of life expectancy, education, and Gross National Income (GNI) per capita (Roser, 2014). The index sets a minimum and a maximum value for each dimension and then shows where each country stands in relation to these values, expressed as a number between zero and one (OPHI, 2011b). An HDI score closer to 1 indicates a higher level of human development (and vice versa). The cutoff points are HDI of less than 0.550 for low human development, 0.550-0.699 for medium human development, 0.700-0.799 for high human development and 0.800 or greater for very high human development (UNDP, 2019).

The HDI has been applied to inform policy making at different levels. On a global scale, the 2019 HDI report indicates that Norway, Switzerland and Ireland have the highest HDI score of 0.954, 0.946 and 0.942, respectively. Furthermore, the report shows that Namibia, with a score of 0.645, is ranked number 129 on a global scale, while most of the African countries scored low human development. (UNDP, 2019). While the report suggests that the overall trend globally is toward continued human development improvements, with many countries moving up through the human development categories, Roser (2014) highlighted that the lowest HDI values are found in central Africa.

Different authors have further tried to explain the factors linked to low human development in Africa. Escosura (2011) reported that stagnating life expectancy due to the spread of HIV/AIDS (and the resilience of malaria) together with arrested growth, largely resulting from economic mismanagement, political turmoil, and civil wars, have made advances in human development dependent slow in the continent.

Sarkodie and Adams (2020) used a non-parametric regression model to examine the nexus between access to electricity, human development index, political system environment, income level, and income inequality, in sub-Saharan Africa. They found that income inequality reduces human development, and as such, social protection policies that reduce poverty are essential to minimize the vulnerability to poverty. Furthermore, the findings of the study highlighted that effective promotion of labor markets and the improvement of socio-economic capacity to manage unemployment, infirmity, and disability will decrease income inequality, hence, promote human development.

The application of the HDI out of the African context is also noteworthy. Antony, Rao and Balakrishna (2011) calculated HDI for Indian states in order to study its behavior with variations in demographic, socio-economic, health, dietary habits and nutritional status. Their results indicated that HDI values were significantly different between various regions of India, with regions in the West, North and South recording higher values than the regions of Central and East India. Per capita income and educational levels of parents were found to have significant effect on the HDI variations.

The development and use of the HDI has received both positive and negative assessment in literature. Klasen (2018) noted that the HDI offered a new narrative of development based on the human development paradigm, thereby challenging the sole focus on economic efficiency and per capita income, with a strong link to Amartya Sen's capability approach as an alternative conception of what development is all about. The index provides a better picture of a nation's development because it incorporates primary social and economic factors, and it emphasizes the importance of individuals and their ability to unleash their maximum potential. has political appeal, which may reduce civil disturbances and increase political stability.

The general criticism of the HDI stated by Dervis and Klugman (2011) is the choice of dimensions and indicators, noting that it captures only a few dimensions of human empowerment and leaves out many others that people may value such as social and political freedom and protection against violence. The functional form of the HDI has also received criticism in literature. UNDP (2015) noted that since 2010, the overall HDI is calculated by taking the geometric mean of normalized indices measuring achievements in each dimension. This revision was done based on the reasoning that geometric mean reduces the level of substitutability between dimensions and at the same time ensures that a 1 percent decline in one dimension has the same impact on the HDI as a 1 percent decline in another (OPHI, 2011b). However, as referenced by Klasen (2018), Amartya Sen expressed that the geometric mean is not very intuitive, simple, or transparent, thereby undercutting one of the key advantages of the HDI. Bilbao-Ubillos (2013) emphasized that it may conceal significant pockets of population who are excluded from the average achievement measured: i.e. there may be large groups in society who do not share in the achievements inherent in the apparent level of development enjoyed by their country.

Furthermore, Rodriguez (2015) argued that the revised functional form may make Sub-Saharan African countries appear worse than they really are. He argues that according to the 2010 Human Development Report, Africa's average HDI stands at 0.389, or 62.3 percent of the world HDI, but with the application of the old functional form, then Africa's HDI would have been 64.1 percent of the world average. Based on these limitations of the HDI, another poverty measure which is based on the Capability Approach, the Multidimensional Poverty Index was developed.

2.3.3. Multidimensional Poverty Index (MPI)

The MPI was developed by Alkire and Santos (2010) for the 2010 Human Development Report. It is based on the capability-related definition of poverty, measuring wellbeing as the freedom that people have to enjoy valuable activities and states which enables them to achieve valuable functioning's. Alkire et al (2015) explained that functioning's are beings and doings that people value and have reason to value. Functioning's can include quite elementary achievements, such as being safe, well-nourished, and literate, or quite complex achievements, such as waging a political campaign for election or performing a classical dance routine exquisitely. They be conceived as a collection of the observable achievements of each person such as their health, education or having a meaningful job. The MPI is a composite index that measures acute poverty through social indicators not considered before as joint when measuring poverty (Shokunbi, 2017).

Alkire and Santos (2010) identified three dimensions to be included in the global MPI: health, education, and the standard of living. Ravallion (2012) explained that the global MPI has 10 indicators across the three dimensions: two for health (malnutrition and child mortality), two for education (years of schooling and school enrollment) and six aimed to capture living standards (cooking fuel, sanitation, drinking water, electricity, housing and assets).

Furthermore, Alkire and Foster (2007, 2009) noted that in the compilation of the index, each dimension is equally weighted; each indicator within a dimension is also equally weighted. Dotter and Klasen (2014) noted that the three dimensions of the global MPI have been chosen as there is consensus that any multidimensional poverty measure should at least include these three dimensions; for the ease of interpretability; and finally for reasons of data availability. However, when developed specifically for a given society, the measure is open for additional dimensions and indicators that are deemed as measures of wellbeing in that society. Dotter and Klasen (2014) however noted that while there are arguments to include additional dimensions such as powerlessness, deprivations of rights, violence, shame, time use, among others, there is often no data available and there is disagreement about which dimensions are appropriate.

Although the dimensions of the global MPI mirror the HDI, there is significant differences in the two measures. The MPI uses different indicators and its method of computation is not similar to HDI (Shokunbi, 2017). Ravallion (2012) further noted that while the HDI uses aggregate country-level data, the MPI uses household-level data, which is then aggregated to the country-level. Additionally, the data sources used for the analysis of the two indices differ. Additionally, UNDP (2015; 2019) indicated that the computation of the HDI (global, regional, national or sub-national) relies on data from multiple sources, whereas OPHI (2011b) stated that the first fundamental requirement for any MPI is that all the information for the individual or household must come from the same survey. Dawas (2018) stated that the aim of using one data source is to determine whether a person is deprived in a number of things altogether.

With the adoption of the Sustainable Development Goals (SDGs), Goal 1: No Poverty, calls for nations to eradicate of extreme poverty by 2030. Successful implementation of this development agenda will require a solid understanding of poverty and inequality in the region, across countries and population groups, and in different dimensions (Beegle et al, 2016). Since its launch in 2010, the MPI has been used widely applied as discussed later in this subsection. UNDP notes that multidimensional poverty indices can shed further light on the people furthest behind by capturing overlapping deprivations in households and clusters of households in a geographic area, adding that some people might be multidimensionally poor even if they live above the monetary poverty line (UNDP, 2019). Additionally, the MPI is a much more actionable and policy-relevant indicator for countries and agencies than the HDI through its base on household survey information. One can decompose the MPI by region, by particular groups, and by indicator, thereby allowing countries to directly see which groups suffer most and in which dimensions they are deprived (Dotter and Klasen, 2014).

The MPI was launched in 2010 by the UNDP and OPHI, and it is based on the Alkire-Foster (AF) method, developed by Sabina Alkire and James Foster at OPHI, as a flexible technique for measuring poverty or wellbeing (OPHI, 2020). The AF methodology is described as follows.

To identify the poor, the AF method counts the overlapping or simultaneous deprivations that a person or household experiences in different indicators of poverty. Different dimensions, indicators, and cut-offs can be used to create measures tailored to specific uses, situations, and contexts. The indicators may be equally weighted or take different weights. The selection and weighing of dimensions and indicators is the first step of the methodology.

The second step entails defining a deprivation cutoff is set for each indicator. This step establishes the first cutoff in the methodology. Every person can then be identified as deprived or non-deprived with respect to each indicator.

The third step then defines a poverty cutoff value denoted as *k* as a threshold, number of dimensions in which an individual is deprived, by which they would be classified as multidimensionally poor or not. The value *k* can be determined by various methods. The first method is the union approach, when an individual is considered as multidimensionally poor if they are deprived in at least one dimension (Bourguignon & Chakarvarty, 2003). However, Ozdamar and Giovanis (2019) cautioned that this method may lead to overestimated values of poverty as the number of dimension increases. Another method of selecting *k* was discussed by Alkire and Foster (2007, 2009) and it is referred to as the intersection method, which requires a person to be deprived in all indicators across all dimensions at the same time to be considered multidimensionally poor, and therefore corresponds to a value k=1. This method of k=1 may however underestimate poverty because many individuals may not necessarily be deprived in all dimensions, and it further makes it difficult for analysts to measure variety in the depth of poverty in a given society.

Another possible method to select the value of k is the intermediate-value method, which requires the researcher to identify an intermediate cutoff value for k that lies between the two extremes of the union and intersection approaches. As such, multidimensionally poor individuals will be identified as persons who are deprived in any specific number of dimensions, greater than one but not equal to the number of dimensions. The intermediate-value method is widely used as opposed to the union and intersection methods. Although the union and intersection methods have the advantage of identifying the same people as poor regardless of the relative weights set on the dimensions, the union approach identifies a very large proportion of the population as multidimensionally poor, whereas an intersection approach identifies a vanishingly small number of people as multidimensionally poor, both which may lead to misleading results.

In the fourth step, the methodology is then used to calculate the headcount ratio (H), intensity (A) of multidimensional poverty. The headcount ratio (H) is the proportion of people who are poor in at least k of indicators, out of the entire population. The intensity (A) is the average number of deprivations a poor person suffers, and it is calculated by adding up the proportion of total deprivations each person and dividing by the total number of poor persons.

The AF method has three unique advantages over other composite indices. The first is that measures created using the AF method reflect the intensity of poverty (the average number of deprivations or weighted sum of deprivations that each individual experiences). Secondly, the method is flexible, because different dimensions, indicators and cut-offs can be selected to create measures adapted to particular contexts. Thirdly, measures based on the AF method can be disaggregated. This means that they can be broken down easily by region, social groups, and dimensions, in order to provide information to policymakers about the priorities and needs of specific regions and groups (OPHI, 2020). This is critical in striving to meet the Sustainable Development Goals' goal of 'leaving no one behind'.

The global MPI is one of the most considerable applications of the MPI and AF methodologies. UNDP and OPHI (2020) explains that in the analysis of the global MPI, a person is identified as multidimensionally poor or MPI poor if they are deprived in at least one third of the weighted MPI indicators. In other words, a person is MPI poor if the person's weighted deprivation score is equal to or higher than the poverty cutoff of 33.3 percent.

The 2020 Global MPI report, according to UNDP and OPHI (2020), indicates that across 107 developing countries, 1.3 billion people live in multidimensional poverty, and about 84.3 percent of these multidimensionally poor people live in Sub-Saharan Africa. To further understand the nature of multidimensional poverty at national level, a national analysis for Namibia, which follows the structure of the global MPI, was carried out by OPHI using the 2013 Namibia Demographic and Health Survey (DHS) data. The results indicate that 38.0 percent of the population is multidimensionally poor. Additionally, Ohangwena, Omusati and Kunene regions are amongst the poorest regions in the country. The results further indicates that most individuals in Namibia are deprived in cooking fuel (35.5 percent), sanitation (34.7 percent) and Electricity (34.1 percent). (OPHI, 2020b).

However, the analysis did not provide any insight pertaining to the youth in the country, nor did it attempt to identify the determinants of multidimensional poverty in the country.

The MPI has also been widely used in academic literature. Mahoozi (2015) applied the MPI methodology to estimate multidimensional poverty, and its variation based on spatial and demographic factors amongst the population of Iran. While the selection of dimensions and indicators followed the structure of the global MPI, there were adjustments to the index based on normative decisions and data availability. For instance, Mahoozi (2015) explained that because of data constraint, the set of dimensions does not contain health dimension, although it would have been ideal to include health indicators such as child mortality or malnutrition. Furthermore, while the indicators for the education dimension in the global MPI are based on children, Mahoozi (2015) based the indicators on heads of households instead. In Iranian culture, the head of the household has a very significant role as the person who not only brings in income, but also decides how income can be allocated and spent. Therefore, a head of household who is illiterate and cannot read, write, or count can negatively influence the household welfare (Mahoozi, 2015). The analysis was thus based on three, equally weighted dimensions; expenditure, education and living standards. The results imply that poverty in Iran varies among provinces and the amount and breadth of multidimensional poverty in some provinces are greater than others are. The results further revealed that the probability of multidimensional poverty for a rural family is, on average, four times greater than an urban family with the same circumstances, while the probability of poverty for a female-headed family is, on average, twice that of a male-headed family with the same circumstances.

Ozdamar and Giovanis (2019) measured multidimensional poverty amongst the youth, aged 15-24, in selected countries of the Middle East and North Africa (MENA) region using the Alkire-Foster (AF) method, as well as to explore the determinants of the MPI in the youth population. The dimensions selected for the MPI in the study were based on existing literature. The analysis was therefore based on five, equally weighted dimensions; education, health, employment, material deprivation and dwelling characteristics. The results from the analysis indicated that by comparing youth multidimensional poverty in 2012 and 2018, there is reduction in the case of Egypt and Tunisia, and an increment in Jordan and Iraq. The findings suggest an improvement in the living standards of the youth population, except for Jordan and Iraq. Young males report lower levels of MPI, except for Tunisia, while rural households experience higher poverty levels.

Ataguba et al (2011) explored factors that predict multidimensional poverty in Nsukka, Nigeria. With the application of the AF methodology, the dimensions and indicators used to construct the Nsukka MPI was based on normative decisions. Specifically, Ataguba et al (2011) indicated that the dimensions were largely selected on the basis of existing literature, the Millennium Development Goals (MDGs) theory and availability of relevant data. The analysis was thus based on 10 dimensions; consumption expenditure, housing characteristics, health, education, employment, employment quality, physical safety, empowerment, shame/humiliation and psychological wellbeing. According to the results, 70-78 percent of the population is poor, and the major determinants of deprivations include large family size, low level of education, poor employment, rural location and poor health. In its conclusion, the paper promotes the approach of tackling poverty at different levels, as aimed by this study. Ataguba et al (2011) stated that in order to effectively alleviate poverty, an integrated approach that accounts for inter-linkages between factors associated with poverty is required.

Table 1 summarizes the discussed poverty measures, highlighting their characteristics, strengths and shortcomings.

Table 1: Summary of poverty measures

Cost of Basic Needs (CBN)	Human Development Index (HDI)	Multidimensional Poverty Index (MPI)
	Structure	
Stipulates a consumption bundle that is deemed to be adequate, with both food and non-food components and then estimates the cost of the bundle for each subgroup. An individual is considered to be poor if they cannot afford the cost of the determined consumption bundle.	Uses multiple data sources to measure achievements in three dimensions of human development, namely; a long healthy life, access to knowledge and a descent standard of living.	Draws data from one data source to measure deprivation in education, health and living standards, as well as deprivation in additional dimensions and indicators that may be considered to define wellbeing in a given society, that an individual experiences simultaneously.
	Strength	

Based on income/consumption expenditure which has the potential of expanding people’s choices to improve wellbeing.	Premised on the fundamental idea that poverty is multidimensional and encompasses multiple aspects of human development	Captures multiple deprivations that a person faces at the same time, in dimensions or indicators that may be deemed as measures of wellbeing for a particular society.
	Limitation	
Not all aspects of welfare can be properly priced or monetarily valued.	Focuses only on three dimensions and cannot track whether deprivations are being experienced at the exact same time.	Dimensions and indicators vary by country/society which makes comparisons quite difficult.

The application of the MPI and the strengths of the AF method discussed above motivated the approach of this study. However, this study adds value based on the limitations in the discussed applications. Firstly, the selection of dimensions and indicators have been aligned to the youth context in order to identify deprivations that matter most to the wellbeing of the youth. As a result, the analysis in this study provides a description of youth multidimensional poverty, unlike most studies that have applied the methodology to populations of all age groups. Secondly, while there are studies on determinants of multidimensional poverty, they have not considered a three level structure of analysis, in order to inform poverty eradication efforts at individual, household and regional level. To the researcher's knowledge, the application of the MPI to understand the nature of multiple deprivations faced by the youth will also be a first attempt for Namibia.

2.4. Multilevel modelling

Fullerton (2014) defined Multilevel Models (MLM) as a set of statistical techniques for analyzing quantitative data measured at two or more levels of analysis. The models are particularly useful in estimating population parameters that vary at more than one level, when the data are structured into groups and the regression coefficients vary by groups. MLM differs from classical Ordinary Least Squares (OLS) regression models in modeling the variation between groups, by estimation of group-level effects. They are appropriate whenever data has multiple units of analysis, one nested within another, such that the errors of the response variable are correlated and not independent as required by the Ordinary Least Squares (OLS) regression. Leckie (2019) and Alkire, et al (2015) both reported that the purpose of multilevel regression is to model the relationship between a response variable and a set of covariates (predictors or explanatory variables), when the covariates are defined at different levels of analysis.

Muhammad and Rehan (2017) describe that although multilevel model equations will differ depending on the distribution of data, the general equation can be specified as;

$Y_{ij} = \beta_{0ij} + \beta_{1j}X_{ij} + \beta_{1j}W_j + e_{ij} + \mu_{oj}$, where;

- Y_{ij} refers to the score on the dependent variable for an individual i at level one in group j
- β_{0ij} refers to the vector of intercepts of the dependent variable in group j

- β_{1j} refers to the slope
- X_{ij} refers to the matrix of level one predictor variables
- W_j refers to a matrix of level two predictor variables
- e_{ij} refers to the random errors of prediction for the level one predictors
- μ_{ij} refers to the error component for the slope i.e. the deviation of the group slopes from the overall slope

There is various motivations for choosing MLM over classical OLS regression models. Gelman and Hill (2007) documented a detailed comparison of the classical linear modeling approach and the Bayesian multilevel modeling approaches. They highlight two main advantages of using MLM. Firstly, the approach accounts for both individual- and group-level variation in estimating group-level coefficients. Rasbash (2020) acknowledged this by noting that MLM recognize the existence of data hierarchies by allowing for residual components at each level in the hierarchy. This allows researchers to obtain better estimates for a given group by borrowing information from other groups.

Secondly, the multilevel modelling approach enables analysis of variation among individual-level regression coefficients across groups, useful in making predictions for new groups or accounting for group-level variation in the uncertainty for individual-level coefficients. Kuppens and Yzerbyt (2014) stated that multilevel modelling is useful in analyzing intra-individual and inter-individual variability at the same time and it is thus a very promising technique for studying variability. Furthermore, Rasbash et al (2012) highlighted that the consequence of failing to recognize hierarchical structures is that standard errors of regression coefficients will be underestimated, leading to an overstatement of statistical significance. Allegue et al (2017) further cautioned that ignoring group-level effects leads to residuals that are not normally distributed, and although this violation of assumptions of regression does not affect the estimates of regression coefficients, it does lead to errors in significance testing. In using the MLM approach however, it is important to ensure that each group in the hierarchy is fully represented by the sample, as Ponce (2013) cautioned that in order to yield accurate results, researchers need to think about having sufficient sample size at all levels of the model.

The assumptions underlying the multilevel model are (i)linear relations, (ii)a normal distribution for the individual-level residuals, and (iii) a multivariate normal distribution for the group -level residuals (Hui, et. al., 2017). In research studies when the data has a nested structure, the multilevel logistic regression analysis becomes useful than the traditional single-level regression modelling approach. Considering multiple levels in modelling enables the simultaneous examination of the effects of group level and individual level variables on individual level outcomes while accounting for the inter-dependence of observations within groups. Using MLMs further allows the examination of both between group and within group variability as well as how group level and individual level variables are related to variability at both levels.

In using MLMs, an increased sample size is beneficial because it allows the MLM to have accurate predictions even when standard errors are not normally distributed. This is explained by Byran and Jenkins (2016) who stated that non-normal distributed residual errors on the group level of a multilevel regression model appear to have little or no effect on the estimates of the fixed effects. When the group sizes are large, there is hardly a difference between the fixed effects and the random effects specification for the estimation of parameters that they have in common. Sommet and Morselli (2017) explained that in multilevel linear modeling, simulation studies show that 50 or more level-2 units are necessary to accurately estimate standard errors.

Although the earliest formulations and applications of the multilevel model focused on two levels of analysis and a continuous outcome, the basic model has been extended in recent years to include three or more levels of analysis and a wide variety of different outcome types (Fullerton, 2014). Particularly, the approach has gained vast application within the context of logistic generalized linear models, often applied to study poverty determinants. This study used this model in assessing the effect of socioeconomic and demographic factors on the prevalence of multidimensional poverty amongst the youth.

MLM have been applied widely across literature. Reinstadler and Ray (2010) examined macro determinants of individual income poverty in 93 regions of Europe, by considering a multilevel model that takes regional characteristics into account. Specifically, they employed a binary logistic regression, where the probability of being at risk of poverty was explained. The model took three levels into account: time (measured in years), individuals and regions. At the individual level, variables such as gender and age were found to be significant. Moreover, the study also concluded that regional unemployment rate and Gross Domestic product (GDP) were significant determinants of poverty. Unlike this study, however, their analysis was based on the economic definition of poverty, which is the relative percentage of individuals living in a household whose equivalent income is below the poverty threshold- 60% of the national median equivalent income.

Furthermore, Imam, Islam and Hossain (2018) used a two-level random intercept binary logistic regression model to determine factors affecting income poverty in rural

Bangladesh, aiming to capture the unobserved heterogeneity between communities along with revealing important factors associated with poverty. The analyses found that the potential factors having significant association with income poverty were age and education of household head, household size, household types and per capita income, amongst others. The definition of poverty, however, was based on the CBN approach, and did not account for the multidimensional nature of the concept. Additionally, the study did not explain the effects of individual level characteristics on monetary poverty.

Blekking et al (2020) used a multilevel mixed-effects linear model to empirically study the interplay between individuals and household variables in the attainment of urban food security in Sub Saharan Africa. The study concluded that individual's income and education level increased food consumption, unlike their employment status. At the household level, household size and time taken (walking) to purchase vegetable from the location were also found to be significant variables. In contrast to this study's consideration of multidimensional poverty status as the response variable in explaining poverty, however, their approach used the household's food consumption score as the model's dependent variable.

With the multidimensional definition of poverty gaining recognition in recent years, literature review reveals how researchers have analyzed multilevel determinants of multidimensional poverty. The consideration of hierarchical models in studying factors that determine the prevalence of multidimensional poverty is clearly motivated by Pham, Mukhopadhaya and Vu (2020) who used random intercept multilevel models to decompose the variation of multidimensional poverty at the household, commune, district and province levels in Vietnam. Their findings revealed that the poverty ranking of provinces departs widely from those obtained through traditional single-level analysis, a finding that suggests that poverty in Vietnam can be explained not only by characteristics at the household level, but also by contextual factors at higher levels (commune/village, district, province).

Birhanu, Ambaw and Mulu (2017) used multilevel mixed effect logit models to incorporate fixed and random effects in capturing the effect of cluster level and time varying variables on multidimensional child poverty transition in Ethiopia. The paper argues that multidimensional child poverty has dynamic nature that would possibly result from the interaction of multiple factors including household demographic, household capital (human, social and resources), household economic activities, geographic locations, and household shocks. Moreover, the study ephasized the relevance of considering cluster level differences during multidimensional poverty analysis to generate information relevant for designing targeted policies and strategies that would help to distribute available development resources efficiently and achieve sustainable poverty reduction in developing countries.

The use of logistic models demonstrated above in analyzing determinants of multidimensional poverty is appropriate because poverty status is bounded between 0 (non-poor) and 1 (poor). Logistic regression is the standard econometric method of modelling binary outcomes. Gelman and Hill (2007) illustrated how multilevel Generalized Linear Models (GLM) can be fit to multilevel structures by including coefficients for group indicators and then adding group-level models. Alkire, et al (2015) further explained that GLMs extend classic linear regression to a family of regression models where the dependent variable may be normally distributed or may follow a distribution within the exponential family. As a result, the classic linear regression falls short because the range of the dependent variable is bounded and may not be continuous or follow a normal distribution that is often assumed in linear regression models.

In this study, the value of zero denotes the relative chance that the individual youth is not multidimensionally poor, while the value of one denotes the relative chance that the individual youth is poor. Alkire, et al (2015) explained that within the GLM framework, such a binary dependent variable is estimated by specifying a Bernoulli distribution and a logit link function. To ensure that the conditional mean given by the conditional probability stays between zero and one, GLM commonly considers two alternative link functions, probit or logit, given by the quantile functions of the standard normal distribution function. Gelman and Hill (2007) further explained that the choice of using logit and probit link functions is a matter of taste or convenience. In their book, "Data Analysis Using regression and Multilevel Hierarchical Model", they explain that the probit model is the same as the logit, except it replaces the logistic by the normal distribution. The probit model is close to the logit with the residual standard deviation of the error terms set to 1 rather than 1.6. As a result, coefficients in a probit regression are typically close to logistic regression coefficients divided by 1.6. Alkire, et al (2015) noted that in a GLM context, the logit of π is the natural logarithm of the odds that the binary variable Y takes a value of one rather than zero.

Mahoozi (2015) applied the MPI methodology to estimate multidimensional poverty, and its variation based on spatial and demographic factors amongst the population of Iran. The study took a multi-level modelling approach. A hierarchical logit model was applied to study variation in the incidence of poverty, because the data structure had two levels, where I (level 1) referred to the number of households and j (level 2) referred to the number of provinces. Mahoozi (2015) further explained that a logit regression model was applicable because the response variable, which was the probability of poverty incidence was binary, with two response options; 'poor' and 'non-poor'. Furthermore, in order to analyze the inequality amongst the poor, a two-level linear regression model was used, where the response variable was the average deprivation value for the poor. Notably, the modelling approach followed by Mahoozi (2015) inspired this study, to understand the variation in the prevalence of multidimensional poverty amongst the youth in Namibia. However, Mahoozi (2015) only considered household and individual, but not regional characteristics in his study. Additionally, Mahoozi (2015) did not consider youth specific variables to explain multidimensional poverty. Furthermore, at the second level of modelling, where household characteristics were considered, Mahoozi (2015) only considered one variable which is urban/rural location.

Although the multilevel regression modelling approach has been used to identify determinants of poverty, most of the application has been in the context of monetary poverty. Additionally, there appears to be limited literature on the application of multilevel linear regression in modelling disparities in the intensity levels of poverty. Those that were carried out did not look beyond three levels, neither did they consider youth-specific models. The current study is of a hierarchical design, considering information at three levels: individual, household and regions. This enabled the researcher to used multilevel regression models in the generalized linear models framework, to model disparity in poverty intensity levels, and the effects of various variables on the prevalence of multidimensional poverty amongst the youth. Various explanatory variables were considered in the models, as listed in Table 3.

2.5. Prioritizing the youth

According to the United Nation's 2015 Sustainable Development Goals (SDGs), sustainable development focuses two pillars on young people, namely; to substantially reduce youth unemployment and secondly, to ensure that young people who are out of school have productive and meaningful employment options (UN, 2015). Furthermore, Namibia is a signatory to the 2013 Addis Ababa Declaration on Population and Development in Africa Beyond 2014, signed at the 2013 African Regional Conference on Population and Development, under the theme "Harnessing the Demographic Dividend: The Future We Want for Africa". According to the conference report by UNECA (2013), the declaration recognizes the role of population dynamics in socio-economic transformation and seeks to unleash the full potential of the youth to boost socio-economic development, by ensuring high level political commitment and provision of sufficient resources towards implementing relevant and appropriate policies and programs, including enhancing the human capital of young people to ensure adequate capabilities to spur social and economic innovation. The declaration further acknowledges a rapid increase of the youth population, and notes that harnessing the benefits of the youth bulge depends on high-level political commitment and provision of sufficient resources towards implementing relevant and appropriate policies and programs, including enhancing the human capital of young people to ensure adequate capabilities to spur social and economic innovation. World Bank (2017) further agreed by noting that with the number of youth in Africa growing rapidly, right policies and programs in place offers tremendous opportunities for a "demographic dividend". It is therefore imperative to enrich literature that can potentially inform such policies.

In 2018, the NPC analyzed the population dynamics and age-structure changes in Namibia in the medium to long-term and the implications these will have on the ability of the country to maximize its Demographic Dividend. The study highlights that the youthful population is Namibia's greatest resource, who, if properly supported, will positively contribute to Namibia's socio-economic development. (NPC, 2016b).

The Ministry of Sport, Youth and National Service (MSYNS) was formed in 2005, mainly to promote the welfare of the youth in Namibia through its mandate of promoting sports, developing and empowering the youth. According to the MYSNS's 2017/18-2021/22 strategic plan by MYSNS (2016), The ministry's directorate of youth aims to empower the youth through capacity building and provide opportunities for the youth to develop relevant life skills to enable them to become responsible and self-reliant members of the community.

Moreover, as discussed in the fifth National Development Plan (NDP) by NPC (2017), the government of Namibia targets to expand vocational education and link trained, but unemployed youth, with employers. Furthermore, the government aims to encourage youth entrepreneurship through a value chain approach of providing skills, and access to finance and market information through rural development centers. Despite various government interventions implemented, however, many youth continue to live in deteriorating conditions. Although the 2016 Inter-censal Demographic survey report shows that the youth literacy rate of about 94 percent, various socio-economic challenges still prevail amongst the youth.

The Namibia's Labor Force Survey (NLFS) conducted by NSA (2019) revealed that the youth made up only about 25 percent of the country's labor force. Furthermore, while the country's unemployment rate was reported at 34 percent, the youth unemployment rate was much higher at 46.1 percent. This indicates that many youth face the disadvantages of unemployment such as living without income and direct participation in the economic development of the country. Besides these economic impacts, unemployment also has social effects on individuals. As asserted by McQuaid (2020), it may lead to having lower skills or to a general loss of confidence by the individual, as it lowers an individual's self-discipline, inter-personal skills, communication, adaptability, consistency, persistence and self-confidence. The LFS findings from the NLFS by NSA (2019) further showed that the youth made up 68 percent of the country's economically inactive population, which means that they were not in employment and not available to take up any form of employment due to various reasons. Moreover, about 35 percent of the youth population was Not in Education and Not in Training (NEET). Another challenge facing the youth in Namibia is monetary poverty. Calculations based on the 2015/16 NHIES data shows that about 32 percent of the monetary poor population in Namibia is the youth, which implies that they do not have enough money to afford basic needs.

Ozdamar and Giovanis (2019) highlighted that measuring youth poverty and identifying its main causes can enable the formulation of policies that promote young people's needs and interests, and empower them to recognize their right to education, skills, and employment. Haaften (2018) stated that with the population of Africa expected to double in the next 30 years, young people living in these countries, if healthy and educated, have the potential to create the economic growth that can change the course of extreme poverty.

Usha (2014) inspected youth monetary poverty in Africa and found that it is higher in Africa than in other regions, and remains on a rise, despite economic growth. His findings showed that about 47 percent of the youth in Africa are below the international monetary poverty line of one United States Dollar (USD) per day.

By analyzing youth unemployment in Namibia, Mulama and Nambinga (2017) provided evidence that youth unemployment was high, and more prevalent amongst women and those that were less educated. Muhammad and David (2019) stated that unemployment increases the risk of poverty and contributes to inequality, and so it therefore becomes interesting to analyze youth poverty not only in the context of money, but also focusing on labor related indicators, including individual's health and education status, across various demographic characteristics.

3. CHAPTER THREE: RESEARCH METHODS

3.1. Introduction

This chapter presents the methodology used in this study. The chapter explains the research design, as well as the statistical methods that were used to analyze the objectives of the study.

3.2. Research design

The design of the study was a hierarchical, quantitative and descriptive model. Firstly, the study considered three (3) levels of hierarchy in analyzing youth multidimensional poverty, namely; individual, household and regional level characteristics. Secondly, the study was quantitative because statistical inferences made herein were based on analysis of numerical data. Thirdly, the descriptive nature of the study is explained by McCombes (2020) who indicated that a descriptive research aims to accurately and systematically describe a population, situation or phenomenon by answering what, where, when and how questions, but not why questions.

This study described multidimensional poverty amongst the youth in Namibia, demographic and socio-economic variables from secondary data sources. The data was deduced from three (3) nationally representative surveys, namely, 2015/16 Namibia Household Income and Expenditure Survey (NHIES), 2016 Namibia Inter-censal Demographic Survey (NIDS) and 2016 Namibia Labor Force Survey (NLFS). These are all nationally representative surveys carried out by the Namibia Statistics Agency, for the purpose of creating welfare indicators fit for national planning. The NHIES collects data on income, consumption and expenditure patterns of individuals and households, in addition to their demographic and socio-economic characteristics such as education levels and ICT access. The 2015/16 NHIES is the most recent in the country, with other waves having been conducted in 2009/10, 2003/4 and 1993/4 respectively. The NIDS provides data on the demographic characteristics of the population such as population growth, fertility and mortality trends. The 2016 NIDS is the most recent in the country, with the previous one having been conducted in 2006. The NLFS collects data on employment, unemployment, occupations, wages and salaries. The most recent NLFS in the country was conducted in 2018, with previous waves having been conducted in 2016, 2014, 2013, 2012, 2008, 2004, 2000 and 1997. While the 2015/16 NHIES and the 2016 NIDS surveys were used because they are the latest versions, the researcher decided to use the 2016 LFS as it's time period was close enough to the other surveys being used for the study, therefore the indicators from all three surveys were computed from a relatively similar population

The data has a hierarchical structure, with individuals nested within households, and households nested within regions. The NIDS and NLFS were only used to provide regional level variables. The considered demographic and socio-economic variables from the afore-mentioned three surveys are listed in Table 3.

3.3. Population

The study population was all individuals from the 2015/16 NHIES data file who were aged 15 to 34 years old.

3.4. Procedure

The 2015/16 NHIES, 2016 NIDS and 2016 NLFS data files were obtained from the Namibia Statistics Agency (NSA). A list of regional indicators from the 2016 NIDS and 2016 NLFS were compiled and merged in one Stata data file. Using region as the unique identifier, the regional indicators data file was then merged to the 2015/16 NHIES persons' data file. Consequently, the merged file used for data analysis was at individual level, where household characteristics were the same for all youths who resided in one household, and the regional characteristics were similar for all youths in the same region. The merged data file, therefore contained variables at individual, household and regional level, where the individual and household records were as they appeared in the original 2015/16 NHIES file, and additional regional characteristics were added for each individual depending on the region that they resided in. The merging procedure enabled the researcher to make inferences on youth multidimensional poverty using regional indicators on demographic and labor characteristics, that were not initially available in the 2015/16 NHIES data file.

The procedure also allowed the researcher to carry out a three-level generalized regression analysis, firstly using a multilevel ordered logistic regression to model the disparities in intensity levels of youth multidimensional poverty, and secondly, using a multilevel probit regression to model the factors affecting the prevalence of youth multidimensional poverty.

3.5. Data analysis

Data analysis was carried out in Stata version 13 and R version 4.0.3. All syntaxes are presented in the appendix section of this report. Data compilation, cleaning and validation, as well as the derivation of new variables was carried out in Stata. Moreover, in order to answer the overall objective of the study, three specific objectives were statistically analyzed. The specific data analysis methods are described below, per each objective.

Objective 1: Applying the Alkire-Foster (AF) method to determine the prevalence of youth multidimensional poverty in Namibia

The AF method is a multidimensional poverty measurement framework that each user must complete with their own specifications, as per their own research purposes. As stated by OPHI (2020a), the AF framework requires that each user defines the purpose and the space of the measure, selects the unit of identification, dimensions, indicators, deprivation cut-offs (to determine when a person is deprived in a given indicator), weights (to indicate the relative importance of the different deprivations) and poverty cut-off (to determine when a person has enough deprivations to be considered poor). The flexibility of the AF method makes it easy to adapt in diverse contexts.

Four dimensions have been selected for this study, following earlier studies (such as Vijaya et al., 2014; Klasen & Lahoti, 2016; Bérenger, 2017; Espinosa-Delgado & Silber, 2019 and Ozdamar and Giovanis, 2019). Furthermore, the selection of the dimensions was informed by the recommendation of Meyer and Nishimwe-Niyimbanira (2016), who stated that to be lifted out of poverty, the poor need to be granted access to economic opportunities, while also receiving adult education regarding financial management and reproductive health. Based on the challenges that are facing the Namibian youth, as discussed in Chapter 2, the study therefore adopted four dimensions at the individual unit level of analysis, which were education, health, employment activities and monetary welfare of the youth. Table 2 presents the dimensions and the deprivation indicators employed in the youth MPI. The dimensions and indicators were weighted equally, as used by Ozdamar and Giovanis (2019), Alkire and Foster (2007, 2009) and followed the approach in the computation of the global MPI by UNDP and OPHI (2020). This enabled the researcher of the current study to measure multidimensional poverty at individual level among the youth population.

Table 2: Dimensions and indicators

Dimension	**Indicator**	**Relative weight**	**Cut-off threshold**
Education	Highest grade completed	1/4	Deprived in education if they have not completed secondary level of education
Health	Disability	1/4	Deprived in health if they are living with a disability
Employment activities	Employment status	1/4	Deprived in employment status if they are unemployed
Monetary welfare	Consumption expenditure	1/4	Deprived in monetary welfare if their consumption expenditure falls below the official poverty line of $520.8 per month

The calculation of the youth MPI in the current study was based on the AF methodology discussed in section 2.3.3 of this report. The study considered the intermediate-value method of selecting the poverty cutoff value (k), specifically using a middle threshold $k=0.5$, since unlike the union and intersection methods, the middle threshold value has limited chance of overestimating or underestimating multidimensional poverty, as suggested by Alkire and Foster (2011), Bérenger (2017, 2019) and Ozdamar and Giovanis (2019). As a result, an individual, in this study, was considered to be multidimensionally poor if they were deprived in at least two (2) of the total four (4) dimensions listed in Table 2. For an individual to have been deprived in a dimension, they must have been deprived in the dimension's indicator. The indicator thresholds are also listed in Table 2.

In reporting multidimensional poverty, the AF method defines two poverty measures: (i) headcount ratio (denoted by H) and (ii) intensity of poverty (denoted by A). (Alkire & Foster, 2011). UNDP and OPHI (2019) described the headcount ratio (H), also referred to as the incidence of poverty, as the proportion of people identified as multidimensionally poor. It is the percentage of people, out of the total population, whose weighted deprivation score is greater than or equal to the poverty cut-off k. Furthermore, the intensity of poverty (A), is described as the average proportion of indicators in which poor people are deprived—the average deprivation score across all poor people. Mahoozi (2015) and Ozdamar and Giovanis (2019) note that the use of the two measures not only identifies who is poor but also innovates by incorporating how acute or intense the situation of multidimensional poverty is for the poor.

To determine the level of youth multidimensional poverty in Namibia, the headcount ratio (H) and the intensity (A) of multidimensional poverty were computed and compared between demographic groups and across regions using Stata software. Specifically, results were analyzed across gender, urban/rural location, sex of head of households, household size as well as across the 14 administrative regions of Namibia. The estimated H and A values simply indicate what percent of the youth in each demographic group are multidimensionally poor (the prevalence of poverty) and which demographic groups and regions contain more multidimensionally poor youth (depth of poverty), respectively. However, the effect of individual, household and regional characteristics as a component of poverty variation or how similar the residents of a region are, remains unknown. In order to answer these questions, the study further conducted regression analyses using multilevel models.

Objective 2: Assessing the disparity in the intensity of poverty amongst the youth based on socio-economic characteristics at individual, household and regional levels.

This is a measure of inequality to show the variation in the breadth of poverty amongst the youth, in terms of the percentage of indicators in which the youth are deprived 9the indicators are presented in Table 2). A multilevel ordered logistic regression model was applied in the Stata software. The response variable was an ordered categorical outcome having five ordered categories: 1 (Not poor- if deprived in 0 indicators), 2 (Almost poor- if deprived in 1 indicator), 3 (Borderline poor- if deprived in 2 indicators), 4 (Above average poor- if deprived in 3 indicators) or 5 (Severely poor- if deprived in all 4 indicators considered in this study). These categories were constructed to rank and indicate the difference in the severity of multidimensional poverty being experienced by the youth; for instance, an individual who is deprived in all four indicators (see list of indicators Table 2) is worse off than another individual who is deprived in three indicators, and both are worse off than another individual who is deprived in two indicators. In constructing the categories, the study followed the approach of Kallesta et. al. (2020), who assessed multiple dimensions of monetary poverty in northern Nicaragua, and created a poverty likert scale of five (5) categories; namely; poorest fairly(1) poor(2), poor(3), rich(4) and richest(5), indicating variation in the intensity of monetary poverty amongst the poor. Using ranked categories to explain the variation and inequality in the intensity of multidimensional poverty ensures that multidimensional poverty alleviation policies prioritize those who are most deprived amongst the poor, so that the poorest are not left behind.

The response variable in the multilevel ordered logistic regression, i.e. Intensity of youth multidimensional poverty, was treated as ordinal under the assumption that the levels of the intensity in multidimensional poverty have a natural ordering (Not poor to Severely poor), but the distances between adjacent levels are unknown, hence the use of the five categories. This variable took on one of the values 1,2,3,4 or 5 and therefore had an ordinal, non-normal nature distribution, hence the application of the ordered logistic regression models. The regression model were applied in a multilevel set-up, because of the nested structure of the data; Each individual youth was nested within a household, and each household was nested within a region. The multilevel models thus estimated the residual at both household and regional level. The total residual variance was divided into three parts, one for between regions (level three, region residuals), one for between households (level two, household residuals) and one for between individuals (level one, individual youth residuals). The variables considered in this model are presented in Table 3 of this report.

The independent variables were considered at three different levels; i refers to the individual youth (level 1), j refers to the households where the youth resides (level 2), and k refers to the regions where the youth's households are located (level 3). The general form of the multilevel ordered logistic regression model for a response variable Y with i categories and a set of predictors X having the effect parameters the probability of response variable being less than or equal to category c can be modeled by multilevel ordered logistic regression model as;

$Y_c = Pr\ (Y \leq y_i|X$

$Pr(Y \leq y_i|X\ = \frac{e^{[\alpha_c-(\beta_1 X_{i1}+-\beta_2 X_{i2}+\cdots+-\beta_k X_{ik})]}}{1+e^{[\alpha_c-(\beta_1 X_{i1}+-\beta_2 X_{i2}+\cdots+-\beta_k X_{ik})]}}$, where $c = 1,2,3,4,5$ categories of the response variable, where

- Y is the response variable
- $X_{i1}, X_{i2} \dots . X_{ik}$ are the predictor variables
- y_i is the cumulative probability of response variable being less than or equal to category c
- i represents the level one units
- $c = 1,2,3,4,5$, are the ordered categories of the response variable Y
- k is the total number of independent variables across all groups
- α_c is the vector of the intercepts
- $\beta_1, \beta_2, \dots \beta_k$ are the slope coefficients for all predictor variables across all groups

Considering the three-level hierarchy of the current study, the cumulative ordered log-odds model with a three-level random intercept to estimate the intensity level of youth multidimensional poverty with fixed predictors can be written as:

$$\mathrm{Log}(\frac{\gamma^{(c)}{}_{ijk}}{1-\gamma^{(c)}{}_{ijk}} = \alpha_{(c)} + \beta_{1jk}X_{1jk} + \beta_{2jk}X_{ijk} + \beta_{3jk}X_{ijk} + \beta_{4jk}X_{ijk} + \mu_{0jk}$$

Where;

- $c = 1,2,3,4,5$, are the ordered categories of the response variable
- $\gamma^{(c)}{}_{ijk}$ is the probability of the i^{th} individual youth in household j and region k less than or equal to category c where $c = 1,2,3,4,5$
- $Log(\frac{\gamma^{(c)}{}_{ijk}}{1-\gamma^{(c)}{}_{ijk}}$ is the log odds of each of the five categories of the intensity of youth multidimensional poverty ("not poor", "almost poor", "borderline poor", "above-average poor" and "severely poor", relative to the remaining four categories.
- α_c is the vector of the intercepts
- X_{ijk} is the matrix of the predictor variables. The complete list of multilevel predictors that were considered for this model are presented in table 3.
- $\beta_{1jk}, \beta_{2jk}, \ldots \beta_{4jk}$ are the slope coefficients for all predictor variables across all three levels.
- μ_{0jk} is the random effect of level two (household) and level three (region) units.

Objective 3: Examining the socioeconomic and demographic factors affecting the prevalence of multidimensional poverty amongst the youth.

The analysis was carried out by applying a hierarchical multilevel generalized linear model with Bernoulli distribution and a logit link function in the R software. The Bernoulli distribution was applied because the response variable, multidimensional poverty status, had a distribution of only two (2) mutually exclusive outcomes; 1= multidimensionally poor and 0= non-poor. The explanatory variables considered were at individual, household and regional levels as shown in Table 3. The multilevel model with a logit link function was therefore deemed appropriate since the response variable was binary. The conditional distribution of the response given the random effects was assumed to be Bernoulli, with success probability determined by the logistic cumulative distribution function. The researcher firstly fitted a model with no predictors, i.e. the intercept-only model in order to determine youth multidimensional poverty status in the absence of any predictors, to help explain if the presence of multilevel predictors indeed affect multidimensional poverty status. This was then followed by various models with individual, household and regional predictors as presented in Table 11, and this was done in order to select the best-fitting model based on lowest Akaike Information Criterion (AIC) value.

The independent variables were considered at three different levels; i refers to the individual youth (level 1), j refers to the households where the youth resides (level 2), and k refers to the regions where the youth's households are located (level 3).

The general form of the logit multilevel regression model was;

$(\Pr(Y_{ijk}) = \beta_0 + \beta_1 X_{ijk} + \mu_j + \alpha_k + \epsilon_{ijk})$, where;

- Y_{ijk} denoted the relative chance for the i^{th} individual youth in household j and region k to be multidimensionally poor
- X_{ijk} denoted the explanatory variables, at the individual, household and regional levels
- μ_j represented the group 1 (household) residuals
- α_k represented the group 2 (region) residuals
- ϵ_{ijk} denoteed the individual level residual error

The Alkaike Information Criterion (AIC) measure was used to assess which model improves the goodness of fit, as recommended by Smith and Shively (2019). The complete list of multilevel predictors that were considered for this model are presented in Table 3. Alkire at al. (2015) cautioned that including MPI indicators in the multilevel models as individual variables will lead to endogeneity, and recommended for the restriction of the set of explanatory variables to non-indicator measurement variables. As a result, the indicators used to identify youth as multidimensionally poor (highest grade completed, disability, employment status and consumption expenditure) which were presented in Table 2, were not included in the set of explanatory variables in the multilevel modelling of the intensity of youth poverty and its determinants.

Table 3: Explanatory variables considered in multilevel models

Variable	Variable Type	Categories
	Individual level	
Age	continuous	n/a
Sex	categorical	Female Male
Marital status: in a marital union	categorical	Never married In a marital union Have not left a marital union
Orphan hood status	categorical	Orphan Not an orphan
Relationship to head	categorical	Not closely related to head of household Closely related to head of house
	Household level	

Urban/rural	categorical	Urban Rural
Sex of head of household	categorical	Female Male
Age of head of household	continuous	n/a
Household size	continuous	n/a
Dwelling unit type	categorical	Living in an improvised dwelling unit Not living in an improvised dwelling unit
Internet access	categorical	Household with internet access Household without internet access
Employment status of the head	categorical	Employed head of household Unemployed head of household
Regional level		
Total youth population	continuous	n/a

Youth unemployment rate	continuous	n/a
Youth informal employment rate	continuous	n/a
Crude Birth Rate	continuous	n/a
Crude Death Rate	continuous	n/a
Gini coefficient	continuous	n/a
Total consumption expenditure	continuous	n/a

For the variables that were originally numeric, the researcher had an option to include them in the models as a continuous variables or to divide them into groups as a categorical variables. In the current study, these variables were; Age of the individual youth, Age of head of household, household size, regional youth population, as well as the regional youth unemployment rate, youth informal employment rate, crude birth rate, crude death rate, Gini coefficient and total consumption expenditure. While Naggara, et. al. (2013) stated that categorization of continuous variables makes the analysis and interpretation of results simple because categories are easy to understand, Sauerbrei et. al. (2014) argued that such simplicity is gained at a high cost and may well create problems rather than solve them. Dawson & Weiss (2017) highlighted that categorizing continuous variables has influential drawbacks because it results in a loss of real information about the distance between the real values, so the model returns parameter estimates that only gives information about the response categories, specifically, the difference in the means of the response for the categories, but not the detailed information about the variation of values in the predictor.

A further disadvantage of categorization of numerical variables stated by Sauerbrei et. al. (2014) was that it does not make use of within-category information, because all grouped individuals are treated as equal, yet their individual frequencies may vary considerably. To illustrate this, Figure 1 shows the percentage distribution of youth’s single ages. Figure 1 indicates a wide variation in the distribution of single ages, that would not be considered if the age variable was categorized. The age variable has been widely used as a continuous variable in measuring multidimensional poverty by different researchers including Mahoozi (2015), Ozdamar and Giovanis (2019), Shokunbi (2017) and Ataguba et al

(2011). For these reasons, Age and the rest of the numerical variables afore-mentioned, were all considered as continuous predictors in the regression models.

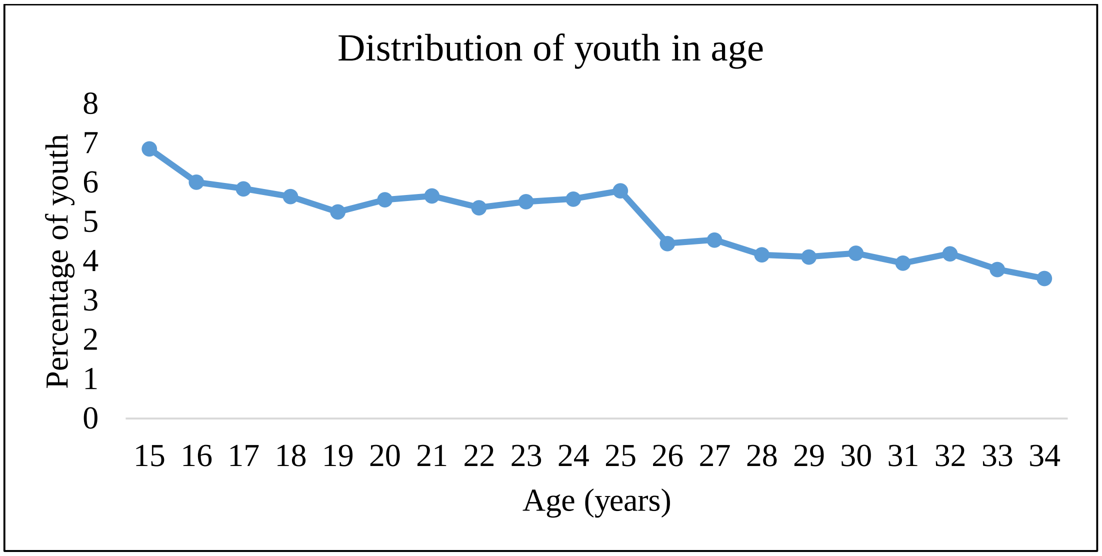

Figure 1: Percentage distribution of youth's single ages.

3.6. Research ethics

Ethical clearance and permission to conduct research was obtained from the University of Namibia, Research Ethics Committee and Centre for Postgraduate Studies. All datasets used in this study were freely available for research on the NSA website, and were anonymized. The results of the study therefore does not allow re-identification of the survey participants.

4. CHAPTER FOUR: RESULTS

4.1. Introduction

This chapter presents the findings of the statistical analyses of the three objectives discussed in chapter 3.

4.2. Results

4.2.1 Descriptive statistics and youth MPI measures (H and A)

Table 4 shows the description of how the youth population varies across categorical predictor variables; sex, marital status, orphan hood, relationship to head of household, urban/rural location, sex of head of households, housing unit, internet access, employment status of the head of household and regions. The total number of youth considered in the study was 13 785, and they were residing in 7 339 households across 14 regions in Namibia . The table shows that 52.5% of the youth were female, while 47.5 % were males. With regards to marital status, majority of the youth were never married (79.2%), followed by those who were in marital unions (19.0%), while only 1.8% had left previous marital unions. As for the youth's place of residence, 47.6% of the youth resided in urban areas, while 52.6 % resided in rural areas.

Furthermore, 51.7% of the youth lived in households headed by males, while 48.3% lived in households that were headed by females. As for the regional distribution of the youth population, the most populated regions were Khomas (11.41%), Oshana (9.38%) and Ohangwena (9.31%). The region with the least youth population in the country was Omaheke, with 4.43%.

Table 4: Decomposition of the youth population by selected predictor variables

Variable	Categories	Frequency (count)	Percentage (%)
Total youth		**13,785**	**100**
Total number of households		**7,339**	**100**
Total number of regions		**14**	**100**
Sex	Female	7,234	52.5
	Male	6,551	47.5
Marital status	Never married	10,919	79.2
	In a marital union	2,620	19.0
	Have a left a marital union	246	1.8
Orphan hood	Not an orphan	13,044	94.6
	orphan	741	5.4
Area	Urban	6,555	47.6
	Rural	7,230	52.6

Sex of head of household	Female	6,657	48.3
	Male	7,128	51.7
Employment status of the head of household	Unemployed head of household	5,949	43.2
	Employed head of household	7,836	56.8
Relationship to head	Not closely related to the head of households	5,310	38.5
	Closely related to the head of household	8,475	61.5
Dwelling unit type	Not living in an improvised dwelling unit	11,440	83.0
	Living in an improvised dwelling unit	2,345	17.0
Household internet access	Household with internet access	4,042	29.3
	Household without internet access	9,743	70.7

Region	!Karas	600	4.35
	Erongo	937	6.8
	Hardap	664	4.82
	Kavango East	1,054	7.65
	Kavango West	912	6.62
	Khomas	1,573	11.41
	Kunene	638	4.63
	Ohangwena	1,284	9.31
	Omaheke	610	4.43
	Omusati	1,157	8.39
	Oshana	1,293	9.38
	Oshikoto	1,221	8.86
	Otjozondjupa	1,019	7.39
	Zambezi	823	5.97

In the first objective of this study, the rate of multidimensional poverty and its depth were estimated for the youth (aged 15-34 years) in Namibia. Table 5 presents the national youth multidimensional poverty measures according to the AF methodology, the headcount ratio and intensity level. The results showed that 31.4% of individuals aged 15-34 years in Namibia were living in multidimensional poverty, each of them deprived in about 57.7 % of the weighted indicators, on average.

Table 5: Youth national multidimensional poverty measures

Poverty cutoff (k value)	Index	Value (%)
k=50%	Headcount ratio (H)	31.4
	Intensity (A)	57.7

Figure 2 shows the headcount ratio of youth multidimensional poverty across sex, age-groups, urban/rural residence, household size and sex of head of household, in order to show the distribution of multidimensional poverty across the youth population. Figure 2 shows that multidimensional poverty was slightly more for female youths (32.2%) than males (30.5%). With respect to age, the figure indicates that the rate of multidimensional poverty was higher for the 15-19 age group (43.1%) followed by the 20-24 years age group (27.6%). The study also analyzed youth poverty by rural/urban location, and the results show that the rate of youth who were multidimensionally poor was higher in rural areas, reported at 42.8% compared to the poverty rate of urban youth of 18.8%. Furthermore, decomposition of poverty rates by household size shows that the rate of youth multidimensional poverty was highest amongst the households of size 16 or more members (60.3%). The results were finally decomposed by the sex of the head of households where the youth reside. Figure 2 further shows that the rate of multidimensional poverty was higher amongst the youth who reside in female-headed households (33.7%) compared to those who reside in male-headed households (29.2%).

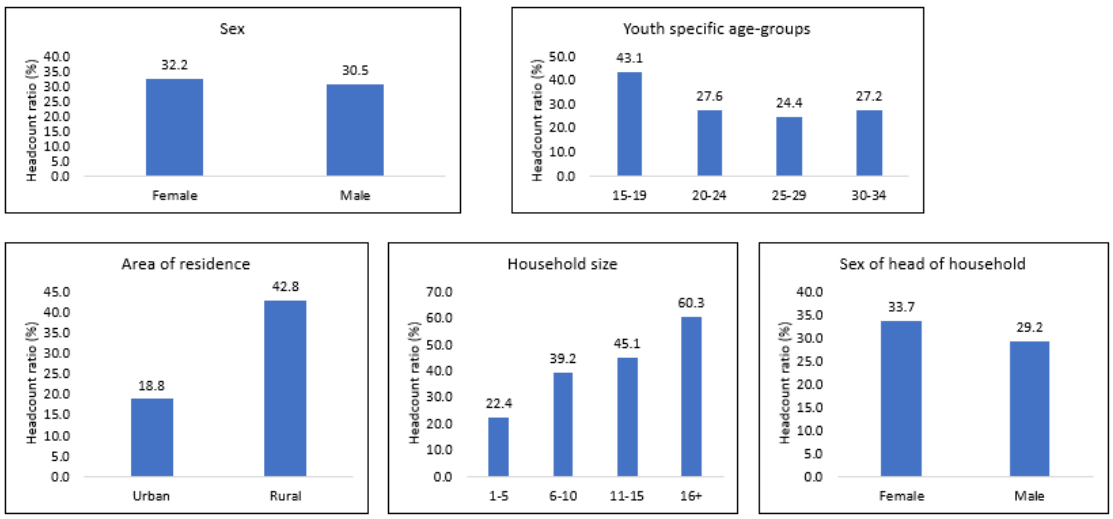

Figure 2: Incidence of youth multidimensional poverty by demographic characteristics

Figure 3 presents the decomposition of intensity levels of poverty across sex, age-groups, urban/rural residence, household size and sex of head of household, in order to describe the depth of youth multidimensional poverty amongst the youth. Figure 3 indicates that the intensity levels of multidimensional poverty for female and male youths were 57.8% and 57.5% of the indicators respectively, indicating that both poor male and female youths in Namibia experience almost equal deprivations/intensity of multidimensional poverty. With respect to age groups, the poorest amongst the poor youth fell in the 30-34 years age group, deprived in 58.9% of the weighted indicators. Figure 3 further shows that the intensity of multidimensional poverty was higher for the youth who reside in rural areas than it was for the youth who reside in urban areas, reported at 58.3% and 56.1%, respectively. This implies that the poor youth in rural areas were slightly more deprived than the poor youth that were residing in urban areas. Moreover, the intensity of youth multidimensional poverty was higher amongst the youth who were residing in households of size 16 or more, indicating that they were deprived in about 59% of the weighted indicators. Finally, a decomposition by sex of heads of household shows that the depth of multidimensional poverty was slightly more for those that were residing in male-headed households (58.0%) than those that were residing in female-headed households (57.4%). This indicates that the poor youth in male-headed households was slightly more deprived than the poor youth in female-headed households.

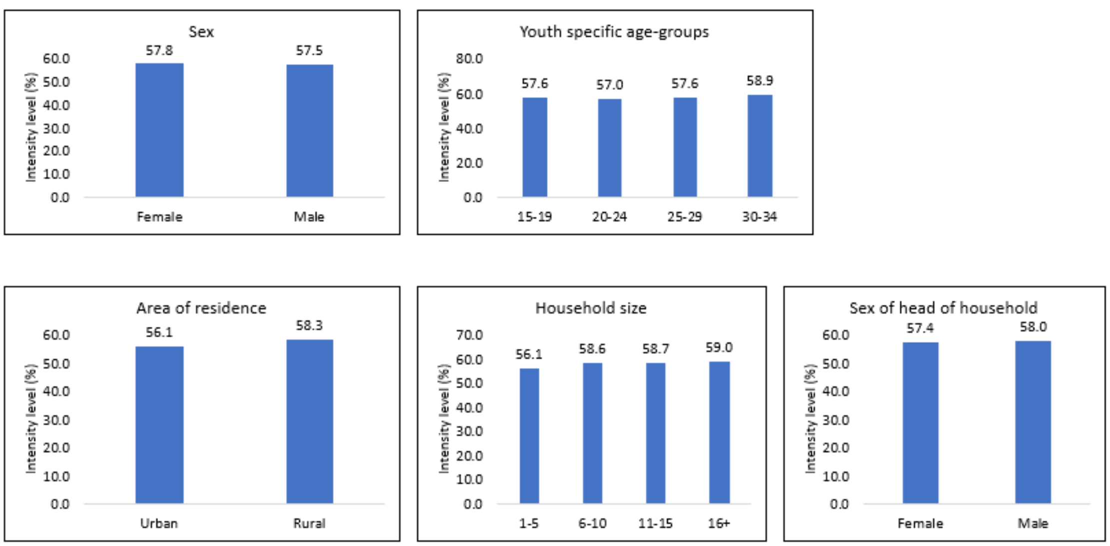

Figure 3: Intensity of youth multidimensional poverty by demographic characteristics

Figure 4 presents multidimensional poverty rates across the 14 administrative regions of Namibia, demonstrating the amount of incidence and intensity of youth multidimensional poverty. Figure 4 shows that the five (5) regions with the highest youth multidimensional poverty rates were Kunene (56.1%), Kavango West (53.3%), Kavango East (50.4%)

Omaheke (40.8%) and Zambezi (40.6%). The highest intensity levels were also reported for these regions, which indicated that the regions with the most poor youth also had the most severe multidimensional poverty.

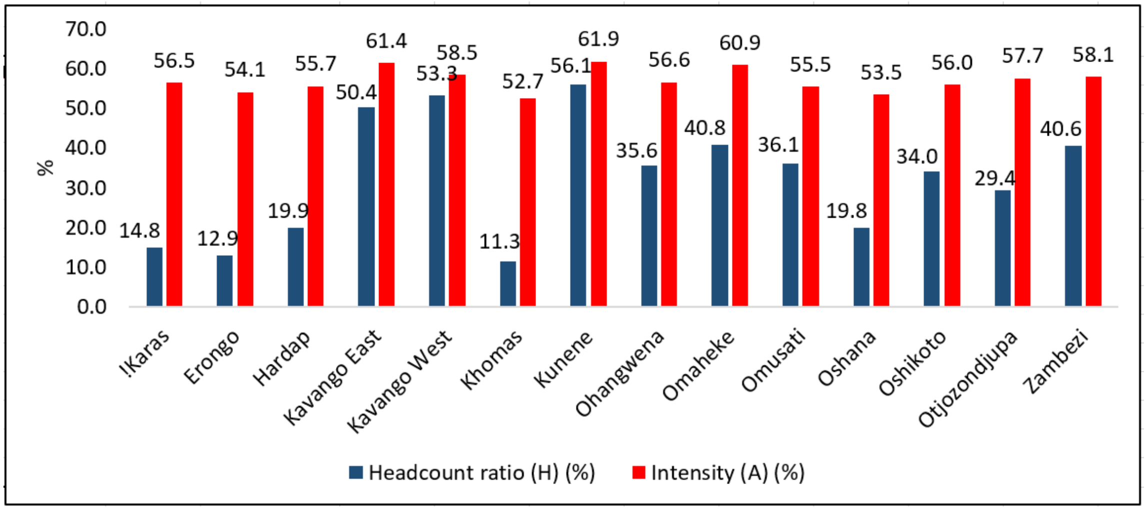

Figure 4: Incidence and intensity of youth multidimensional poverty by region

Figure 5 depicts the spatial distribution of youth multidimensional poverty in Namibia. As indicated by the legend, the darker the color for a given region, the higher its headcount ratio or intensity level. It can be seen that regions in the northern parts of the country generally had the highest poverty and intensity rates. Figure 5 further shows that there were some regions such as Karas and Erongo that had low headcount ratios of poverty, but the intensity of poverty experienced in those regions was high.

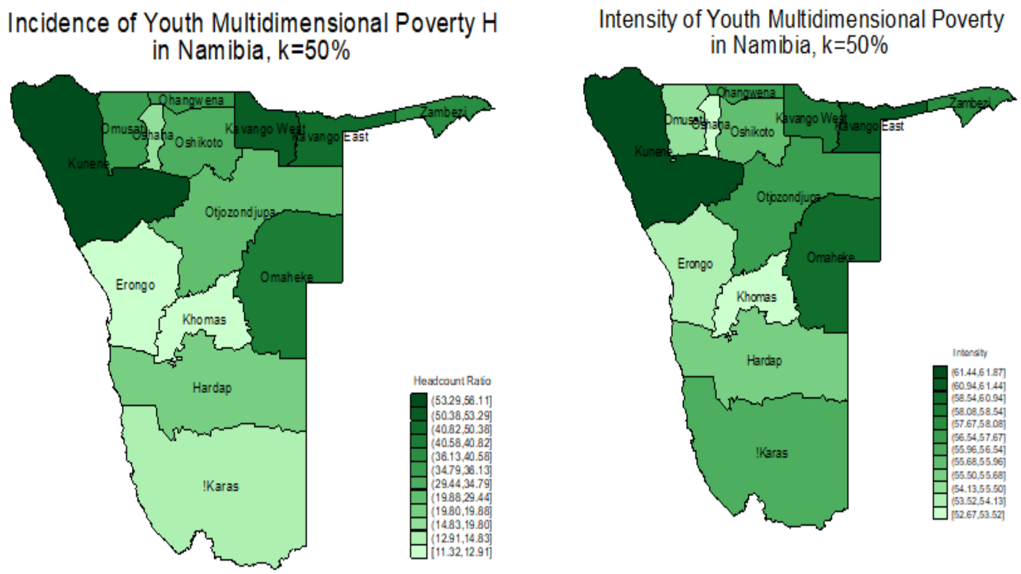

Figure 5: Spatial depiction of regional incidence and intensity rates of youth multidimensional poverty

Figure 6 compares the regional distribution of the rate of youth multidimensional poverty with the count of number of poor youth in each region. Youth multidimensional poverty rates are dependent on the total population of each region and therefore may not necessarily give an indication of the number of poor youth per region, because a low youth multidimensional poverty rate for a highly populated region will represent more poor youth (in terms of count) than a high poverty rate for a region with a relatively small youth population.

To further depict the spatial distribution of youth multidimensional poverty, the poverty rates were mapped against the number of poor youth population per region. In reading the maps, a darker for a region indicates a higher incidence of youth multidimensional poverty, and a higher number of multidimensionally poor youths for a that given region, as indicated by the legend. It can be seen from the map that Kunene region which had the highest youth multidimensional poverty rate, did not necessarily have the highest number of poor youths. Instead, the regions with the highest count of poor youth were Kavango East, Kavango West and Ohangwena, as they have the darkest colors in the map showing number of poor youths.

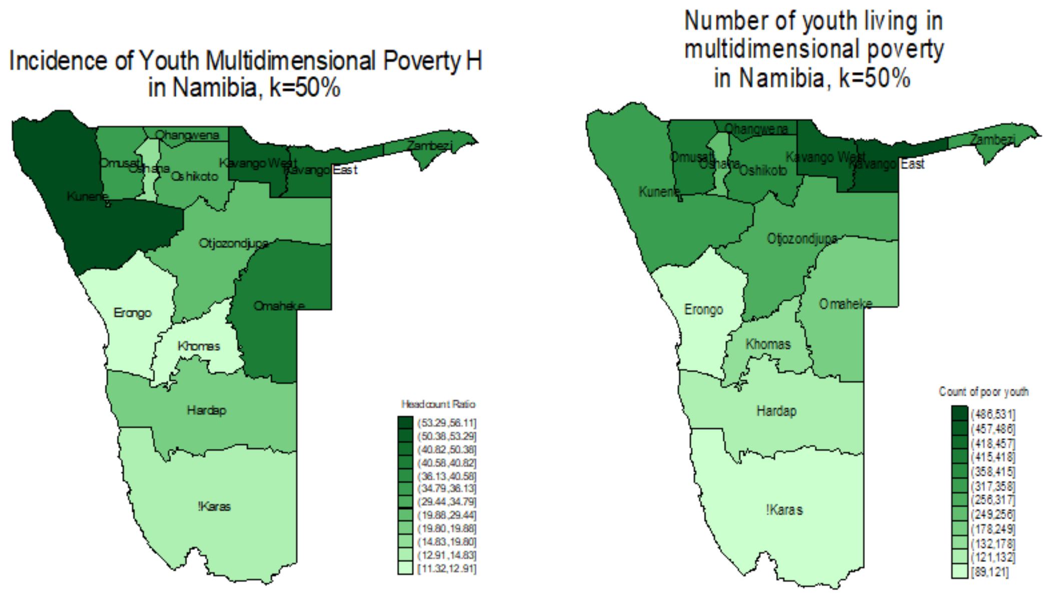

Figure 6: Spatial depiction of regional youth multidimensional poverty rates against multidimensional poverty counts

Figure 7 shows the drivers of youth multidimensional poverty by percentage contribution. Figure 7 indicates that deprivation in employment contributes the highest to the MPI, reported at 39.3%. This was followed by deprivation in education (28.9%), monetary welfare (21.2%) and health (10.6%).

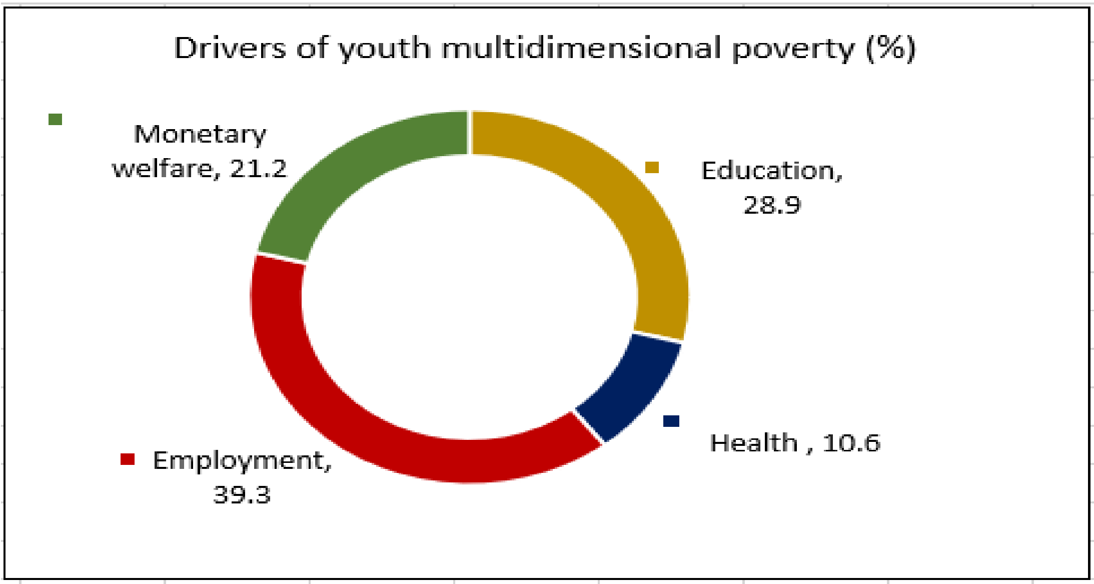

Figure 7: Drivers of youth multidimensional poverty

4.2.2. Multilevel Ordered Logistic Regression Model

Table 6 presents the distribution of youth multidimensional poverty intensity across five (5) categories which represent the severity of multidimensional poverty based on the four (4) selected dimensions, namely; education, health, employment and monetary welfare. The categories were ranked as follows; 1 (Not poor), 2 (Almost poor), 3 (Borderline poor), 4 (Above average poor) or 5 (Severely poor), depending on how many indicators a youth is deprived in, as discussed under objective two (2) in Section 3.5 of this report. Table 6 shows that 68.6% of the youth were considered as not poor, which means they were not deprived in any of the four (4) dimensions. Moreover, none of the youth were deprived in one(1) dimension, while 22.6% of the youth population were deprived in two (2) out of four (4) dimensions, and hence they were classified as borderline poor. Additionally, 7.9% of the youth population were deprived in three (3) dimensions and were therefore classified as above-average poor. Lastly, only 0.9 % of the youth population were deprived in all four (4) dimensions, and were classified as severely poor.

Table 6: Frequency distribution of intensity of youth multidimensional poverty

Intensity of multidimensional poverty	**Frequency**	**%**
1= Not poor (deprived in 0 dimensions)	9,461	68.6
2= Almost poor (deprived in 1 dimension)	0	0
3= Borderline poor (deprived in 2 dimensions)	3,117	22.6
4= Above average poor (deprived in 3 dimensions)	1,086	7.9
5= Severely poor (deprived in all 4 dimensions)	121	0.9

Table 7 presents the variation in the intensity of multidimensional poverty across sex, marital status, relation to head of household, orphan hood, urban/rural residence, sex of head of household, employment status, housing unit, and internet access. Unlike Table 6 which only showed the total number of youth per each of the five multidimensional poverty intensity levels (not poor, almost poor, borderline poor, above average poor and severely poor), Table 7 decomposed the totals across socio-economic characteristics listed above. With regards to the Sex variable, the table shows that amongst all male youth, 69.5% were non-poor, which indicates that they were not deprived in any of the four (4) dimensions. Furthermore, 22.2% of the male youth population were classified as boarder line poor, as they were deprived in two (2) of the four (4) dimensions. Moreover, 7.5% of the male youth population were classified as above average poor, as they were derived in three (3) of the four (4) dimensions, while only about one (1) percent were deprived in all four (4) dimensions and were therefore classified as severely poor. The intensity of multidimensional poverty amongst the female youth population follows a similar trend, with 67.8% classified as not poor, while about one (1) percent were classified as severely poor. All other variables are similarly interpretable.

Table 7: Decomposition of youth multidimensional poverty intensity by categorical predictor variables

Variables	Categories	Intensity of multidimensional poverty				
		1= Not poor	2= Almost poor	3= Borderline poor	4= Above average poor	5= Severely poor
		Count (%)	Count (%)	Count (%)	Count (%)	Count (%)
Sex	Male	4,553 (69.5)	0 (0)	1,453 (22.2)	491 (7.5)	54 (0.8)
	Female	4,908 (67.8)	0 (0)	1,664 (23.0)	595 (8.2)	67 (0.9)
In a marital union	Yes	1,782 (68.0)	0 (0)	574 (21.9)	236 (9.0)	28 (1.1)
	No	7,679 (68.8)	0 (0)	2,543 (22.8)	850 (7.6)	93 (0.8)
Have left a marital union	Yes	142 (57.7)	0 (0)	58 (23.6)	40 (16.3)	6 (2.4)
	No	9,319 (68.8)	0 (0)	3,059 (22.6)	1,046 (7.7)	115 (0.8)
Closely related to Head of HH	Yes	5,924 (69.9)	0 (0)	1,809 (21.3)	657 (7.8)	85 (1.0)
	No	3,537 (66.6)	0 (0)	1,308 (24.6)	429 (8.1)	36 (0.7)

Orphan hood status	Orphan	363 (49.0)	0 (0)	279 (37.7)	90 (12.1)	9 (1.2)
	Not an orphan	9,098 (69.7)	0 (0)	2,838 (21.8)	996 (7.6)	112 (0.9)
Urban/rural residence	Urban	5,322 (81.2)	0 (0)	956 (14.6)	253 (3.9)	24 (0.4)
	Rural	4,139 (57.2)	0 (0)	2,161 (29.9)	833 (11.5)	97 (1.3)
Sex of head of HH	Male	5,046 (70.8)	0 (0)	1,468 (20.6)	560 (7.9)	54 (0.8)
	Female	4,415 (66.3)	0 (0)	1,649 (24.8)	526 (7.9)	67 (1.0)
Employment status of the head of HH	Employed	6,207 (79.2)	0 (0)	1,202 (15.3)	392 (5.0)	35 (0.4)
	Unemployed	3,254 (54.7)	0 (0)	1,915 (32.2)	694 (11.7)	86 (1.4)
Improvised dwelling unit	Yes	1,662 (70.9)	0 (0)	502 (21.4)	163 (7.0)	18 (0.8)
	No	7,799 (68.2)	0 (0)	2,615 (22.9)	923 (8.1)	103 (0.9)

Internet access	No	6,062 (62.3)	0 (0)	2,586 (26.6)	971 (10.0)	117 (1.2)
	Yes	3,399 (83.9)	0 (0)	531 (13.1)	115 (2.8)	4 (0.1)

In order to assess the disparity in the intensity of poverty amongst the youth at individual, household and regional levels, hierarchical regression models were fitted to examine the relationship between the ordered categorical response variable of the intensity of youth multidimensional poverty and the results are presented here below. The study considered eight(8) models in order to determine whether adding variables at individual, household and regional levels resulted in the best fitting model. Specifically, the researcher firstly fitted a random intercept-only model to determine the intensity of youth multidimensional poverty in the absence of any predictors, to better show these predictors' effect on the response variable in the proceeding model. Thereafter, the researcher then fitted various fixed-effects multilevel models as well as various mixed-effects multilevel regression models, adding predictors at different levels as shown in Table 8. Eight (8) models were considered in total, and a description of each model is presented in Table 8.

Table 8: Descriptions of the ordered logistic regression models that were considered

Model name	**Model description**
Model 1	-Fixed intercept only. The effect on the intercept is fixed from group to group, both at household and regional levels. -Explanatory variables: *none*
Model 2	-Fixed intercept model with fixed individual level predictors. The effect on the intercept is fixed from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual-level predictors: *Age, Sex, Marital status, Relationship to head of house, orphan hood*
Model 3	-Fixed intercept model with fixed individual and household level predictors. The effect on the intercept is fixed from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual and household-level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access*

Model 4	-Fixed intercept model with fixed individual, household and regional level predictors. The effect on the intercept is fixed from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual, household and regional level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access, Regional youth population, Regional youth unemployment rate, regional informal employment rate, Regional crude birth rate, Regional crude death rate, Regional income inequality rate, Regional total consumption expenditure*
Model 5	-Random intercept only model. The effect on the intercept varies from group to group, both at household and regional levels. -Explanatory variable: *none*
Model 6	-Random intercept model with individual level predictors, and random slopes of these predictors varying by household and region -The outcome of the response variable is being explained by individual-level predictors: *Age, Sex, Marital status, Relationship to head of house, orphan hood*

Model 7	-Random intercept model with individual and household level predictors, and random slopes of these predictors varying by household and region -The outcome of the response variable is being explained by individual and household-level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access*
Model 8	-Random intercept model with individual, household and regional level predictors, and random slopes of these predictors varying by household and region -The outcome of the response variable is being explained by individual, household and regional level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access, Regional youth population, Regional youth unemployment rate, regional informal employment rate, Regional crude birth rate, Regional crude death rate, Regional income inequality rate, Regional total consumption expenditure*

For model comparison and selection, the model with the lowest AIC score is preferred. Table 9 presents the AIC value of each model. The table indicates that overall, the model-fit improves (i.e. AIC decreases) as more predictors at different levels are added to the list of explanatory variables, which demonstrates the strength of using multilevel modelling approach in modelling youth multidimensional poverty. The model fit further improves when the effect of the predictor variables varies from group to group at both household and regional levels, as opposed to the fixed effects model. For the overall best model, the table indicates that based on the lowest AIC criteria, model 8, which had the AIC of 18729.23 was the best fitting model.

Table 9: Selection of best fitting multilevel ordered logistic regression model based on AIC

Fitted Model	Type of effect on the intercept	AIC value
Model 1	Fixed	23,061.7
Model 2	Fixed	22,626.5
Model 3	Fixed	20,600.3
Model 4	Fixed	20,093.6
Model 5	Random	19,969.3
Model 6	Random	19,723.7
Model 7	Random	18,732.4
Model 8	Random	18,729.2

For multilevel estimation, Table 10 shows the results of the best-fitting multilevel mixed-effects ordered logistic model (i.e. Model 8). The logit of each cumulative probability was assumed to be a linear function of the covariates with regression coefficients constant across response categories (Rampichini & Grilli, 2014). The response variable, i.e. Intensity of youth multidimensional poverty, was treated as ordinal under the assumption that the levels of the intensity in multidimensional poverty have a natural ordering (Not poor to Severely poor), but the distances between adjacent levels are unknown. The model had a random intercept with fixed individual, household and regional predictors. The random intercept varied within households and regions, within which the individual youth were nested. The household-level predictors therefore only had a fixed (average) effect and were the same for individuals from the same household. Similarly, regional-level predictors were also fixed across individuals and households from the same region. The total number of observations considered in the model was all youth in the data file, (N=13 785), and the response variable being predicted was the intensity of poverty (A), which was an ordered categorical variable that took on the values 1 (Not poor), 2 (Almost poor), 3 (Borderline poor), 4 (Above average poor) or 5 (Severely poor) depending on how many indicators a youth is deprived in as discussed in Chapter 3. At 95% confidence level, the significant predictors are indicated by three asterisks *** in Table 10.

Table 10: Results of best fitting multilevel ordered logistic model

Parameter	Odds ratio	Standard error	P value	95% Confidence Interval	
Individual level predictors (level 1)					
Age	-0.0571	0.0057	<0.0001***	-0.0683	-0.0459
Female *(Reference: male)*	0.0763	0.0536	0.1550	-0.0288	0.1814
In a marital union *(Reference: never married)*	0.4102	0.0908	0.1270	0.2322	0.5882
Have left a marital union *(Reference: never married)*	0.3037	0.1989	<0.0001***	-0.0862	0.6935
Closely related to Head of Head of Household (HH) *(Reference: Not closely related)*	0.0499	0.0635	0.4320	-0.0745	0.17422
Orphan *(Reference: not being an orphan)*	0.5738	0.1098	<0.0001***	0.3586	0.7810
Household level predictors (level 2)					

Urban/rural residence *(Reference: rural)*	-1.2246	0.0966	<0.0001***	-1.4139	-1.0352
Female head of HH *(Reference: male)*	0.0070	0.0759	0.9260	-0.1418	0.1559
Age of head of HH	-0.0003	0.0025	0.8970	-0.0052	0.0045
Household size	0.1761	0.0126	<0.0001***	0.1515	0.2007
Employed head of HH *(Reference: Not employed)*	-1.1633	0.0852	<0.0001***	-1.3304	-0.9963
Improvised dwelling unit *(Reference: Non-improvised dwelling)*	0.8313	0.1071	<0.0001***	0.6213	1.0413
No internet access *(Reference: Have internet access)*	0.9087	0.0948	<0.0001***	0.7229	1.0946
Regional level predictors (level 3)					
Total youth population	-2.4E-05	0.000012	0.0460***	-4.7E-05	-3.86E-07
Youth unemployment rate	0.0380	0.0388	0.3270	-0.0380	0.1141

Youth informally employed rate	0.0257	0.0132	0.0520	-0.0003	0.0516
Crude Birth Rate	0.0237	0.0378	0.5310	-0.0504	0.0978
Crude Death Rate	0.0406	0.0510	0.4260	-0.0593	0.1406
Gini coefficient	3.8360	3.6372	0.2920	-3.2928	10.9646
Total consumption expenditure	0.0002	8.36E-05	0.0590	-6.16E-06	0.0003

From Table 10, the odds estimate for a one unit increase in an individual's age on the expected intensity category given the other variables were held constant in the model is -0.0571. This implies that, if an individual's age was to increase by one year, their odds of being in a higher multidimensional poverty intensity category would decrease by 0.0571 with all other variables in the model held constant. The results further indicated that the odds for individuals who have left a marital union being in a higher multidimensional poverty intensity category was 0.4102 more than those who were never married. Furthermore, the odds for orphaned youth being in a higher multidimensional poverty intensity category was 0.5738 more than more than those whose either one or both parents were alive, with all other variables in the model held constant. At the household level, the results indicated that the odds for the youth who resided in urban areas being in a higher multidimensional poverty intensity category was 1.2246 less than for those who resided in rural areas, with all other variables in the model held constant.

With regards to household size, for a one (1) person increase in household size, the odds of being in a higher multidimensional poverty intensity category would increase by 0.1761 with the other variables in the model held constant. Additionally, the odds of being in a higher multidimensional poverty intensity category for the youth who resided in a household being headed by an employed head was 1.1633 less than for those who were being headed by unemployed heads, with all other variables in the model held constant. On the other hand, residing in an improvised housing unit increased the odds of being in a higher multidimensional poverty intensity category by 0.8313, with the rest of the variables in the model held constant.

The results further indicated that for the youth who resided in a household that had no internet access, the odds of being in a higher multidimensional poverty intensity category was 0.1761 more than those who resided in non-improvised dwellings, with all other variables in the model held constant. At regional level, the odds estimate for a one unit increase in the region's total youth population on the expected intensity level if the other variables were held constant in the model was -2.4E-05. Therefore, if the region's youth population was to increase by one person, the youth's odds of being in a higher multidimensional poverty intensity category would decrease by 2.4E-05 if all other variables in the model were held constant.

Finally the results also showed that there were some individual, household and regional level characteristics that lowered the odds of being in a higher multidimensional poverty intensity category of poverty, however their effect was not found to be statistically significant at a 95% confidence level. These factors, amongst others, were; being male, being closely related to the head of household, residing in a female-headed household, residing in a household that is headed by an older, employed person, as well as residing in a region that has a high total consumption expenditure.

4.2.3. Logit Multilevel Regression Model

Various hierarchical regression models were also considered in modelling the determinants of youth multidimensional poverty in order to determine the best model that predicts socioeconomic and demographic factors affecting the prevalence of multidimensional poverty amongst the youth based on individual, household and regional level characteristics. The study first considered a random intercept-only model, to determine the youth multidimensional poverty status in the absence of any predictors. The study considered eight(8) models in order to determine whether adding variables at individual, household and regional levels resulted in the best fitting model. Specifically, the researcher firstly fitted a random intercept-only model to determine the odds of a youth being multidimensionally poor in the absence of any predictors, to better show these predictors' effect on the response variable in the proceeding model. Thereafter, the researcher then fitted various fixed-effects multilevel models as well as various mixed-effects multilevel regression models, adding predictors at different levels as shown in Table 11. Eight (8) models were considered in total, and a description of each model is presented in table 11.

Table 11: Descriptions of logit multilevel models

Model name	**Model description**
Model A	-Random intercept only. The group-specific effect on the intercept is a random effect because it varies from group to group, both at household and regional levels. -Explanatory variables: *none*
Model B	-Random intercept model with fixed individual level predictors. The group-specific effect on the intercept is a random effect because it varies from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual-level predictors: *Age, Sex, Marital status, Relationship to head of house*, *orphan hood*
Model C	-Random intercept model with fixed individual and household level predictors. The group-specific effect on the intercept is a random effect because it varies from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual and household-level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household,*

	Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access
Model D	-Random intercept model with fixed individual, households and regional level predictors. The group-specific effect on the intercept is a random effect because it varies from group to group, both at household and regional levels. -The outcome of the response variable is being explained by individual, household and regional level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access, Regional youth population, Regional youth unemployment rate, regional informal employment rate, Regional crude birth rate, Regional crude death rate, Regional income inequality rate, Regional total consumption expenditure*
Model E	-Random intercept model with fixed individual level predictors, and a random slope of selected individual level predictors varying by region -Explanatory variable: *none*
Model F	-Random intercept model with fixed individual and household predictors, and a random slope of selected individual level predictors varying by region

	-The outcome of the response variable is being explained by individual-level predictors: *Age, Sex, Marital status, Relationship to head of house, orphan hood*
Model G	-Random intercept model with fixed individual, household and regional level predictors, and a random slope of selected individual level predictors varying by region -The outcome of the response variable is being explained by individual and household-level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access*
Model H	-Random intercept model with individual, household, regional and cross-level level predictors, and a random slope of selected household level predictors varying by region -The outcome of the response variable is being explained by individual, household and regional level predictors: *Age, Sex, Marital status, Relationship to head of house, Orphan hood, Urban/rural residence, Sex of Head of household, Age of head of household, Household size, Employment status of the head of the household, Type of dwelling unit for thee household and Household internet access, Regional youth population, Regional youth unemployment rate, regional informal employment rate, Regional crude birth rate, Regional crude death rate, Regional income inequality rate, Regional total consumption expenditure*

Table 12 presents the AIC of each logit model, and indicates that based on the lowest AIC criteria, model D, which had the AIC of 13451.5 was the best fitting model.

Table 12: Selection of best fitting logit model based on AIC

Fitted Model	Type of effect on the intercept	AIC value
Model A	Fixed	14,857.1
Model B	Fixed	14,569.5
Model C	Fixed	13,459.3
Model D	Fixed	13,451.5
Model E	Random	15,624.6
Model F	Random	14,200.7
Model G	Random	14,189.9
Model H	Random	14,182.2

Table 13 shows the results of the best-fitting mixed effect multilevel logit regression model (i.e. Model D). The model had random intercept with fixed individual, household and regional predictors. The total number of observations was the number of youth (N=13 785), and the response variable was multidimensional poverty status. This variable was of a binary nature, coding every individual as 1=poor and 0=non-poor. At 95% confidence level, the significant predictors are indicated by *** in Table 13.

Table 13: Results of best fitting logit model

Parameter		Estimate	Standard error	P value
Intercept	β_0	-4.8420	1.369e+00	0.0004 ***
Individual level predictors (level 1)				
Age	β_1	-6.3880	5.636e-03	< 2e-16 ***
Sex *(Reference: male)*	β_2	3.0700	5.359e-02	0.5668
In a marital union *(Reference: never married)*	β_3	3.4180	8.871e-02	0.0001***
Have left a marital union *(Reference: never married)*	β_4	-3.5250	2.003e-01	0.8603
Closely related to Head of HH *(Reference: Not closely related)*	β_5	1.0630	6.213e-02	0.0871
Orphanhood status *(Reference: not being an orphan)*	β_6	5.7620	1.127e-01	3.15e-07 ***
Household level predictors (level 2)				

Urban/rural residence *(Reference: rural)*	β_7	-1.1890	8.572e-02	< 2e-16 ***
Sex of head of HH *(Reference: male)*	β_8	5.1380	6.882e-02	0.4553
Age of head of HH	β_9	-1.6750	2.244e-03	0.4556
Household size	β_{10}	1.5790	1.119e-02	< 2e-16 ***
Employment status of the head of HH *(Reference: Not employed)*	β_{11}	-1.2020	7.470e-02	< 2e-16 ***
Improvised dwelling unit *(Reference: Non-improvised dwelling)*	β_{12}	8.0920	9.623e-02	< 2e-16 ***
No internet access *(Reference: Have internet access)*	β_{13}	8.4970	8.459e-02	< 2e-16 ***
Regional level predictors (level 3)				
Total youth population	β_{14}	-2.1231	7.877e-06	0.0070 ***

Youth unemployment rate	β_{15}	4.1940	2.554e-02	0.1005
Youth informally employed rate	β_{16}	1.7510	8.869e-03	0.0484 ***
Crude Birth Rate	β_{17}	2.0020	2.503e-02	0.4237
Crude Death Rate	β_{18}	5.1200	3.378e-02	0.1296
Gini coefficient	β_{19}	1.4000	2.414e+00	0.5621
Total consumption expenditure	β_{20}	1.4000	5.499e-05	0.0109 ***

On the basis of alpha=0.05, the results henceforth are interpreted at the 95% confidence level. B_0 = -4.8420 is interpreted as the odds that an individual was multidimensionally poor, when the effect of independent variables at all three levels was zero, and is referred to as the overall intercept. Table 13 shows that the variables that significantly determined the odds of a youth being multidimensionally poor were; age of the youth, being in a marital union, orphan hood status, urban/rural residence, household size, employment status of the head of household, living in an improvised dwelling unit, having no internet at home, total regional youth population, regional youth informal employment rate as well as regional total consumption expenditure.

The results showed that with an increase in the youth's age, the likelihood of being multidimensionally poor seems to decrease. Additionally, the youth who were in marital unions were significantly more likely to be multidimensionally poor compared to the youth who were never married. Furthermore, the orphaned youth were significantly more likely to be living in multidimensional poverty than the youth who are not orphaned.

With regards to household level characteristics, the results indicated that based on the urban/rural residence, the youth who resided in urban areas had a significantly lower probability of being multidimensionally poor compared to the youth who resided in rural areas. Furthermore, the results in Table 13 show that the youth from households with larger number of members were significantly more likely to be multidimensionally poor. The regression analysis further shows that the youth from households being headed by employed persons have a significantly lower likelihood of being multidimensionally poor than the youth who resided in households where the head was unemployed. Moreover, the youth who lived in improvised housing units had a significantly higher likelihood of living in multidimensional poverty than their counterparts, just as those who resided in households with no internet access.

At regional level, the results presented in Table 13 show that the likelihood of youth multidimensional poverty decreased significantly as the total regional youth population increased. Similarly, as the regional number of youth who are employed in the informal sector increased, the youth in the region had a higher probability of being multidimensionally poor. Finally, the likelihood of multidimensional poverty increased as the regional total consumption expenditure also increased.

5. CHAPTER FIVE: DISCUSSIONS

5.1. Introduction

In order to get a better understanding of the results presented in Chapter 4, this chapter provides a more detailed discussion of the findings.

5.2. Discussions

The study broadens the common monetary-based phenomenon of poverty, which only captures deprivation in income or expenditure, to the multidimensional definition of poverty. Specifically, the study applied the Alkire-Foster method, to compute the incidence and intensity of poverty for all youth aged 15-34 years, and analyzed disparity and inequality of multidimensional poverty across social and demographic subgroups of the youth population. The study considered four, equally weighted dimensions at the individual unit level of analysis, which is the education, health, employment activities and monetary welfare of the youth. An individual was considered to be multidimensionally poor if they were deprived in at least two (2) dimensions. The study reveals a novel image of the prevalence, intensity and disparity in youth multidimensional poverty in Namibia.

The analysis of this study showed that 31.4% of the youth were living in multidimensional poverty, each of them deprived in about 57.7% of the weighted indicators, on average. This indicates the magnitude and depth of multidimensional poverty amongst the youth in Namibia, highlighting the need for implementation of youth targeted, poverty-alleviation policies. This is notable, given that the recommendation from the most recent global multidimensional poverty report by United Nations Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI)

(2020) was for governments to rather focus on alleviating poverty amongst children aged below the age of eighteen (18) years.

Decomposing the results by sex showed that that youth multidimensional poverty was higher for female youths than the male youths. This indicates that female youth are slightly more deprived in welfare than the male counterparts in Namibia, as it appears to be in other societies of the world. The trend shown by these results goes back to the phenomenon of “feminization of poverty” which was discovered back in the 1960’s and argues that in many rural areas of the developing world, females and female-headed households accounts for majority of the poor population (McFerson, 2010). Furthermore, Ozdamar & Giovanis (2019), who analyzed the prevalence of multidimensional poverty amongst the youth who are aged 15-24 years in selected countries of the Middle-East and North Africa (MENA) region, found that multidimensional poverty was more prevalent in females than males.

Vijaya, et. al. (2014) who measured multidimensional poverty in India, found that males and females were evenly distributed across poor and non-poor households and that there was no major gender difference in multidimensional poverty. Ozdamar and Giovanis (2019) linked the multidimensional poverty gap to the lack of women’s participation in the labor market, and recommended that developing countries must strongly enable equal opportunities for young women to be employed in similar jobs and positions given to men. The disparity in youth multidimensional poverty between female and male youth in Namibia could therefore be linked to the gender gap in employment, given that the country’s labor statistics reports by NSA(2017, 2019) also highlighted that youth unemployment is higher for females youths than males. The gender gap in multidimensional poverty showed by the results of the current study could possibly therefore be solved by addressing youth unemployment.

Youth multidimensional poverty was found higher in rural areas as compared to urban areas. Although the 2016 Namibia Inter-censal demographic Survey by NSA (2016) reported a high rural-to-urban migration, the overall rural population in the country was still higher compared to the urban population. The notion of “Theories of development” as described by Nguyen et. al. (2021) argues that the rate of absolute poverty in urban areas is often lowered through the opportunities created by vast industrialization and technological developments which begin in urban areas. For the Namibian youth, the trend could be explained by challenges of high monetary poverty and unemployment rates in rural areas as compared to urban areas in Namibia, as reported in the country’s NHIES report by NSA (2018) and the labor force report by NSA (2019).

The urban/rural trend established in the current study concurs with Mahoozi (2015) whose findings revealed a remarkable disparity in multidimensional poverty among different subgroups in Iran in which rural households are more deprived compared to their peers in urban areas. The finding of the current study further agreed with Bird et. al., (2011) who examined the relationship between chronic poverty and Remote Rural Areas (RRAs) in Asia and Sub-Saharan Africa and concluded that rural populations experience higher levels of deprivation, mainly because of lack of access to natural resources, information, opportunities and connections in rural areas.

Bertolini (2019) also reported that the cumulative negative effects of vicious circle of labor market, demography, education and remoteness transmit rural poverty. The finding of the current study is further in line with that of Ozdamar & Giovanis (2019) who stated that the urban-based population in the Middle East and Northern Africa (MENA) region were less likely to experience higher levels of deprivation and poverty, compared to those who lived in rural areas.

This study further decomposed poverty rates by household size, and findings showed that as household size increased, the intensity of poverty also increased. The Namibia Inter-censal Demographic Survey (NIDS) report by NSA(2017) showed that Namibian households consisted of 3.9 persons on average, and indicated that majority of households with larger sizes were headed by females. This could explain the high rate of youth multidimensional poverty in bigger households based on the phenomenon of "feminization of poverty" which states that female-headed households are more likely to live with deprivations, as discussed by (McFerson, 2010). Large household size appears to be associated with high poverty rates for other societies in developing countries, both by multidimensional and monetary definitions. Abu-Ismall et al (2015) who measured multidimensional poverty in Jordan, Iraq and Morocco, found that deprivation rates varied for different household sizes with consistently higher rates for larger households and rural residents. Additionally, Meyer and Nishimwe-Niyimbanira (2016), who analyzed the relationship between household size and money-metric poverty in various low-income townships in the Free State province of South Africa and found a positive relationship between household size and poverty in eleven of the twelve low-income communities.

There are however other authors who have found contradicting results, such as Fonta et. al., (2020) who examined the drivers of multidimensional poverty among children aged 5 to 18 years in the Mouhoun region of Burkina Faso, and argued that increment in household size does not always worsen poverty, concluding that households with seven or more members had a reduced risk of experiencing multidimensional poverty.

Youth multidimensional poverty was more prevalent in female-headed households, compared to those headed by males. The finding agrees with the money-metric poverty results in the NHIES report by NSA (2018), who reported that the incidence of monetary poverty is higher amongst female-headed households. Similarly, the findings furthermore agrees with Rogan (2015) and Mahoozi (2015) who both acknowledged that female-headed households relatively experience more poverty. Rogan (2015) further examined the gender gap observed in the two measures of poverty in South Africa. His findings suggested that while the multidimensional gender poverty gap was similar to the poverty gap measured by the conventional money-metric approach at several national poverty lines, the MPI poverty differential between female- and male-headed households was slightly narrower than the income poverty gap between these two household types.

Similarly, Jose and Stephan (2017) who estimated the incidence, intensity and inequality of multidimensional poverty in Nigeria, reported that overall, they found statistically significant gender differences in multidimensional poverty in Nicaragua, however, the gender differential in inequality suggested that the multi-dimensionally poor female-headed were living in very intense poverty when compared to the multi-dimensionally poor male-headed counterparts. This type of analysis is therefore crucial for Namibia too, not only for the alleviation of poverty but also in the achievement of gender equality at household levels as stipulated in Namibia's fifth National Development plan by NPC (2017).

The results further showed that while Khomas and Erongo regions had the lowest rates of youth multidimensional poverty, the top five regions that were found to have the highest rates were Kunene, Kavango West, Kavango East, Omaheke and Zambezi. Spatially, youth multidimensional poverty was thus more concentrated in the northern part of Namibia. This indicated that youth multidimensional poverty can be closely linked to monetary poverty and youth unemployment, because it is similar to the trend of the results reported for regional monetary poverty and youth unemployment trends by NSA (2018) and NSA (2019) in Namibia's NHIES and labor force reports, respectively. In examining the root causes of poverty in Namibia, NPC (2015) highlighted that Namibia's previous governments historically invested very little in regions in the northern part of Namibia in the way of infrastructure, government services and other amenities relative to the more urban central parts and the southern regions such as Khomas and Erongo regions. The findings of the current study actually indicate that Khomas and Erongo regions are amongst the regions that have the lowest incidences of youth multidimensional poverty, and it could be associated to their largely urban populations and due to them being economic hubs of the country, with relatively more youth employment opportunities. Khomas region is home to Windhoek, the political and economic capital city of Namibia, while Erongo region not only has most of the existing mines in Namibia but also borders the Atlantic Ocean which produces fish, a major export commodity for Namibia. Erongo region also has the Namib Desert, an important tourist destination.

Youth multidimensional poverty in Namibia was mainly driven by deprivation in employment, followed by deprivation in education, monetary welfare and lastly by

deprivation in health. Employment, whether in the formal or informal sector, is a means of income needed to improve an individual's welfare. In Namibia, however, youth unemployment remains a challenge. The 2018 Namibia's labor force report by NSA (2019) showed that the overall, youth unemployment rate was high at 46.1%, which indicated that almost half of the youth population were jobless, without a solid source of income to sustain proper living standards by themselves. The 2019 labor force report further indicated that at regional level, the youth unemployment rates were particularly highest for Kavango East (62.5%) and Kunene (53.0%) regions respectively- and these were the same regions found to have had the highest youth multidimensional poverty rates in the current study. Furthermore, the NEET rate, which is defined in the same report as the percentage of youth aged 15-34 years who were not in employment and not in education or training, also provided an insightful link to the findings of the current study which indicated deprivation in employment and education as the main drivers of youth poverty. The NEET rate were found to be highest in rural areas, amongst the female youth, in the regions that were also found to have the highest youth multidimensional poverty rates. The results of this study therefore highlight the indicators that need to be prioritized by youth poverty reduction efforts in Namibia. Meyer and Nishimwe-Niyimbanira (2016) stated that to be lifted out of poverty, the poor need to be granted access to economic opportunities, while also receiving adult education regarding financial management and reproductive health. Additionally, the finding of the current study is consistent with Ataguba et. al. (2011) who concluded that the major determinants of multiple deprivations included poor employment, rural location and poor health, large family size and low level of education.

The results of the hierarchical ordered logistic regression showed that the best model selected for analysis was a mixed effects model, with individual, household and regional level predictors, and random slopes of these predictors varying by household and region. The results indicates that overall, the model-fit improved (see Table 9) as more predictors at different levels were added to the list of explanatory variables (see variables list in Table 8), which demonstrates the strength of using multilevel modelling approach in modelling youth multidimensional poverty.

At the individual level, the current study found that the youth who had left marital unions had a statistically significant higher chance of experiencing more intense poverty than those who were either never married or were still in marital unions. Divorce or separation implies changes of great economic significance. Hogendoorn (2019) argued that the most important change caused by divorce concerns the loss of partner income. According to Hogendoorn (2019), marital separation further posed additional challenges when children were involved, hence, individuals who left marital unions experienced sizable drops in household income, per capita income, and income-to-needs ratios, all which would lead to multidimensional poverty.

At the household level, the findings showed that residing in urban areas significantly decreased the odds of experiencing more intense poverty. While this finding agrees with the findings of Mahoozi (2015), the conclusion differs from Ozdamar & Giovanis (2019) who concluded that young people located in urban areas reported higher poverty rates, and added that this could be explained by the high urbanization rates that lead to higher competition to the labor market and thus on employment opportunities for young people. Namibia's National Development Plan by NPC (2017) also argues that while migration offers a possible pathway out of poverty for rural-born individuals and rural households, there is also some pressure on the urban labor market, with many migrants being unsuccessful through either unemployment or low wages earned in vulnerable urban employment.

The findings of this study further shows that the youth who resided in households of large size had a higher chance of experiencing more intense multidimensional poverty. As the number of household members increased, so did the odds of experiencing more intense poverty. The finding is consistent with Abu-Ismall et al (2015) who found that the intensity of multidimensional poverty in Jordan, Iraq and Morocco, all increased with large household size. Additionally, Meyer and Nishimwe-Niyimbanira (2016) recommended that the composition of a household should be of consideration in studying the relationship between household size and poverty.

Another important factor which was found to have a significant impact on increasing the odds of experiencing more intense poverty in this study was household internet access. Internet access enhances scientific research, upgrades the technological capabilities of individuals and also encourages innovation. One of the targets in Namibia's fifth NDP by NPC (2017) was to have universal access to information, affordable communication and technology infrastructure and services in the country, by 2022. Thompson, Thompson and Tayo (2015) studied the impact of the digital divide on computer use and internet access on the poor in Nigeria. One of their notable findings was that most of the households referred to Information and Communications Technology (ICT) as a crucial factor that created efficient way for resolving daily problems including communication, business transactions, increasing income, and opening career opportunities. Additionally, Yebowaah (2018) and Yesilyurt et al. (2014) both linked the benefit of internet access to enhanced education, and highlighted that access to a home computer and internet connection contributed positively to students' academic performance as well as self-learning skills.

The results obtained from the logit regression showed that the probability of youth multidimensional poverty in Namibia was also significantly increased not only by individual level characteristics, but also household and regional ones. This indicates that fighting youth multidimensional poverty in Namibia will have to take all three levels into consideration. Ataguba et al (2011), who studied the prevalence of multidimensional poverty in Nigeria also recommended that an integrated approach which accounts for inter-linkages between factors associated with poverty is required in order to effectively alleviate multidimensional poverty.

At individual level, the odds of being multidimensionally poor decreased with age. The improvement in the lives of the youth as they grew older in Namibia could be explained by policies that allow young people to legally access funds such as pension funds, study loans and inheritance after the age of eighteen (18) years. Furthermore, employment opportunities in the country also open up after completion of secondary education, with NSA (2019) reporting that out of all employed youth in the country; only 5.1% are below the age of twenty (20) years. The result of the current study resembles that of Ozdamar & Giovanis (2019) who examined youth multidimensional poverty in the middle-east and northern Africa regions and concluded that the youth's age was negatively associated with multidimensional poverty.

The current study also found that the youth who were in marital unions were more likely to be multidimensionally poor compared to those that had never been married or those who had left marital unions. The legal age to get married with a certificate in Namibia is 18 years, however, the analysis of the current study also included the youth that were married traditionally, which often takes place at a younger age. According to Dahl (2010), children and teenagers who married at a young age often had an increased chance of dropping out of school and were often victims of child abuse and neglect, had academic and behavioral problems in school, and were more likely to engage in crime.

At household level, the variables that were found to have significant and positive correlations with poverty incidence were household size, rural residence, living in an improvised housing unit, being headed by an unemployed persons as well as having no internet access at home. Concerning the household size, the findings conforms to the results of Imam, Islam and Hossain (2018) who used a two level random intercept binary logistic regression model to determine factors affecting extreme multidimensional poverty in rural Bangladesh, as they found that household size increased the chances of being multidimensionally poor. With regards to employment status of the household head, Ozdamar & Giovanis (2019) found that the employment status of both the youth and the parents were important determinants of multidimensional poverty.

The results of the current study pertaining household size further agree with Ataguba et al (2011), who concluded that the major determinants of deprivations included large family size, low level of education, poor employment, rural location and poor health. Concerning housing, land prices in Namibia have escalated to a point where they are out of reach for many people. Shifotoka (2015) stated that the growing lack of affordable housing was one of the most critical housing challenges facing Namibia. Additionally, Shortt and Hammett (2013) argued that lack of decent housing and rapid urban population growth leads to the extensive production of informal dwellings using makeshift materials (shacks) in overcrowded urban settlements. This is a concern for Namibia too, where improvised housing units (shacks) made up approximately 40% of all households in urban areas in 2016, as stated in the 2016 NIDS report by NSA (2017).

At regional level, the odds of being multidimensionally poor were found to be higher in regions that had high youth population, high youth informal employment rate and high consumption expenditure. An increased youth population implies that there is a sharp competition for opportunities in employment, education and training. The findings concerning informal employment differ with other authors who link informal employment to development. De Beer et. al (2013) stated that informal activities were seen to play a critical role in alleviating poverty, increasing employment, providing competition in the economy, supplying the formal sector, and fostering adaptation and innovation. For the youth in Namibia, however, the positive correlation of informal work and poverty could be justified by working conditions. In his article titled *"Formalizing Namibia's Informal Economy"* in *The Namibian* newspaper, Kamwanyah (2018) stated that Namibian informal economy workers were paid less, had insecure income, had no employment benefits and social protection, and were subjected to exploitative and adverse working conditions. Kamwanyah (2018) further added that most of the informal employers were themselves struggling entrepreneurs who lacked skills, education, and training. They also had no access to information, modern infrastructure, and technology.

Finally, the study found a negative relationship between consumption expenditure and youth multidimensional poverty in Namibia, indicating that the probability of being multidimensionally poor for the youth who resided in regions with high consumption expenditure, was more. This finding draws back onto high inequality discussed under objective two of this chapter, because a high total consumption expenditure may not necessarily imply shared prosperity, because the distribution of consumption expenditure may also be heavily skewed towards the upper percentiles of the population. As a result, many youths were still be living in poverty even if the regional total consumption expenditure showed an increment. Total consumption could be concentrated in the upper deciles of the income distribution, which are not representative of overall consumption. Kouam (2020) therefore cautions that as a gauge for economic development, per capita consumption should be used as a true reflection of economic progress.

6. CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The main objective of this study was to describe youth multidimensional poverty rates in Namibia, examining not only the incidence and intensity levels, but also the determinants impelling the prevalence of youth poverty across different demographic groups of the youth population.

In measuring youth multidimensional poverty, the study used the Alkire-Foster methodology, considering a youth to be multidimensionally poor if they were deprived in at least two (2) of the four (4) study dimensions, namely; education, health, employment activities and monetary welfare. The study used data from three sociodemographic nationally representative surveys conducted by the Namibia Statistics Agency, namely; 2015/16 NHIES, 2016 NIDS and 2016 NLFS. The results indicated that the prevalence of youth multidimensional poverty in Namibia stood at 31.4%. Moreover, each of the multidimensionally poor youth in Namibia was deprived in about 57.7% of the weighted indicators, on average. The incidence and intensity of poverty varied across population subgroups. Specifically, youth multidimensional poverty in Namibia was found to be more prevalent amongst females, the youth who were aged 15-19 years, those who resided in rural areas, as well as those who lived in households that were headed by females. Concerning intensity of poverty, both males and female youth in the country were found to have been experiencing the same deprivation level of about 58%. When considering age groups, the most severe multidimensional poverty was experienced by the youth aged 30-34 years. Additionally, youth multidimensional poverty was more intense in rural areas, households of large size as well as amongst the youth who resided in male-headed households.

The disaggregation of youth multidimensional poverty measures by regions indicated that the five regions with the highest rates were Kunene (56.1%), Kavango West (53.3%), Kavango East (50.4%) Omaheke (40.8%) and Zambezi (40.6%). The highest intensity levels of youth multidimensional poverty were also reported for these regions, which indicated that the regions with the most poor youth also had the most severe youth multidimensional poverty.

Concerning the drivers of youth multidimensional poverty in the country, the study found that deprivation in employment contributed the highest to the youth MPI, reported at 39.3%. This was followed by deprivation in education (28.9%), monetary welfare (21.2%) and health (10.6%).

Furthermore, the study's multilevel modelling approach also found that both the incidence and the intensity of youth multidimensional poverty in Namibia were significantly affected by individual, household and regional factors. At the individual level, age, orphan hood and marital status played a significant role in determining the likelihood of being poor and the intensity of poverty- the youth that were young, orphaned or those that had left marital unions were found to have a significantly higher chance of experiencing intense multidimensional poverty. At household level, three variables were significant in both the intensity and incidence models, and they were household size, urban/rural location as well as home internet access. The youth who resided in large households, rural areas, without access to the internet at home were found to be vulnerable to multidimensional poverty and its severity. At the regional level, an increased youth population played a significant role in minimizing the prevalence and intensity of youth multidimensional poverty. Additionally, regions with a high youth population who were either employed in the informal sector or unemployed were found to have higher rates of youth multidimensional poverty.

6.2. Recommendations

The study focused on estimating youth multidimensional poverty and its disparities amongst the youth in Namibia, using a hierarchical design that may be beneficial for policy design, based on targeted implementation of poverty eradication activities. Having found significant determinants of youth multidimensional poverty at individual, household and regional levels, the study firstly recommends an integrated approach in the fight against youth multidimensional poverty, that is based on statistics and considers a comprehensive set of factors that impact the welfare of the youth not only at regional level, but also household and individual levels.

Secondly, the study found that the prevalence and the intensity of youth multidimensional poverty was higher amongst female youth and female-headed households, mainly driven by unemployment. The study therefore recommends promotion of policies aimed at narrowing the gender gap, specifically by strengthening female's integration into the labor market with equal access to social protection and developing women's individual and collective capacities to recognize and vindicate their rights and to build social capital.

Finally, having found youth multidimensional poverty to have been higher in rural areas than urban areas, the study recommends that the regional and local governments further enhance policies that reduce migration from rural to urban areas. Such policies should address the level of economic inactivity in rural setups and access to services, in order to reduce the inequality being experienced by the youth who reside in rural areas, promoting equal opportunities in the labor, health and education sectors.

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APPENDICES

APPENDIX 1. Stata codes: data validation, cleaning and processing, estimation of poverty

```
clear all

set more off

/*

Author: Selma Ngula Megameno Shifotoka

Student number 201152614

This dofile: MSc Applied Statistics and Demography

Data source: "youth three levels.dta"

Last update: march 2021*/

*-----------------------------------------------------------------------------------------------------------------------------------------------


/*This dofile analyzes the Namibia Youth MPI using the file titled youth three levels data.

*The dataset is a combination of individual, household and regional variables from 2015/16 NHIES, 2016 NIDS and 2018 LFS

*This file has codes for all the stages of the analysis, outlined herebelow;

1.  DEFINE WORKING DIRECTORIES

2.  BUILD THE COMBINED DATASET

2.  BUILD THE DEPRIVATION MATRIX

3.  DEFINE AND KEEP THE RELEVANT SAMPLE

6.  UNCENSORED HEADCOUNT RATIOS

7.  SETTING EQUAL WEIGHTS

8.  WEIGTHED DEPRIVATION MATRIX

9.  COUNTING VECTOR

10. IDENTIFICATION

11. MULTIDIMENSIONAL HEADCOUNT RATIO (H), INTENSITY OF POVRTY AMONG THE POOR (A) , ADJUSTED HEADCOUNT RATIO (M0)ALL POSSIBLE CUTOFFS

12. FOR SELECTED K

     a)censored deprivation matrix

        b)headcount/incidence of multidimensional poverty (H) for k

        c)Intensity of poverty among the poor (A) for k

        d)adjusted headcount ratio (M0) for k

        e)censored headcount ratios

13. DIMENSIONAL BREAKDDOWN: PERCENTAGE CONRIBUTIONS

14. SUBGROUP DECOMPOSITION

15. COLLAPSE RESULTS FOR MAPPING PURPOSE
```

```
16. CREATING POVERTY MAPS

     a) INCIDENCE OF POVERTY (H)

        b) MONETARY POVERTY */


//------------------------------------------------------------------------------------------
------------------------------------------------------------

global path "C:\Users\sshifotoka\Documents\Desktop\MSC THESIS"

global input "$path\Input"

global output "$path\Output"

capture log close

log using "$path\Log\YouthMPI.smcl", replace


use "$input/ind_level_tab", clear

**save it as a youth file

save "$output\youth persons.dta", replace


**Import the excel regional file

clear all

import excel "$input\Regions.xlsx", sheet("Sheet11") firstrow

ren A region

#delimit

lab def regioncode

1 "Karas" 2 "Erongo" 3 "Hardap" 4 "Kavango East" 5 "kavango West" 6 "khomas" 7 "Kunene" 8
"Ohangwena" 9 "Omaheke"

10 "Omusati" 11 "Oshana" 12 "Oshikoto" 13 "Otjozondjupa" 14 "Zambezi" ;

#delimit cr

lab val region regioncode

tab region

drop if region==.

save "$output\Regional file.dta", replace


//load NHIES individuals

use "$output\youth persons.dta", clear

drop _merge

//merge to it using region

merge m:1 region using "$output\Regional file.dta"

gen youth =1 if inrange(q01_06_y,15,34)

rename region Region

rename q01_06_y Age
```

```
rename q01_07 Marital_status
rename hhsize Household_size
rename urbrur Urban_rural
rename orphan_1 Orphanhood_status
rename attain Education_level
rename q03_09_mn currentGrade
rename q03_04_mn completedGrade

gen Disability=1 if inrange(disability,1,6)
replace Disability=0 if Disability==.
label define disa 1"disabled" 0"Not disabled"
label val Disability disa

drop disability
//Poverty variables
gen Monetary_poor = 1 if pae<=6249.6
replace Monetary_poor=0 if pae>6249.6
label define poor 1"Poor" 0"Not poor"
label val Monetary_poor poor
lab var Monetary_poor "Monetary Poverty status: poor"
label var Age "age(years)"
label var Disability "Disability status"
save "$output\youth persons regions.dta", replace

//Load HH data
 use "$input\hh_level_tab.dta", clear

 rename q05_02_38 hh_internet_access
fre hh_internet_access
save "$output\youth households.dta", replace
//merge the household file to the file with ind_region info
use "$output\youth persons regions.dta", clear
drop _merge
merge m:1 hhid using "$output\youth households.dta"
keep Region Age q01_02 Marital_status q01_03 Household_size Urban_rural  ///
 Orphanhood_status  Education_level  currentGrade  completedGrade  xx_employment_status
Disability  ///
 Monetary_poor TotYouthPop YouthUnempRate ///
 YouthInformalRate CrudeBirthRate ///
```

```
 CrudedeathRate Gini TotalConsumptionMilionsN ///
 hhid sex_of_head age_of_head q02_01 hh_internet_access


rename q01_02 Sex
rename q01_03 Relation_to_head
rename xx_employment_status employment_status
rename q02_01 DU_type


//Employment status of the head
gen EmpHeadHH =.
replace EmpHeadHH=1 if Relation_to_head==1 & employment_status==1
replace EmpHeadHH=0 if Relation_to_head==1 & inlist(employment_status,2,3)


//sort hhid household head's employment status
bys hhid :egen HH_EmpStatus =max(EmpHeadHH)
drop EmpHeadHH


order  Age  sex  Marital_status  Relation_to_head  Orphanhood_status  Education_level
currentGrade completedGrade ///
employment_status Disability Monetary_poor   ///
hhid Urban_rural sex_of_head age_of_head Household_size HH_EmpStatus ///
DU_type hh_internet_access Region TotYouthPop YouthUnempRate ///
YouthInformalRate CrudeBirthRate ///
CrudedeathRate Gini TotalConsumptionMilionsN


//Final dataset for analysis
save "$output\youth three levels.dta", replace
use "$output\youth three levels.dta", clear


gen new_edu=Education_level
replace new_edu=1 if inlist(currentGrade,10,11) & completedGrade==. & inrange(Age , 15,34)
replace new_edu=2 if inrange(currentGrade,12,17) & completedGrade==. & inrange(Age , 15,34)
replace new_edu=3 if inrange(currentGrade,22,64) & completedGrade==. & inrange(Age , 15,34)
replace new_edu=4 if inrange(currentGrade,65,92) & completedGrade==. & inrange(Age , 15,34)
replace new_edu=. if new_edu==5


tab new_edu if inrange(Age, 15,34)


#delimit
```

```
label def educ
1 "No formal education" 2 "Primary" 3 "Secondary" 4 "Tertiary" 5 "Not stated" ;
#delimit cr
lab val new_edu educ

drop currentGrade completedGrade Education_level
rename new_edu Education_level

tab Education_level if inrange(Age, 15,34)
gen     Agecat=.
replace Agecat=1  if inrange(Age,15,19)
replace Agecat=2  if inrange(Age,20,24)
replace Agecat=3  if inrange(Age,25,29)
replace Agecat=4  if inrange(Age,30,34)

lab def Age 1 "15-19" 2 "20-24" 3 "25-29" 4 "30-34"
lab val Agecat Age
lab var Agecat "Age (age groups)"

gen hhsize_cat=.
replace hhsize_cat=1  if inrange(Household_size,1,5)
replace hhsize_cat=2  if inrange(Household_size,6,10)
replace hhsize_cat=3  if inrange(Household_size,11,15)
replace hhsize_cat=4 if hhsize>=16
lab def size 1 "1-5" 2 "6-10" 3 "11-15" 4 "16+"
lab val hhsize_cat size
lab var hhsize_cat "HH size categories"

order Age Agecat Sex Marital_status  Relation_to_head Orphanhood_status Education_level ///
employment_status Disability Monetary_poor ///
hhid  Urban_rural sex_of_head age_of_head Household_size hhsize_cat HH_EmpStatus ///
hh_internet_access Region TotYouthPop YouthUnempRate ///
YouthInformalRate CrudeBirthRate ///
CrudedeathRate Gini TotalConsumptionMilionsN

*_____________________________________________________________________________
*Descriptives
tab Region
```

```
tab Urban_rural
tab Sex
tab Agecat
*________________________________________________________________________________
//BUILD THE DEPRIVATION MATRIX
*Dimension 1: Education
*!!!!!!!!!!!!!!!!INDICATOR: Highest level of education
*A youth is deprived in education if they have not completed secondary level of education

*Explore the variables: labels, codes, frequencies
fre Education_level

gen Poor_educ = 1 if inlist(Education_level,1,2)  & inrange(Age,15,34)  //Deprived
replace Poor_educ = 0 if inlist(Education_level,3,4) & inrange(Age,15,34) //Not Deprived

*Label the variable
label variable Poor_educ "Youth deprived in education"

*Label the values
label define education 1 "1-Deprived" 0 "0-Non-deprived"
label val Poor_educ education

//Tabulate the new variable
tab Poor_educ if inrange(Age,15,34) //to get the table of the deprivations
*____________________________________________________________
*Dimension 2: Health
*!!!!!!!!!!!!!!!!INDICATOR: Disability
*A youth is deprived in health if they are disabled

*Explore the variables: labels, codes, frequencies
fre Disability
gen Poor_health = 1 if Disability==1  & inrange(Age,15,34)  //Deprived
replace Poor_health = 0 if Disability==0 & inrange(Age,15,34) //Not Deprived

*Label the variable
label variable Poor_health "Youth deprived in health"

*Label the values
```

```
label define health 1 "1-Deprived" 0 "0-Non-deprived"
label val Poor_health health

//Tabulate the new variable
tab Poor_health if inrange(Age,15,34) //to get the table of the deprivation
*____________________________________________________________
*Dimension 3: Employment
*!!!!!!!!!!!!!!!!INDICATOR:
*A youth is deprived in employment if they are not employed
*Explore the variables: labels, codes, frequencies
fre employment_status

gen Poor_employ = 1 if inlist(employment_status,2,3) & inrange(Age,15,34)  //Deprived
replace Poor_employ = 0 if employment_status==1 & inrange(Age,15,34) //Not Deprived

*Label the variable
label variable Poor_employ "Youth deprived in economic activity"

*Label the values
label define economic 1 "1-Deprived" 0 "0-Non-deprived"
label val Poor_employ economic

//Tabulate the new variable
tab Poor_employ if inrange(Age,15,34) //to get the table of the deprivations

*____________________________________________________________
*Dimension 4: Monetary wellbeing
*!!!!!!!!!!!!!!!!INDICATOR:
*A youth is deprived in monetary wellbeing if their expenditure is below the national monetary poverty line
*Explore the variables: labels, codes, frequencies
fre Monetary_poor

gen Poor_money = 1 if Monetary_poor==1 & inrange(Age,15,34)  //Deprived
replace Poor_money = 0 if Monetary_poor==0 & inrange(Age,15,34) //Not Deprived

*Label the variable
label variable Poor_money "Youth deprived in economic activity"
```

```
*Label the values

label define money 1 "1-Deprived" 0 "0-Non-deprived"

label val Poor_money money


//Tabulate the new variable

tab Poor_money if inrange(Age,15,34) //to get the table of the deprivations

*______________________________________________________________________________________


* Construct a filter variable that identifies the observations with data for all relevant
indicators

gen sample = (Poor_educ~=. & Poor_health~=. & Poor_employ~=. & Poor_money~=.)

*According to the AF method, keep only those observations with information for all relevant
indicators

keep if sample==1


di _N

*N= 13785 observations

*_______________________________________________________________________________________


*Uncensored headcount ratios

foreach var in Poor_educ Poor_health Poor_employ Poor_money {


        sum `var'

        gen     uncen_H_`var' = r(mean)*100

        lab var uncen_H_`var'  "Uncensored Headcount Ratio: Percentage of people who are
deprived in â€šÃ„Â¶"

        }

//


*Setting weights

foreach var in Poor_educ Poor_health Poor_employ Poor_money {


        gen     w_`var' = 1/4

        lab var w_`var' "Weight `var'"

        }

//

*The following commands multiply the deprivation matrix by the weight of each indicator.

foreach var in Poor_educ Poor_health Poor_employ Poor_money {
```

```
        gen     g0_w_`var' = `var' * w_`var'
        lab var g0_w_`var' "Weigthed Deprivation of `var'"
        }
//
*Generate the vector of individual weighted deprivation score, 'c'

egen c_vector = rowtotal(g0_w_Poor_educ g0_w_Poor_health g0_w_Poor_employ g0_w_Poor_money)
lab var c_vector "Counting Vector"
tab     c_vector, m

*Identification
local k = 50
gen     multid_poor_`k' = (c_vector >= `k'/100)
lab var multid_poor_`k' "Poverty Identification with k=`k'%"

* Generate the censored vector of individual weighted deprivation score, 'c(k)',
* providing a score of zero if a youth is not poor
local k=50
gen     cens_c_vector_`k' = c_vector
replace cens_c_vector_`k' = 0 if multid_poor_`k'==0

*Censored deprivation matrix

local k = 50
foreach var in Poor_educ Poor_health Poor_employ Poor_money {

        gen     g0_`k'_`var' = `var'
        replace g0_`k'_`var' = 0 if multid_poor_`k'==0
        }

//
* Headcount/incidence of multidimensional poverty for k=50% (H)
local k = 50
sum     multid_poor_`k'
gen     H = r(mean)*100
lab var H "Headcount Ratio (H): % Youth that is multidimensionally poor"

*Intensity of poverty among the poor for k=50%  (A)
local k = 50
```

```
sum     cens_c_vector_`k' if multid_poor_`k'==1

gen     A = r(mean)*100

lab var A  "Intensity of deprivation among the poor youth(A): Average % of weighted deprivations"


* Adjusted headcount ratio (M0) for k=50%

local k = 50


sum     cens_c_vector_`k'

gen     M0 = r(mean)

lab var M0 "Adjusted Headcount Ratio (M0 = H*A): Range 0 to 1"


* The Censored Headcount Ratio

local k=50

foreach var in Poor_educ Poor_health Poor_employ Poor_money {


        sum     g0_`k'_`var'

        gen     cen_H_`var' = r(mean)*100

        lab var cen_H_`var'  "Censored Headcount Ratio: % of youth who are poor and deprived in â€šÃ„Â¶"

        }


//

//to see full variable names first

local k=50

fsum uncen_H_* cen_H_*

local k=50

        sum uncen_H_* cen_H_*, sep(15)


*__________________________________________________________

*Percentage contribution

foreach var in Poor_educ Poor_health Poor_employ Poor_money  {


        gen     perc_cont_`var' = (cen_H_`var' * w_`var') / M0

        lab var perc_cont_`var' "Percentage contribution to M0"

        }

//

local k=50

fsum perc_cont_*
```

```
sum perc_cont_*, sep(15)

*____________________________________________________________

*Subgroup decomposition:
* H and A by region
local k=50
tabstat multid_poor_`k' , by(Region)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(Region)

* H and A by urban/rural
local k=50
tabstat multid_poor_`k' , by(Urban_rural)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(Urban_rural)

* H and A by sex
local k=50
tabstat multid_poor_`k' , by(Sex)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(Sex)

* H and A by age categories
local k=50
tabstat multid_poor_`k' , by(Agecat)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(Agecat)

* H and A by hh size
local k=50
tabstat multid_poor_`k' , by(hhsize_cat)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(hhsize_cat)

* H and A by sex of head
local k=50
tabstat multid_poor_`k' , by(sex_of_head)
tabstat cens_c_vector_`k'  if multid_poor_`k'==1, by(sex_of_head)
*___________________________________________________________________

*censored HCR by sex
local k=50
foreach var in Poor_educ Poor_health Poor_employ Poor_money {
```

```
        forvalue r = 1/2 {
                sum     g0_`k'_`var'  if Sex==`r'
                gen     Sex_CH_r`r'_`var' = r(mean)*100
                lab var Sex_CH_r`r'_`var'  "Censored Headcount Ratio - Sex `r'"
                }
        }
//
fsum Sex_CH_r*
sum Sex_CH_r* , sep(8)
*censored HCR by urbrur

local k=50
recode Urban_rural (99=2)
foreach var in Poor_educ Poor_health Poor_employ Poor_money {
        forvalue r = 1/2 {
                sum     g0_`k'_`var'  if Urban_rural==`r'
                gen     UR_CH_r`r'_`var' = r(mean)*100
                lab var UR_CH_r`r'_`var'  "Censored Headcount Ratio - Urban_rural `r'"
                }
        }
//
fsum UR_CH_r*
sum UR_CH_r* , sep(8)

*____________________________________________
*             MAPS
*_____________________________________________
save "$output/Youth MPI.dta", replace

set more off
*Less complicated when you run it all at once because of the collapsing codes
use "$output/Youth MPI.dta", clear

* Collapse H
* The mean of multid_poor_*: H

local k=50
rename multid_poor_`k' H_`k'
```

```
rename cens_c_vector_50 MPI_50

gen A_50 = MPI_50 if H_50 ==1

* Uncensored Headcount Ratios
* The mean of hh_d*

* Censored Headcount Ratios
* The mean of g0_`k'_`var'

local k=50
collapse w_* Poor_educ Poor_health Poor_employ Poor_money g0_`k'* H_* A_* MPI_* , by(Region)
save "$output/Collapsed_region.dta", replace

*** National Results ***
use "$output/Youth MPI.dta", clear

local k=50
rename multid_poor_`k' H_`k'

rename cens_c_vector_50 MPI_50

gen A_50 = MPI_50 if H_50 ==1

local k=50
collapse w_* Poor_educ Poor_health Poor_employ Poor_money g0_`k'* H_* A_* MPI_*

* appending regional data to national data *
append using "$output/Collapsed_region.dta"

order Region H* Poor_educ Poor_health Poor_employ Poor_money g0*

replace Region = 0 if Region==.
label def lab_reg 0 "National", modify


save "$output/Collapsed_national_region.dta", replace
```

```
*** Namibia ***


* change directory to the one where shapefiles are stored *

cd "C:\Users\sshifotoka\Documents\Desktop\MSC THESIS\shp"


* to create stata files from the shapefiles *

* you create one database file (els_db) and one coordinate file (els_coord)


//ssc install shp2dta

shp2dta using regional_boundaries, database(regional_boundaries_db) coord(regional_boundaries_coord) gencentroid(center) genid(identity) replace


//check that the codings correspond to those in Collapsed_results_by_region.dta file

use "C:\Users\sshifotoka\Documents\Desktop\MSC THESIS\shp\regional_boundaries_db.dta", clear

list identity region_nam

*Codes don't correspond

*3 region codes (Zambezi, karas and Kavango East) in the boudaries_db.dta file do not correspond to the codes in regional.dta

*We'll keep the codes in the db.dta file as is, and (for the purpose of mapping only) we will align the regional.dta file codes to it

use "$output/Collapsed_region.dta", clear


fre Region


replace Region = 100 if Region==1  //karas is now coded 100, and we'll code it as 4 next

replace Region = 200 if Region==4  //Kavango east is now coded 200, and we'll code it as 14 next

replace Region = 300 if Region==14 //zambezi is now coded 300, and we'll code it as 1 next


replace Region = 1 if Region==300

replace Region = 4 if Region==100

replace Region = 14 if Region==200


#delimit

lab def regi  1 "Zambezi" 2 "Erongo" 3 "Hardap" 4 "Karas" 5 "Kavango West" 6 "khomas" 7 "Kunene" 8 "Ohangwena" 9 "Omaheke"

10 "Omusati" 11 "oshana" 12 "Oshikoto" 13 "Otjozondjupa" 14 "Kavango East";

#delimit cr

lab val Region regi
```

```
//The regions in here are now coded the same as in the boundaries_db.dta file. These codes
are for the purpose of mapping only


* use region_map as the variable for regional decompositions and mapping

gen identity = Region

* -----------------------------------------------------------------------------

* INCIDENCE OF POVERTY (H)

* -----------------------------------------------------------------------------

replace H_50 = H_50*100


format H_50 %12.2fc

*ssc install spmap

spmap H_50 ///

 using "$path\shp\regional_boundaries_coord.dta", ///

 id(identity)  label(data("regional_boundaries_db.dta") ///

 label(region_nam) xcoord(x_center) ycoord(y_center)      ///

 size(*.9) pos(0) ) clnumber(12) fcolor(Greens2)            ///

legend(pos(5) subtitle("Headcount Ratio", size(vsmall)))    ///

title("Incidence of Youth Multidimensional Poverty H" "in Namibia, k=50%")


gr export H_nam.emf, replace


**************

**Youth monetary poverty graph


gen monetary_poor=.

replace monetary_poor = 8.99 in 1

replace monetary_poor = 3.62 in 2

replace monetary_poor = 7.37 in 3

replace monetary_poor = 35.22 in 4

replace monetary_poor = 26.23 in 5

replace monetary_poor = 3.62 in 6

replace monetary_poor = 30.99 in 7

replace monetary_poor = 15.22 in 8

replace monetary_poor = 31.31 in 9

replace monetary_poor = 20.07 in 10

replace monetary_poor = 9.03 in 11

replace monetary_poor = 15.10 in 12

replace monetary_poor = 15.08 in 13
```

```
replace monetary_poor = 32.77 in 14

spmap monetary_poor ///
 using "$path\shp\regional_boundaries_coord.dta", ///
 id(identity)  label(data("regional_boundaries_db.dta") ///
 label(region_nam) xcoord(x_center) ycoord(y_center)      ///
 size(*.9) pos(0) ) clnumber(12) fcolor(Greens2)            ///
legend(pos(5) subtitle("Poverty rate", size(vsmall)))       ///
title("Incidence of Youth Monetary Poverty" "in Namibia")

gr export Monetary_nam.emf, replace

* ------------------------------------------------------------------------------
* INTENSITY OF POVERTY (A)
* ------------------------------------------------------------------------------

replace A_50 = A_50*100
format A_50 %12.2fc

spmap A_50 ///
 using "$path\shp\regional_boundaries_coord.dta", ///
 id(identity)  label(data("regional_boundaries_db.dta") ///
 label(region_nam) xcoord(x_center) ycoord(y_center)      ///
 size(*.9) pos(0) ) clnumber(12) fcolor(Greens2)            ///
legend(pos(5) subtitle("Intensity", size(vsmall)))   ///
title("Intensity of Youth Multidimensional Poverty" "in Namibia, k=50%")

gr export A_nam.emf, replace
*__________________________________________________________________

set more off
*REGRESSION ANALYSIS
use "$output/Youth MPI.dta", clear

//gen Persons id
 gen pid =_n
 //gen Household id
egen hid = group(hhid)
```

```
//gen Region id
egen rid = group(Region)
order pid, b(Age) //puts variable A after variable R
order hid, a(hhid) //puts variable A after variable R
order rid, a(Region) //puts variable A after variable R
save "$output/final data", replace
//REGRESSIONS
use "$output/final data", clear
*___________________________________________________________________________________________

*DUMMYS FOR REGRESSION MODELS
//IND Level

//Relationship to head (not immediate  relation is ref)

/*Grouped as follows
1  Head of household
2  Spouse/ Partner
3  Daughter/Son
6  Parent
4  Daughter/ Son In-Law
5  Grandchild
7  Parent-In-Law
8  Sister/ Brother
9  Sister/ Brother In-Law
10 Other relative (
11 Domestic worker
12 Other non-relative */
gen ImmediateRelHead =.
replace ImmediateRelHead = 1 if inlist(Relation_to_head,1,2,3,6)

replace ImmediateRelHead = 0 if inlist(Relation_to_head,4,5,7,8,9,10,11,12)

*Marital_status (ref is never married)

gen Marriage=1 if Marital_status==1
replace Marriage=2 if inlist(Marital_status,2,3,4)
replace Marriage=3 if inlist(Marital_status,5,6,7)
```

```
//married
gen InUnion=1 if Marriage==2
replace InUnion=0 if InUnion==.

//were married but not anymore
gen OutUnion=1 if Marriage==3
replace OutUnion=0 if OutUnion==.

*Orphanhood_status (not being orphan is ref)
recode Orphanhood_status (1=1) (2=0)

*Sex (male is reference)
recode Sex (1=1) (2=0)
**________________________________________
*HH level

*Urban/rural (rural is reference)
recode Urban_rural (1=1) (2=0)

*sex_of_head (male is reference)
recode sex_of_head (1=1) (2=0)

*age_of_head (this is numerical)
*Household_size (this is numerical)

*DU_type (non-improvised is ref)

gen DU=1 if inlist(DU_type,1,2,3,4,5,6,7,8)
replace DU=2 if inlist(DU_type,9,10)

gen ImprovisedDU=1 if DU==2
replace ImprovisedDU=0 if ImprovisedDU==.

*hh_internet_access (int at home is ref)

gen Intelswhere=1 if hh_internet_access==2
replace Intelswhere=0 if Intelswhere==.
```

```
gen IntAccess=1 if hh_internet_access==3

replace IntAccess=0 if IntAccess==.


gen NoInt=1 if hh_internet_access==4

replace NoInt=0 if NoInt==.


**______________________________________________

*REGIONAL level

/*

No need for binary variables as the Regional variables are all numeric and not categorical


TotYouthPop

YouthUnempRate

YouthInformalRate

CrudeBirthRate

CrudedeathRate

Gini

TotalConsumptionMilionsN

*/

*_________________________________________________________________________________________
________

save "$output/MDPoverty1fri", replace

use "$output/MDPoverty1fri", clear

di _N


saveold    "C:\Users\sshifotoka\Documents\Desktop\MSC    THESIS\Output\MDPovertyfri.dta",
replace
```

APPENDIX 2. Stata codes: multilevel ordered logistic regression models

```
set more off

use "C:\Users\Selma\Desktop\SELMA\MSC THESIS\Output\MDPoverty1.dta", clear


//Households: drop and regenerate hid

drop hid

egen hid = group(hhid)

summ hid

//2741 households


//REGIONS

summ Region

//14 regions

tab cens_c_vector_50 //There is no youth deprived in only one of the four variables


//model 1

set more off

ologit cens_c_vector_50

estimate stats


//model 2

//level 1 prdictors: Individuals

set more off

ologit cens_c_vector_50 Age Sex InUnion OutUnion ImmediateRelHead Orphanhood_status

estimate stats


//model 3

//level 2 predictors: Households

set more off

ologit  cens_c_vector_50  Age  Sex  InUnion  OutUnion  ImmediateRelHead  Orphanhood_status
Urban_rural sex_of_head age_of_head Household_size HH_EmpStatus ImprovisedDU NoInt

estimate stats


//model4

//level 3 predictors: Regions

set more off

ologit  cens_c_vector_50  Age  Sex  InUnion  OutUnion  ImmediateRelHead  Orphanhood_status
Urban_rural  sex_of_head  age_of_head  Household_size  HH_EmpStatus  ImprovisedDU  NoInt
```

```
TotYouthPop YouthUnempRate YouthInformalRate CrudeBirthRate CrudedeathRate Gini
TotalConsumptionMilionsN

estimate stats


//NOW CONSIDERING RANDOM EFFECTS AT REGION AND HOUSEHOLD LEVEL


//model 5

//Random intercept only modelset more off

set more off

meologit cens_c_vector_50 || rid: || hid: , or

estimate stats


//model 6

//Random intercept, random slope with ind level predictors

//level 1 prdictors: Individuals

set more off

meologit cens_c_vector_50 Age Sex InUnion OutUnion ImmediateRelHead Orphanhood_status ||
rid: || hid:, or

estimate stats


//model 7

//Random intercept, random slope with ind and hh level predictors

//level 2 predictors: Households

set more off

meologit cens_c_vector_50 Age Sex InUnion OutUnion ImmediateRelHead Orphanhood_status
Urban_rural sex_of_head age_of_head Household_size HH_EmpStatus ImprovisedDU NoInt || rid:
|| hid: , or

estimate stats


//model 8

//Random intercept, random slope with all ind and hh and regional level predictors

//level 3 predictors: Regions

set more off

meologit cens_c_vector_50 Age Sex InUnion OutUnion ImmediateRelHead Orphanhood_status
Urban_rural sex_of_head age_of_head Household_size HH_EmpStatus ImprovisedDU NoInt
TotYouthPop YouthUnempRate YouthInformalRate CrudeBirthRate CrudedeathRate Gini
TotalConsumptionMilionsN || rid: || hid:

estimate stats
```

APPENDIX 3. R codes: multilevel logit regression models

```
# set working directory

#setwd("C:/Users/SShifotoka/Desktop/MSC THESIS")


#Load dataset

library(foreign)

MDPoverty <- read.dta("C:/Users/sshifotoka/Documents/Desktop/MSC THESIS/Output/MDPovertyfri.dta")

MDPoverty$rid.F<-as.factor(MDPoverty$rid)

MDPoverty$hid.F<-as.factor(MDPoverty$hid)


View(MDPoverty)

summary(MDPoverty$Region)

names(MDPoverty)


#Install multilevel regression packages

install.packages("Matrix")

library(Matrix)


install.packages("lme4")

library(lme4)


install.packages("glmer")

library(glmer)


install.packages("nlme")

library(nlme)


install.packages("MASS")

library(MASS)

#LOGIT multilevel model: being poor or not


#################################################################

#                    RANDOM INTERCEPT

################################################################

#Random Intercept only

summary(modelA<-glmer(multid_poor_50~1+(1|rid.F/hid.F),data=
MDPoverty,family=binomial(link="logit")))
```

```
#With individual predictors

summary(modelB<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+(1|rid.F
/hid.F), data = MDPoverty,family=binomial(link="logit")))


#with HH predictors

summary(modelC<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+Urban_ru
ral+sex_of_head+age_of_head+Household_size+HH_EmpStatus+ImprovisedDU+NoInt+(1|rid.F/hid.F
), data = MDPoverty,family=binomial(link="logit")))


#With regional predictors

summary(modelD<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+Urban_ru
ral+sex_of_head+age_of_head+Household_size+HH_EmpStatus+ImprovisedDU+NoInt+TotYouthPop+
YouthUnempRate+YouthInformalRate+CrudeBirthRate +CrudedeathRate
+Gini+TotalConsumptionMilionsN +(1|rid.F/hid.F), data =
MDPoverty,family=binomial(link="logit")))


#################################################################

#                    RANDOM SLOPE

################################################################

#slopes varying at level 3, region


#with ind level only

summary(modelE<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+(InUnion
+OutUnion|rid.F),data = MDPoverty, family = binomial))


#with both HH level

summary(modelF<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+Urban_ru
ral+sex_of_head+age_of_head+Household_size+HH_EmpStatus+ImprovisedDU+NoInt+(InUnion+OutUn
ion|rid.F),data = MDPoverty,family = binomial))


#with all ind, HH and regional level

summary(modelG<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+Urban_ru
ral+sex_of_head+age_of_head+Household_size+HH_EmpStatus+ImprovisedDU+NoInt+TotYouthPop+
YouthUnempRate+YouthInformalRate+CrudeBirthRate +CrudedeathRate +Gini
+TotalConsumptionMilionsN+(InUnion+OutUnion|rid.F),data = MDPoverty,family = binomial))

#With cross levels: Age * HH size and Urbrur*gini

summary(modelH<-
glmer(multid_poor_50~Age+Sex+InUnion+OutUnion+ImmediateRelHead+Orphanhood_status+Urban_ru
ral+sex_of_head+age_of_head+Household_size+Age*Household_size+HH_EmpStatus+ImprovisedDU+N
oInt+TotYouthPop+ YouthUnempRate+YouthInformalRate+CrudeBirthRate +CrudedeathRate +Gini
+TotalConsumptionMilionsN+Urban_rural*Gini+(InUnion+OutUnion|rid.F),data =
MDPoverty,family = binomial))
```