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Child's Multidimensional Welfare and Pro-Poor Growth in South Africa

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Declaration

I declare that this thesis titled "Child's Multidimensional Welfare and Pro-poor Growth in South Africa" is my own original work that was undertaken in fulfilment of the Doctor of Philosophy degree in Agriculture (Agricultural Economics) in the North-West University, Mafikeng Campus, South Africa. The thesis has never been submitted to any other institution, and all the sources that have been used or quoted have been acknowledged by means of complete references.

T.C. Molelekoa

Dedication

I dedicate this thesis to my pumpkins (Leano Laone Lemolemo) who inspire my ambition to succeed.

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List of Abbreviations and Acronyms

ADB – Asian Development Bank

AF- Alkire Foster

AFD- Agence Française de Développement

AIDS- acquired immunodeficiency syndrome.

ANC - African National Congress

ARI - Acute Respiratory Infection

CA - Correspondence Analysis

CHIC - Change Incidence Curve

DEADP- Department of Environmental Affairs and Development Planning

DHS - Demographic Health Survey

EC – Eastern Cape

ECD – Early Childhood Development

FAO- Food and Agriculture Organization

FOD - First Order Dominance

FS – Free State

GDP - Gross Domestic Product

GEAR - Growth, Employment, and Redistribution

GHS - General Household Survey

GIC – Growth Incidence Curve

GP – Gauteng

GRIM - Growth Rate in Mean

HDI- Human Development Index

HIV- Human Immunodeficiency Virus

IDC – Industrial Development Corporation

KZN – KwaZulu-Natal

LP – Limpopo

MCA - Multiple Correspondence Analysis

MDGs - Millennium Development Goals

MP – Mpumalanga

MPI – Multidimensionally Poverty Index

MS - Master Sample

NC – Northern Cape

NDP - National Development Plan

NIGIC - Non-Income Growth Incidence Curve

NIP - National Integrated Policy

NW – North West

OECD - Organization for Economic Cooperation and Development

PBG - Poverty Bias of Growth

PBG - Poverty Biased of Growth

PCA - Principal Component Analysis

PEGR - Poverty Equivalent Growth Rate

PPCH - Pro-Poor Change

PPGI - Pro-Poor Growth Index

PPGR - Pro-Poor Growth Rate

PSUs - Primary Sampling Units

RDP - Reconstruction Development Programme

SA – South Africa

SDGs - Millennium Development Goals

SMMEs - Small Medium and Micro Enterprises

SSA- Sub-Saharan Africa

Stats SA- Statistics South Africa

UN – United Nations

UNICEF - United Nations Children's Fund

WC – Western Cape

WCG- Western Cape Government

WHO – World Health Organization

Abstract

Poverty and hunger have been recognized as part of South Africa's development challenges. These issues are also foremostly ranked in the Sustainable Development Goals (SDGs). This study constructed indicators of children's multidimensional poverty index (MPI) using the Alkire-Foster and fuzzy set approaches and examined its pro-poorness. The data were the General Household Survey (GHS) for 2017, 2018 and 2019, and the 2016 Demographic and Health Survey (DHS). The MPI was decomposed and analyzed with Tobit regression model, while children's health outcomes were analyzed with logistic regression model. The pro-poorness of multidimensional wealth index (MWI) was analysed with Growth Incidence Curve (GIC), Pro-Poor Growth Index (PPGI) and Poverty Equivalent Growth Rate (PEGR).
The results showed that children from Eastern Cape had the highest Alkire-Foster (AF) MPIs of 0.34. 0.33, and 0.29 in 2017, 2018, and 2019, respectively, while KwaZulu Natal had 0.31, 0.30, and 0.29. In the combined dataset, AF MPIs were 0.26, 0.25, and 0.28 in 2017, 2018 and 2019, respectively. Similarly, Eastern Cape had the highest average fuzzy sets child MPI (0.12), followed by KwaZulu-Natal (0.10) and Mpumalanga (0.10). The Tobit regression results revealed that children from Eastern Cape province had significantly higher ($p<0.05$) AF and fuzzy MPIs in 2017, 2018 and in the combined dataset. Residence in traditional areas significantly increased ($p<0.05$) fuzzy MPIs across the periods, while farm residence significantly increased AF and fuzzy MPIs. Being a Coloured, Indian/Asian and White child and biological children of the households' heads significantly reduced MPIs ($p<0.05$).

The logistic regression results showed that the chance of stunting among the 0-5 significantly increased ($p<0.05$) with health insurance, sharing toilets, number of living children and residence in the Northern Cape, Free State and Gauteng provinces, while being discharged the same time with the mothers and being a boy child reduced it. Among the 6-23, stunting significantly increased ($p<0.05$) among male children, but reduced with residence in Eastern Cape, Free State, breastfeeding, milk and dairy products' consumption, birthweight and maternal years of education. Moreover, the change of stunting among the 24-59 months old children reduced ($p<0.05$) with residence in urban areas and birthweight but increased with residence in the Free State and KwaZulu Natal. The chance of wasting also reduced among children 0-5 and 24-59 with birthweight, and dairy and milk products' consumption reduced it among the 0-5. Among the 0-5 and 6-23, the number of living chidren, increased the chances of wasting. The chance of being underweight among 0-5 children reduced with consumption of dairy and milk products, while birthweight and mother being employed reduced it among the 24-59 children. Among the 6-23, underweight increased with number of living children,

and residence in KwaZuluNatal, North West, Gauteng, and Limpopo provinces, but decreased with consumption of snacks and fruits and vegetables.
On the examination of pro-poor growth, the fuzzy MWIs were pro-poor between 2017 and 2018 with PPGI of 1.33, 1.84 and 2.56 for poverty incidence, depth and severity, respectively, but only pro-poor for poverty incidence in 2018/2019 with PPGI of 1.714. The fuzzy MWIs were largely pro-poor among Black/African and White children and those who resided in traditional areas, Eastern Cape, North-West, and Mpumalanga across different poverty measures between 2017 and 2019.

It was concluded that although interventions to reduce poverty in South Africa had shown some level of pro-poorness, multidimensional poverty is still high among children. Also, MPI computation using the AF and fuzzy set can have different and the same policy implications. It was among others recommended that government's efforts for poverty alleviation and enhancement of health outcomes among South African children should focus on nutrition and marginal reforms that target African and coloured children and those residing in Eastern Cape and KwaZulu Natal provinces. An upward review of social grants will also benefit the poorest among the children.

Keywords: Pro-Poor Growth, Multidimensional Poverty, GIC, Alkire-Foster, Fuzzy Set, Multidimensional Poverty Indicator, South Africa

CHAPTER ONE

INTRODUCTION

1.1 Background

Child's poverty remains one of the major development challenges in the world. Available statistics reveal that although children constitute about one-third of global population, they account for half of those living below the international poverty line of $1.9 per day (UNICEF, undated). Welfare deprivation among children is even worse when poverty is considered from the multidimensional perspective. Specifically, about one billion children are globally multidimensionally poor, lacking adequate access to healthcare facilities, nutritious food, clean energy, improved sanitation, improved water and a generally conducive dwelling environment for physical and social development (UNICEF, undated). Before the COVID-19 pandemic, Sub-Saharan Africa (SSA) was the hotspot of child poverty, accounting for about two-thirds of the 356 million children that were globally living in extreme poverty (World Bank, 2020). Currently, child poverty may have worsened due to the economic impacts of the COVID-19 pandemic. Some statistics have shown that households with children suffered more economic losses due to the pandemic (World Bank and UNICEF, 2021). Specifically, it had been reported that during the pandemic, income losses were reported by 55% of households without children as against 76% for those with many children (World Bank and UNICEF, 2021). Therefore, COVID-19 seems to have aggravated global poverty.

In South Africa, excessive poverty and hunger have been recognized as part of the major economic development challenges. The seriousness of these issues can be evaluated by their foremost rank in the Millennium Development Goals (MDGs), as well as the newly approved Sustainable Development Goals (SDGs) (Watson et al., 2021). Addressing poverty and hunger, especially among children has been a major research interest for which policy making processes in developing countries have greatly benefitted. In some instances, national governments have observed the living conditions of children to ensure improvement in their welfare and other demographic/economic development indicators (Barnes et al., 2017).

South Africa has a considerable history of measuring poverty, dating from the 1940s (May, 2012). Poverty trends in South Africa are rooted in income approach and this has been significantly debated in the past. It was understood that in the 2000s, the rate of poverty will decrease. But even today, poverty reduction has not been so much achieved by successive governments. Poverty has been defined as a state of having access to limited monetary resources that are required to meet daily financial obligations and being unable to participate in some economic activities that are essential for living an acceptable life (Townsend, 1979; Sameti et al., 2012; Loibl, 2017). This definition, which is income focused has been used to empirically investigate monetary poverty in South Africa. Research on poverty in the South African context have been using the traditional approach.

The World Bank (1995) issued the first official post-apartheid poverty research utilizing two descriptions of poverty which were those belonging to the poorest 40% of the households (poor) and those belonging to the poorest 20% of the households (ultra-poor). Haarmann (1999) also made use of income poverty and classified children as being poor when the total expenditure of their households was below R319 a month. Furthermore, Woolard (2002) made use of two poverty lines which were R200 and R400. Many income poverty lines were preferred by Children's Institute under the University of Cape Town from 2005 in measuring child poverty. Hoogeveen and Özler (2006) piloted their study on small area also using certain thresholds to differentiate the poor and the non-poor. With the passing of time, Statistics South Africa continuously adjusted the poverty line thresholds. Barnes (2007) used the 2007 upper bound poverty line and discovered that 81% of children lived in poverty. The South African Child Gauge (2012) used a R575 per person per month poverty line and discovered that in 2010, 60.5% of all children in South Africa lived in households that were classified as poor. In South Africa, Streak et al. (2009) made use of the 2005 Institute of Education Science (IES) dataset and found similar results as those of the South African Child Gauge (2012). Hall and Budlender (2013) in another study used the $1 per day poverty line and found that 12% of the children were living in poverty. This income approach was also applied by Hall and Sambu (2016) and found that 11.7 million children were living in poverty, 8.5 million for the lower bound poverty and 5.6 million for food poverty.

Although the income approach to poverty analyses has a valuable way of measuring absolute poverty, it is not able to record the multiple deprivations which often affect poor people (Statistics South Africa, 2014). Therefore, poverty definitions have been expanded from the monetary concept to non-monetary welfare deprivations such as lack of education, inadequate access to healthcare facilities, and prevalence of poor standard of living (Sen, 1976, Duclos et al., 2001, Omotoso and Koch, 2018). This study analyzed child's multidimensional welfare indicators among South African children. Focusing on children is important because the socio-economic needs of children are often different from those of adults. Specifically, the underlying causes of welfare deprivation being experienced by children may display some effects and child poverty has life-long mental and economic consequences (Bradbury et al., 2001 and Grantham-McGregor et al., 2007).

UNICEF (2008) noted that poverty among children could slow down their mental, physical, emotional, and spiritual development. Dercon (2012) also mentioned that children's welfare is inclusive of various dimensions such as their nutritional status, educational level, and opportunities, whether they are faced with material poverty or not as well as their psychosocial status. According to Jenkins et al. (2007), the monetary measurement of poverty assumes equality in the distribution of resources within the households. Therefore, it would be prudent and satisfactory to use the income approach to measure poverty if we were living in a world where markets are complete and perfect.

A child who lives in poverty experiences material, spiritual and emotional deprivations, and lacks the essential resources they need to survive and develop (UNICEF, 2004). These resources, among others, may include living in a household with sufficient income, proper residence type, access to basic services such as education, improved sanitation, health and clean water. According to the benchmark of the African Child Policy Forum (2013), a child is referred to as every human being under the age of 18 years. Based on this, in South Africa, children constitute 37% of the country's population which is approximately 18.6 million (Hall and Meintjes, 2016).

There is quite an extensive volume of studies conducted in South Africa which observed poverty using the multidimensional approaches. According to a study that was conducted by Proudlock (2014) using the non-monetary approach, it was found that 18% of children lived in overcrowded dwellings, 21% lived in more than 30 minutes away from the local health centers, and 30% lived in households with unemployed adults. Moreover, Omotoso and Koch (2017) conducted a study in South Africa using the Alkire-Foster multidimensional poverty approach and found that more than 38% of South African children were living in houses with deficient standard. It was also found that the multidimensional headcount poverty ratio was 32.8% in 2002, which decreased 22.2% in 2004. Moreover, they discovered that the intensity of poverty decreased from 48.9% in 2002 to 40.7% in 2004. Pierre and Kodzo (2016) also conducted a multidimensional poverty study with the Multiple Correspondence Analysis (MCA) to evaluate households' multidimensional poverty in Cameroon. The results revealed that 73% of the under-5 children were multidimensionally poor.

Available empirical evidence has shown that government is failing to fulfill its pledge to protect the rights of children through enhanced welfare. Barnes et al. (2012) highlighted that South African children possess the same constitutional rights although poverty makes the rights of many children to be violated. Section 28 (1) of the South African Constitution enforces the government to make sure that, children under 18 are granted access to adequate nutrition, housing, health, and social services (South African Constitution, 1996). As a result, there are several policies, programs, and projects that had been developed to improve children's welfare. One of the routes taken by the government to address child poverty is the provision of social grants and school feeding schemes, but many children are still deprived in some essential welfare indicators (Finn et al., 2014).

The nexus between economic growth and poverty reduction is well documented in development economic literature. Economic growth is expected to promote poverty reduction, while poverty reduction can also promote economic growth (Islam, 2004; Malik et al., 2022; Zhu et al., 2022). Although some studies have shown some improvements in South Africa's economic growth (Leibbrandt et al., 2010; Van Der Westhuizen, 2012), this growth has not been equally distributed among the population. Researchers are therefore interested in analyzing pro-poorness of economic growth to properly evaluate their child's poverty-reducing impacts. Due to the dualistic economy in South Africa, economic growth can be of significant benefit to a very small share of the population, thereby resulting in slow poverty reduction (Van Der Westhuizen, 2012). May et al. (2016) revealed that after 1994, South Africa realized fast economic growth until the 2009 global economic disaster. The economy grew by 1.7% in 2016 and 1.9% in 2017. However, the pro-poorness of this growth is not well recorded in literature. For that reason, this study analyzed multidimensional pro-poor growth in South Africa. In line with Ravallion and Chen (2003), this study considers 'growth' as pro-poor if it reduces the poverty of poor children in South Africa or benefits poor children than it does the non-poor.

1.2 Growth in South Africa

High unemployment rates are shown to be one of the drivers of child poverty in South Africa (National Treasury, undated). Ever since the inception of democracy, the South African economy has experienced major transformation. Its average growth rate was 3.3% annually between 1994 and 2012. In 2012, the South African Gross Domestic Product (GDP) was 77% greater in tangible terms relating to 1994 with the consistent increase for the global economy reaching 90% (IDC, 2013). Regarding per capita basis, South Africa's actual GDP was 31%

greater by the end of the period. However, serious challenges continued. The speed of economic growth has not only dropped come short of its capability but has failed to make a noteworthy impact on the unemployment problem, particularly among the youth in South Africa. Even with increase in formal as well as informal employment in different sectors of the country's economy ever since 1994, the unemployment rate was 24.9% by the end of 2012, and this represented one of the highest worldwide. The country is also reported to be struggling to sustain its international competitiveness, mainly in manufacturing and mining industries, due to a range of internal aspects, worsened by vicious competition from foreign national counterparts in external and internal markets.

South Africa's inequality is among the highest in the world with 0.63 Gini coefficient in 2015 (Bundy, 2020). High inequality is worsened by inheritance of exclusion and the pattern of economic growth, which is not pro-poor and fails to create sufficient employment (Triegaardt, 2006; Hoogeveen, 2006). Inequality regarding wealth is also high in the country (May, 1998; Francis et al., 2020). In terms of mineral endowments, South Africa is among the richest countries in the world with deposits of gold, diamonds, coal, iron ore and platinum (Nex and Kinnaird, 2019). It has more land holdings with full capacity for agricultural production.

The past years have seen a progressively greater attention regarding the impact that economic growth has on poverty (Duclos and O'Connell, 2009; Duclos and Grégoire, 2002; Duclos and Araar, 2006; McKaya and Thorbecke, 2015). The South African economy around 2011 to 2015, has been driven by both global and local factors like poor and lower economic growth with higher unemployment rates, low commodity prices, high consumer prices, low levels of investments, as well as higher reliance on credit. This period witnessed a decrease in the financial wellbeing of South Africa under several economic policies (Lewis 2001; Rena and Msoni, 2014; Anyanwu 2014). It has been obvious for some time that the South African economy transformed into one which has higher demand for more educated and great skilled employees.

The agricultural sector reflected huge drops which had a major effect on the overall growth rates. Coronavirus (COVID-19) is also having a big effect on the South African economy. In 2020, the World Bank predicted a contraction of 7% in the South Africa's GDP as the virus weighed heavily on both the international and local markets (De Villiers et al, 2020). This decline was projected to increase poverty by 2 million people. The country got into the pandemic just after years with low levels of growth. In 2019, there was a 0.2% increase in the economy (0.8% increase in 2018) which was partly triggered by the reappearance of load shedding related to Eskom's financial and operational problems (Mbatha 2020; Kilic et al, 2020). The pandemic's perseverance at international and local level will linger to pressure recovery for the period of six months of 2021. Furthermore, as the restraints were eased and economic activities resumed, the structural challenges that the country faces with drastic shortages in energy became more prominent. GDP growth was anticipated to recover to about 3% in the year 2021.

1.3 Problem Statement

Poverty reduction has been on the concurrent legislative and policy interventions in South Africa. The apartheid government selectively implemented economic development programmes with significant bias against some population groups. Therefore, the current manifestation of poverty and inequality in South Africa is the aftermath of past governance structure and selective implementation of social welfare packages as characterized by the apartheid era (Seekings and Nattrass, 2015). Although policy interventions to address poverty under the democratic governance have yielded some positive results, the overall performance is still falling short of people's expectations on improvement in standard of living and wealth creation. Specifically, some statistics have shown that using US $5.5 as poverty line, poverty incidence increased from 71.10% in 1993 to 74.30% in 2000, before declining to 61.60% in 2014 (World Bank, undated). However, using the US $1.9 international poverty line, it was revealed that poverty incidence declined from 33.8% in 1996 to 18.8% in 2015 (World Bank, 2018).

Most of the South Africa's Black population in rural areas suffer multiple deprivations. This can be supported by the study of Dieden and Gustafsson (2003), which found that 40% of rural children were living in poverty as compared to 12% in urban areas and townships. Streak et al. (2009) further emphasized on the severity of child poverty in rural areas with 83% of the children living in poor households, as compared to 49% for urban children. Similarly, despite some development efforts in the country, many children are still suffering from multiple deprivations. In South Africa, some of the children do not benefit from the government's grants due to a lack of birth certificates (The Presidency, 2009). Low level of education or its complete lack, unskilled labor participation, residence in informal houses or shacks, lack of access to improved water, sanitation and inadequate food consumption are among the indicators of poverty in South Africa. Moreover, these conditions have some long-term consequences which can promote generational poverty. In addition, attention is not paid to whether improvement in the child's welfare indicators benefits the poor than it does the non-poor or decreases poverty. According to Dorrington (2014), healthy childhood development is greatly threatened by poverty. It was realized in 2015 that more than 13 million children in South Africa are living in poverty.

However, poverty measurement has graduated from an income-based approach to a multiple deprivation approach. This is in line with African National Congress's (ANC, 1994) assertion that poverty is not merely the lack of income. From the multidimensional perspective, there have been some improvements in poverty reduction over the past few decades. Available statistics show that deprivation in improved sanitation decreased from 47% in 2001 to 40% in 2011. However, in 2001, deprivations in improved water, clean energy, and adequate dwelling type were 38%, 49% and 30%, which declined to 27%, 38%, and 22%, respectively in 2011 (Stats SA, 2014). Multiple welfare deprivation seems to have improved based on United Nations Development Programme (UNDP) (2022) that indicated multidimensional poverty incidence was 6.3%, while poverty intensity was 39.8% in 2016. Efforts to address poverty include the Reconstruction Development Programme (RDP) which seeks to reduce multidimensional poverty by catering for people's needs of land, shelter, access to clean water and sanitation. There are other poverty reducing programmes in South Africa such as the Growth, Employment, and Redistribution (GEAR) and the National Development Plan (NDP). The empirical evidence in literature reveals that early life interventions are crucial for a country to realize poverty alleviation (Currie and Vogl, 2012).

UNICEF (2005) submitted that children who lived in poverty not only experienced economic resources' deprivation, but also faced some emotional shocks. These deprivations prevent them from attaining their potentials for participating in development activities within the society (UNICEF, 2005). This underscores the importance of child's welfare, since malnourished and illiterate children often grow up to become poor illiterate adults (UNICEF, 2000). More importantly, Bird (2013) noted that being affected by poverty at the childhood stage of life can promote intergenerational poverty. In South Africa, it has been submitted that stunting among children decreased from 28% in 2016 to 27% in 2018. However, sufficient progress has not been made because by 2025, it was estimated that there will be 1.7 million stunted South African children, and this can be compared to the 900,000 target that was set by government (United Nations, 2021).

One of the fundamental pathways to poverty reduction is economic growth. However, researchers have shown some pessimisms on the expectation that economic growth will always translate into poverty reduction. More importantly, the peculiarity of South Africa as one of the most unequal countries in the world raises serious concern on the impact of previous economic growth on poverty reduction (Tshishonga and De Vries, 2011). To achieve economic development, poverty reduction and economic growth are essential prerequisites. Bhorat et al. (2012) noted that in South Africa, economic growth has not necessarily transformed into significant financial freedom for most of the people. It was emphasized that even though there is economic growth in South African economy since 1994, the country has not witnessed significant improvement in people's welfare. Jansen et al. (2015) also pointed out that poverty analyses in South Africa reveal declining poverty rates, while a large percentage of individuals are experiencing excessive deprivations. OECD (2017) noted that numerous people are vulnerable to unemployment, ill-health, social exclusion, and insufficient resources that promote and strengthen the bonds of poverty.

According to the Bakker and Messerli (2017), improvement in other dimensions of poverty will strengthen pro-poor growth than a scenario of economic development alone. Lack of human capability development among the poor decreases the rate of growth and the degree to which it can be pro-poor (Klasen, 2005). Most of the previous studies have explored unidimensional and multidimensional poverty among households. Little is generally known about poverty from its multidimensional perspective, focusing on children. Similarly, while some studies have addressed pro-poor growth from some time series aggregated poverty and income/expenditure data, less is known about pro-poor growth from the multidimensional welfare perspective. This study seeks to add to existing body of knowledge by answering the following questions. What are the indicators of child poverty and how can they be used to construct some indices of multidimensional welfare? How can a child's multidimensional welfare be decomposed across households' geographical, racial, and socioeconomic characteristics? What is the effect of food intakes on child's health outcomes? What are the determinants of a child's multidimensional welfare? Has growth in child's multidimensional welfare indicators been pro-poor?

1.4 Research Objectives

The main objective of this study is to analyse the child's multidimensional welfare and its pro-poorness in South Africa.

The specific objects are to:

i. Construct indicators of children's multidimensional poverty index (MPI) using the Alkire-Foster and fuzzy set approaches;
ii. Decompose children's MPI across child's selected demographic characteristics;
iii. Analyse the determinants of children's MPI;
iv. Analyse the effect of food intakes on the health outcomes of under-5 children; and
v. Examine the pro-poorness of child's multidimensional wealth indicators.

1.5 Hypotheses

i. $H0_1$: Selected socio-economic and demographic characteristics do not significantly influence child's multidimensional welfare indicators in South Africa.

ii. $H0_2$: Children nutrition patterns and households' characteristics do not influence the chances of being stunted, wasted or underweight.

iii. $H0_3$**:** Child's Multidimensional welfare indicators' growth is not pro-poor in South Africa.

1.6 Significance of the Study

UNICEF (2017) has been promoting the issue of child's welfare through research as one of its objectives. There is a growing need for research that deals with initiatives to enhance a child's welfare (Barnes et al, 2017). Therefore, this study is in alignment with current international policy debates because it seeks to analyze some indicators of children's welfare status some period and determine if multidimensional welfare growth has been significantly pro-poor. Measuring poverty and looking at empirical evidence provided by other researchers will provide a better understanding of what causes child poverty, the meaning of growing up in poverty, the effects of child poverty as well as factors that can contribute to breaking the poverty cycle from one generation to the next.

Knowledge will also be gained on the percentage of children who are multidimensionally deprived. Moreover, this study used the recently accepted and internationally used approaches by Alkire and Foster (2011) and Zadeh's (1965) fuzzy set to facilitate comparison of their results. The Human Development Report (2016) also confirmed the need to conduct studies on child's poverty to inform some policies reforms and programmes. The significant difference between overall welfare and child welfare has been overlooked. Therefore, some policies and programs do not specifically address children's concerns (McMahon-Howard and Reimers, 2013). This study looked at programs and policies that are addressing child concerns in South Africa. Policy recommendations can be provided to the government for proper improvement and development of policies and programs that can make some differences in promoting a child's welfare.

Regarding children's' health status, Grantham-McGregor (2007) mentioned that occurrence of childhood deaths is caused by malnutrition, the ones that continue to survive are approximately 200 million children who are below five years, they fail in reaching their full potential as far as cognitive development is concerned due to factors such as poverty, ill-health and nutrition and lacking care. Hence, this study identified the demographic characteristics of multidimensionally poor South African children. This can also guide implementation of programs to welfare among children. The study will also contribute to the existing works on multidimensional welfare and pro-poor growth in South Africa

Even though South Africa has been experiencing economic growth, it is not well recorded in literature whether this growth has benefited the poor more than the non-poor or reduced poverty. This study made some vital contributions to literature as well as providing a better understanding of economic growth in benefiting the poor and reducing poverty. This was also done since the OECD (2001) mentioned that the emergence of pro-poor growth concept was intended to give a sign that growth has transformed the reduction of poverty. The study will also make vital contributions regarding the kind of pro-poor growth that is experienced within the country (absolute/relative). WHO and UNICEF (2013) also mentioned that the linkage between future economic developments and a health promoting environment for today's' children should be at the center of sustainable development.

1.7 Division of Chapters

The thesis is organized into eleven chapters. Chapter one provides the introduction and background to the study and sheds some light on the significance of the study. The chapter also contains the problem statement, objectives, and research hypotheses. Chapter two covers the literature review on poverty theoretical framework. Chapter three contains multidimensional poverty concepts, indicators, and measurement thereof. Chapter four focuses on pro-poor growth concepts and applications. Chapter five presents the research methodology, which explains and give details on the study area, population of the study, sample size and sampling procedures, method of data collection and analyses. It plainly explains how the objectives of the study were realized vis-a-vis the stated hypotheses. Chapter six presents the children's demographic characteristics and welfare attributes' deprivations. The seventh chapter presents the construction and decomposition of child MPI. Chapter eight focused on the correlates of child multidimensional welfare indicators. Chapter nine presented food intakes and determinants of under-5 health outcomes. Chapter ten presented multidimensional pro-poor growth measurement results. Chapter eleven is concluding on the findings of this study. Hence, it shortened the findings this research, described the main findings arising from it and finally stated the recommendations arising from the research for policy developers.

CHAPTER TWO

POVERTY THEORETICAL FRAMEWORK

2.1 Introduction

This chapter presents the theories on multidimensional poverty, concept of poverty, and poverty as a multidimensional concept. According to Gordon and Pantazis (2018), to obtain valid and reliable measures, theories and definitions are needed. They further mentioned that without theoretical framework, all poverty measures remain simply the opinions of their advocates. For that reason, this chapter presents poverty concepts and some of the theories that inform multidimensional poverty.

2.2 Poverty Concept

Poverty undermines the welfare of the society (Apablaza et al., 2013). It is a concept with diverse definitions. Before poverty can be properly measured, it must be defined. The definition of poverty is very complex given its multidimensional nature. Sarshar (2010) stated that to comprehend the poverty concept, there must be a purpose as to who to be included in the concerned subject as well as the determining factor of approximating poverty. Hence, this study focuses on child's welfare and uses different methods to measure it to develop robust and reliable results.

According to Ravallion (1994) and Duclos and Araar (2006), there are two main approaches to the measurement of poverty, namely the welfarist and the non-welfarist approaches. Literature (Atkinson, 2003; Duclos and Araar, 2006) shows that welfarists emphasize the occurrence of imperfect markets and poor correlation between dimensions of welfare, while non-welfarists stress the need to flee from concepts of utilities to a different and broad concept which addressed multiple dimensions that are fundamentally important. Motivation that poverty transcends monetary measures comes from approaches such as social exclusion/inclusion, basic needs, and capabilities, among others that are under the welfarist, non-welfarist and the new concept of extra-welfarist. These approaches are different from one another. However, each approach directly addresses human welfare (Pinillos et al., 2016).

2.2.1 Welfarist approach

The welfarist approach of poverty largely stands on the monetary point of view (Haughton and Khandkler, 2009). The approach defines poverty according to a person's belongings and consumption. Its idea is centered on only one indicator, that is income or expenditure (Apablaza et al., 2013). This approach carries an assumption that individuals should be independent and "rational maximizers" of their own contentment (Ravallion, 2008). According to this money metric view, child poverty refers to a headcount of children who live in households where resources are expressed in money metric sense and fall under a particular level that is deemed as having shortage cash for procurement of goods needed for material wellbeing (Noble et al. 2007). Duclos and Araar (2006) indicated that this view implies that individuals lack economic commands over commodities because of low incomes or consumption. According to Wasswa (2015), this approach is attached to classical micro-economics, where the word like "utility" account for individuals' behavior as well as their welfare. Moreover, the two concepts of poverty, the absolute and the relative poverty, are considered and defined using the one-dimensional approach.

When it comes to absolute poverty, it does not matter where or when an individual lives, it is based on basic goods and experiences that are needed for survival (Sedmak, 2019). Basic goods may include food, shelter, education, and health, among others. These basic needs are measured by calculating how much it can cost to buy what is needed for ones' survival (Sedmak, 2019). Research conducted in South Africa on child poverty used the absolute poverty approach. However, this approach has limitations because while it addresses survival issues, the broader inequalities in the community are not addressed, where poverty is crucial on the variety of relative wealth. When conceptualizing and measuring relative poverty, a broader situation regarding child welfare is taken. Absolute deprivations of basic needs for survival are considered, taking inequalities of the community into consideration (Messner et al., 2010). According to Leatt (2006), it is expressed as individuals living in households below the half of average income. However, that can be a danger when below subsistence level.

This approach was criticized by Sen (1980) by mentioning that since there are market imperfections, individuals are unable to maximize their satisfaction, imperfect information, discrimination, and there are absolute minimum levels that need to be realized and value judgments are not included in the aggregation of utilities.

2.2.2 Poverty concept under welfarist approach

Every national government, international organization or non-political institution has poverty reduction as their main policy objective (Fuentes, 2005). The first definitions of poverty are addressed using the welfarist approach i.e., the insufficiency to have sufficient nourishment and other necessities. Individuals in any society are perceived as poor if their standard of living is below an acceptable minimum according to prevalent social customs and cultural norms (Nssah, 2004). There is also a definition by Ravallion (1994) who refers to poverty as resource deprivation that is perceived by individual as having access to a level of income or expenditure to acquire an acceptable standard of living.

According to Aluko (1975), poverty is lack of access and control over basic needs. Poverty can also mean the insufficient access to material, economic, social, political, or cultural means that are necessary for the fulfillment of basic needs (Philip and Rayhan, 2004). The World Bank (2000) views poverty as the economic state whereby people lack sufficient income to get a basic level of health services, food, shelter, clothing, and education which are important to safeguard an acceptable standard of living. Meth (2006), states that poverty refers to the distribution of resources and is the reflection of the impact of the past and the choices of the president, as a result poverty is also political. This traditional approach uses different and adjusted poverty lines to distinguish the poor from the non-poor and is represented in monetary terms (Ravallion, 1998). Usually, authors use income or expenditure information at household or individual level to measure poverty.

2.2.3 Non-welfarist approach

This approach comprises of two approaches i.e., the basic needs approach and the capability approach. The first approach, (basic needs) tries to understand the need to obtain some basic multidimensional results that can be easily observed and monitored. The results are either explicit or implicit (Sen, 1992). The explicit or implicit outcomes are usually linked with functioning approach. This approach pays attention to acquiring numerous outcomes that are specific and separate like enjoying consumption of a certain commodity. This can be enjoying being health, educated, well clothed, living in beautiful house as well as social empowerment (Wasswa, 2015). According to Apablaza et al. (2013), non-welfarist approach is beneficial as it includes the use of other outcomes besides utility. They further mention that this approach makes use of different sources of estimates which differ from own individuals, it applies principles to weigh outcomes and it enables wellbeing comparisons using different dimensions.

2.2.4 Basic needs approach

This approach is grounded on Rawl’s theory of justice. The approach was discontented with monetary measurement of poverty. It argues that in a good society, everyone should have the ability to satisfy the basic needs (Watson II, 2014). When a person cannot meet their basic needs, they are referred to as poor. Its focus is on a set of primary goods which are essential elements of welfare and are deemed essential to living a desirable life (Streeten et al., 1981). In the mid-70s, poverty was perceived as unsatisfied basic needs index. The index was developed from basic needs approach (Herrera et al., 1976). This approach pays attention to a set of primary commodities which are considered as the essentials of welfare and required for living a good life. According to Streeten (1981), basic needs can be defined in relation to minimum quantity specifications like food, clothes, housing, drinking water, as well as public health. These are the resources that prevent individuals from ill-health, malnutrition, and poor livelihoods. The philosophy behind this approach was that every individual should be able to pursue welfare (Wong, 2012).

This method was criticized for having equal weights on indicators. This implies that when indicators are used in a particular dimension and they are more than one, some of the dimensions may be extremely weighed over other dimensions (Feres and Mancero, 2001). Alkire and Foster (2011) also argued that this approach aggregates the multidimensional headcount ratio, therefore, in case where the poor are deprived in one more indicator, the approach will not be able to reflect that. Boltvinik (1992) also mentioned that by relying on the multidimensional headcount ratio, the basic needs approach overlooks the depth of deprivation which is very significant.

2.2.5 Capability approach

The capability approach which was initiated by Sen (1979), criticizes the focus on money metric terms and utility and suggests that welfare should be agreed to be multidimensional and indicated in the space of capabilities. Sen (1979) as a developer of this approach argues in three main options which are to focus on people’s resources i.e., income and wealth, their level of satisfaction or happiness and what they can do or become (their capabilities). This implies moving from means of living to opportunities that are available. This approach is explained by the capacity to achieve a combination of functioning which reflects a person’s free will to choose the type of life to lead. Sen (1979) further argues that even when there is perfect information in comparing individuals, the welfarist approach cannot deal with underlying principles such as liberty, discrimination, entitlement to social security, among others, because it provides non-utility information a role of its own.

The approach recommends that welfare should be defined by a set of functioning that a person or household can achieve (Sen, 1980). This functioning refers to a person's or household's accomplishments or the current state that they find themselves in or the opportunities that are available. Therefore, capability is a set of vectors of functioning that reflect a person's free will to live the type of life they are living (Sen, 1992). In addition, because people have different feelings about different things i.e., some may be regarded as poor while they do not see themselves poor, the approach puts considerable freedom of choice. This implies that a person cannot be categorized as poor even when they choose not to achieve some opportunities available to them (functioning), if they are able to achieve what they chose to achieve (Lubrano, 2013). These functioning do not compress multidimensional dimensions into a single dimension i.e., utility or happiness, instead, it focuses on the achievements of multiple dimensions like the enjoyment of a specific basic needs such as good health, education, nice clothes, good shelter and social empowerment, among others (Lubrano, 2013).

Poverty can also be measured using the objective or subjective approach. On the objective approach, normative judgments are involved on what creates poverty as well as what is needed to take people out of it (Makoka and Klaplan, 2005). The subjective approach is based on "premium on people's preferences" point of view i.e., the extent to which individuals value goods and services. Therefore, this point of view explains poverty based on individuals' perceptions of poverty reputation (Statistics South Africa, 2015). This study follows the objective approach.

Nevertheless, there are limitations that Sen was concerned with when it comes to this approach. Firstly, he mentioned that when looking at people's resources (wealth and income), they have different levels and kinds of resources to achieve same outcome. Moreover, people may face discrimination as their resources determine what they can be or do. Sen (1987) also argues that people's preferences are adaptive for example, someone might be sick, undernourished and living in a poor dwelling type and still be happy if they learned to have realistic desires and they take pleasure in the little that they have.

2.2.5 Multidimensional poverty concept

Sen (1985) proposed a broad approach to measuring and conceptualizing poverty. In 1999, Sen emphasized that real poverty should be understood in a capability deprivation sense which refers to opportunities, choices, and entitlements deprivations. From that time, literature began to focus on the broader sense or multidimensionality of poverty. Bastos (2001) also argued that welfare concept analysis should be based on household living circumstances not on the level of household income. For that reason, this study focuses on the broader sense of poverty. The multidimensional view of welfare is favored by both the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs). According to Statistics South Africa (2014), poor health, low level or no education, poor living conditions, inadequate income, lack of empowerment as well as threat from violence or crime are the factors that make up multidimensional poverty. Worldwide, it is currently accepted that poverty is a multidimensional concept.

According to Ortiz et al. (2003), child poverty may be defined as the poverty experienced during childhood. Feeney and Boyden (2003) indicated that poverty is dynamic and child poverty includes three interconnected domains. First one is deprivation, which involves poor material conditions and services that are perceived to be important for children to develop to their full potential. Second one is exclusion, which refers to unfair processes that deny children's voices and rights and threatens their existence. Third one is vulnerability, which refers to the societies or households' inability to cope with existing threats or risks to their children. Moreover, majority of the studies conducted in the past focused on overall poverty and poverty among adults not taking children into consideration. Arieh (2000) noted that is currently accepted in research, in social as well as in economic policies that children belong as an autonomous group in community. That is, their standard of living should be conceptualized and measured distinctly from that of adults to get informative child poverty or deprivation reduction. According to McGregor et al. (2007), a high dependency for the satisfaction of basic needs on elders by children is the reason why children hold a special position in a household. As a result, this study focused on children. According to Wasswa (2015), child multidimensional poverty refers to children's deprivations in household and child-specific indicators of welfare. These indicators include access to clean running water, good sanitation and other housing needs.

2.2.6 Human rights-based approach

This approach argues that poverty is not only the absence of income or material resources but a violation of human dignity and their human rights. According to Strauss and Horstein (2013), a human rights-based definition of poverty can lead to sustainable reaction to many facets of poverty whereas considering daily violations of human dignity joined together with poverty. If human rights were acknowledged and thoroughly implemented worldwide, poverty would not exist. According to Kaltenborn et al. (2020). Human rights are one of the normative cornerstones of contemporary international law and worldwide governance. This approach defines poverty as inadequate satisfaction of an individual's human right to basic capabilities to live a dignified life (Strauss and Horsten, 2013).

2.2.7 Stochastic dominance approach

The stochastic dominance approach has been used in analyzing poverty to overcome the problem of multidimensional poverty indicators. This approach was developed by Atkinson (1987) and Forster and Shorrocks (1988) using a one-dimensional approach to poverty. It was later extended by Duclos et al. (2006) using a multidimensional approach to poverty. According to García-Gómez et al. (2019), the approach captures relationships between poverty dimensions as they depend upon their joint distribution based on marginal distributions. Atkinson and Bourguignon (1982) indicated how stochastic dominance can be applied to draw comparisons of population groups through broad classes of underlying social wellbeing functions. The approach relies on predictions which are formulated using a specific sign on the second-order partial or cross-derivatives of underlying individual utility function that is considered by a utilitarian planner (Channing and Fin, 2017). Duclos and Échevin (2011) assumes substitutability between health and income. This implies that a basic utility function with a negative cross-partial derivative between health and income.

2.2.8 Counting approach

The counting approach process involves determining the poverty line, in each dimension, aggregation of dimensions for each individual and across individuals to summarize measurement of deprivations among different characteristics/indicators (Alkire and Foster, 2008). The MPI is grounded on the counting approach that is developed by Alkire and Foster (2011) and assesses poverty along the same dimensions as the Human Development Index (HDI). This approach portraits the breadth of poverty and counts the portion of population that is deprived in at least 30% of all the dimensions (Alkire and Foster, 2008). The approach is commended for its ability to allow identification of the multi-dimensionally poor individuals.

2.2.9 Effects associated with child poverty

Children from very poor households undergo adverse effects of being exposed to multiple risks they cannot handle leading to multiple deprivations. Even children from less poor households may undergo limited access to services and resources (Singh and Sarkar, 2014). Children that are conceived in poor and socially excluded families have a greater possibility of being caught in the poverty trap i.e., poverty will be experienced from one generation to the next (Ortiz et al., 2012). These children have little or no chance of getting good education; this might result in dropping out of school and only a few will find jobs due to the overcrowding of unskilled labour. Moreover, those employed will not have security and will not be well paid (Research of Socio-economic Policy, 2014). It is widely accepted that children welfare differs from adult welfare as children have particular and various needs. Ortiz et al. (2012) mentioned that adults can fall in and out of poverty, but for a child it can last for a lifetime.

A child living in poverty is under the risk of lifetime consequences which can affect a child's social and economic cost in their communities (Grantham-McGregor et al., 2007). Duncan et al. (2010), Johnson and Schoeni (2011) found out that when a child is deprived at an early phase of their growth, they face adverse effects such as inadequate achievement in academics, inadequate health, low economic status, and behavioral problem. There are many disadvantages associated with children who are growing up in poverty. These disadvantages enlarge throughout a child's life cycle (Hills et al., 2010) i.e., children who grow up in poverty usually become parents who live in poverty (Allen, 2011). Also, Ortiz et al. (2012) emphasized that being malnourished; having poor health and lack of education may affect child's long-term development.

According to UNICEF (2007) children's involvement in their societies is restricted since they are deprived in numerous basic needs and are socially excluded, which can lead to complicated concerns. Children living in poverty are robbed opportunities which can assist them in their development as adults (Azzi- Lessing, 2017). UNICEF (2011) reported that children reside in households that are faced with material deprivation, violence, malnutrition as well as poor health and education. Factors such as poor cognitive development, health, education as well as psychological development were mentioned by Hills et al. (2010) as multiple negative impacts of poverty. Shelter (2006) pointed out that housing is one of the most crucial resources which influences a child's well-being. It was found out that 25% of children living in poor dwelling type have higher chances of severe ill-health during their childhood and early adulthood. These includes meningitis, asthma, lower levels of educational attainment as well as mental health problems. The main cause of chronic poverty according to Makhalima et al. (2014) is child poverty and its alleviation stands to be a common objective around the world. Wasswa 2015 mentioned that a child who is brought up in poverty has more chances to suffer from different illnesses, unemployment as well as becoming involved in criminal activities such as drug abuse, alcohol abuse and being in abusive relationships.

Poverty has grave repercussions for children, this includes high chances of experiencing early deaths from simply preventable diseases, or lifetime health problems because of deprivations. (Ortiz et al, 2012) mentioned that child poverty has strong gender dimensions, and social institutes most of the times participate in leading to and continuing long-lasting poverty, weakness, and discrimination during the period of childhood and into adulthood for girl children. Since poverty can greatly affect social (age or gender) groups in different ways; its overwhelming effects are on children, to them it poses a greater danger by affecting children's education, health, nutrition as well as security (UNICEF 2015).

2.3 Governments' Efforts to Reduce Child's Poverty

According to Adams et al. (2015) large scale economic programs aiming at different economic objectives were implemented by the government. These objectives include fast economic growth, creation of jobs, enhanced methods deliver public services as well as reduction of poverty and inequality. Moreover, other measures like, social safety nets (social protection), child support grants, disability grants, school nutrition (poverty reduction initiatives) and food relief programs have been implemented. According to Mbuli (2009) national skills development for job creation have been implemented through initiatives such as learner ships. There has also been an institution established (Khula) to increase access to monetary and non-monetary assistance to Small Medium and Micro Enterprises (SMMEs). This institution helps individuals to get access to shelter i.e., Reconstruction and Development Program (RDP), free education and primary health care (Mbuli, 2009).

Ortiz et al. (2012) pointed out that to achieve MDGs, key area interventions require to be speeded. The UN convention has South Africa as its participant. Therefore, from that convention the country has taken some efforts to support and promote the development of children as stated in the Constitution and children's Act both giving their attention to children's rights (Proudlock and Mahery, 2010). According to Oyekale (2015), to address economic deprivation and poverty, economic development programs should be used. In South Africa, there is social assistance which provides social grants to the rightful beneficiaries. According to the presidency (2009), these social grants do not only alleviate income poverty, but poor children are able to realize their constitutional rights by accessing basic education and basic health services. There are health care services that are free to pregnant women who can access them at any time and 91% child deliveries were done by professional nurses and doctors for free. Approximately 85% of children receive free immunization and advice is given to mothers regarding neonatal care and child feeding practices (The presidency, 2009). The government also introduced the no-fee schools which is functional in 58% of the schools in south Africa i.e., 5 million children are attending schools for free (The presidency, 2009). For spiritual, sensory, physical, and social development of children, the social development is ensuring that children are accessing Early Childhood Development programs that will prepare them for schooling (The residency, 2009). There is also the Extended Public Works Program that is dealing with income poverty alleviation.

The National Integrated Policy (NIP) on ECD approved South Africa's first national policy in 2015. The policy aims to transform ECD service delivery and address crucial gaps in the system. The policy covers children from birth until they begin formal schooling. When the child is disabled, the policy covers them until they turn seven years. The major gap in literature is the ability to unlock the impacts of these programmes on child's welfare. Our basic understanding of this is essential for determining the welfare implications and distributional patterns of the welfare growth indicators across time. This study therefore seeks to fill this gap by evaluating the welfare indicators among children and analyzing their pro-poorness. This is of policy relevance because the notion of equal benefit accruing to children across different economic status cannot be justified given the high level of income inequality in South Africa.

CHAPTER THREE

MULTIDIMENSIONAL POVERTY CONCEPTS, INDICATORS AND MEASUREMENT

3.1 Introduction

This chapter presents the multidimensional framework for the understanding and analysis of child's poverty. It also presents some analytical procedures for computing some indicators of multidimensional poverty.

3.2 Fuzzy Set Approach for Poverty Analysis

This method originated from Zadeh (1965) who characterized aggregation of fuzzy set as a set of continuous membership. The method was then applied by Costa (2002) and reported that the degree of being poor by the ith household $(i = 1, \dots, n)$ with respect to certain characteristic (j) given that $(j = 1 \dots., m)$ can be defined as $\mu\beta[Xj\ (ai)] = Xij, 0 \leq Xij \leq 1. Xij = 1$ when a household does not have wellbeing improving characteristic and Xij=0 when a household possesses it. When categorical welfare indicators are put together to construct composite indices, one needs to make an important decision when assigning numerical values to such welfare indicators to ordered categories as well as the weighting and scaling of measures (Betti et al., 2005). In this case individual items that present non-monetary deprivation should take the form where Xij should be 0 or 1. On the other hand, Zani (1990) pointed out that it is possible for some of these individual items to have more than two ordered categories which will reflect degrees of deprivations that differ. X_{ij} is not necessarily assigned values 0 or 1, however, $0 \leq X_{ij} \leq 1$ when the jth indicator possesses many categories, and the household/individual has the characteristic with an intensity. Categorical indicators can also be assigned values if arranged in certain order of desirability (Betti et al., 2005). In this situation, $0 \leq X_{ij} \leq 1$. The multidimensional welfare index of a household, $\mu\beta\ (ai)$ shows the level of wellbeing and membership to set B is described as the weighted average of X_{ij},

$$\mu\beta\ (ai) = {\sum_{j=1}^{m} x_{ij} w_j} \Big/ {\sum_{j=1}^{m} w_j} \qquad 3.1$$

w_j is the weight given to the jth attribute. The strength of deprivation with respect to X_{ij} is measured by weight w_j which is an inverse function of the degree of deprivation. Therefore, the smaller the number of households and the amount of their deprivation, the greater the weight. The weight that fulfills the above-mentioned property was suggested by Cerioli and Zani (1990). This method can assess the deprivation intensity and it considers diverse weights to aggregate data developed from selected indicators (Bastos and Machado, 2009). It can be expressed as:

$$w_j = \left[log\ [{\sum_{i=1}^{n} g(ai)}\Big/{\sum_{i=1}^{n} x_{ij} g(ai)}\right] \quad 3.2$$

According to Bastos and Machado (2009), the fuzzy set approach lacks a definite rule like the poverty line to outline which elements fit into a given poverty set. It focuses on the degree to which an individual belongs to a set of poverty that a movement from being totally deprived (1) to not deprived (0). The advantage of this is that it accommodates the estimation of qualitative variables. In this approach, there are three phases namely the description phase, aggregation phase and the inference phase. These phases are used to make poverty measurement in order to find answers (Sen, 1976).

3.2.1 Selection of indicators

In the description phase, the first thing to do is to construct a poverty measure by selecting suitable indicators. The selection of basic variables is heavily dependent on the arbitrary selections of researchers that must face a trade-off among potential redundancies due to overlapping of information and the danger of losing this information (Perez-Mayo, 2005). A solution to this arbitrariness can be obtained using multivariate statistical tools such as Principal Component Analysis (PCA).

3.2.2 Weighting

By outlining a poverty measurement method established on deprivation counts and simple averages, an equal weight of $wj = 1$ per dimension j must be allocated implicitly. This is suitable when the dimensions were carefully selected to be of reasonably equal importance. As Atkinson et al. (2003) states that equal weighting has an innate appeal: "the analysis of the set of indicators is greatly relieved where the separate components have degrees of importance that, even though not precisely equal, they are not wholly different (Atkinson et al., 2003)

As soon as a first set of variables is chosen, their aggregation into a composite index designates selecting a suitable weighting structure. A lot of diverse weighting methods have been employed in literature. Firstly, other investigations use equal weighting for each variable (Townsend, 1979), by this avoided the necessity for attaching different importance to many dimensions. Secondly, to depart from purely arbitrary weights, in the construction of the composite poverty indices, variables are joined by weights determined by a form of advice-giving process between poverty specialists and policy experts. Even though this approach is a development on the initial solution, it still contains subjective decisions in relation to the wellbeing value of individual component. Thirdly, weights can be used to show the underlying data quality of the variables by providing low weight to variables experiencing data problems or with big quantities of missing values (Rowena et al. 2004).

The dependability of a composite poverty index can be enhanced if it provides additional weight to good quality data. On the other hand, this may put more weight on variables that are easy to measure and are easily accessible rather than more important issues relating to the wellbeing that are more difficult to detect with good data. Fourthly, variables are weighted utilizing the decision of people based on study methods to stimulate what they prefer (Smith, 2002). The problem met here refers to whose preferences was be utilized in the application of the weights, meaning it can be the preferences of policymakers, households, or the public. Firth, the most unbiased method is to carry out a set of weights using the prices of different items.

3.2.3 Description phase

The first thing to do in this phase is to identify the evaluative areas and corresponding indicators. The General Household Survey has dimensions such as education, health, housing, economic activities which can be considered in this study. These dimensions each have indicators with the correspondent scale of deprivation.

The description phase is a type of extension of the identification step in the primitive approach to the analysis of poverty: in an uncertain environment, the conventional “hard” threshold, that controls an unmistakable difference amongst “poor” and “not poor”, is replaced by a “soft” threshold that portrays an intermediate, ongoing representation between satisfactory and unsatisfactory levels of welfare, without forming a single cut-off point (Zhao et al., 2009). This makes it possible to consider poverty analysis and welfare not as two separate exercises, as it has been the case traditionally, but as two entangled aspects of a wider theoretical framework, like the capability approach. Another benefit of the fuzzy set theory is that the kind of membership it uses is not limited to quantitative variables only, it can also be used to represent qualitative indicators as well as linguistic attributes, and hedges or qualifiers too, that are normally included in questionnaires or data sets on subjective or objective welfare and are central from a capability perspective (Martinetti, 2006). The identification of poor or deprived households or individuals needs the definition of a threshold, a matter which brings up several theoretical and empirical problems. The independence of the specific choice regarding the threshold, the identification of those to be classified as poor always indicates some degree of arbitrariness (Martinetti, 2006).

3.2.4 Aggregation

When poverty is perceived as a multidimensional concept, it has to be measured by the aggregation of the different deprivation variables experienced by individual people in society (Alkire and Foster, 2011). Therefore, measuring multidimensional poverty generally includes the combination of data given by numerous variables into a composite poverty index. For the aggregation of the indicators in their basic units (categories), it is suitable to classify the phases into two working stages: (1) the specification of membership for each indicator, and (2) the specification of the weighting structure (Alkire and Foster, 2011).

3.2.5 Inference phase

It is debatable that there is probably a collection of living standards from the poor to the non-poor, which renders any cut-off point random (Mack and Lansley, 1985). With the fuzzy set approach, it is not necessary to indicate a set poverty line as it might be essential when defining poverty using headcount ratio. In opposition to the money-metric approaches, the fuzzy set approach does not dichotomize population into non-poor through a set poverty line (Nimishe-Niyimbanira, 2016).

3.2.6 Decomposition

According to Oyekale et al. (2009), the poverty ratio of multidimensional welfare indicators can be decomposed based on their contributions. Decision makers can be guided by this decomposition method to have more precision on the state of social exclusion. Another method to evaluate the pattern of poverty is by decomposing the population into groups. This decomposition allows decision makers to decrease poverty by identifying the most affected groups (regions, religion, gender, and so on), particularly the groups that contribute to the increase. Mussard and Pi Alperin (2007) also indicated that a good way to assess the structure of the overweight problem is by providing a decomposition by sub-population groups. Total population can be separated according to gender which makes it possible to calculate the contribution of the intensity of poverty on men group to the intensity of poverty for the whole population.

Dagum and Costa (2004) initiated the decomposition by attribute indicating that it is possible to calculate the contribution of the j-th attribute to the total poverty index. This type of decomposition makes it possible for the decision and policy makers to acquire more information on diverse dimensions of poverty, thereby allowing better accuracy in the implementation of suitable socio-economic policies in to decreasing the state of poverty (Diallo, undated).

3.3 Multidimensional Poverty Index (MPI)

The MPI is based on Alkire and Foster (2011) and gives a high degree of flexibility in the selection of indicators. These indicators may be developed to suit the definite requirements of each country and depict the pre-occupations of policy developers. Multidimensional poverty indices are developed by many countries as official national statistics of poverty. Measuring poverty consist of two important steps i.e., identification (determining who is poor) and aggregation (extent of poverty) (Sen, 1976). The Multidimensional Poverty Index reflects mixture of deprivations faced by a household at the same time. When a household is deprived in some combination of indicators that exceed 30% when weighted, that household is identified as poor. The product of headcount ratio (% of people who are poor) and poverty intensity gives the MPI.

In the computation of MPI, the dual cut-off method is utilized to identify the poor. The initial cut-off is to determine if a person is deprived in each dimension, while the second cut-off involves certain dimensions an individual must be deprived in to be classified as poor (Ortiz et al. 2012). In one-dimensional analysis, identification is generally attained by utilizing a poverty line or threshold, with poor individuals being identified as the ones whose resources are below the poverty line. In the multidimensional measurement setting, since there are many variables, identification is considerably the most challenging exercise.

The aggregation phase is an extension of the existing uni-dimensional well-being methodology suggested by Foster-Greer-Thorbecke (1984). The headcount ratio refers to the percentage of the population that is identified as multidimensionally poor. The poverty severity is the average deprivation shared among the poor. This poverty intensity shows the average multidimensionally poor person is deprived.

The choice of weights is considered as one of the major challenges when constructing the multidimensional poverty indices (Decancq and Lugo, 2008). These weights determine the intensity with which a selected attribute may be used or its overall relevance. Authors such as Rahman et al. (2003) and Ram (1982) proposed the equal weights technique, frequency-based weights, most favorable weights, MCA based weights, multivariate statistical weights, regression-based weights as well as normative weights (Decancq and Lugo, 2008). However, Omotoso and Koch (2018) mentioned that not any of these techniques have been proved to be the best. On the other hand, different approaches that are used to measure poverty do not provide appropriate methods to address the issue of weighting (Omotoso and Koch, 2018). Therefore, the choice of weights had been left to the discretion of researchers. According to Alkire and Foster (2007), equal weights is a random normative weighting system that is appropriate even when it is not in all situations.

3.4 Principal Component Analysis (PCA)

PCA was first introduced by Pearson (1901) and Hoteling (1933) who developed it based on the circumstance that it is a natural choice as data exploration approach. This approach focuses on describing the variance-covariance structure for a set of variables through combinations that are linear (Krishnakumar and Nagar, 2007). The approach provides weights for each indicator based on the covariance matrix. Moreover, the objective of this approach is to reduce data. A major weakness of PCA is that it was developed for quantitative variables. According to Schiel (2012), PCA is a multivariate approach that is usually utilized in the analysis of well-being to construct asset index which act as an alternative for the wealth of a household. PCA assumes that in the long run, maximum variance in asset variables explains the well-being of a household. For that reason, the approach is a linear index of all variables capturing the largest amount of common information to all the variables (Filmer and Pritchett, 2001). Variance of a set of variables is decomposed into a few orthogonal components. These components are inclusive of weighted total of individual variables. The weighting of each separate variable is proportional to the share of total variance that is indicated (Van De Berg et al., 2003).

Yu (2012) pointed out that weights are allocated to asset variables on their standard deviation. The higher the standard deviation of asset variables, the higher the weight allocated to it. PCA permits for the aggregation of numerous asset ownership variables into a single dimension (Moser and Felton, 2007). Because each linear combination is not associated with others, diverse dimensions of poverty are captured in the data. It has the advantage of allowing patterns to be identified in the data, and that data can be compressed by reducing the dimensions, very less information can be lost. In addition, it can extract shared information from a set of variables that are interrelated (Bhorat et al. 2014). There is easy interpretation of weights assigned to each asset variable; unequally distributed assets in a family would be assigned more weight because the weight given to asset variables depends on their standard deviation. Asset variables having positive weights are related to higher socioeconomic status. PCA limitations include accuracy, which can be an issue regarding the covariance matrix. The approach does not specify or capture invariance (Karamizadeh et al. ,2013).

3.5 Multiple Correspondence Analysis (MCA)

Multiple Correspondence Analysis (MCA) may be defined as a statistical measure which quantifies non-income poverty trends (Adams et al. 2015). The method was introduced by Benzecri (1973) as a technique of finding the interrelationship among variables and the strength of connection (Greenacre, 2007). The approach is opposite to that of PCA. MCA allows a pattern of relationships of several categorical dependent variables to be analyzed. The approach is best suited for nominal variables. MCA can accommodate quantitative variables even when captured as nominal observations (Njong and Ningaye, 2008). According to Kabubo-Mariara et al. (2010), MCA is the application of Correspondence Analysis (CA) algorithm to multivariate categorical data captured in the form of indicator matrix (0 or 1). When MCA approach is used, notions are made. MCA is essential for both the selection and the categorization of indicators when constructing multidimensional measures (Alkire et al., 2015). The benefit of applying the MCA approach is that the indicator would possess various desired features of a poverty indicator which would be inclusive of the monotonicity axiom and the piece that categories with less observations obtain a higher weighting in the indicator score (Fransman, 2017). MCA is an appropriate technique for the construction of indices because it has no limits on the data (Blasius and Greenacre, 2006).

MCA does a correspondence analysis on Burt matrix which is achieved by multiplying the disjuncture matrix by its transpose. MCA was perceived to be more sensitive to deprivation (Njong and Ningaye, 2008). Although MCA has some strengths, it also has a few weaknesses. These include the fact that its results are data focused, as a result making it problematic for inter-temporal and cross-country comparisons (Alkire et al, 2015).

3.6 Determinants of Child's Multidimensional Welfare

Different factors can explain poverty among children. This section provides a comprehensive review of some of these factors.

3.6.1 Age of the household's head

The age of the household's head is one of the factors that affects child's welfare (Sekhampu and Muzindutsi, 2014). UNICEF (2017) submitted that the chances of a child to be deprived multi-dimensionally are high when the household's head is between the ages of 15 to 29 years. Young parents have a high probability of experiencing financial challenges due to high economic insecurities at the early stage of life (Lunn and Kornrich, 2018). However, households that have older heads (60 and above) are likely to have reduced poverty rates.

3.6.2 Gender of the household's head

Female household's headship is generally high in South Africa (Nwosu and Ndida, 2018). These households have a general tendency of facing financial hardships. This is a result of the country's history of male-controlled systems which are still taking place in the communities (Nwosu and Ndinda, 2018; Sun et al., 2020). Most of the time, females are paid less salaries/wages compared to males, resulting in insufficient incomes to meet the needs of the family. The gender of the households' heads is important in explaining child's welfare (Heuveline and Weinshenker, 2008). Buvinic and Gupta (1997) contended that there is a high dependency on females. Woolard (2002) discovered that households that are headed by females had a greater chance of experiencing poverty. Patel (2012) also highlighted that on a fifteen-year period, there was a decline in aggregate poverty among the African population, and majority were among male headed households. Sekhampu and Muzindutsi (2014) calculated poverty rate at 68% and 59% for female and male-headed households, respectively. A study that was conducted by Raja (2009) found that females were poorer than males.

3.6.3 Education level of household head

Parental education is one of the factors that many researchers have integrated as a strong determinant of child's welfare. Literacy of the household's head also plays an important role in explaining household's poverty. One of the major effects of parents' educational attainment is child's academic successes (Yang, 2017). Attainment of low-level education by household's head increases the probability of being poor, as compared to households' heads with high level of education (Botha, 2010). Yang (2017) sought to magnify the study to speculate whether high level of parental education, especially that of the mothers have a significant effect on child's poverty.

3.6.4 Child's educational level

Poor parents have a higher tendency of raising illiterate children who also stand a higher chance of being poor in the future (Giovetti, 2020). Most of the times, education can promote successful job hunting and provide the requisite skills for gainful employment. Therefore, access to early childhood development and education programs can promote child's wellbeing as a way of terminating intergenerational poverty (Giovetti, 2020). Education provides empowerment, productivity, health, and reduces the likelihood of indulging in degrading practices like child labor (Adegboye and Kotze, 2011). Appleton et al. (1996) stated that the skills that are acquired during basic education by children will increase their chance of completing post-primary education. Singh and Sarkar (2014) submitted that years of schooling is a crucial contributor toward child's welfare.

3.6.5 Marital status

Children residing in female headed households or with an unmarried parent, have higher chances of becoming poor compared to those residing in households where household's head is a male or married (Lu et al., 2020). The marital status of the household's head is therefore a significant factor influencing child's welfare. The children that are raised in households where both parents are married seem have their needs adequately met. However, parents' contribution as well as how much each child costs depends on a households' specific needs (Gray and Stanton, 2010). These children can also benefit from accrued wealth of married parents and subsequently inherit some resources upon their demise (Anyanwu, et al., 2013).

3.6.6 Geographic location

Geographical location can also affect the poverty status of children. According to Research of Socio-economic Policy (2014), South African children who are poor are black and coloured and are in previously disadvantaged parts of basic education. As a result, the poverty cycle may continue. According to Singh and Sarkar (2014), a high level of welfare deprivation is usually experienced by children from rural areas. Therefore, most poverty-stricken people in the world are found mainly in the rural areas. Many of the rural poor people are subsistence farmers, and landless agricultural workers (Hedge et al., 2019). Roche's (2009) results revealed that children were deprived on better sanitation services and that this deprivation was mainly witnessed in rural areas compared to urban areas. Similar results were found by Adetola and Olufemi (2012) regarding children under the age of five years by looking at five dimensions, i.e., water, nutrition, housing, health, and sanitation. Leibbrandt et al. (2006) realized that rural poverty rates are higher when compared to urban poverty rates, regardless of the poverty line chosen.

3.6.7. Maternal occupation

Employment status may be perceived as one of the integral determinants of household's welfare. According to a logistic regression conducted by Makhalima (undated) on the determinants of child's poverty, it was found that unemployment increased the possibility of a child being poor. Sekhampu (2013) and Zizzamia and Schotte (2019) also found that households with employed heads had lesser chances of being poor. Another study conducted by Maloma (2016) discovered that poor households were most of the times characterized by unemployed heads.

3.7 Determinants of Child's Health Outcomes

Reduction in child's mortality was one of the eight Millennium Development Goals (MDGs), with enhancement of child's nutrition being emphasized as one of the major targets. Community development is therefore tailored towards the understanding of the primary factors that influence child nutrition. Nutritional status is an imperative health outcome that is influenced by food intake and use of nutrients (Mutisya, 2019). Adequacy of child's nutrition is imperative to avoid inadequate child's growth (Tibilla, 2007). Shortage or excess intake of one or more nutrients and/or poor use of nutrients results in malnutrition, a condition resulting from nutritional imbalance that is responsible for 15.9% of total global problem of disease and responsible for more than one third of all childhood deaths (Merchant et al., 2003). Malnutrition can be classified as over-nutrition and under-nutrition with the former leading to obesity and overweight, while the former is responsible for stunting and wasting (Mutisya, 2019). The major determinants of child's health outcomes are hereby highlighted:

3.8.1 Household's economic status

The global health report indicated that the degree of wealth in the household is an indicator for bigger risk of under nutrition. Children from wealthy households are 57% less likely to be stunted when compared with those from poor households (Darteh, 2014). This is because wealthier households have the financial means to meet their children's basic needs (Mutisya, 2019). Children from poor households will lack access to safe drinking water and appropriate sanitation practices which are imperative determinants of child's health outcomes. More specifically, Groeneveld et al. (2007) reported a higher likelihood of stunting among children from low socio-economic status, while overweight and obesity are considerably higher among children from wealthy households. A lot of researchers have revealed that children in low earning households are more susceptible to diseases like diarrhoea, measles, and acute respiratory infection (ARI) (Currie et al., 2007). The economic status of households ultimately defines child's access to improved health care services, nutritious food, healthcare services (Brooks-Gunn and Duncan, 1997).

3.7.2 Child's age and gender

Many studies have highlighted the importance of child's age as a determinant of nutritional status. Darteh et al. (2017) showed that there is a lower likelihood of wasting and stunting in children aged between 36-47 months. Compromised health at a young age can also result in poor health outcome of the child (Appaix, 2003). The highest occurrence of stunting and underweight was detected in children under five years. Nyaruhucha et al. (2006) also discovered that under-nutrition was predominant among children between 24 and 35 months, while children below a year were less likely to be undernourished. Children between 12 and 59 months were less nourished than those between 0-11 months (Kamiya, 2011).

Besides age, the gender of the child is also of significant importance in explaining child's health outcomes. Lefebvre (2006) highlighted the role of gender in explaining child's preferential treatments which ultimately go in favour of male children. Therefore, malnutrition is more prevalent among girls. FAO (2005) indicated that girls eat less proteins as compared to their male counterpart, thereby promoting iron deficiency among females. Furthermore, boys can be more prone to stunting as compared to girls (Kandala et al., 2011). In addition, boys are more susceptible to underweight compared to girls and the relationship is statistically significant (Kumar et al., 2006).

3.7.3 Household size

Household size is an important determinant of child's health outcomes. Chaudhury (2009) noted that as family size increases, the children's nutritional status is adversely affected due to drastic reduction in per capita income. Therefore, children from large households are more likely to be underweight due to perpetual competition for the limited resources (Maganga and Maganga, 2018). Household size is also inversely related to child's nutritional status due to high competition for food and other resources (Kbubo-Mariara and Ndenge, 2008).

3.7.4 Maternal age

Empirical studies have demonstrated the role of maternal age in the nutritional and health outcomes of their children. Specifically, young mothers are at the risk of poor pregnancy outcomes that may also affect the health of surviving children (Allen and Gillespie, 2001). Latham (2001) found that young women who are too undeveloped to feed their children are also not knowledgeable in terms of providing them with adequate maternal care and financial support. Smith et al. (2003) submitted that the mothers who were less than 20 years and above 35 years are likely to have children born with low birth weight, prematurely, and with some clinical complications.

3.7.5 Maternal education level and occupation

Behrman and Déolalikar (1988) differentiated between five channels through which maternal education has an impact on the growth of a child. Firstly, education has a direct impact on the attainment of knowledge in relation to health and hygiene. Secondly, it increases overall capabilities in terms of reading and subsequently, it allows for an improved understanding of instructions given by caregivers for the control of some diseases. Thirdly, education increases the probability of being employed and earning sufficient income to meet the nutritional and health needs of one's children. Fourthly, education increases the opportunity cost of working hours and therefore reduces the time set aside for childcare. Lastly, parental education could affect the preferences of parents in an orderly manner, particularly in their choice of the number of children they can have.

Studies have indicated the role of maternal education in explaining the health outcomes of children (Boccanfuso and Bruce, 2010). It has been stated that well-educated mothers have a higher likelihood of postponing childbearing with consequential reduction in infant mortality (Chen, 1986). According to Sufiyan et al. (2012), children with uneducated mothers are at a higher risk of being stunted. In another study that was conducted by Ali et al. (2005), stunting and underweight were found to be associated with low educational attainments. Maternal education can also have some relationships with child's employment status. Abbir et al. (2006) confirmed that the employment status of mothers can affect a child's nutrition negatively. This is because of time constraints that may prevent working-class mothers from giving the desired attention and care to their children. Empirical evidence has revealed that young maternal age is related to high occurrence of malnourishment, while children with older mothers have lesser chances of suffering from malnutrition (Nyaruhucha et al., 2006).

3.7.6 Birth interval

Inadequate child spacing influences mothers' and children's health (Das and Roy, 2021). The closer the intervals between births, the lower the quality of breastmilk because of bodily and mental fatigue on the mother (Ambapour and Hylod, 2008). This means that the mothers' bodies have not yet fully recovered from previous births. Research has proved that the period between births is inversely related to lower weight of a child. Lengthier birth interval gives some considerable chances to the mothers to give maximum attention to the newborns (Rayhan and Khan, 2006).

The impact of contraception is anticipated to have an impact on fertility (increased birth interval) which enables a mother maximum period for breastfeeding (Ssewanyana, 2003). Children born in shorter birth intervals have considerably higher rates of adverse pregnancy results such as stillbirth, neonatal, post neonatal, and childhood mortality as compared to those born after longer intervals (Molitoris et al, 2019). The logistic regression depicts a 28% escalation in stunting of children born within a birth interval shorter than 24 months. Furthermore, there is a 26% rise in underweight of children within birth interval shorter than 24 months. It is clear that lower birth weight, poor services in the course of pregnancy are statistically connected with inadequate nutritional status of children (Chungkham et al., 2020)

3.7.7 Access to healthcare services

Lack of adequate access to healthcare services and incomplete immunization are instant causes of under-nutrition and have been recognized as potential modifiable risk factors (Charkaborty, 2011). Immunization against six vaccines avoidable diseases such as poliomyelitis, diphtheria, pertussis, tetanus, tuberculosis, and measles remain the most cost-effective interventions to decrease childhood illnesses and mortality (UNICEF, 2008). In a Bangladesh's study of children aged between 12 and 23 months, it was revealed that about 51.0% of children who took measles immunization were not stunted, compared to the ones with incomplete immunization. Non-immunized children often show a higher likelihood of being sick and hospitalized (Chowdhury et al., 2006). Another study that was conducted in Indonesia revealed a higher occurrence of underweight, stunting and anemia among children that were not completely immunized (Semba et al., 2007).

3.7.8 Sanitation

As revealed by Jalan and Ravallion (2003), children who reside in households with no running water were more vulnerable to diarrhea which adversely affected their general health status as compared to children residing in households with access to running water. Child wasting, underweight and stunting are constantly higher in households without improved toilet (Dobe, 2014). In relation to hand washing habits among children, 80% of the children who had diarrhea during the week before the survey did not use soap to wash their hands after visiting the toilets. Wondimu (2016) applied bivariate logistic analysis and showed that households with unimproved sources of drinking water had higher odds of having stunting in children compared to children from households with improved drinking water sources. The chances of children being infected by parasitic infections and diarrhea were both highly associated with poor hand hygiene and poor sanitation (Shrestha, 2020).

3.7.9. Feeding practices

The World Health Organization (WHO) gives some guidelines on the feeding practices for infants and children. These guidelines promote and encourage breastfeeding only for the first six months, and introduction of solid foods thereafter (Dhall and Bagga, 1995). The practices of infant feeding are strong factors influencing stunting and underweight among children below five years. Research has proved that the numbers of underweight, as well as stunted children are considerably lower in children who were introduced to breastfeeding within six hours of birth. When a child is not properly fed, they are at high risk of being underweight (Kumar et al., 2006)

3.7.10 Geographical features

Child’s nutritional status is greatly affected by the area where they reside (Hien and Kam, 2008). It had been revealed that children residing in rural areas are at a greater risk of being undernourished in the three anthropometric indices compared to children residing in urban areas. It was also observed that children in rural areas are more likely to be stunted compared to those in urban areas. Majority of stunted children are found among the ones not born at hospitals (Kandala et al., 2011).

3.8 Identified Knowledge Gaps

Although several approaches had been proposed in the literature for evaluating indicators of households' welfare, only few studies have provided a comprehensive comparison of their performances. This study seeks to fill this gap by comparing the results from Alkire-Foster and fuzzy set methodologies. Specifically, one of the fundamental bone of contentions in literature is the choice of weight. While Alkire-Foster proposed arbitrary selection of weight, fuzzy set is built upon methodology that allows weight computation. It is therefore of interest in this study to evaluate the performances of these two methods using comprehensive datasets for three years. More importantly, in the evaluation of multidimensional poverty, segregation of children for concentrated analyses is rarely done. This study therefore presents a significant addition to the existing body of knowledge given the fundamental relevance of child's welfare in achieving the SDGs.

CHAPTER FOUR

PRO-POOR GROWTH CONCEPTS AND APPLICATIONS

4.1 Introduction

This chapter presents a comprehensive review of some conceptual issues on pro-poor growth. The chapter also highlights the different approaches to pro-poor growth from the unidimensional and multidimensional viewpoints.

4.2 Pro-Poor Growth and Poverty Reduction

Sustainable reduction in poverty relies on pro-poor growth (OECD, 2006; Nssah, 2004). Dollar and Kraay (2002) also emphasized the role of economic growth in improving people's standard of living. The 1950s concept of trickle-down is among the foremost foundations of pro-poor growth. This concept implies a vertical flow of resources from the rich to the poor. Jafar (2015) argued that the only way that the trickle-down hypothesis can lead to considerable reduction in poverty is when the shared benefits of growth are large enough to make an impact in the income of the poor.

Furthermore, the redistribution with growth theory has questioned the use of growth in the gross domestic product (GDP) as a measure of economic performance and the fight against poverty (Chenery et al., 1979). Chenery et al. (1979) emphasized that about 75% of the economic assets in most of the countries are owned by the top two percentile income groups. Dagdeviren et al. (2001) proposed that redistribution at the margin is beneficial and more effective in poverty reduction than increases in economic growths with neutral distribution.

In the 1990s, pro-poor growth was also imbedded in the term "broad-based growth" (Menocal, 2011). This signifies a growth process that involved different sectors across the economy of the country. Growth that is broad based across sectors stands a chance of being sustained for longer than growth that is reliant on market circumstances in one or two sectors. This offers greater possibilities for the poor to take part in the growth process, as a result promoting equity (OECD 2007). If the pattern of growth is broad based and inclusive in relation to the sectors from which poor women and men earn their incomes, the locations where they belong, creates jobs for their occupation, and increases access to dynamic assets and markets for products and services they produce, there is a chance that their incomes will increase more speedily and they will be able to purchase the assets they need to continuously increase their incomes in future.

The idea of "inclusive growth" was also promoted from a realization that prioritizing economic growth solely cannot meet the development requirements of the poor people, as it is unable to objectively solve problems like inequity and unemployment. Rather than focusing solely on quick growth, inclusive growth 'brings up both to the speed and pattern of growth' (World Bank, 2009), which are perceived to be connected and as a result should be addressed simultaneously. The idea of inclusive growth is centered on the recognition that economic growth must be progressively 'pro-poor'.

4.3 Pro-poor Growth Concept

The term "pro-poor growth" became well-known in the 1950s and 1960s when it was found that economic growth affects the main components affecting development policies. According to Seers (1970) and Morris (1973), fast economic growth did not decrease unemployment and left some individuals with increased inequalities among the population. Thus, there is the need for clarification on what is meant by pro-poor growth (Duclos and Verdier-Chouchane, 2010). According to the OECD (2001), pro-poor growth must benefit the poor and provide them with more access to economic opportunities. As a result, there are various definitions of pro-poor growth.

Baluch and McCullock (2001) referred to pro-poor growth as a condition in which any change in income distribution associated with economic growth benefits the poor. This implies that poverty declines more when all incomes grow in the same percentage. Ravallion and Chen (2003) defined it as a process where the poor benefits in absolute terms. According to OECD (2001), pro-poor growth refers to the growth that profits the poor and gives them chances to recover their economic situation. Pro-poor growth is experienced when poor people derive more benefits from economic growth and their share in national income rises. Nssah (2004) defined pro-poor growth as economic growth that is favorable to the poor. Pro-poor growth refers to labour absorbing growth that has policies and programs alleviating inequalities and enabling income and employment for those that are poor, focusing on women and the previously disadvantaged groups (ADB, 1999). The United Nations (2000) and OECD (2001) refer to pro-poor growth as economic growth that benefits the poor and offers them the opportunity to participate in the growth of the economy or improve the economic situation.

There were then questions raised from these definitions; what is intended for pro-poor growth and how can it be measured? What kind of policies should be implemented by countries to achieve the pro-poor growth objective? Therefore, these definitions have been criticized for not providing certain explanations such as to what degree should the poor benefit from growth to be considered pro-poor and the required reduction in poverty.

4.3.1 Weak and strong definition

Ravallion (2004) observed that the World Bank's definition of pro-poor growth is weak because it refers to pro-poor growth as growth that decreases poverty, not minding the magnitude. This definition implies that growth is pro-poor even if the poor receives only a small proportion of total benefits of growth. The main drawback of the weak absolute definition of pro-poor growth is that it calls for growth policies regardless of their impact on inequality and can be merged with trickledown growth. Under this definition, a country with a growth rate of 10% and the poor's income increasing by 0.1% would have experienced a pro-poor growth (Abdal, 2016). Other authors such as McCulloch and Baulch, Kakwani and Pernia (2000) and Son (2003) offered a broad definition of pro-poor growth by emphasizing that when measuring pro-poor growth inequality and poverty should be included.

4.3.2 Strong absolute and weak absolute

To overcome the above weakness, a stronger definition of pro-poor growth was introduced which emphasized that if the absolute income gain of the poor is more than that of the non-poor, there is strong absolute pro-poor growth (Klasen, 2008). The easiest form of this definition is based on a relative concept of inequality and basically state that the growth rate of the income of the poorest individuals is greater than the total average growth rate (White and Anderson, 2001). However, one may partner the absolute approach to inequality measurement, by which a decline in inequality is said to occur if a greatest amount of income has benefitted the poor's incomes than the non-poor.

4.2.3 Relative and absolute pro poor growth

Relative pro-poor growth applies when the poor gains proportionally more than those that are not poor. This can reduce relative poverty and inequality (Kakwani and Pernia, 2000). On the other hand, absolute pro-poor growth refers to a condition where the poor benefits from overall growth in the economy of the country. Although provided with different definitions of pro-poor growth, Kacem (2013) mentioned that in some cases, growth can have severe and negative impact on those that are poor. However, there are advantageous impacts that comes with pro-poor growth, i.e., improved participation of the poor in economic activities and pro-longed tax incomes which can result in improvement of social protection. Duclos and Verdier-Chouchane

(2010) mentioned that the impact of growth depends on the level of inequality and the type of growth that is experienced.

4.2.4 Partial and full Approach

The partial approach concept categorizes growth as pro-poor not without any specification of a poverty line and poverty measure (Kakwani and Son, 2003). An approach proposed by Ravallion and Chen (2003) falls under this approach because they based their definition on First Order Dominance (FOD) condition. Son's (2004) pro-poor growth method whose measure is based on using stochastic dominance curves can also be classified under the partial approach. This approach has both advantages and disadvantages. One of the advantages is its validity for all poverty lines and poverty measures. The disadvantage is that if the dominance requirement is not met, it cannot be concluded if growth is pro-poor or not.

The full approach, however, is always able to avail definite result as to whether growth is pro-poor or not. Researchers inclusive of McCulloch and Baulch (2000); Kakwani and Pernia (2000) and Ravallion and Chen (2003) have based their views on the full approach. This approach provides the entire levels of growth processes and is nothing like the partial approach. A growth process under the full approach is evaluated from a rate or an index of pro-poor growth and not from a curve. To utilize the full approach, however, a poverty line and a poverty measure must first be stated. This requires an inevitable value judgment in picking the poverty line and poverty measures. The PEGR can be considered as the full approach (Kakwani and Son, 2003).

4.2.5 Multidimensionality of pro-poor growth

Sen (1987) stated that when introducing non-income indicators in the pro-poor growth measurement, one must start with the selection of non-income indicators responsible for the most vital functioning of human wellbeing. This was also highlighted by Kakwani and Pernia (2001) in a case whereby only the financial aspect is considered. In most cases, it is esteemed that income growth go together with non-monetary growth. However, this is not always true (Klasen, 2000). In this regard, Kakwani and Pernia (2001) noted that it is "shallow" to do research on the operationalization of pro-poor growth by utilising only the income aspect of poverty, while poverty is a complex phenomenon.

The non-monetary approach to poverty relates to a non-utilitarian vision. It has two main methods which are the Sen's (1985) "capability approach" and the basic needs approach. The first defines welfare as the ability or the capability for realising functioning, such as being sufficiently fed and being in good health and contributing to the community life. Following this method, an individual should have specific basic features required for realizing a certain standard of living. The second, the basic needs method, states that a person should be able to satisfy certain important needs (access to education, health services, sanitation, clean drinking water, adequate shelter, and access to basic infrastructures) to realise a particular feature of life (Boccanfuso et al., 2009).

According to the OECD (2007), poverty is widely accepted as a multidimensional phenomenon, therefore, pro-poor growth is strengthened by looking at the different dimensions of poverty. The relationship between economic growth and the variance in the occurrence of poverty or the people who benefit from that change in economic growth (pro-poor growth) is multidimensional since poverty is a complex concept.

Pro-poor growth has always been measured using income, however, this concept goes beyond having sufficient income (Grosse et al, 2005). Without assessing the effects of economic growth on education and health, among others, it will not be possible to design pro-poor growth policies (Hague et al., 2008). Grosse et al. (2005) stated that one existing weakness of the present pro-poor growth models and measurements is that they are entirely concentrated on reduction of income. Income poverty does not secure a reduction in the non-income dimensions of poverty, and they show that it is possible to lengthen pro-poor growth measurement of non-income variables such as education or health by identifying non-income growth incidence curve (NIGIC). The Non-Income Growth Incidence Curve was developed by Grosse et al (2005), Klasen et al. (2008) following the GIC concept, but it focuses on non-income household characteristics to measure pro-poor growth. Grosse et al. (2005), Klasen (2008) considered the limitation of not taking non-monetary approach and presented the Non-Income Growth Incidence Curve (NIGIC) as conditional and unconditional. The conditional NIGIC ranks individuals by their income and calculate based on population percentiles of the non-income variables. The NIGIC provides an additional instrument used to investigate how progress of social well-being has been distributed over income distribution. Grosse et al. (2006) supported the NIGIC approach because it offers an additional tool to explore how the progress in non-income dimensions of the MDGs is shared over the income distribution.

4.3 Computing Pro-Poor Growth Indices

According to Cheema and Sial (2012) the primary focus of Poverty Biased of Growth (PBG), poverty equivalent growth rate (PEGR), and pro-poor growth index (PPGI) is change in the distribution of wealth among the population. These approaches focus on how individuals below and above the poverty line benefit and it is a relative approach. In relation to weak approach, pro-poor growth is attained when inequality decreases or stays constant during the growth process (Kakwani and Son, 2008). When inequality increases, a negative impact on growth is realized. This then means that measures that take poverty and improvement of inequality into consideration have negative distributional effect in all poverty decomposition methods (Kakwani and Son, 2003).

Furthermore, strong approach refers to when redistribution is in favors of the poor. It is necessary to have a balanced interaction among pro-poor growth and multidimensional poverty indicators. According to Anderson (2009), the information is presented in graphical form as Growth Incidence Curve (GIC). The graph gives a full illustration of changes in welfare and poverty over a particular period. Since it is broadly acknowledged that poverty is multidimensional and it would not be sufficient to measure it by a single indicator, there is now the Non-income Growth incidence Curve (NIGIC) based on non-income indicators (Anderson, 20089). This NIGIC captures multidimensionality of growth and is applied in this study. The central argument of pro-poor growth is monotonicity axiom which must be satisfied when measuring pro-poor growth. The following measurements have been used to measure pro-poor growth by different authors.

4.3.1 Kakwani and Pernia (2000) Pro-poor Growth Index

Kakwani and Pernia (2000) proposed the pro-poor growth index. This method fails to address the monotonicity axiom. When growth situation is pro-poor, Pro-poor Growth Index is greater than one. This index is expressed as the ratio of poverty elasticities, which ought to be positive when a growth condition is pro-poor. There are two factors which poverty reduction basically depends on. The first one is the degree of economic growth rate implying that the larger the economic growth rate, the larger the reduction of poverty. Growth is complemented by variations in inequality and an increase in inequality decreases the effect of growth on poverty reduction.

4.3.2 Growth Incidence Curve (GIC)

Ravallion and Chen (2003) suggested a measurement of pro-poor growth in the form of the Growth Incidence Curve which is drawn from the first order stochastic dominance conditions. GIC examines the effect of economic growth that is aggregated on various percentiles of income distribution between two periods of time. It is possible to use this approach for any welfare indicator. The GIC can be well-defined for the Watts measurement of poverty, violates monotonicity axiom and is categorized under partial definition of pro-poor growth (Son, 2012). Ravallion and Chen (2003) illustrated the processes of growth and defined the GIC as the growth rates in income in various percentile points. When the GIC is positive at all regions, there is a definite poverty reduction between two periods. When the GIC moves or shifts upward, poverty reduction increases.

4.3.3 Poverty Bias of Growth

McCulloch and Baulch (2000) suggested measurement of pro-poor growth known as the poverty bias of growth (PBG). This method pays a specific attention to the reduction in inequality. The PBG is resulting from negative component of inequality acquired from symmetric decomposition of poverty methodology, which was recommended by Kakwani (2000). Kakwani (2000) decomposes the adjustment in poverty to both growth and distribution effects. The growth effect measures the adjustments in poverty when there is no change in the distribution of income, and the change in poverty is recorded by the distribution effect when inequality changes in the absence of growth. Whether the later becomes negative or positive solely depends on whether growth goes along with improving or strengthening inequality. McCulloch and Baulch (2000) presented a measure of pro-poor growth by making a comparison between the real distribution of income and the one that can arise under the distribution-neutral situation. As a result, a relative approach in defining pro-poor growth is revealed by their measure. The main problem with the PBG is that it cannot satisfy the requirement of monotonicity criterion. Since poverty depends on the growth effect sometimes the higher values of the PBG do not indicate greater reduction in poverty. As a result, when it is supposed that the growth effect is unbroken (which is not likely, then the PBG measure will meet the satisfactory requirements of the monotonicity criterion.

4.3.4 Poverty Equivalent Growth Rate (PEGR)

Since PPGI does not consider the level of actual growth rate, Kakwani and Son (2007) reacted to this by suggesting a pro-poor growth measure known as the Poverty Equivalent Growth Rate (PEGR). The PEGR refers to the growth rate that results in the same level of poverty reduction as the present growth rate when the growth process has not been complemented by any change in inequality. One of the pro-poor debates is that the monotonicity axiom (the proportional reduction in poverty is a monotonically increasing function of the pro-poor growth measure) must be satisfied in measuring pro-poor growth (Kakwani and Son, 2003). The PEGR is a measure that can satisfy this axiom. The PEGR takes into consideration the extent of growth and how its benefits are distributed among the poor and the non-poor. They also stated that the larger the poverty equivalent growth rate, the greater the proportional reduction in poverty. The PEGR is measured by multiplying the PPGI by the growth rate mean of income growth rate. If it occurs that the PEGR lies between 0 and the mean growth rate, then the growth is complemented by an increasing inequality. However, poverty will decrease even in this case (Kakwani and Son, 2003).

PEGR holds a strong character which is to link the changes in inequality with the losses or gains of growth rate. When inequality decreases, there is gain in the growth rate and vice versa. PEGR also takes into consideration the scale of growth and benefits that are reaped by the poor. This PEGR can be calculated distinctly for the whole group of poverty measures i.e., headcount ratio, poverty gap ratio, severity of poverty index as well as the Watts poverty measure. Kakwani and Son (2008) suggested that if any government wants to achieve maximum poverty reduction, policies need to be structured in a way that they focus on getting the best out of PEGR. This approach can also be used as an indicator to monitor poverty across socioeconomic over time and demographic groups. This approach is considered by Kakwani and Son (2008) to be general since it contains all decomposable poverty measures.

4.4 Determinants of Pro-Poor Growth Pro-poor growth is essential for poverty reduction. This section of the thesis presents the macroeconomic determinants of pro-poor growth.

4.4.1 Agriculture

The role of agriculture in economic development has drawn the attention of economists, with primary focus on rural poverty reduction (Cervantes and Dewbre, 2010). Enhancement in agricultural efficiency contributes to economic growth through economic transformation, promotion of industrial manufacturing activities and other essential services. Increased agricultural productivity must contribute to ensure growth of the incomes of the poor, mainly through a productivity growth in the non-farm sectors (Datt, 1998). Slow agricultural growth are less pro-poor (AFD, 2005). Due to the agrarian nature of some countries, growth will only be pro-poor when accompanied by sufficient agricultural productivity.

Timmer (2005) stated that Africa's poor countries that are not practicing agriculture are urged to participate to develop. It was emphasized that technical change in the agricultural sector, there will be increases in labour productivity of the rural economy, wages can be raised, eventually eliminating the dimensions of poverty. When growth occurs in agricultural productivity, it does not only imply increase in income but also encourages linkages to non-farm rural economy, as a result, countries experience economic growth as well as quick poverty reduction (Hazell and Haggblade, 1993). The poor are mostly found in the agricultural sector and the developing economy. Productivity development in this sector is the main factor influencing pro-poor growth, especially in poor rural countries (Klasen, 2007).

4.4.2 Human capital

Human capital development is essential for pro-poor growth (Klasen, 2003). Developing human capital is vital since it results to developing skills and assists those that are poor to obtain the required skills (Fufa, 2021). This was also stressed by Nickolas et al. (2021) who indicated that there is a strong correlation between human capital and economic growth. Economic growth is affected by human capital by expanding the poor people's knowledge as well as improving their skills. Berg (2008) noted that human capital can decrease poverty in three main ways through the fact that higher educational achievement leads to higher earnings, better quality and higher levels of education are related to economic growth and more economic opportunities, and the higher the level of education, the higher the social benefits resulting in improved health care services of the poor.

Klasen (2003) stated that there are paybacks for investing in human capital of the poor because economic growth increases and growth can more pro-poor. According to Amuka et al. (2020), when employment opportunities are increasing, there is a positive and significant impact on pro-poor growth. A study lead by Fufa (2021) has shown development of human capital has resulted to a significant decrease in the poor's' income share in Ethiopia between 1990 and 2018. Developing human capital is emphasized to be important because of its impact on the poor's skills development. These skills can provide the poor with opportunities for promotions with higher earnings in their working environments (Amuka et al., 2020).

4.4.3 Employment

Attention has been paid to the significance of employment in poverty reduction and economic growth. When economic growth results in continuous increase in employment opportunities, poverty reduction results (Rushidan and Islam, 2003). Higher earnings would make it possible for employees to spend most of their time on education and skills development. Therefore, there are higher chances of having high levels of economic growth when productive capacity is increased. Fufa (2021) discovered that there is a positive impact on pro-poor growth when employment opportunities are increased.

4.4.4 Inflation

Inflation is one of the determinants of pro-growth (Barro, 1995). It has been debated that inflation decreases the real wages of the poor (Pasha and Palanivel, 2004). If inflation is caused by higher food prices, then this could have an uncertain impact on the level of poverty. The structuralists agree that there is a positive effect of inflation on economic growth while on the other hand, capitalists observed that there is a negative impact of inflation on economic growth (Mamo, 2012). According to Neo classical interpretations, economic growth increases through inflation by shifting the distribution of income. Furthermore, Keynesians also stated that it is possible for inflation to boost economic growth by increasing profit rate, resulting in an increase in private investments (Mamo, 2012).

4.4.5 Inequality

Escalating inequality in most developing countries is an additional factor that justifies the impact of growth on poverty (Klasen, 2007). As regional inequality rises, economic growth is hindered from its ability to influence poverty. In Sub-Saharan Africa, there is high gender inequality regarding education and non-formal jobs, which undermines pro-poor growth. There are some devastating impacts of these inequalities because female-headed households are largely affected, and they lead to decrease in the general economic growth and poverty alleviation.

4.5 Identified Gaps in the Literature

The major identified gaps in the literature dwells with the conventional applications of the relative and absolute pro-poor growth. This study seeks to add to existing literature by using multiple welfare indicators to analyze pro-poor growth. The study relates the results from the GICs with those computed after transforming the multidimensional poverty indicators into multidimensional wealth indicators and setting appropriate poverty lines. There have not been such contributions in most of existing literature.

CHAPTER FIVE

METHODOLOGY

5.1 Introduction

Generally, the objective of this study is to analyze child's multidimensional welfare and pro-poor growth in South Africa. Therefore, this chapter presents the study area where the research was conducted, the research design, how data was collected, sampling procedures and sample size, ethical consideration procedures, methods of how data was analyzed to address the objectives of this study as well as the limitations that were faced by this study

5.2 Study Area

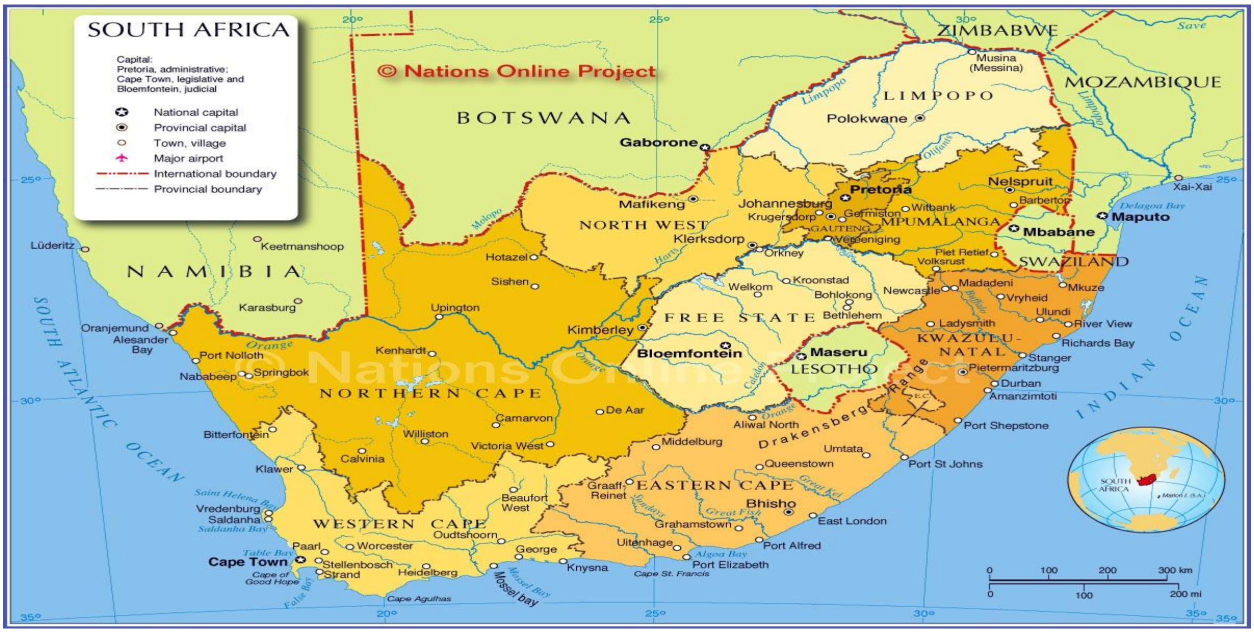

Figure 5.1: South African Map.

Source: OrangeSmile Tours (2002)

According to Luis (2017) South Africa is Southern Africa's largest country with around 56 million people. The country has nine provinces. It is in the southern region of Africa with a huge flat plateau with altitude between 1 000m and 2 100m. The country accomplished a transition from apartheid to complete democracy in the year 1994, giving the world an influential demonstration that it is possible for a nation to shift from political conflicts to peaceful cooperation. Since then, the country has shown a significant sociopolitical stability, resulting in a very strong influence in the continent and the world. In Africa, South Africa is a country with the most advanced economy. It gets its privilege from its geographical position as a gateway to Sub-Saharan Africa, and since the democratic transition in 1994, the country's economy experienced a quick growth. South Africa's major economic sectors are mining, manufacturing, and services. The agricultural sector contributes about 4% of the GDP. SA has a well-developed financial infrastructure (Duclos and Verdie-Chouchane, 2010). According to Duclos and Verdie-Chouchane (2010), South Africa's unemployment rate was very high between the year 1995 and 2005 (about 30%). It was further indicated that high levels of unemployment affect the youth, those with no education or low levels of education and the ones living in homelands and remote areas.

5.3 Research Design

Due to the nature of this study, the quantitative research design was used. This design is systematic research approach where quantitative data are gathered for some quantitative analyses. The socio-economic and demographic features of children and their households were parts of the required data. Also, multidimensional poverty and pro-poor growth analyses were carried out using some secondary data.

5.4 Sampling Procedures and Sample Size

This study used the 2017, 2018 and 2019 dataset that were collected by the Statistic South Africa as the General Household Survey (GHS) and the Demographic Health Survey (DHS) data of 2016. These surveys were conducted by Statistic South Africa to inform economic.

5.4.1 General Household Survey (GHS)

The GHS survey contains ten (10) sections. These include household characteristics, health, social security, economic activities, welfare and food security and mortality which can be useful for this study. Comprehensive data collection procedures had been provided by Statistic South Africa (2017, 2018 and 2019). Since 2015, the General Household Survey (GHS) utilizes a Master Sample (MS) structure that was created in 2013 as a general-purpose sampling structure to be utilized for all Statistic South Africa's household-based surveys. The master sample framework comprises of detail areas that are found within some primary sampling units (PSUs). The sampling frame takes cognizance of the geographic location of the households (urban, traditional, or farm). Stratified two-stage sample design was used to select the households. There are 3,324 primary sampling units (PSUs) in the Master Sample, with an anticipated sample of approximately 33000 dwelling units. After data were sorted and merged, a total of 25,915; 25,224; 20,083 and 71,711 of children were selected in the 2017, 2018, 2019 and combined datasets, respectively.

5.4.2 Demographic and Health Survey (DHS)

This study used the data from the 2016 Demographic and Health Survey (DHS) to analyze child health outcomes. The use of this dataset was inspired by absence of anthropometric data in the GHS datasets. The sampling frame for data collection was based on the 2011 national census enumeration areas that were provided by the Statistics South Africa (Stat SA). The sampling frame took cognizance of the estimated number of housing units within each of the geographical areas, classified either as urban, traditional or farm units. Using the dwelling units as the basis for sampling, the survey was implemented to ensure representativeness of key indicators considering the population distributions across geographical settings and provinces.

Sampling was implemented with stratification of each province into three geographical settings: urban, farm, and traditional areas. Two stage stratified sampling procedures were followed with sample sizes allocation proportionately according to size of PSUs at the first stage. The second stage involved systematic sampling of some dwelling units. The country was divided into 26 sampling strata among which 750 PSUs were selected with 468 from urban areas, 224 from traditional areas, and 58 from farm areas. Comprehensive listing of the dwelling units within the PSUs was carried out between January and March 2016 to facilitate the conduct of systematic sampling. Twenty dwelling units were selected from each of the PSUs, and questionnaires were allocated to selected respondents within the odd and even dwelling units following some predefined protocols.

The data were collected by trained enumerators and experienced supervisors from the Statistics South Africa. The listing identified 15,292 eligible households, of which 13,288 were occupied and 11,083 successfully completed the interviews. The study used the file comprising information on children that were less than 5 years of age within each of the households. The questionnaire among others probed into the nutrition and food intakes, immunization, breastfeeding, illnesses and medical services' utilization and anthropometric data (age, height, and weight) (National Department of Health et al., 2019).

5.5. Ethical Consideration

The study observed ethical approval from the Ethics Committee of the Faculty of Natural and Agricultural Sciences at the North-West University, Mafikeng Campus. Moreover, the ethical mandates for the utilization of GHS and DHS datasets were also observed.

5.6. Method of Data Analysis

5.6.1. Descriptive statistics

This study used descriptive methods of data presentation such as frequency, percentage, mean, and standard deviation for data analyses. The descriptive statistics were largely used to present the results of the socio-economic and demographic features of the respondents.

5.6.2 Child's multidimensional poverty index and its decomposition using Alkire-Foster Method

This study used the Alkire and Foster (2011) method to compute the multidimensional poverty index (MPI). Table 5.1 shows the selected welfare dimensions and attributes. For dimensions were identified which are: standard of living; health; education; and perceived happiness. The Table reveals that in all, there were ninety-one (91) welfare attributes of which seventy-six (76) belonged to the standard of living category, eleven (11) belonged to health, two (2) belonged to education, and two (2) belonged to perceived happiness. The standard of living was broken into six (6) indicators, while health was broken into two (2). The Alkire-Foster method begins with proper definition of poverty cutoff for identifying the children that were multidimensionally poor. Each of the selected attributes was coded as 1 for the deprived children and 0 for the non-deprived. The ninety-one selected attributes are defined in Table 5.1.

Table 5.1. Child MPI dimensions, indicators, Deprivation cut-offs and weights

Dimension (Weight)	Indicator (Weight)	Deprived if…
Standard of living (76/91)	Assets (22/91)	Lacking the following: Ownership of a motor vehicle; ; Radio ownership TV Set; Swimming Pool; DVD Player/Blu-ray Player Pay TV (M-Net/DSTV/Top TV) Subscription; Air Conditioner (Excluding Fans); Computer/ Desktop/ Laptop; Vacuum Cleaner/Floor Polisher; Dish washing machine; Washing Machine; Tumble Dryer Deep Freezer – free standing; Refrigerator or Combined Fridge Freezer; Electric Stove; Microwave Oven; Built-in Kitchen sink; Home Security Service Home Theatre System; Geyser providing hot running water; Solar hot water geyser; Solar electrical panel
	Telecommunications (7/91)	Lacking the following: Internet connection in the household; Internet in a library or community hall/Thusong centre; Internet for students at a school/university/college; At place of work; Internet Café ≤2km from the household; Internet Café and Telephone.
	Waste removal (6/91)	A child resides in a household that there is irregular or no waste removal, littering, water pollution, outdoor/indoor air pollution, land degradation and excessive noise.
	Housing characteristics (10/91)	A child resides in an informal/traditional dwelling type (shack, caravan or other), without bricks or cement for walls and without materials such as tile, corrugated iron, asbestos, and others for roof; with unimproved floor materials, more than two persons per room; using unimproved drinking water; distance of water source from the dwelling more than 30 minutes, using unimproved toilet facilities, and sharing toilet facilities.

Source: Own Computation, 2022

Table 5.1. Child MPI dimensions, indicators, Deprivation cut-offs and weights cont.

Standard of living (76/91)	Safety (10/91)	Responded yes to the following: Motor vehicle injury – occupant; Bicycle related; Gun shots wounds; Severe trauma due to violence, assault, beating; Crime- related injury; Fire or burn; Accidental poisoning; Intentional poisoning; Sports related injuries; and other injuries.
	Energy (21/91)	A child resides in a household with the following features: lack access to electricity; uses paraffin for lighting; uses candles for lighting; uses no energy source for lighting; uses other unclean sources for cooking; uses paraffin for cooking; uses wood for cooking; uses coal for cooking; uses animal dung for cooking
Health (11/91	Nutrition/hunger (8/91)	Responded yes to the following: run out of money to buy food; run out of money 5 or more days in the past 30 days; cut the size of meal or skip any meals; cut size of meals 5 or more days in the past 30 days; Skipped meals; skipped meals 5 or more days in the past 30 days; smaller variety of food; smaller meals 5 or more days in the past 30 days
	Healthcare Facilities and Health Status (3/91)	A child is not covered under any medical aid scheme; A child resides in a place that takes more than 30 minutes to reach the health facility; A child has a fair or poor health status
Education (2/91)	Early Childhood Development (ECD) (2/91)	A child of 0-59 months is not attending any ECD centre; A child who is old enough to attend school (6-18 years) does not attend and school/education institution
Perceived happiness (2/91)	Perceived Happiness (2/91)	A child resides in a household where the head says they are poor; A child resides in a household where the head is not happy or same as before.

Source: Own Computation, 2022

After coding the selected attributes as either 0 or 1, the Alkire-Foster method begins with definition of the cut-off, which identifies whether a child is multidimensionally poor based on his or her total weighted deprivation. In this study, the ninety-one attributes were equally weighted and the sum of the attributes in each dimension defines the assigned weight.

In other words, the cut off it is a portion of weighted deprivations a child must have in order to be considered poor, and it is symbolized with p. Therefore, a child is considered poor if his/her deprivation score is equal or greater than the poverty cut-off i.e., a child is poor if $c_j \geq p$. Following recommendation from Alkire and Foster (2011), the child's MPI assumes a one-third poverty cut off which, based on the ninety-one attributes constitutes 30.33 MPI. A child is multi-dimensionally poor if he/she has a deprivation score higher than or equal to 30. For children with a deprivation score that is below the poverty cut-off, even if it is non-zero, it is replaced by zero '0'. This is referred to as censoring in poverty measurement.

Using the notation $c_j(z)$ for the censored deprivation, such that when $c_j \geq z$, then $c_j\,(z) = c_j$, but if $< z$, then $c_j(z) = 0$; hence, $c_j(z)$ is the deprivation score of those who are poor. Like with the weights, the choice of poverty cut-off is also flexible in the Alkire-Foster method, depending on a particular context. The child's MPI, therefore, is the combination of the incidence of children who experience multiple deprivations as well as the intensity of their deprivation. The first component is called the child multidimensional headcount ratio (H) which is expressed as:

$$H = \frac{m}{N} \qquad 5.1$$

Where m is the number of children who are multi-dimensionally poor, and N is the total population of children. The second component refers to the intensity of poverty (A). It is the average deprivation score of the multi-dimensionally poor children, expressed as:

$$A = \frac{\sum_{j=1}^{n} c_j(z)}{m} \qquad 5.2$$

Where $c_j(z)$ is the censored deprivation score of children j. mathematically, the child MPI is the product of H and A, this means child MPI = (H $*$ A).

MPI can be decomposed into its component dimensions and censored indicators. The MPI decomposition can be expressed as:

$$MPI(x; y; z) = \frac{n(x)}{n(x;y)} MPI(x; z) + \frac{n(y)}{n(x;y)} MPI(y; z) \qquad 5.3$$

Where $n(x)$ refers to the number of individuals in x (the same goes for $n(y)$ and $n(x; y)$

For this study child MPI was decomposed by socio-demographic factors: gender, race, province focusing on surroundings. Decomposing the child MPI by gender yields:

$$DMPI_{child\ gender} = \frac{n_m}{n} MPI_m + \frac{n_f}{n} MPI_f \qquad 5.4$$

m Represents males while f represents females, and $\frac{n_m}{n}$ is the proportion of males in the total population (same goes for $\frac{n_f}{n}$ (assuming that $n_m + n_f = n$. Successively, the contribution of each factor to the overall Child MPI follows:

$$CMPI_{childgender} = \frac{\frac{n_m}{n} MPI_m}{MPI_{child}} * 100 \qquad 5.5$$

In the same manner, the decomposition of the child's MPI into its component censored indicators can be computed by:

$$DMPI_{child} = \sum_{j=1}^{n} w_j CH_j \quad j = (1; 2; 3; \dots \dots \dots ..; n) \qquad 5.6$$

w_j is the weight of indicators j, CH_j is the censored headcount ratio of indicators j and $\sum_{j=1}^{n} w_j = 1$. Similarly, the contribution of each indicator to the overall child poverty measure becomes:

$$CMPI_{child} = \frac{w_j CH_j}{MPI_{child}} * 100 \qquad 5.7$$

5.6.3 Child's multidimensional poverty index and its decomposition using the fuzzy set

The theory of Fuzzy Set was introduced by Zadeh (1965) based on an idea that certain classes of objects may not be defined by precise criteria of membership i.e., in some cases a researcher may be unable to determine which elements belong or do not belong to a given set. Dagum and Costa (2004) highlighted that the fuzzy set theory is highly efficient and rigorous for performing a multidimensional analysis of poverty. Following Zadeh (1965), multidimensional welfare indicators were computed using the fuzzy set theory. Authors like Costa (2004), Oyekale (2017), among others have used the fuzzy approach.

The fuzzy set was characterized as a class with continuous grades on membership. This implies that in a population of A of n households $[A = a_1, a_2, a_3, \dots a_n]$, the subset of the poor households B includes any household i.e., $a_i \in B$. These households present some degree of poverty in some of the m poverty characteristics (X). The degree of being poor by the ith household $(i = 1, \dots, n)$ with respect to a particular attribute (j) given that $(j = 1, \dots., m)$ is defined as $\mu_B\left[X_j(a_i)\right] = X_{ij}, 0 \le X_{ij} \le 1$. Specifically, $X_{ij} \; = \; 1$ when a household does not have a welfare enhancing characteristic and $X_{ij} = 0$ when a household possess it. Putting categorical indicators of deprivation together for individual items to construct composite indices requires decisions about assigning numerical values to the ordered categories and weighting measures (Betti et al. 2005). This implies that X_{ij} is 0 or 1. However some items involve more than two ordered categories which reflect different degree of deprivation. With an assumption by Zani (1990) that categorical ranks represent equally spaced matric variable, an individual deprivation score can be presented as:

$$X_{ij} = (C - c_i)/(C - 1) \qquad 5.8a$$

Where $1 \le c_i \le C.$ Therefore, X_{ij} is not compulsorily 0 or 1 but $0 \; \le \; x\_(X_{ij}\,) \le \; 1$ provided there are numerous categories jth indicator and a household have a characteristic with an intensity. The multidimensional poverty ratio ($\mu_B(a_i)$)) which highlights the welfare level of deprivation and membership to set B is defined as the weighted average of X_{ij},

$$\mu_B(a_i) = \sum_{j=1}^{m} X_{ij} w_j / \sum_{j=1}^{m} w_j \qquad 5.8b$$

Where:

w_j is the weight attached to the jth characteristic. The intensity of deprivation with respect to X_j is measured by the weight w_j. It is an inverse function of the degree of deprivation and the smaller the number of households and the amount of their deprivation, the bigger the weight. In practice, a weight that justifies the above material goods was proposed by Cerioli and Zani (1990). This can be expressed as:

$$w_j = \left[log \sum_{i=1}^{n} g\ (a_i)/\sum_{i=1}^{n} X_{ij}\ g(a_i)\right] \geq 0 \qquad 5.9$$

First, $g\ (a_i)/\sum_{i=1}^{n} g\ (a_i) > 0$ and $g\ (a_i)/\sum_{i=1}^{n} g\ (a_i)$ is the relative frequency represented by the sample observation a_i in the total population. Therefore when $X_{ij} = 0$, the welfare characteristic is to be removed.

The poverty ratio of the population μ_B is obtained as a weighted average of the poverty ratio of the ith household $\mu_B(a_i)$

$$\mu_B = \sum_{i=1}^{n} \mu_B\ (a_i) g(a_i)/\sum_{i=1}^{n} g\ (a_i) \qquad 5.10$$

Equally,

$$\mu_B(X_j) = \sum_{i=1}^{n} x_{ij} g\ (a)/\sum_{i=1}^{n} g\ (a_i) \qquad 5.11$$

In this way it is possible to decompose the multidimensional poverty ratio of the population μ_B as the weighted average of $\mu_B(X_j)$, with weight w_j

$$\mu_B = \sum_{i=1}^{n} \mu_B(a_i) g(a_i)/\sum_{i=1}^{n} g\ (a_i) = \sum_{i=1}^{n} \mu_B\ (X_j) w_{j/} \sum_{i=1}^{n} w_j \qquad 5.12$$

Sub-group decomposition is done across households' geographical, racial, and socioeconomic characteristics. There are several ways of dealing with inequality in multidimensional poverty indices by using multidimensional poverty Gini index proposed by Mussard and Alperin (2006). The widely applied approach is that of Sen (1976) with the Gini index of poverty gap ratio that is a fundamental component of Sen's poverty index. From equation (5.12), the dimension that tends to increase the level of poverty of each household can be determined by decomposition of the household poverty index:

$$\mu_B(a_i) = \sum_{j=1}^{m} y_{ij} \qquad 5.13$$

Where: y_{ij} is the contribution of the jth characteristic to the overall quantity of the household poverty index $\mu_B(a_i)$:

$$y_{ij} = X_{ij} w_j/\sum_{j=1}^{m} w_j \qquad 5.14$$

Following Mussard and Pi Alperin (2005), multidimensional poverty indices can be decomposed by sub-population. Assuming that the total economic surface is divided into K groups, S_k of size n_k (k=1,…,K). The intensity of poverty of the ith household of S_k is given as:

$$\mu_B(a_i^k) = \frac{\sum_{j=1}^{m} x_{ij}^{k} w_j}{\sum_{j=1}^{m} w_j} \quad 5.15$$

Where X_{ij}^k is the degree of membership related to the fuzzy sub-set B of the i-th household ($i = 1, \ldots, n$) of S_k with respect to the j-th characteristic (j=1,…,m). Hence, the fuzzy poverty index associated with group S_k is:

$$\mu_B^k = \frac{\sum_{j=1}^{nk} \mu_B\left(a_i^k\right) g(a_i^k)}{\sum_{j=1}^{nk} g(a_i^k)} \quad 5.16$$

Following equation (5.14), the overall poverty index can be computed as a weighted average of the poverty within each group:

$$\mu_B = \frac{\sum_{k=1}^{k} \sum_{j=1}^{nk} \mu_B\left(a_i^k\right) g(a_i^k)}{\sum_{j=1}^{nk} g(a_i)} \quad 5.17$$

Therefore, the contribution of the $k-th$ group to the global index of poverty is:

$$C_{\mu_B}^k = \frac{\sum_{j=1}^{nk} \mu_B\left(a_i^k\right) g(a_i^k)}{\sum_{j=1}^{nk} g(a_i)} \quad 5.18$$

5.7 Tobit Regression Model of the Determinants of Child's MPI

The third objective was analyzed using Tobit regression model. The Tobit regression model was employed to quantify the factors affecting child's multidimensional welfare indicators and is specified in the equation below:

$$Y^* = \emptyset_0 + \varphi_{kj} \sum_{k=1}^{d} X_{ij} + e_i \quad 5.19$$

Y^* = 0 if y ≤ 0, y = Y* if y > 0

Y* = Multidimensional poverty

βs = estimated parameter or coefficient

ei = error term and is normally distributed with zero mean and constant variance.

*X*i= explanatory variables which are difficulty with seeing (yes = 1, 0 otherwise), difficulty with hearing, (yes = 1, 0 otherwise), difficulty with walking (yes = 1, 0 otherwise), difficulty with remembering (yes = 1, 0 otherwise), difficulty with selfcare (yes = 1, 0 otherwise), difficulty with communication (yes = 1, 0 otherwise), Eastern Cape (yes = 1, 0 otherwise), Northern Cape (yes = 1, 0 otherwise), Free State (yes = 1, 0 otherwise), KwaZulu-Natal (yes = 1, 0 otherwise), North West (yes = 1, 0 otherwise), Gauteng (yes = 1, 0 otherwise), Mpumalanga (yes = 1, 0 otherwise), Limpopo (yes = 1, 0 otherwise), child's gender (male = 1, 0 otherwise), child age (years), coloured (yes = 1, 0 otherwise), Indian/Asian (yes = 1, 0 otherwise), White (yes = 1, 0 otherwise), son or daughter of household's head (yes = 1, 0 otherwise), father alive (yes = 1, 0 otherwise), father part of household (yes = 1, 0 otherwise), mother alive (yes = 1, 0 otherwise); mother part of household (yes = 1, 0 otherwise), domestic worker service (yes = 1, 0 otherwise), household size, traditional area (yes = 1, 0 otherwise), farms (yes = 1, 0 otherwise), salaries/wages commission (yes = 1, 0 otherwise), Income from business (yes = 1, 0 otherwise), pensions (yes = 1, 0 otherwise), grants (yes = 1, 0 otherwise), social grants (yes = 1, 0 otherwise), sales of farming products/service (yes = 1, 0 otherwise), other income sources (yes = 1, 0 otherwise), backyard garden (yes = 1, 0 otherwise), school garden (yes = 1, 0 otherwise), and communal garden (yes = 1, 0 otherwise).

5.8 Child's Health Outcomes

We used the z-score to compute three indicators of child's health outcomes. These are wasting, stunting and underweight. The z-score can be expressed as:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \qquad 5.20$$

In equation 5.20, i denotes individual child and j refers to the health outcome indicators (j = 1, 2, 3) with Z_1 being the height-for-age z-score, Z_2 is the weight-for-height z-score, and Z_3 = weight-for-age z-score. In addition, X_{ij} is the observed value for the ith child, μ is the mean value for reference group and σ is the standard deviation for reference group. Conventionally, a cut-off point of -2 standard deviation is the most adopted cut off for all nutrition indicators. Consequently, children with weight-for-height z-scores less than -2 standard deviation WHO Child Growth Standards median are wasting, those with weight-for-age z-scores less than -2 standard deviation WHO Child Growth Standards median are underweight and those with height-for-age z-scores less than -2 standard deviation WHO Child Growth Standards median are stunting. The z-scores were generated using the procedures provided by the *zscore06* command invoked in STATA 17 software. The determinants of child's health outcomes were analyzed with logistic regression. This model is implemented with binary response variable. The model is advantageous for being able to utilize ordinal and continuous independent variables (Sperandei, 2014). Logistic regression model analyses the chance of obtaining a particular outcome given the child's, maternal and household's characteristics. The general equation can be specified as:

$$log\left(\frac{\pi}{1-\pi}\right) = \gamma_0 + \beta_{kj} \sum_{k=1}^{d} X_{ij} + e_i \qquad 5.21$$

In equation 5.21, π is the probability of a particular child's health outcome and β_{kj} are the reference group's estimated parameters given the explanatory variables X_{ij}. The explanatory variables are currently breastfeeding (yes = 1, 0 otherwise), gave child juice (yes = 1, 0 otherwise), gave child coke (yes = 1, 0 otherwise), gave child butter (yes = 1, 0 otherwise), gave child chocolate (yes = 1, 0 otherwise), gave child snacks (yes = 1, 0 otherwise), gave child grain, root and tuber (yes = 1, 0 otherwise), gave child legumes and nuts (yes = 1, 0 otherwise), gave child meats or flesh, gave child eggs (yes = 1, 0 otherwise), gave child vitamin A fruits and vegetables (yes = 1, 0 otherwise), gave child milk and dairy products (yes = 1, 0 otherwise), gave child fruits and vegetables, child discharged same time with mother (yes = 1, 0 otherwise), gender of child (male = 1, 0 otherwise), covered by health insurance (yes = 1, 0 otherwise), mother working (yes = 1, 0 otherwise), provinces (Western Cape [yes = 1, 0 otherwise], Eastern Cape [yes = 1, 0 otherwise], Northern Cape [yes = 1, 0 otherwise], Free States [yes = 1, 0 otherwise], KwaZulu Natal [yes = 1, 0 otherwise], North West [yes = 1, 0 otherwise], Gauteng [yes = 1, 0 otherwise], Mpumalanga [yes = 1, 0 otherwise] and Limpopo [yes = 1, 0 otherwise]), shared toilet (yes = 1, 0 otherwise), child's birth weight, household's wealth index, mother's years of education, and number of living children.

5.9 Multidimensional Pro-Poor Growth Analysis

5.9.1 Non-income Growth Incidence Curve

The Grosse et al. (2005) NIGIC approach was used for objective four. By focusing on the lower tails of income distribution growth rates of the poor can be investigated whether growth is pro-poor and to what extent is growth pro-poor. The GIC approach used by Ravallion and Chen (2003) shows the mean growth rate $g_t$in income y at each centile p of the distribution between two points in time, t-1 and t. The GIC links the growth rates into one curve, and it is given by:

$$GIC: g_t(p) = \frac{y_t(p)}{y_t-1(p)} - 1 \qquad 5.22$$

The GIC plots the population centiles from 1-100 ranked by income on the horizontal axis and the annual per capita growth rate in income on the vertical axis. When GIC is above 0 for all centiles i.e., gt (p) > 0 for all p, it indicates weak absolute pro-poor growth. When the GIC is negatively sloped then it is assumed that there is relative pro-poor growth. Ravallion and Chen (2003) refer to pro-poor growth rate (PPGR) as the area under the GIC up to the headcount ratio (H). This PPGR is expressed by:

$$PPGR = g_t^p = \frac{1}{H_{t-1}} \int_0^{H_t} g_t(p)dp \qquad 5.23$$

This is equivalent to the mean growth rates of the poor till the headcount. The process involved in assessing poverty is comparing PPGR with the growth rate in mean (GRIM). The GRIM is given by:

$$GRIM = \gamma_t = \frac{\mu_t}{\mu_{t-1}} - 1 \qquad 5.24$$

Where μ is the mean income. When the PPGR transcends the GRIM growth is acknowledged to be relative. Researchers are to concentrate on the absolute changes of income of population centiles between two periods when examining pro-poor growth in the strong absolute sense. Absolute GIC or change incidence curve (CHIC) is given by:

$$CHIC: c_t(p) = y_t(p) - y_{t-1}(p) \qquad 5.25$$

This links absolute changes for each centile into one curve. The absolute GIC plots population centiles on the horizontal axis and the annual per capita changes in income on the vertical axis; this is done by comparing two periods. When experiencing a negatively sloped GIC there is strong absolute pro-poor growth. From the absolute GIC pro-poor change (PPCH) is defined as the area below the absolute GIC till the headcount (H). The PPCH is given by:

$$PPCH = c_t^p = \frac{1}{H_{t-1}} \sum_1^{H_t} c_t(p) \qquad 5.26$$

This is equivalent to the mean of the changes of those who are poor till the headcount (H). The PPCH is then compared with the change in mean (CHIM) which is expressed as:

$$CHIM = \delta_t = \mu_t - \mu_{t-1} \qquad 5.27$$

When the PPCH exceeds CHIM, growth is pro-poor in the strong absolute sense. Following Grosse et al. (2004), they declared that the non-income growth incidence curve (NIGIC) follows the GIC concept. However, non-income indicators were measured in a distinct manner rather than on a continuous manner.

5.9.2. Poverty Equivalent Growth Rate (PEGR)

To measure growth benefits and how they are distributed across the population, φ and φ* are the two indices of pro-poor growth used. On the other hand, these two indices are not enough to determine all changes in poverty. An indicator that takes the growth rate in mean income as well as the distribution of benefits from growth is required. As a result, the PEGR is employed. It is the growth rate γ* that can result in the same proportional change in poverty in poverty like the current growth rate γ when the growth process is not perfected by any change in relative inequality. This suggests that everyone in society obtains the same proportional benefits of growth. Hence, the definite proportional change in poverty is given by δγ where δ is the growth elasticity of poverty. Once inequality does not change, then the growth rate γ* can experience a proportional change in poverty equal to ηγ* which should be equal to δγ. Therefore, PEGR represented by γ* is given by:

$$\gamma^* = \left(\frac{\delta}{n}\right) \gamma = \varphi\gamma \qquad 5.28$$

Which can also be presented as:

$$\gamma^* = \frac{\int_0^H \frac{\partial P}{\partial x} x(p)g(p)dp}{\int_0^H \frac{\partial P}{\partial x} x(p)dp} \quad 5.29$$

This shows that PEGR is the weighted average of growth rates of income at each percentile point, with the weight depending on the poverty approach/measure that is applied (Foster et al. 1984). The PEGR is given by:

$$\gamma_\alpha^* = \int_0^H \left(\frac{z-x(p)}{z}\right)^{\alpha-1} x(p)g(p)dp \Bigg/ \int_0^H \left(\frac{z-x(p)}{z}\right)^{\alpha-1} x(p)dp \; for \; \alpha \geq 1 \quad 5.30$$

The PEGR for the Watts measure is attained by substituting $P\ (z; x) = Ln(z) - Ln(x)$ into equation 37 and it can be defined as: $\gamma_w^* = \frac{1}{H}\int_0^H g(p)dp$. This is the PPGI proposed by Ravallion and Chen (2003). Since η is always negative, equation 37 implies that if $\varphi\gamma$ is negative (positive) γ^* might be positive (negative). Equally, PEGR is constant with the direction of change in poverty i.e., a positive value of the PEGR means reduction in poverty, vice versa. This approach therefore satisfies the basic requirement that poverty reduction should be monotonically increasing function of PEGR. Maximization of PEGR means reduction in poverty. The higher the PEGR, the greater the reduction in poverty (Kakwani and Son, 2008). For that reason, PEGR is the effective and relevant measure of pro-poor growth.

After this, it should be examined if growth is pro-poor or not. To do so we present:

$$\gamma^* = \gamma + (\varphi - 1)\gamma \quad 5.31$$

As mentioned earlier, when γ>0 and φ>1 or when γ<0 and φ<1 growth is in relative sense. These situations means that the second term in the right-hand side of γ^*=γ+(φ-1) γ is positive. Therefore, when γ^*>γ growth will be pro-poor in relative sense.

Regarding measurement of pro-poor growth in absolute sense, γ^*=γ+(φ-1) γ is written as:

γ^*=γ [1+ (φ-φ^*)] + (φ^*-1) γ 5.32

Growth is pro-poor in absolute sense when $\gamma > 0$ and $\varphi^* > 1$ or when $\gamma < 0$ and $\varphi^* < 1$. These situations means that the second term in the right side of $\gamma^* = \gamma[1 + (\varphi-]$is positive. Therefore, growth is absolute in the absolute sense. Since $\varphi > \varphi^*$ always holds, pro-poor growth in the absolute sense will always mean pro-poor growth in the relative sense however, not the other way round (Kakwani and Son, 2008). This shows that pro-poor growth in the absolute sense is a much robust requirement compared to relative pro-poor growth. According to Kakwani and Son (2008) the absolute pattern of pro-poor growth will result in a quick reduction in poverty compared to the relative growth when the mean income experiences the same growth rate. According to Ravallion and Chen's (2003) definition of pro-poor growth which is satisfied when $\gamma^* > 0$. When growth rate $\gamma > 0$ then $\gamma^* > \gamma$ will always mean $\gamma^* > 0$. Therefore, relative pro-poor growth will always mean a poverty reducing pro-poor growth. When using the same reasoning, it can be demonstrated that poverty reducing pro-poor growth is a stronger requirement compared to the absolute pro- poor growth when the growth rate in mean income becomes negative (Kakwani and Son, 2008).

CHAPTER SIX
CHILDREN'S DEMOGRAPHIC CHARACTERISTICS AND WELFARE ATTRIBUTES' DEPRIVATIONS

6.1. Introduction

This chapter presents the selected demographic characteristics of the sampled children. The chapter also presents the results on the distribution of child's welfare attributes' deprivations.

6.2. Selected Child's Demographic Characteristics

The results presented in Table 6.1 show the selected demographic characteristics of the children in 2017, 2018, 2019 and in the combined data. Across the provinces, the results showed that in 2017, 2018, 2019 and in the combined data, KZN had the highest number of children with 19.1%, 19.4%, 20.1%, respectively. These were followed by Gauteng (18.8%, 18.5%, 19.7% and 19.0% in 2017, 2018, 2019 and in the combined dataset, respectively. The Eastern Cape (EC) was the third province with the largest number of respondents with 15.0%, 14.6%, 14.8% and 14.8% in 2017, 2018, 2019 and in the combined dataset, respectively. The Limpopo (LP) province had 13.1%, 13.4%, 11.0% and 12.6% of the respondents in 2017, 2018, 2019 and in the combined dataset, respectively. Mpumalanga had 9.3%, 9.3%, 9.6% and 9.4% respondents in 2017, 2018, 2019 and combined dataset, respectively. The Northern Cape had the least number of respondents with 4.7%, 4.8%, 4.9% and 4.8% in 2017, 2018, 2019 and in the combined dataset, respectively. These results are related to the Stats SA's (2019) and Stats SA (2021) population estimates which revealed that the Northern Cape continues to be the province with the lowest proportion of South African children. However, Hall (2022) revealed the KZN, EC and LP provinces are the top three provinces to accommodate most South African children. Hall (2022) also revealed that the Gauteng province has 50% of the children's population since 2022, making it the province with the highest number of children.

Across the years, male children were slightly higher than female children with 50.4%, 50.1% and 51.4% in 2017, 2018 and 2019, respectively. The results of this study relate to those of the Stats SA's (2020) recording of births that showed male children to be more than female children in South Africa. However, Hall (2022) found the number of female children to be equal to that of male children. In Botswana, Lekobane and Roelen (2020) found that male children were more than female children in their samples. The finding of this study is related to that of Fransman and Yu (2018) and Mdluli (2015).

Based on the gender of households' heads in South Africa. the results showed similar results for the gender of children. Male headed households were more in number compared to their female headed counterparts. In 2017 there were 54.4% male-headed households, which slightly increased to 54.90% in 2018. In 2019, this percentage slightly declined to 53.3. These results are related to those of Stats SA (2021) that indicated that 42.1% of households were female-headed.

This study also observed the households' heads age groups. It was found that in 2017, 2018 and the combined dataset, the 30<35 age group had the highest number of respondents with 12.2%, 12.3% and 12.4, respectively. However, in 2019 the 30<35 age group had the second largest respondents. A study conducted by Nedombeloni and Oyekale (2015) revealed that majority of households heads in a rural area in South Africa were in the 40<50 years age group, while the <30 years had the lowest value.

The results also showed that across all the datasets, majority of the sampled children were Black. In 2017, Blacks children constituted 87.6%, compared 88.1% and 87.8% in 2018 and 2019, respectively. Table 6.1 further shows that most of the sampled children had their fathers being alive. However, majority of those living fathers were not part of the household. Specifically, in 2017, 86.8% of the children had their fathers alive, which can be compared to 31.5% who indicated to be residing in the same household with their children. In 2018, 87.2% of the children had their fathers being alive, and 30.7% of the children were residing with their fathers in the same household. The dataset for 2019 shows that 84.3% of sampled children had their fathers alive and 13.6% did not. The findings further reveal that only 31.1% of the children had their fathers being were part of their household. The combined data shows that 86.2% of the children had living fathers, while 31.1% had their fathers being part of their households.

The presence of mothers in the households was also probed by the questionnaire. The results showed that 93.6%, 93.9%, 92.3% and 93.3% of the children had living mothers in 2017, 2018, 2019 and the combined dataset, respectively. However, 70.9%, 71.0%, 68.7% and 70.3% of the children had their mothers residing with them in the same households. The results of this study are in line with those of the Stats SA (2022) which revealed that majority of South African children (93%) have both their mothers and fathers alive, from this 93% of children with both parents alive only 36% of them reside with both the mother and the father, 43% of them reside in the same household with as their mothers and only 2% of these children reside in the same household as their fathers. Lekobane and Roelen (2020) also revealed that majority of children in Botswana had both parents especially the mothers and stay in the same households with their mothers. In addition, Madhavan et al. (2008) mentioned that when a parent is absent in their children's lives, it does not necessarily imply that they have abandoned their children because majority of them are providing support to these children although they reside elsewhere. Moreover, these parents may be away looking for employment so that they could meet the children's basic needs such as education, health, clothing, among others.

The Table further shows that majority of the sampled children's households had between 4<6, 2<4 and 6<9 members while the lowest percentages were in those households with ≥19 17<19 and 15<17 members in a household. Specifically, 4<6 members category had 32.8%, 32.6%, 32.4% and 32.6% respondents in 2017, 2018, 2019 and the combined data, respectively. The 2<4 members had 30.5%, 31.1%, 30.25 and 30.6% respondents in 2017, 2018, 2019 and combined dataset, respectively. Large family sizes are indisputably related to poverty (Stats SA 2021; Anyanwu, 2013; Bradshaw et al. 2006; Fransman and Yu, 2018).

The results further showed that across all the dataset observed, majority of the children resided in urban areas, followed by traditional areas and farms. In 2017, the children from urban areas constituted 54.1%, compared to 42.2% from traditional areas and 3.5% from farms. In 2018, there were 53.9% children from urban areas, 42.6% from traditional areas, and 3.4% from farms. In 2019, 55.8% of the children resided in urban areas, 41.15% were in traditional areas and 3.1% were in farms. It was further revealed that 54.5% of the children resided in urban areas, 42.1% were from traditional areas, and 3.4% were residing in farms in the combined data. The results are contrary to those of Hall (2022) on children in South Africa, who revealed that the largest proportion of children in South Africa were residing in rural areas.

The results further revealed that only 18.4%, 17.4%, 22.6% and 19.3% of the children were from households where no one received grants in 2017, 2018, 2019 and the combined data, respectively. Regarding children that were receiving social grants, the results of this study revealed that 71.5%, 72.6%, 71.9% and 72.0% of the sampled children were not receiving social grants in 2017, 2018, 2019 and the combined data, respectively. The findings also showed that 79%, 79.7%, 80.5% and 79.7% of the children did not have backyard gardens in their households in 2017, 208, 2019 and combined data, respectively.

Table 6.1. Child's Selected Demographic Characteristics

Characteristics		2017		2018		2019		All	
		Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Province	Western Cape	1990	7.7	1989	7.9	1450	7.0	5429	7.6
	Eastern Cape	3900	15.0	3689	14.6	3050	14.8	10639	14.8
	Northern Cape	1211	4.7	1207	4.8	1016	4.9	3434	4.8
	Free State	1566	6.0	1510	6.0	1246	6.1	4322	6.0
	KwaZulu Natal	4944	19.1	4898	19.4	4141	20.1	13983	19.5
	Northern Western	1615	6.2	1519	6.0	1368	6.6	4502	6.3
	Gauteng	4883	18.8	4674	18.5	4052	19.7	13609	19.0
	Mpumalanga	2400	9.3	2346	9.3	1985	9.6	6731	9.4
	Limpopo	3406	13.1	3392	13.4	2264	11.0	9062	12.6
Child gender	Male	13049	50.4	12643	50.1	10570	51.4	36262	50.6
	Female	12866	49.6	12581	49.9	10002	48.6	35449	49.4
Household Head gender	Female	14100	54.4	13843	54.9	10972	53.3	39404	54.3
	Male	11815	45.6	11381	45.1	20572	44.3	32307	45.1
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0

Source: Own Computation, 2022

Table 6.1. Child's Selected Demographic Characteristics Cont.

HH head Age group	<15	2702	10.4	2517	10.0	981	4.8	6200	8.6
	15<20	2916	11.3	2737	10.9	2234	10.9	7887	11.0
	20<25	2978	11.5	2961	11.7	2472	12.0	8411	11.7
	25<30	3041	11.7	2924	11.6	2499	12.1	8464	11.8
	30<35	3173	12.2	3109	12.3	2608	12.7	8890	12.4
	35<40	3000	11.6	2992	11.9	2659	12.9	8651	12.1
	40<45	2878	11.1	2942	11.7	2523	12.3	8343	11.6
	45<50	2465	9.5	2545	10.1	2412	11.7	7422	10.3
	50<55	2762	10.7	2497	9.9	2184	10.6	7443	10.4
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Population group	Black/African	22702	87.6	22212	88.1	18084	87.9	62998	87.8
	Coloured	2204	8.5	2085	8.3	1650	8.0	5939	8.3
	Indian/Asian	253	1.0	250	1.0	225	1.1	728	1.0
	White	756	2.9	677	2.7	613	3.0	2046	2.9
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Father alive	No	2952	11.4	2748	10.9	2794	13.6	8494	11.8
	Yes	22488	86.8	21985	87.2	17341	84.3	61814	86.2
	Do not know	475	1.8	491	1.9	437	2.1	1403	2.0
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0

Table 6.1. Child's Selected Demographic Characteristics Cont.

Father part of the household	No	17746	68.5	17489	69.3	14166	68.9	49401	68.9
	Yes	8169	31.5	7735	30.7	6406	31.1	22310	31.1
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Mother alive	No	1578	6.1	1442	5.7	1527	7.4	4547	6.3
	Yes	24251	93.6	23684	93.9	18986	92.3	66921	93.3
	Do not know	86	0.3	98	0.4	59	0.3	243	0.3
Total		25915	100.0	25224	100.0	20572	100.0	71711	100.0
Mother part of the household	No	7543	29.1	7306	29.0	6441	31.3	21290	29.7
	Yes	18372	70.9	17918	71.0	14131	68.7	50421	70.3
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Household size group	<2	855	3.3	823	3.3	724	3.5	2402	3.3
	2<4	7914	30.5	7843	31.1	6222	30.2	21979	30.6
	4<6	8506	32.8	8226	32.6	6656	32.4	23388	32.6
	6<9	4681	18.1	4228	16.8	3689	17.9	12598	17.6
	9<11	2571	9.9	2721	10.8	1740	8.5	7032	9.8
	11<13	663	2.6	687	2.7	858	4.2	2208	3.1
	13<15	410	1.6	411	1.6	408	2.0	1229	1.7
	15<17	173	0.7	132	0.5	161	0.8	466	0.6
	17<19	90	0.3	58	0.2	67	0.3	215	0.3
	≥19	52	0.2	95	0.4	47	0.2	194	0.3
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0

Table 6.1. Child's Selected Demographic Characteristics Cont.

Geographical type	Urban	14019	54.1	13607	53.9	11477	55.8	39103	54.5
	Traditional	10992	42.4	10753	42.6	8454	41.1	30199	42.1
	Farms	904	3.5	864	3.4	641	3.1	2409	3.4
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Grants	No	4777	18.4	4383	17.4	4656	22.6	13816	19.3
	Yes	21138	81.6	20841	82.6	15916	77.4	57895	80.7
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Social grants	No	18542	71.5	18317	72.6	14797	71.9	51656	72.0
	Yes	7373	28.5	6907	27.4	5775	28.1	20055	28.0
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Backyard garden	No	20467	79.0	20096	79.7	16564	80.5	57127	79.7
	Yes	5448	21.0	5128	20.3	4008	19.5	14584	20.3
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
School garden	No	25890	99.9	25198	99.9	20538	99.8	71626	99.9
	Yes	25	0.1	26	0.1	34	0.2	85	0.1
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0
Communal garden	No	25845	99.7	25130	99.6	20478	99.5	71453	99.6
	Yes	70	0.3	94	0.4	94	0.5	258	0.4
	Total	25915	100.0	25224	100.0	20572	100.0	71711	100.0

Source: Own Computation, 2022

Table 6.2: Distribution of assets in children's households across the datasets

Assets	2017		2018		2019		All	
	Freq	%	Freq	%	Freq	%	Freq	%
Ownership of motor								
Yes	6223	24.0	6047	24.0	5129	24.9	17399	23.0
No	19692	76.0	19177	76.0	15443	75.1	54312	71.8
Radio ownership								
Yes	13426	51.8	13274	52.6	7548	36.7	34248	45.3
No	12489	48.2	11950	47.4	13024	63.3	37463	49.5
TV set								
Yes	22278	86.0	21809	86.5	18106	88.0	62193	82.2
No	3637	14.0	3415	13.5	2466	12.0	9518	12.6
Swimming pool								
Yes	603	2.3	480	1.9	467	2.3	1550	2.0
No	25312	97.7	24744	98.1	20105	97.7	70161	92.7
DVD player								
Yes	13355	51.5	12237	48.5	9077	44.1	34669	45.8
No	12560	48.5	12987	51.5	11495	55.9	37042	49.0
Pay TV								
Yes	11078	42.7	12057	47.8	11232	54.6	34367	45.4
No	14837	57.3	13167	52.2	9340	45.4	37344	49.4
Air conditioner								
Yes	832	3.2	718	2.8	632	3.1	2182	2.9
No	25083	96.8	24506	97.2	19940	96.9	69529	91.9
Computer/Laptop								
Yes	3994	15.4	3716	14.7	3328	16.2	11038	14.6
No	21921	84.6	21508	85.3	17244	83.8	60673	80.2
Vacuum cleaner								
Yes	1595	6.2	1414	5.6	1199	5.8	4208	5.6
No	24320	93.8	23810	94.4	19373	94.2	67503	89.2
Dish washing machine								
Yes	1004	3.9	820	3.3	516	2.5	2340	3.1
No	24911	96.1	24404	96.7	20056	97.5	69371	91.7
Washing machine								
Yes	8881	34.3	8722	34.6	8067	39.2	25670	33.9
No	17034	65.7	16502	65.4	12505	60.8	46041	60.8
Tumble dryer								
Yes	1620	6.3	1394	5.5	1002	4.9	4016	5.3
No	24295	93.7	23830	94.5	19570	95.1	67695	89.5
Deep freezer								
Yes	5999	23.1	5721	22.7	4863	23.6	16583	21.9
No	19916	76.9	19503	77.3	15709	76.4	55128	72.9
Refrigerator/combined								
Yes	20535	79.2	20221	80.2	17080	83.0	57836	76.4
No	5380	20.8	5003	19.8	3492	17.0	13875	18.3
Electric stove								
Yes	23011	88.8	22571	89.5	18703	90.9	64285	85.0
No	2904	11.2	2653	10.5	1869	9.1	7426	9.8

Source: Own Computation, 2022. Freq=Frequency, %= Percentage

Table 6.2: Distribution of assets in children's households across the datasets Cont.

Microwave oven								
Yes	14501	56.0	14445	57.3	12133	59.0	41079	54.3
No	11414	44.0	10779	42.7	8439	41.0	30632	40.5
Built-in kitchen sink								
Yes	8267	31.9	7991	31.7	7067	34.4	23325	30.8
No	17648	68.1	17233	68.3	13505	65.6	48386	63.9
Home security service								
Yes	1529	5.9	1241	4.9	1126	5.5	3896	5.1
No	24386	94.1	23983	95.1	19446	94.5	67815	89.6
Home theatre system								
Yes	3347	12.9	3095	12.3	2348	11.4	8790	11.6
No	22568	87.1	22129	87.7	18224	88.6	62921	83.2
Geyser providing hot								
Yes	4534	17.5	4186	16.6	3581	17.4	12301	16.3
No	21381	82.5	21038	83.4	16991	82.6	59410	78.5
Solar hot water geyser								
Yes	721	2.8	670	2.7	655	3.2	2046	2.7
No	25194	97.2	24554	97.3	19917	96.8	69665	92.1

Source: Own Computation, 2022, Freq=Frequency,%= Percentage

6.2 Distribution of Welfare Attributes Across the Years

6.2.1. Distribution of assets indicators across datasets

This section seeks to fulfil the first objective of the study. Table 6.2 presents the distribution of assets in 2017, 2018, 2019 and the combined dataset. It reveals that 24.0% of the children's households were owning a motor vehicle in 2017 and 2018. In 2019, 24.9% owned motor vehicles. It was further revealed that 51.8%, 52.6%, 36.7% and 45.3% households owned radios in 2017, 2018, 2019 and combined dataset, respectively. The results further revealed that majority of the households owned TV sets with 86.0%, 86.5%, 88.0% and 82.2% in 2017, 2018, 2019 and combined data, respectively. The results also showed that majority of the South African children's households did not own a swimming pool with 97.7%, 98.1%, 97.7% and 92.7 in 2017, 2018, 2019 and combined data, respectively.

In 2017, 51.5% of children's households owned a DVD player, which declined to 48.5% in 2018. In 2019, DVD player was owned by 44.1% of the children's households. It was further revealed that 57.3% of the children's households in 2017 were paying for TV subscriptions such as DSTV, while 47.8%, 54.6% and 45.4% were not paying for any TV subscriptions in 2018, 2019 and the combined data, respectively. Households that owned air conditioner were 42.7%, 47.8%, 54.6%

and 45.4% in 2017, 2018, 2019 and combined data, respectively. It was also revealed that majority of the households did not own a computer/laptop. The household that did not own computer/laptop were 84.6%, 85.3%, 83.8% and 80.2% in 2017, 2018, 2019 and combined data, respectively. Majority of the households did not own a vacuum cleaner with 93.8%, 94.4%, 94.2% and 89.2% in 2017, 2018, 2019 and combined data, respectively. It was further revealed that majority of the households, with 96.1%, 96.7%, 97.5% and 91.7% did not own dish washing machine in 2017, 2018, 2019 and the combined data, respectively. Even though most of the households did not have washing machine, the numbers were decreasing through the years with 65.7%, 65.4%, 60.8% and 60.8% in 2017, 2018, 2019 and combined data, respectively. Only a few households owned a tumble dryer, 6.3%, 5.5%, 4.9% and 5.3% in 2017, 2018, 2019 and combined data, respectively.

The majority of the children's households did not own deep freezers with 76.9%, 77.3%, 76.4% and 72.9% in 2017, 2018, 2019 and combined data, respectively. The refrigerator/combined freezer was owned by 79.2%, 80.2%, 83% and 76.4% in 2017, 2018, 2019 and the combined data, respectively. The results also revealed that majority of the household owned an electric stove. It was revealed that 88.8%, 89.5%, 90.9% and 85.0% of the households were owning electric stove. The majority also owned microwave ovens at 56%, 57.3%, 59% and 54.3% in 2017, 2018, 2019 and the combined data, respectively. Built-in kitchen sink was owned by a few of the children's households with 31.9%, 31.7%, 34.4%, 30.8% in 2017, 2018, 2019 and combined data, respectively. It is revealed that most of the household did not have home security services, home theatre system, geyser and solar geyser. A study conducted by Oluwatayo (2022) on asset ownership and poverty in South Africa revealed that personal, real assets, real estate asset and financial assets were the top ranked assets owned by households in SA.

6.2.2. Distribution of nutrition/hunger indicators across datasets

Figure 6.1 presents the distribution of nutrition or hunger indicators among the children across the datasets. The results, which are presented in Figure 6.3 revealed that there was an improvement for children with households that ran out of money to buy food between 2017, 2018 and 2019 with 28.8%, 28.0% and 19.8%, respectively. In the combined data, 24.6% of the children's households ran out of food. Wills at al. (2020) in reported that 47.0% of the people interviewed reported that they ran out of money to buy food. It is revealed that a smaller number of children's households had to cut the size or skip meals with 25.5%, 23.9%, 20.7% and 22.3% in 2017, 2018, 2019 and combined data. Opperman (2022) found out that 81% of SA population is cutting down on food due to increased food prices. It is further revealed that 20.9%, 19.0%, 17.6% and 18.3% of the sampled children skipped meals and 7.7%, 7.7%, 90.4% and 29.8% of those children skipped meals for five days or more in 2017, 2018, 2019 and combined data, respectively. Naicker (2015) also revealed that 70% of South Africans skipped meals or ate the same food for days. The results of this study revealed that 25.8%, 24.9%, 24.6% and 23.8% of the sampled children were eating smaller variety of food and 85.8%, 87.1%, 86.4% and 81.9% of those children were eating smaller variety of food for five days or more in 2017, 2018, 2019 and combined data, respectively. A study conducted by Tsegay and Rusare (2014) on South Africa's hidden hunger showed that one of four people in the country suffers from hunger.

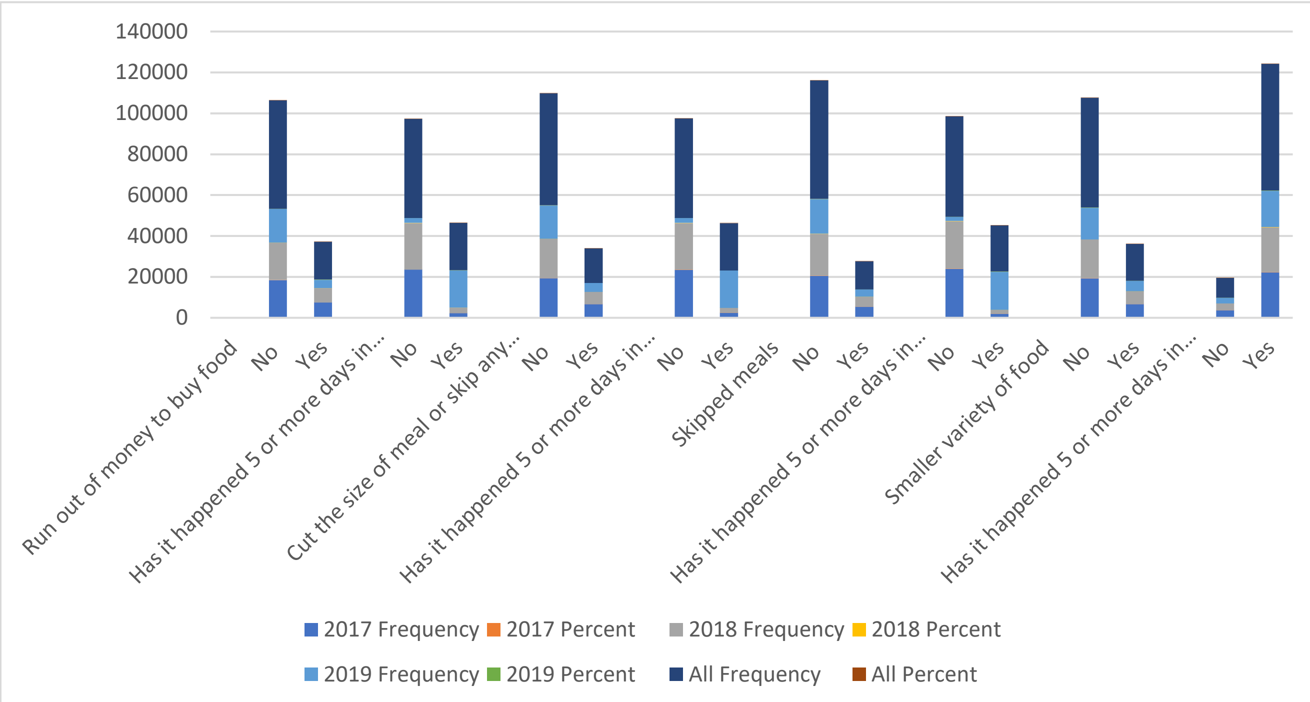

Figure 6.1: Distribution of nutrition/hunger across datasets

Source: Own Computation, 2022

6.2.3. Distribution of access to telecommunications indicators across the datasets

The results presented in Figure 6.2 shows the distribution of access to telecommunication by the sampled respondents in 2017, 2018, 2019 and combined datasets. The results revealed that majority of the sampled children did not have access to internet connection in their households in 2017, 2018, 2019 and combined data with 94.9%, 95%, 97.3% and 90.6%, respectively. It was further revealed that 97.6%, 97.6%, 98% and 92.6% of the children had access to the internet in the library/community hall in 2017, 2018, 2019 and combined data, respectively. The results further revealed that most of the children, that is, 94.4%, 94.6%, 95% and 89.7% did not have internet connections in 2017, 2018, 2019 and combined data, respectively. There were 11.3%, 10.6%, 12.4% and 10.8% respondents whom their households had access to internet. at their places of work in 2017, 2018, 2019 and combined data, respectively. The results of this study also revealed that 3.5%, 2.1%, 2.4% and 2.6% of the sampled respondents were residing in households that were less than 2km from the internet café in 2017, 2018, 2019 and combined data, respectively.

It was also revealed that 2.7%, 2.6%, 2.4% and 2.4% of the sampled respondents were residing in households that were more than 2km from the internet café. The respondents that had telephones were 4%, 3.3%, 4.8% and 3.8% in 2017, 2018, 2019 and combined data, respectively.

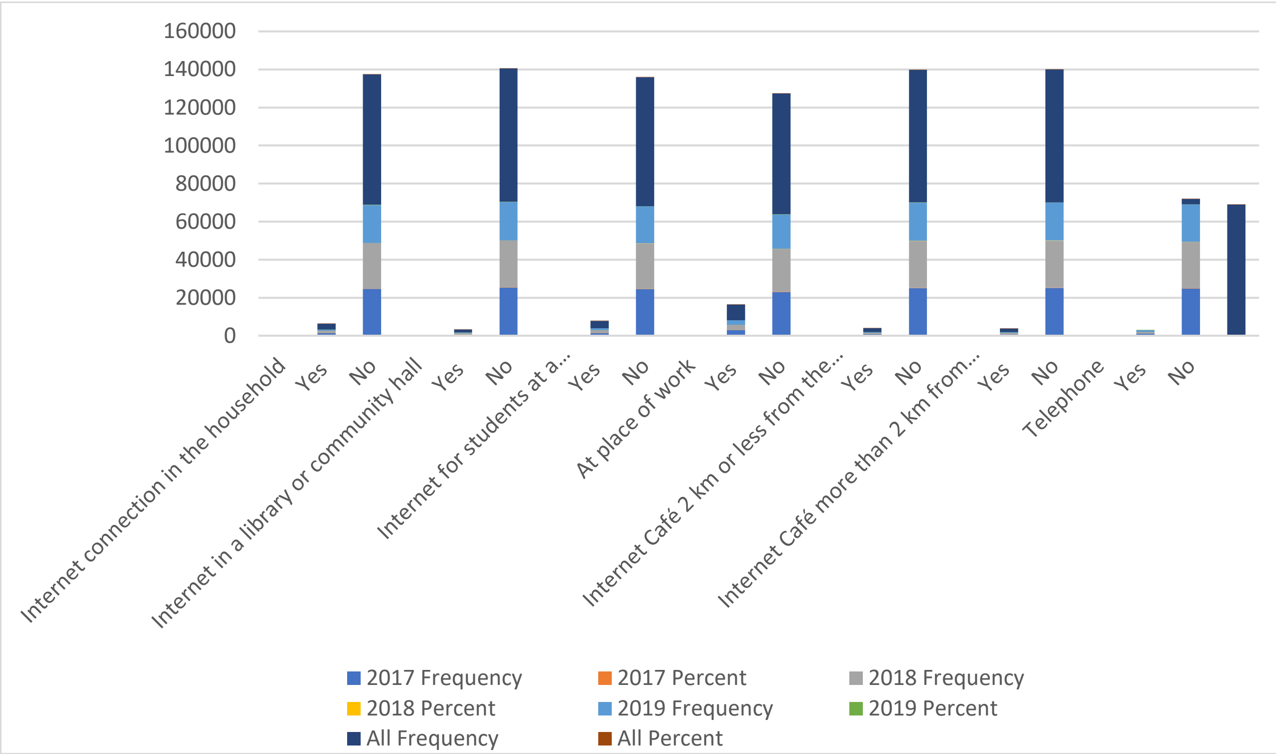

Figure 6.2: Distribution of access to telecommunications across datasets

Source: Own Computation, 2022

6.2.4 Distribution of education and health status indicators across the datasets

The results presented in Figure 6.3 show the distribution of access to education and the health status of the sampled respondents. The UNICEF (2020) mentioned that factors such as education has significant contribution to the welfare status of children. The results revealed that across most of the years, majority of the children between 0-59 months were attending ECD. The results also revealed that most of the children of school going age were attending school. Regarding the health status of children, the results revealed that majority of South African children are not covered in any medical aid schemes in 2017, 2018, 2019 and combined data, respectively with 88.2%, 89.1%, 87% and 83.6%. The findings of this study also show that the majority of the children were residing closer to health facilities as 79%, 79%, 80.3% and 75.2% of them were travelling less than 30 minutes to a health facility in 2017, 2018, 2019 and the combined data, respectively.

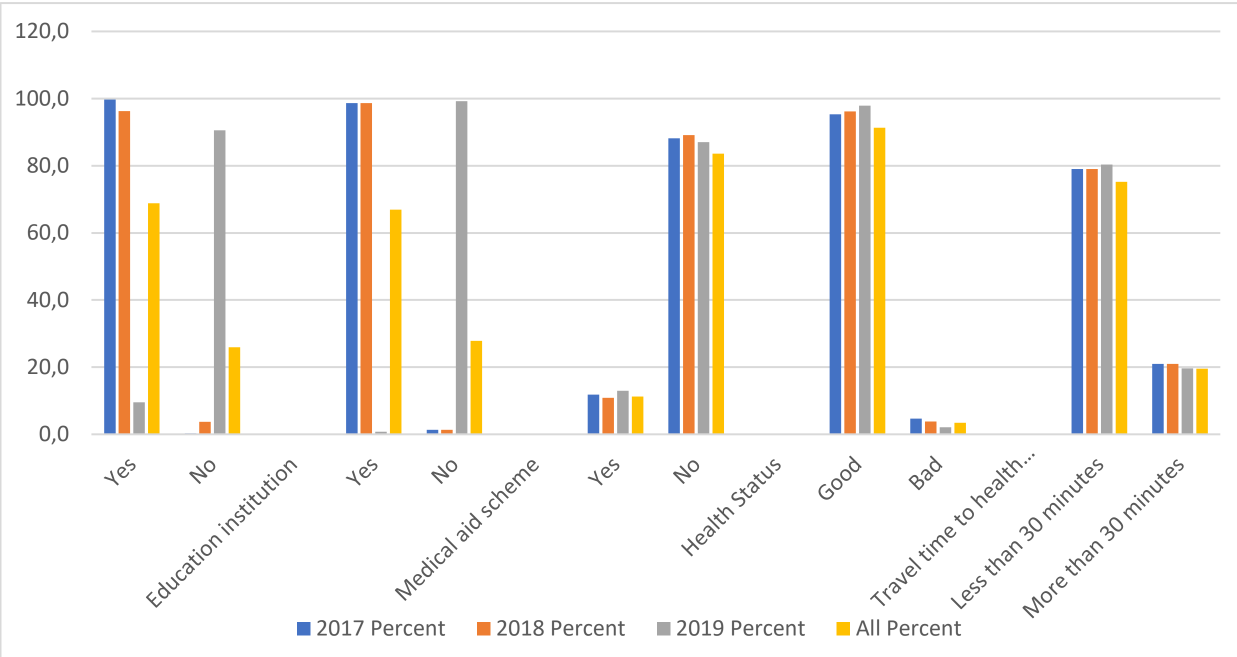

Figure 6.3: Distribution of education and health status across datasets

Source: Own Computation, 2022

6.2.5. Distribution of safety/injuries indicators across datasets

Figure 6.4 presents the distribution of safety/injuries indicators among the children in the different datasets. The results revealed that majority of the sampled children did not experience any injuries related to motor vehicle. It is shown in Figure 6.4 that 99%, 99.2%, 100% and 94.1% of children did not experience any motor vehicle related injuries as occupants in 2017, 2018, 2019 and combined data, respectively. It is also revealed that the majority of the children did not experience any injuries related to bicycle riding. Only 0.8%, 1%, 0% and 0.6% of the sampled children had gun shots wounds in 2017, 2018, 2019 and combined data, respectively. The study also revealed that there was a smaller number of children who experienced severe trauma due to violence, assault or beating, that is, 0.9%, 1%, 0% and 0.6% in 2017, 2018, 2019 and combined data, respectively. It is also revealed that most children were not affected by crime since 99.2%, 99.1%, 100% and

94.1% of them did not experience any crime related injuries in 2017, 2018, 2019 and combined data, respectively. Figure 6.4 also shows that there were 99%, 98.9%, 100% and 94.1% of children who did not have and burns or fire related injuries in 2017, 2018, 2019 and combined data, respectively. Accidental poisoning was experienced by 0.9%, 1%, 0% and 0.6% of the sampled children and intentional poising was experienced by 0.9%, 0.9%, 0% and 0.6% of the sampled respondents in 2017, 2018, 2019 and combined data, respectively. Children that did not experience any injuries related to sports were 99%, 98.9%, 99.9% and 94% in 2017, 2018, 2019 and combined data, respectively. Children who experienced other injuries were 1.8%, 1.5%, 0.1% and 1.2 in 2017, 2018, 2019 and combined data, respectively.

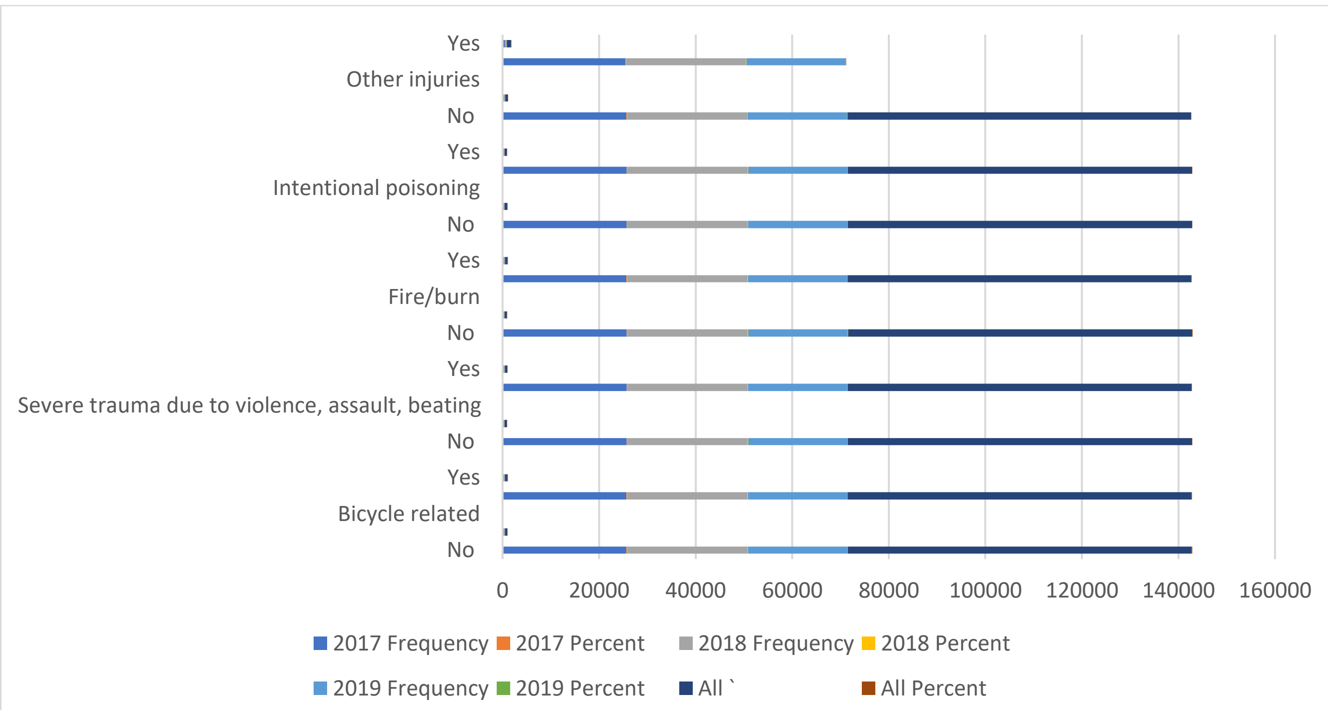

Figure 6.4. Distribution of safety/injuries across datasets

Source: Own Computation, 2022

6.2.6. Distribution of housing characteristics indicators across the datasets

The results presented in Table 6.3 revealed the distribution of housing characteristics in children's households. The results revealed that most of the sampled respondents had improved main dwelling and shows that the numbers improved across the years. It is revealed that 76.8%, 80.9%, 82.8% and 79.8% of the sampled children were residing in improved type of main dwelling, that is, a house built with bricks and cement in 2017, 2018, 2019 and combined data, respectively. The results also show that most of the children had improved wall materials with bricks and cement and the numbers of children having improved wall material were increasing through the years. It is revealed that 76.9%, 80.9%, 82.8% and 80% of the children have improved wall materials in their households in 2017, 2018, 2019 and the combined data, respectively. It is also revealed that majority of the children were residing in households with unimproved roof material such as tile, corrugated iron, asbestos, among others. There were 69.4%, 98.2%, 11.1% and 98.3% of children that did not have improved roof material in 2017, 2018, 2019 and combined data, respectively. The results also revealed that most of the children have improved floor material like tiles and cement across the years. It is also shown that 88.4%, 94.1%, 91.4% and 94% of the children were residing in households that had <2.5 persons per room in 2017, 2018, 2019 and combined data, respectively. Majority of the children had improved main source of drinking water, that is, 88.1%, 93.2%, 93.2% and 92.6% in 2017, 2018, 2019 and combined data, respectively. There were 73.9%, 98.2%, 28.3% and 97.9% of children who were residing closer to main water sources in 2017, 2018, 2019 and combined data, respectively. It is also shown that most of the children (92.1%, 97%, 97.9% and 96.8%) had improved type of toilet facility (flush) in 2017, 2018, 2019 and combined data, respectively. It is also revealed that only a few children were residing in households where a toilet is shared, there were 15.3%, 16.6%, 13.3% and 18% of children who were sharing toilets in their households in 2017, 2018, 2019 and combined data, respectively. Heijnen et al. (2014) revealed that approximately 761 million people are relying on shared sanitation facilities. Socio-Economic Rights Institute of South Africa (SERI) (2018) also mentioned that majority (68%) of South Africans share toilet facilities.

Table 6.3: Distribution of housing characteristics across datasets

	Freq	%	Freq	%	Freq	%	Freq	%
	2017		2018		2019		All	
Main dwelling								
Improved	58123	76.8	20402	80.9	17030	82.8	20691	79.8
Not improved	13588	18.0	4822	19.1	3542	17.2	5224	20.2
Wall material								
Improved	58188	76.9	20409	80.9	17038	82.8	20741	80.0
Not improved	13523	17.9	4815	19.1	3534	17.2	5174	20.0
Roof material								
Improved	19191	25.4	457	1.8	18295	88.9	439	1.7
Not improved	52520	69.4	24767	98.2	2277	11.1	25476	98.3
Type of								
Improved	62904	83.1	21928	86.9	18487	89.9	22489	86.8
Not improved	8807	11.6	3296	13.1	2085	10.1	3426	13.2
Room per								
<2.5	66893	88.4	23727	94.1	18811	91.4	24355	94.0
≥2.5	4818	6.4	1497	5.9	1761	8.6	1560	6.0
Main source of								
Improved	66677	88.1	23500	93.2	19169	93.2	24008	92.6
Not improved	5034	6.7	1724	6.8	1403	6.8	1907	7.4
Distance of								
Less than 30	55949	73.9	24763	98.2	5825	28.3	25361	97.9
More than 30	15762	20.8	461	1.8	14747	71.7	554	2.1
Type of toilet								
Improved	69694	92.1	24465	97.0	20142	97.9	25087	96.8
Not improved	2017	2.7	759	3.0	430	2.1	828	3.2
Toilet facility								
No	60121	79.5		83.4	17843	86.7	21244	82.0
Yes	11590	15.3	4190	16.6	2729	13.3	4671	18.0

Source: Own Computation, 2022, Freq= Frequency, %= Percentage

6.2.7. Distribution of energy sources indicators across the datasets

Table 6.4 presents the distribution of energy sources used by children's households. The findings show that majority of the children had access to electricity over the studied period. Harris (2016) noted that access to electricity is high in South Africa with about 80% of South Africans have access. It is also revealed that most of the children were using unimproved energy for lighting (paraffin), there were 93.9%, 95.5%, 99.1% and 91% children using paraffin for lighting in 2017, 2018, 2019 and combined data, respectively. There were 76.6%, 79.5%, 96.8% and 79.1% children who were using candles for lighting in 2017, 2018, 2019 and combined data, respectively. There were also 99.2%,99.5%, 100% and 94.3% children that did not have energy for lighting in 2017, 2018, 2019 and combined data, respectively. The results also revealed that most of the children

99.1%, 99.4%, 95.9% and 93.1% were using other sources of energy to cook in 2017, 2018, 2019 and combined data, respectively. It is also revealed that most of the children were using paraffin for cooking, there were 88.3%, 91.7%, 98.1% and 87.5% using paraffin for cooking in 2017, 2018, 2019 and combined data, respectively. It was found that there were 69.3%, 71.5%, 86% and 70.9% who were using wood for cooking in 2017, 2018, 2019 and combined data, respectively. Children whose households were using coal for cooking were 96.4%, 97.6%, 99.4% and 92.6% in 2017, 2018, 2019 and combined data, respectively. There were 96.9%, 97.8%, 100% and 93% of children that were using animal dung for cooking in 2017, 2018, 2019 and combined data, respectively. There were 99.2%, 99.5%, 99.9% and 94.3% of children who had no energy for cooking in 2017, 2018, 2019 and combined data, respectively.

Children who were using other sources of energy were 99%, 99.4%, 96.3% and 93.2% in 2017, 2018, 2019 and combined data, respectively. The majority of the children's households, 90.5%, 92.5%, 97.6% and 88.4%) of children used paraffin for water heating in 2017, 2018, 2019 and combined data, respectively. Children that were using wood for water heating were 73.1%, 74.3%, 88.6% and 73.9% in 2017, 2018, 2019 and the combined data, respectively. Majority of the children's households with 96.9%, 98%, 99.6% and 92.9% were using coal for water heating in 2017, 2018, 2019 and combined data, respectively. There were 97.0%, 97.9%, 99.9% and 93% children using animal dung for water heating in 2017, 2018, 2019 and combined data, respectively. There were 98.8%, 99.4%, 99.4% and 94% of children without energy for water heating in 2017, 2018, 2019 and combined data, respectively. There were 89.3%, 90.4%, 92.2% and 85.8% children using paraffin for space heating in 2017, 2018, 2019 and combined data, respectively. In 2017, 2018, 2019 and combined data, there were 74%, 75.5%, 83.6% and 73.3% children who were using wood for space heating, respectively. Children who were using coal for space heating were 96.3%, 97.3%, 98.3 and 92.2% in 2017, 2018, 2019 and combined data, respectively. There were 85%, 79.7%, 75.1% and 76.1% of children without energy for space heating in 2017, 2018, 2019 and combined data, respectively. There were 98.8%, 99.2%, 99.2% and 93.9% children that were using other sources of energy for space heating in 2017, 2018, 2019 and combined data, respectively.

Table 6.4: Distribution of energy sources across datasets

	Freq	Percent	Freq	Percent	Freq	Percent	Freq	Percent
	2017		2018		2019		All	
Access to electricity								
Yes	24569	94.8	24132	95.7	19980	97.1	68681	90.8
No	1346	5.2	1092	4.3	592	2.9	3030	4.0
Paraffin for lighting								
Yes	24344	93.9	24088	95.5	20390	99.1	68822	91.0
No	1571	6.1	1136	4.5	182	0.9	2889	3.8
Candles for lighting								
Yes	19857	76.6	20054	79.5	19919	96.8	59830	79.1
No	6058	23.4	5170	20.5	653	3.2	11881	15.7
No energy source for lighting								
Yes	25711	99.2	25097	99.5	20571	100.0	71379	94.3
No	204	0.8	127	0.5	1	0.0	332	0.4
Other sources for cooking								
Yes	25671	99.1	25075	99.4	19728	95.9	70474	93.1
No	244	0.9	149	0.6	844	4.1	1237	1.6
Paraffin for cooking								
Yes	22872	88.3	23135	91.7	20181	98.1	66188	87.5
No	3043	11.7	2089	8.3	391	1.9	5523	7.3
Wood for cooking								
Yes	17971	69.3	18030	71.5	17683	86.0	53684	70.9
No	7944	30.7	7194	28.5	2889	14.0	18027	23.8
Coal for cooking								
Yes	24978	96.4	24614	97.6	20450	99.4	70042	92.6
No	937	3.6	610	2.4	122	0.6	1669	2.2
No energy source for cooking								
Yes	25699	99.2	25087	99.5	20553	99.9	71339	94.3
No	216	0.8	137	0.5	19	0.1	372	0.5
Other sources of cooking								
Yes	25668	99.0	25083	99.4	19807	96.3	70558	93.2
No	247	1.0	141	0.6	765	3.7	1153	1.5

Paraffin for water heating								
	23462	90.5	23321	92.5	20072	97.6	66855	88.4
	2453	9.5	1903	7.5	500	2.4	4856	6.4
Wood for water heating								
Yes	18931	73.1	18748	74.3	18226	88.6	55905	73.9
No	6984	26.9	6476	25.7	2346	11.4	15806	20.9
Coal for water heating								
Yes	25107	96.9	24715	98.0	20498	99.6	70320	92.9
No	808	3.1	509	2.0	74	0.4	1391	1.8
Animal dung for water heating								
Yes	25149	97.0	24698	97.9	20560	99.9	70407	93.0
No	766	3.0	526	2.1	12	0.1	1304	1.7
No energy source for water heating								
Yes	25605	98.8	25071	99.4	20440	99.4	71116	94.0
No	310	1.2	153	0.6	132	0.6	595	0.8
Paraffin for space heating								
Yes	23137	89.3	22794	90.4	18959	92.2	64890	85.8
No	2778	10.7	2430	9.6	1613	7.8	6821	9.0
Wood for space heating								
Yes	19183	74.0	19047	75.5	17198	83.6	55428	73.3
No	6732	26.0	6177	24.5	3374	16.4	16283	21.5
Coal for space heating								
Yes	24955	96.3	24555	97.3	20230	98.3	69740	92.2
No	960	3.7	669	2.7	342	1.7	1971	2.6
Animal dung for space heating								
Yes	25259	97.5	24747	98.1	20541	99.8	70547	93.2
No	656	2.5	477	1.9	31	0.2	1164	1.5
No energy source for space heating								
Yes	22022	85.0	20102	79.7	15443	75.1	57567	76.1
No	3893	15.0	5122	20.3	5129	24.9	14144	18.7
Other energy sources for space								
Yes	25610	98.8	25033	99.2	20404	99.2	71047	93.9
No	305	1.2	191	0.8	168	0.8	664	0.9

Source: Own Computation, 2022

6.2.8. Distribution of waste management and wealth status across datasets

The UNICEF (2020) mentioned that factors such as sanitation and waste disposal had a significant contribution to the welfare status of children between 0-4 years old. Figure 6.5 presents results on the waste management methods and wealth status of the sampled respondents across different datasets. The results of this study revealed that 20.7%, 20.1%, 17.5% and 18.6% of the households perceived themselves as wealthy or very comfortable in 2017, 2018, 2019 and combined data, respectively while 79.3%, 79.9%, 82.5% and 76.2% of the households were just getting along or poor/very poor. It was further revealed that most of the households felt that they were happier (67.9%, 68.5%, 67.3% and 64.4%) in 2017, 2018, 2019 and combined data, respectively. It is also shown that 29.7%, 31.4%, 29.6% and 28.7% of the sampled respondents have irregular/ no waste removal services in 2017, 2018, 2019 and combined data, respectively. It is also revealed that most of the sampled respondents did not experience littering in their households/communities. In 2017, 2018, 2019 and combined data, 60.5%, 60.8%, 62.7% and 58.1% of the sampled respondents did not experience littering respectively. It is further revealed that 20.3%, 20%, 19.1% and 18.8% of the respondents experienced water pollution in 2017, 2018, 2019 and combined data, respectively. The results further revealed that21.8%, 21%, 18.8% and 19.6% of the sampled respondents experienced outdoor/indoor air pollution in 2017, 2018, 2019 and combined data, respectively. Land degradation was experienced by 59.6%, 60%, 63.7% and 57.7% of the respondents in 2017, 2018, 2019 and combined data, respectively. Excessive noise was experienced by 16.9%, 14.9%, 12.6% and 14.2% of the respondents in 2017, 2018, 2019 and combined data, respectively.

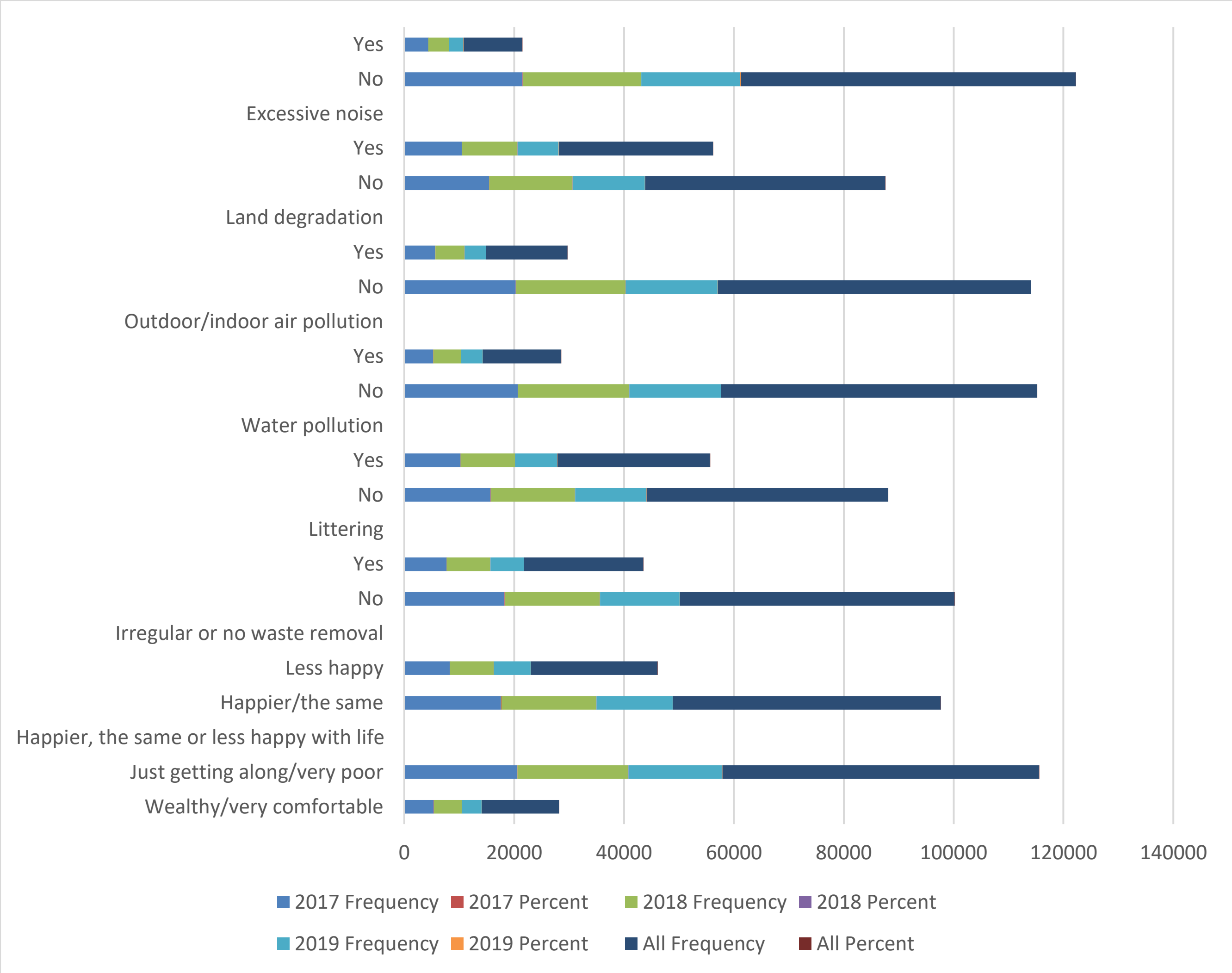

Figure 6.5. Distribution of waste management and wealth status sources across datasets

Source: Own Computation, 2022

CHAPTER SEVEN

CONSTRUCTION AND DECOMPOSITION OF CHILD MPI

7.1 Introduction

This chapter addresses the first objective of this study which seeks to construct the indicators of child's multidimensional poverty index. The chapter presents the procedures and results for the construction of child MPI following the AF and fuzzy set approach. The chapter further presents the AF and Fuzzy Set child MPI averages, intensity, incidence, and adjusted headcount ratio. Finally, the chapter presents the results on the decomposition of child MPI across child's selected characteristics and across different dimensions in fulfilment of the second objective.

7.2 Construction of Child's MPI

When it comes to constructing child MPI indicators, the first step that was taken was to select the relevant dimensions based on the data that is available, select indicators, cut-offs as well as weights. This was done to enable the identification of who is poor and to be able to aggregate the data into a composite poverty index. The construction of the dimensions, indicators, cut-offs, and weights in this study followed the Alkire-Foster and fuzzy set methods. Using the Alkire-Foster approach, the selected indicators were generally weighted, and the weighted sum was computed. The child's MPI for this study comprised of four dimensions, 10 indicators and 91 attributes, where each of the indicators were given weights according to the number of attributes it had. The study further looked at the average child MPIs using the AF and Fuzzy Set approaches. The AF method uses two measures to compute child's MPI which are the intensity (A), incidence (H). The intensity shows the average percentage of weighted indicators where poor children are deprived and the incidence shows the percentage of children that are identified as deprived multidimensionally, out of all children depending on the cut-off. A child's MPI was computed by multiplying A and H (A*H). The study also used the Fuzzy Set approach, this method used the same attributes as those of the AF approach.

7.3 Poverty Incidence, Intensity and MPI Across the Provinces

The results presented in Table 7.1 show the intensity, incidence, and the adjusted headcount ratio (MPI) across the different provinces. The results revealed that children from the Western Cape had the lowest multidimensional poverty incidence, severity and MPI in 2017, 2018, 2019 and the combined data. The incidence of deprivation was 39%, 39%, 32% and 2% in 2017, 2018, 2019 and the combined data, respectively. The intensity of poverty showed that children from the Western Cape province were deprived in 39%, 39%, 88% and 52% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The results further revealed that the Eastern Cape province had the highest MPI which were 34%, 33%, 29% and 6% in 2017, 2018, 2019 and combined data, respectively. The incidences of multidimensional poverty deprivation were 43%, 43%, 32% and 7% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from Eastern Cape province were deprived in 79%, 78%, 33%, and 82% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively.

The incidences of deprivation in the Northern Cape were 40%, 39%, 31% and 2% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from this province were deprived in 56%, 56%, 87% and 65% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The average MPIs were 22%, 22%, 27% and 1% for children from the Northern Cape in 2017, 2018, 2019 and combined data, respectively. In addition, the incidences of multidimensional deprivation in the Free State province were 40%, 39%, 32% and 2% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from Free State were deprived in 59%, 60%, 86% and 79% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio (MPI) showed that 24%, 23%, 27% and 2% of children from the Free State were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively.

KwaZulu-Natal (KZN) province had the second highest number of deprived children. The incidences of deprivation were 41%, 41%, 32% and 9% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from KZN were deprived in 76%, 73%, 90% and 79% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. There were also 31%, 30%, 29% and 7% multidimensionally poor children from KZN in 2017, 2018, 2019 and the combined data, respectively. Moreover, the incidences of deprivation were 41%, 40%, 31% and 3% in the North West province in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from the North West province were deprived in 67%, 67%,85% and 72% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The North West province also had 27%, 27%, 27% and 2% MPI in 2017, 2018, 2019 and combined data, respectively.

The Gauteng province had incidences of deprivation of 40%, 39%, 32% and 6% in 2017, 2018, 2019 and combined data, respectively. The poverty intensities showed for children from Gauteng were deprived in 42%, 43%, 87% and 56% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. Gauteng also had 17%, 17%, 27% and 3% MPI in 2017, 2018, 2019 and combined data, respectively. The incidences of deprivation were 41%, 40%, 32% and 5% in Mpumalanga in 2017, 2018, 2019 and combined data, respectively. The poverty intensity showed that children from Mpumalanga were deprived in 76%, 73%, 88% and 76% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively.

Children who were multidimensionally poor were found to be 31%, 29%, 28% and 3% in MP. Limpopo province had incidences of deprivation of 38%, 38%, 31% and 5% in 2017, 2018, 2019 and combined data, respectively. The poverty intensity showed that children from Limpopo were deprived in 75%, 72%, 86% and 76% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio showed that there were 29%, 28%, 27% and 4% multidimensionally poor children from Limpopo in 2017, 2018, 2019 and combined data, respectively.

The findings of this study are in line with those of the HSRC (2014) who in their report on state of poverty in South Africa revealed that the poorest provinces in the country were KwaZulu-Natal, Eastern Cape and Limpopo. Fransman and Yu (2018) also looked at multidimensional poverty in South Africa and found out that the Western Cape and Gauteng provinces were the least deprived while the Eastern Cape and Limpopo and North West provinces were found to be the most deprived provinces. The HSRC further revealed that the Western Cape, Free State and Gauteng provinces had the lowest incidence of poverty.

Table 7.1: AF Intensity, incidence, and adjusted headcount ratio across provinces

	2017			2018			2019			All		
	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	**MPI**
Province												
Western Cape	0.39	0.39	0.15	0.39	0.39	0.15	0.88	0.32	0.28	0.52	0.02	0.01
Eastern Cape	0.79	0.43	0.34	0.78	0.43	0.33	0.90	0.32	0.29	0.82	0.07	0.06
Northern Cape	0.56	0.40	0.22	0.56	0.39	0.22	0.87	0.31	0.27	0.65	0.02	0.01
Free State	0.59	0.40	0.24	0.60	0.39	0.23	0.86	0.32	0.27	0.67	0.02	0.02
KwaZulu-Natal	0.76	0.41	0.31	0.73	0.41	0.30	0.90	0.32	0.29	0.79	0.09	0.07
North West	0.67	0.41	0.27	0.67	0.40	0.27	0.85	0.31	0.27	0.72	0.03	0.02
Gauteng	0.42	0.40	0.17	0.43	0.39	0.17	0.87	0.32	0.27	0.56	0.06	0.03
Mpumalanga	0.76	0.41	0.31	0.73	0.40	0.29	0.88	0.32	0.28	0.78	0.04	0.03
Limpopo	0.75	0.38	0.29	0.72	0.38	0.28	0.86	0.31	0.27	0.76	0.05	0.04
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28

Source: Own Computation, 2022

7.4 Poverty Incidence, Intensity and MPI Across the Gender of Children

Figure 7.1 presents the intensity, incidence and MPI results on gender of a child. It reveals that male children had a slightly higher intensity, incidence and MPI compared to their female counterparts. The results presented in the Figure revealed that in 2017, male children showed an intensity of poverty and incidence of deprivation of 65% and 41% compared to 64% and 40% of female children, respectively. These results imply that male children were deprived in 65% of the weighted indicators compared to female children who were deprived in 64% of the weighted indicators. The incidence of deprivation for male children was 40% in 2018 compared to the deprivation incidence of 40% for female children. The intensity of poverty in 2018 dataset showed that male and female children were deprived in 63% of the weighted indicators. The 2019 dataset showed the incidence of deprivation to be 40% for both male and female children. The intensity of poverty showed that male and female children were deprived in 88% and 87% of the weighted indicators, respectively. The combined dataset showed an incidence of deprivation to be 15% and 14% for male and female children, respectively. The intensity of poverty showed that both male and female children were deprived in 20% of the weighted indicators. The adjusted headcount ratio showed that 26%, 26%, 28% and 3% of male children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio showed that 26%, 25%, 28% and 3% of female children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. The results of this study can be compared to those of the Stats SA (2021) study on child poverty that also found out that there was no significant difference on the multidimensional poverty status of male and female children.

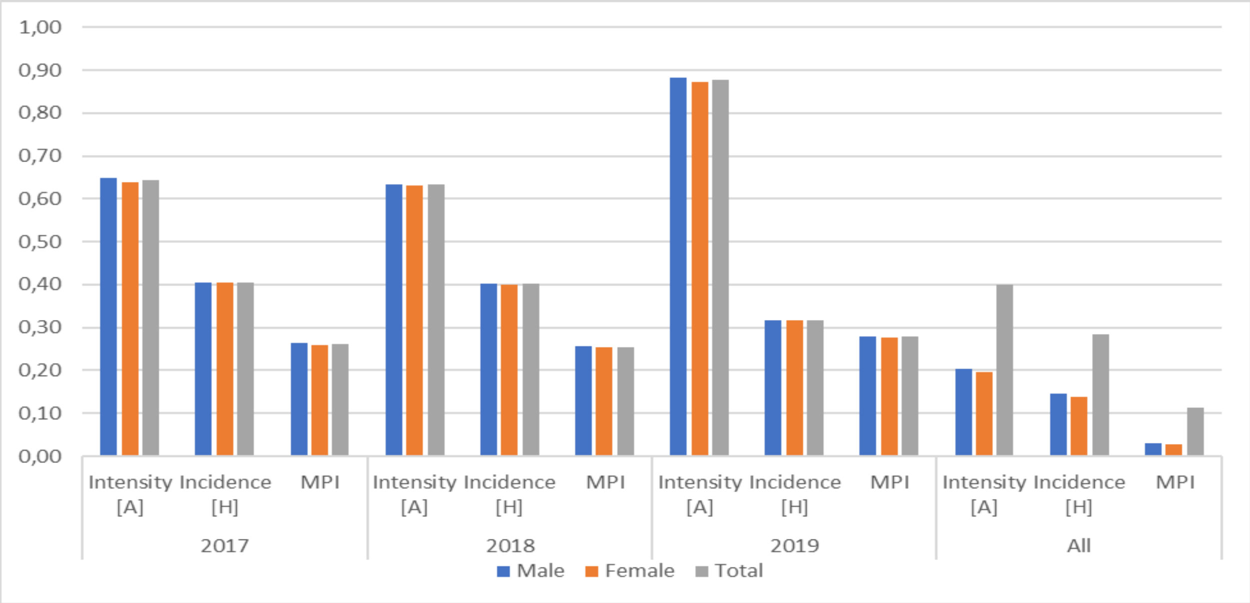

Figure 7.1: Deprivation Intensity, Incidence and MPI across gender of a child

Source: Own Computation, 2022

7.5 Deprivation, Intensity, Incidence and MPI Across Gender of Households' Heads

The results presented in Figure 7.2 showed the deprivation intensity, incidence and MPI across the gender of household head. It is revealed that male headed households were more multidimensionally poor compared to female headed households. The results of this study revealed that in 2017 showed the incidence of deprivation to be 41% for male headed households. The intesnsity of poverty showed that male headed households were deprived in 73% of the weighted indicators. The incidence and intensity for male headed households reduced to 40% and 72% in 2018, respectively. In 2019, male headed households welfare incidence reduced to 32% and intensity increased to 89%. For combined data there were 24% multidimensionally poor male headed households and 77% of male headed households were deprived in 30% of the weighted indicators. The results in Figure 7.2 also showed the deprivation incidence of 40% for female headed households. The intensity of poverty showed that female headed households were deprived in 54% of the weighted indicatots in 2017. The results also revealed that in 2018 dataset, there was a deprivation incidence of 40% for female headed households. The intensity of poverty showed that female headed households were deprived in 53% of the weighted indicators. The incidence of multidimensional poverty among female headed households reduced to 32% while the intensity increased to 88% in 2019. For combined data, the deprivation incidence was 16% for female headed households. The intensity of poverty showed that tfemale headed households were deprived in 63% of the weighted indicators. The adjusted headcount ratio showed that 30% of male headed households were multidimensionally poor compared to 22% of multidimensionally poor female headed households in 2017. In 2018 data set, the the adjusted headcount ratio showed that 29% of male headed houseolds were multidimensionally poor compared to 21% of female haeded households that were multidimensionally poor. It was further revealed that in 2019 dataset the adjusted headcount ratio reduced to 28% for male headed households and increased to 28% for female headed households. The combined data showed 18% of male headed household were multidimensionally poor compared to 10% of female headed households who were multidimensionally poor. These results are contrary to those of Fransman and Yu (2018) who revealed that people from female headed households are more deprived compared to those from male headed households. Presumably, the results of this study may be associated with the fact that the South African government is implementing numerous programmes that are empowering women.

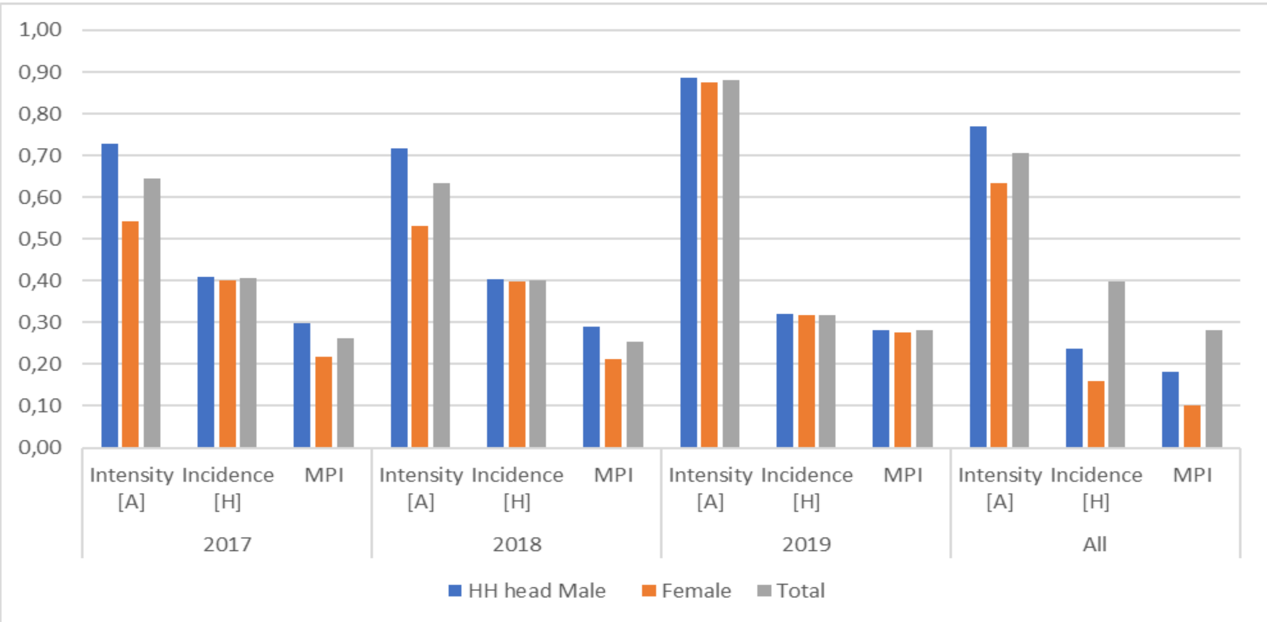

Figure 7.2: Deprivation Intensity, Incidence and MPI across gender of household head

Source: Own Computation, 2022

7.6 Deprivation Intensity, Incidence and MPI Across Households' Heads Age Groups

Table 7.2 presents the deprivation intensity, incidence and MPI results across the head age group. It is revealed in this study that children with household heads that were <15 years old had a deprivation incidence of 41%,41%, 31% and 3% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that children from households- heads that were <15 years were deprived in 50%, 66%, 82% and 69% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ration for children with <15 years heads showed that 20%, 27%, 25% and 2% of those children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The results further showed that in 2017 dataset, children with household heads that were 15<20 years old had a deprivation incidence of 43%. The intensity of poverty showed that those children were deprived in 79% of the weighted indicators. The deprivation incidence for the children with 15<20 years household heads reduced to 40%, 32% and 4% in 2018, 2019 and combined data respectively. The intensity of poverty for children with 15<20 years old heads reduced to 66%, increased to 88% and reduced to 71% in 2018, 2019 and combined data, respectively. The adjusted headcount ratio showed that children with 15<20 years heads, 33%, 27%,27% and 3% of them were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The deprivation incidence was 40%,40%, 31% and 5% for children residing with 20<25 years old heads. the intensity of poverty for these children showed that children with household heads that were 20<25 years old were deprived in 59%, 65%, 84% and 70% of the weighted indicators, in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio showed that children with 20<25 years old heads, 24%, 26%, 26% and 3% of them were multidimensionally poor. The adjusted headcount ratio for children with 15<20 years heads showed that 33%, 27%,27% and 3% were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The deprivation incidence was 41%, 40%, 32% and 5% for children with household heads of 25<30 years old. The intensity of poverty showed that children with 25<30 years old heads were deprived in 76%, 63%, 89% and 71% of the weighted indicators in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio for children with 25<30 years old heads showed that 29%, 24%, 27% and 3% of those children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. The adjusted headcount ratio for children with 15<20 years heads showed that 33%, 27%,27% and 3% of those children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The results of this study also revealed that the deprivation incidence was 41%, 40%, 31% and 3% for children with 30<35 years old household heads. The intensity of poverty showed that children in 30<35 years old household heads were deprived in 72%, 61%, 87% and 70% of the weighted indicators The adjusted headcount ratio for children with 15<20 years heads showed that 33%, 27%,27% and 3% of those children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively.

Household heads who were 35<40 years old their children had a deprivation incidence of 40%, 40%, 33% and 5% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that these children were deprived in 48%, 64%, 93% and 73% of the weighted indicators in 2017, 2018, 2019 and combined data respectively. Household heads between 35<40, 19%, 26%, 30% and 4% of their children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. Household heads between 40<45 years old, their children had deprivation incidence of 40%, 40%, 32% and 5% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that these children were deprived in 46%, 62%, 90% and 71% of the weighted indicators in 2017, 2018, 2019 and combined data respectively. Household heads between 40<45 years old, the adjusted headcount ratio showed that 19%, 25%, 29% and 3% of their children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The results of this study revealed that household heads between 45<50 years old had children with 40%, 40%, 31% and 3% deprivation incidence. The intensity of poverty for these children showed that they were deprived in 75%, 62%, 87% and 71% of the weighted indicators in 2017, 2018, 2019 and combined data respectively. The adjusted headcount ratio showed that household heads between 40<45 years old, 19%, 25%, 29% and 3% of their children were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. The study revealed that household heads between 50<55 years old, their children had deprivation incidence of 38%, 40%, 32% and 4% in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty for these children showed that they were deprived in 75%, 60%, 91% and 70% of the weighted indicators. Furthermore, these children's adjusted headcount ratio showed that 28%, 24%, 29% and 3% of them were multidimensionally poor in 2017, 2018, 2019 and combined data respectively. These results can be compared to those of the HSRC (2014) who revealed that households with heads that were15-24 years were the most MPI poor, declined to age group of 25-34, implying that dependents of older household heads are poorer.

Table 7.2. Deprivation Intensity, Incidence and MPI across head age group

Age group	2017			2018			2019			All		
	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	MPI	Intensity [A]	Incidence [H]	MPI
<15	0.50	0.41	0.20	0.66	0.41	0.27	0.82	0.31	0.25	0.69	0.03	0.02
15<20	0.79	0.43	0.33	0.66	0.40	0.27	0.84	0.32	0.27	0.71	0.04	0.03
20<25	0.59	0.40	0.24	0.65	0.40	0.26	0.84	0.31	0.26	0.70	0.05	0.03
25<30	0.76	0.41	0.31	0.63	0.40	0.25	0.89	0.32	0.29	0.71	0.05	0.03
30<35	0.72	0.41	0.29	0.61	0.40	0.24	0.87	0.31	0.27	0.70	0.05	0.03
35<40	0.48	0.40	0.19	0.64	0.40	0.26	0.93	0.33	0.30	0.73	0.05	0.04
40<45	0.46	0.40	0.19	0.62	0.40	0.25	0.90	0.32	0.29	0.71	0.05	0.03
45<50	0.75	0.40	0.30	0.62	0.40	0.25	0.87	0.31	0.28	0.71	0.04	0.03
50<55	0.75	0.38	0.28	0.60	0.40	0.24	0.91	0.32	0.29	0.70	0.04	0.03
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28

Source: Own Computation, 2022

7.7 Deprivation Intensity, Incidence and MPI Across Population Group, Household Size and Geography Type

Table 7.3 presents the deprivation intensity, incidence and MPI across children's' population group, household size and geography type in different datasets. The results presented in the Table revealed that Black/African children were the most multidimensionally poo population group followed by Coloured, White and Indian/Asian children. It is revealed that there was a deprivation incidence of 41%, 40%,32% and 37% for Black/African children in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty for Black/African children showed that they were deprived in 69%, 68%, 88% and 74% of the weighted indicators. Furthermore, the adjusted headcount ratio showed that 28%, 27%, 23% and 28% of these children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. It was also revealed that there was a deprivation incidence of 39%, 39%, 31% and 2% for Coloured children in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that these children were deprived in 39%, 37%, 87% and 52% of the weighted indicators. Additionally, the adjusted headcount ratio showed that 15%, 15%, 27% and 1% of those children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. It was also revealed that there was a deprivation incidence of 37%, 39%, 31% and 0% for Indian/Asian children in 2017, 2018, 2019 and combined data, respectively. The intensity of poverty showed that Indian/Asian children were deprived in 7%, 6%, 84% and 30% of the weighted indicators. The adjusted headcount ratio showed that 3%, 2%26% and 0% of these children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively. The incidence of deprivation was 40%, 41%, 31% and 0% of for White children. The intensity of poverty showed that White children were deprived in 4%, 3%, 85% and 28% of the weighted indicators. The adjusted headcount ratio showed that 2%, 1%, 26% and 0% of White children were multidimensionally poor in 2017, 2018, 2019 and combined data, respectively.

The results of this study further revealed that in 2017, there was a slight difference between the children's intensity, incidence and MPI across different household sizes. It was revealed that in the 2017 dataset, the children residing in <2, 2<4, 4<6, 17<19 and ≥19 household members had aa incidence of deprivation of 40%. For children residing in household size between 6<9, 9<11, 11<13, 13<15, and 15<17 members in 2017, they had an incidence of deprivation of 41% in 2017, 2018, 2019 and combined data, respectively. Children residing in <2 members per household were deprived in 67% of the weighted indicators and 27% of them were multidimensionally poor. Children in 2<4 members per household in 2017 were deprived in 65% of the weighted indicators. In 2017 children in 4<6 members per household were deprived in 64% of the weighted indicators and had 26% of them were multidimensionally poor. Children from households between 6<9 members children in 2017 were deprived in 63% of the weighted indicators and 26% were multidimensionally poor in 2017. In 2017 dataset, children residing in households with 9<11 members, were deprived in 64% of the weighted indicators and 26% of them were multidimensionally poor. The 2017 dataset also show that children from 11<13 household members were deprived in 66% of the weighted indicators and 27% of them were multidimensionally poor. In 2017 dataset children with 13<15 household members were deprived in 65% of the weighted indicators and 26% of them were multidimensionally poor. Children from 15<17 members in a household were deprived in 68% of the weighted indicators and 28% of them were multidimensionally poor. Children from 15<17 household members in the 2017 dataset were deprived in 56% of the weighted indicators and 22% were multidimensionally poor. Children from ≥19 members in a household were deprived in 63% of the weighted indicators and 26% were multidimensionally poor in 2017.

The results of this study further revealed that in 2018 dataset there was a deprivation incidence of 41%, 40%, 40%, 40%, 40%, 40%, 42%, 44%, 40%, 41% and 40% for children from households with <2, 2<4, 4<6, 6<9, 9<11, 11<13, 13<15, 15<17, 17<19 and ≥19 members, respectively. The intensity of poverty in 2018 dataset showed that children from households with <2, 2<4, 4<6, 6<9, 9<11, 11<13, 13<15, 15<17, 17<19 and ≥19 members were deprived in 69%, 58%, 60%, 69%, 72%, 66%, 84%, 89%, 100% and 97% of the weighted indicators, respectively. The 2018 dataset also revealed that children from households with <2, 2<4, 4<6, 6<9, 9<11, 11<13, 13<15, 15<17, 17<19 and ≥19 members, 28%, 23%, 24%, 28%, 29%, 26%, 35%, 39%, 40% and 40% of them were multidimensionally poor respectively. The 2019 dataset intensity of poverty showed that children residing on households with <2, 2<4, 4<6, 6<9, 9<11, 13<15, 15<17 and ≥19 members were deprived in 93%, 87%, 88%, 88%, 88%, 86%, 89% and 94% of the weighted indicators and 32% of them were multidimensionally poor, respectively. The 2019 dataset also revealed that children residing in households with 11<13 and 17<19 members were deprived in 86% and 90% of the weighted indicators with a deprivation incidence of 31% of and 27% and 28% of them were multidimensionally poor, respectively. The combined data of this study revealed that children residing in households with <2 members were deprived in 78% of the weighted indicators, had 1% incidence of deprivation and only 1% was multidimensionally poor. It is revealed that children residing in households with 2<4 members had an incidence of deprivation of 11%. The intensity of poverty for these children showed that they were deprived in 66% of the weighted indicators and had an MPI of 8% in combined data. The children residing in households with 4<6 members had an incidence of deprivation of 13%. The intensity of poverty showed that they were deprived in 68% of the weighted indicators and 9% were multidimensionally poor in combined dataset. The combined dataset also revealed that children residing in households with 6<9 members had a deprivation incidence of 7%. the intensity of poverty showed that these children were deprived in 75% of the weighted indicators and 6% were multidimensionally poor. It is also revealed that children residing in households with 9<11 members, had a welfare incidence of 4%, intensity of 77% and 3% were multidimensionally poor. It is further revealed that children residing in households with 11<13 members, had deprivation incidence of 1%, intensity of 77% and MPI of 1% in the combined data. It is revealed that children residing in household with 13<15 members, had an intensity of 83%, incidence of 1% and MPI of 1%. Children residing in households with 15<17 members had an intensity of 85% and incidence and MPI of 0% in combined data. The results of this study also revealed that in the combined data, children residing in households with 17<19 members were deprived in 94% of the weighted indicators and had and incidence and MPI of 0%. Children residing in household with ≥19 members had a derivation incidence of 40%. The intensity of poverty showed that these children were deprived in 71% of the weighted indicators and 28% were multidimensionally poor. This study also observed the incidence, intensity and MPI of children across their geography type. The results of this study revealed that children from traditional areas were more deprived compared to those in farms and urban areas. It is revealed that in 2017 dataset, the deprivation incidence for children from traditional areas (41%), urban areas (40%) and farms (44%). In 2017 it was also revealed that children from traditional areas were deprived in (84%), urban areas (48) and farms (77%) of the weighted indicators. The adjusted headcount ration showed that 34% of children in traditional areas, 19% of children in urban areas and 33% of children in farms were multidimensionally poor. The findings of this study further revealed that in 2018 dataset, the intensity, incidence and MPI of children in urban areas reduced to 47%, 39% and remained the same (19%), respectively. For children in traditional areas in the 2019 dataset, it is revealed that only their intensity of poverty reduced to 83% while their incidence (41%) and MPI (34%) remained the same. The 2018 dataset also revealed that the incidence of children residing in farms reduced to 43% while the intensity (77%) and MPI (33%) of those children in the farms remained the same. The intensity in the 2019 dataset of children residing in urban areas increased to 86%, increased to 90% for children in traditional areas and increased to 91% for children in farms. However, the 2019 dataset show that the incidence for children in urban areas decreased to 31%, decreased to 32% for children in traditional areas and reduced to 33% for children in farms. There was an increase on the number of multidimensionally poor children in urban areas (27%), a reduction in the number of multidimensionally deprived children in traditional areas (29%) and reduction in the number of multidimensionally poor children in farms (30%). The combined data shows that children from urban, traditional areas and farms were deprived in 59%, 85% and 81% of the weighted indicators, respectively. The results further revealed that there was an incidence of deprivation of 18%, 21% and 2% of children in urban, traditional areas and farms were multidimensionally poor and 11%, 17% and 1% were multidimensionally poor respectively.

Table 7.3: Deprivation, Intensity, Incidence and MPI across population group, household size and geography type

	2017			2018			2019			All		
	Intensity	Incidence	MPI	Intensity	Incidence	MPI	Intensity	Incidence	MPI	Intensity	Incidence	MPI
Population group												
Black/African	0.69	0.41	0.28	0.68	0.40	0.27	0.88	0.32	0.28	0.74	0.37	0.28
Coloured	0.39	0.39	0.15	0.37	0.39	0.15	0.87	0.31	0.27	0.52	0.02	0.01
Indian/Asian	0.07	0.37	0.03	0.06	0.39	0.02	0.84	0.31	0.26	0.30	0.00	0.00
White	0.04	0.40	0.02	0.03	0.41	0.01	0.85	0.31	0.26	0.28	0.00	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Household size group												
<2	0.67	0.40	0.27	0.69	0.41	0.28	0.93	0.32	0.30	0.78	0.01	0.01
2<4	0.65	0.40	0.26	0.58	0.40	0.23	0.87	0.32	0.28	0.66	0.11	0.08
4<6	0.64	0.40	0.26	0.60	0.40	0.24	0.88	0.32	0.28	0.68	0.13	0.09
6<9	0.63	0.41	0.26	0.69	0.40	0.28	0.88	0.32	0.28	0.75	0.07	0.06
9<11	0.64	0.41	0.26	0.72	0.40	0.29	0.88	0.32	0.28	0.77	0.04	0.03
11<13	0.66	0.41	0.27	0.66	0.40	0.26	0.86	0.31	0.27	0.77	0.01	0.01
13<15	0.65	0.40	0.26	0.84	0.42	0.35	0.86	0.32	0.27	0.83	0.01	0.01
15<17	0.68	0.41	0.28	0.89	0.44	0.39	0.89	0.32	0.28	0.86	0.00	0.00
17<19	0.56	0.40	0.22	1.00	0.40	0.40	0.90	0.31	0.28	0.85	0.00	0.00
≥19	0.63	0.40	0.26	0.97	0.41	0.40	0.94	0.32	0.30	0.94	0.00	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Geographic type												
Urban	0.48	0.40	0.19	0.47	0.39	0.19	0.86	0.31	0.27	0.59	0.18	0.11
Traditional	0.84	0.41	0.34	0.83	0.41	0.34	0.90	0.32	0.29	0.85	0.21	0.17
Farms	0.77	0.44	0.33	0.77	0.43	0.33	0.91	0.33	0.30	0.81	0.02	0.01
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28

Source: Own Computation, 2022

Table 7.4: Deprivation, Intensity, Incidence and MPI across household income sources

	2017			2018			2019			All		
	Intensity	**Incidence**	**MPI**	**Intensity**	**Incidence**	**MPI**	**Intensity**	**Incidence**	**MPI**	**Intensity**	**Incidence**	**MPI**
Salaries/Wages commission												0.00
Yes	0.81	0.41	0.33	0.79	0.41	0.32	0.89	0.32	0.28	0.82	0.20	0.16
No	0.53	0.40	0.21	0.52	0.39	0.21	0.87	0.32	0.28	0.62	0.20	0.13
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Income from business												
Yes	0.66	0.41	0.27	0.65	0.40	0.26	0.88	0.32	0.28	0.72	0.35	0.25
No	0.52	0.39	0.20	0.50	0.39	0.20	0.88	0.32	0.28	0.62	0.05	0.03
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Remittances												0.00
Yes	0.62	0.40	0.25	0.61	0.40	0.25	0.88	0.32	0.28	0.69	0.32	0.22
No	0.73	0.41	0.29	0.71	0.40	0.28	0.89	0.32	0.28	0.76	0.08	0.06
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Pensions												
Yes	0.65	0.41	0.26	0.64	0.40	0.26	0.88	0.32	0.28	0.71	0.39	0.28
No	0.47	0.38	0.18	0.48	0.39	0.18	0.87	0.32	0.28	0.57	0.01	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Grants												
Yes	0.25	0.40	0.10	0.24	0.40	0.10	0.88	0.32	0.28	0.46	0.05	0.02
No	0.73	0.41	0.30	0.72	0.40	0.29	0.88	0.32	0.28	0.77	0.35	0.27
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Social grants												
Yes	0.76	0.41	0.31	0.74	0.40	0.30	0.89	0.32	0.28	0.79	0.32	0.25
No	0.36	0.40	0.14	0.36	0.40	0.14	0.86	0.31	0.27	0.50	0.08	0.04
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
Sales of farming products/services												
Yes	0.64	0.40	0.26	0.63	0.39	0.25	0.88	0.32	0.28	0.71	0.39	0.27
No	0.75	0.41	0.30	0.73	0.01	0.01	0.88	0.32	0.28	0.78	0.01	0.01
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28

Source: Own Computation, 2022

Table 7.4: Deprivation, Intensity, Incidence and MPI across household income sources Cont.

	Communal garden											
Yes	0.60	0.40	0.24	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
No	0.82	0.41	0.34	0.93	0.40	0.37	0.91	0.32	0.29	0.89	0.00	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
	School garden											
Yes	0.64	0.41	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
No	0.88	0.40	0.35	0.69	0.39	0.27	0.94	0.32	0.30	0.85	0.00	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
	Backyard garden											0.00
Yes	0.64	0.40	0.26	0.59	0.40	0.24	0.88	0.32	0.28	0.67	0.30	0.20
No	0.80	0.41	0.33	0.81	0.40	0.33	0.88	0.32	0.28	0.83	0.10	0.08
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28
	Other income sources											
Yes	0.65	0.41	0.26	0.64	0.40	0.26	0.88	0.32	0.28	0.71	0.39	0.28
No	0.47	0.39	0.19	0.47	0.38	0.18	0.88	0.32	0.28	0.59	0.01	0.00
Total	0.64	0.40	0.26	0.63	0.40	0.25	0.88	0.32	0.28	0.71	0.40	0.28

7.8 Deprivation, Intensity, Incidence and MPI Across Household Income Sources

Table 7.4 presents the results of intensity, incidence and MPI across the households' income sources. It is revealed that the intensity of children who did not have a household member earning salary/commission was 53% in 2017, reduced to 52% in 2018 and increased in 2019 to 87%. The combined years show an intensity of poverty of 62% for children who did not have salaries/wages commission in their households. The results of this study also revealed that children residing in households without salaries/wages commission had incidence of deprivation of 40%, 39%, 32% and 20% in 2017, 2018, 2019 and combined years, respectively. There were 21%, 21%, 28% and 13% multidimensionally poor children residing in households without income in 2017, 2018, 2019 and combined years, respectively. The results of this study further revealed that children residing in households without income from business were deprived in 52%, 50%, 88% and 62% of the 30% of the weighted indicators in 2017, 2018, 2019 and combined years, respectively. It is also revealed that there was an incidence of deprivation of 39%, 39%,32% and 5% for children who were residing in households that did not have income from a business. Children who resided in households without business income 20% of them were multidimensionally poor in 2017, remained the same (20%) in 2018, increased to 28% in 2019 while in the combined data they had an adjusted headcount ratio of 3%. The results of this study also revealed that children in households with remittances were poorer compared to children residing in households with remittances. it is revealed that there was an incidence of deprivation of 41%, 40%, 32% and 40% of children in households without remittances in 2017, 2018, 2019 and combined years, respectively. The findings also show that households without remittances had incidence of 41%, 40%, 32% and 8% in 2017, 2018, 2019 and combined years, respectively. Household without remittances, their children 29%, 25%, 28% and 28% of them were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively.

Table 7.4 shows that households without any pension recipient their children were deprived in 47%, 48%, 87% and 71% of the weighted indicators in 2017, 2018, 2019 and combined years, respectively. The results also show an incidence of 38%, 39%, 32% and 1% for children residing in households without pensions recipient in 2017, 2018, 2019 and combined years, respectively. These children, 18%, 18%, 28% and 0% of them were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively. It is also revealed that there was a deprivation incidence of 41%, 40%, 32% and 40% for children who did not receive grants. The intensity of poverty showed that these children were deprived in 73%, 63%,88% and 71% of the weighted indicators in 2017, 2018, 2019 and combined years, respectively. These children who did not receive grants, 30%, 29%, 28% and 27% of them were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively. According to Stats SA (2021) grants is a main source of income for the majority of South Africans. Children from households without social grants were deprived in 36%, 36%, 86% and 50% of the weighted indicators in 2017, 2018, 2019 and combined years, respectively. It is also revealed that children from households without any social grants recipient there was an incidence of 40%, 40%, 31% and 8% of them were multidimensionally poor. There were also 14%, 14% 27% and 4% multidimensionally poor children that did not receive social grants in 2017, 2018, 2019 and combined years, respectively. Households without sales of farming products or services were deprived in 75%, 73%, 88% and 78% of the weighted indicators in 2017, 2018, 2019 and combined years, respectively. it was also revealed that households without sales of farming products or services had a deprivation incidence of 41%, 1%, 322% and 1%. The adjusted headcount ratio showed that 30%, 1%, 28% and 1% of children without sales of farming products/ services were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively. The results of this study also revealed that most of the children without communal gardens were multidimensionally poor compared to those with communal gardens. The results of this study revealed that children who did not have communal gardens had an intensity of 82%, 93%,91% and 89% in 2017, 2018, 2019 and combined years, respectively. These children without communal gardens had an incidence of 41%, 40%, 32% and 0% and had 34%,37%,29% and 0% of them were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively. The results of this study also revealed that children without school gardens had an intensity of 88%,69%, 94% and 85% in 2017, 2018, 2019 and combined years, respectively. The incidence was 40%, 39%, 32% and 0% for children without school gardens with an MPI of 26%, 25%, 28% and 28% in 2017, 2018, 2019 and combined years, respectively. Children without backyard gardens had an intensity of 80%, 81%, 88% and 83% in 2017, 2018, 2019 and combined years, respectively. These children also had an incidence of 41%, 40%, 32% and 10% and 33%, 33%, 28% and 8% of those children were multidimensionally poor in 2017, 2018, 2019 and combined years, respectively. There was an intensity of 65%, 64%,88% and 71% for children from households with other income sources in 2017, 2018, 2019 and combined years, respectively. Children from households with other income sources were also revealed to have a welfare incidence of 41%, 40%, 32% and 39% and 26%26%, 28% and 28% of them were most multidimensionally poor compared to those who resides in households without other income sources in 2017, 2018, 2019 and combined years, respectively. The study conducted by the UNICEF (2020) found that children who are income poor have the highest number of deprivations compared to those with income.

7.9. Average Child MPI Using AF Approach Across Provinces

Figure 7.3. shows the results of average child's Alkire-Foster MPI across different provinces in South Africa. The results of this study revealed that the average AF child MPI for Western Cape was 0.15, 0.15,0.35 and 0.20 in 2017, 2018, 2019 and combined data, respectively. The Western Cape was also revealed to be the province with the lowest AF child MPI compared to all the provinces. The results of this study further revealed that the Eastern Cape province had the highest average AF child MPI compared to all the provinces and a fluctuating AF child MPI of 0.34, 0.33, 0.36 and 0.34 in 2017, 2018, 2019 and combined data, respectively. It is revealed that the Northern Cape had the same average AF child MPI in 2017 and 2018 (0.22) and the average AF child MPI increased to 0.34 in 2019 and was 0.26 in the combined data. The results presented in Figure 7.3 show a fluctuating AF child MPI of 0.24, 0.23, 0.34 in the Free State in 2017, 2018 and 2019 while the combined data show that the average AF child MPI is 0.27. The KwaZulu-Natal province was the second province with the largest average AF child MPI of 0.31, 0.30, 0.36 and 0.32 in 2017, 2018, 2019 and combined data, respectively. The North West was revealed to have an average AF child MPI of 0.27 in 2017 and 2018 while the 2019 and combined datasets show an average of 0.33 and 0.29, respectively. The Gauteng province had an average AF child MPI of 0.17, 0.17, 0.34 and 0.22 in 2017, 2018, 2019 and combined data, respectively. It is also revealed that Mpumalanga was the second largest province with the highest average AF child MPI of 0.31, 0.29, 0.35 and 0.32 in 2017, 2018, 2019 and combined data, respectively. Limpopo province had 0.26, 0.25, 0.35 and 0.28 average AF child MPI in 2017, 2018, 2019 and combined data, respectively.

The results showed some spatial differences in child's multidimensional poverty in South Africa. The AF results are in line with those of Stats SA (2021), Fransman and YU (2018), and Mosasane and Oyekale (2021), who also found that the Eastern Cape and KwaZulu-Natal were the top provinces with higher respondents who were multidimensionally poor, and the Western Cape and Gauteng provinces had the lowest multidimensionally poor respondents. The Stats SA revealed that Eastern Cape had 79%, KZN 76% of multidimensionally deprived children. Philip (2022) mentioned the Eastern Cape as the "home of hardship", this can explain the reason behind its high numbers of multidimensionally poor children. She further mentioned that the Western cape and Gauteng provinces are driven by manufacturing, trade and finance while the EC is run by government alone.

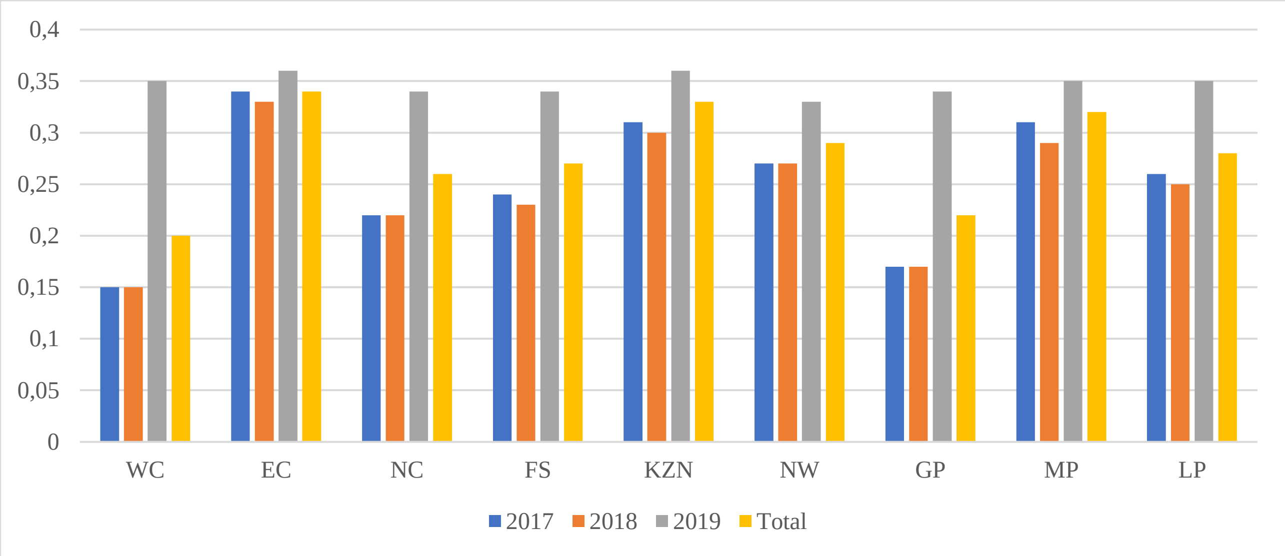

Figure. 7.3: Average Alkire-Foster Child's MPI Across Provinces in 2017, 2018 and 2019

Source: Own Computation, 2022

7.10. Average Child MPI using Fuzzy Sets approach across provinces

Figure 7.4 revealed the average child's fuzzy sets MPI across the provinces. The results presented in this figure revealed that in 2017, the Eastern Cape province had the highest average fuzzy sets child MPI (0.12) followed by KwaZulu-Natal and Mpumalanga (0.10), Free State and North West (0.09), Northern Cape, Gauteng, and Limpopo (0.08) and the Western Cape with the lowest average fuzzy sets child MPI of 0.06. in 2018, the Western Cape, Eastern Cape (0.12), North West (0.09) and Limpopo's (0.08) average fuzzy sets child MPI (0.06) did not change while the Northern Cape, Free Sate, KwaZulu-Natal, Gauteng, and Mpumalanga's average fuzzy sets MPI reduced to 0.07, 0.08, 0.09, 0.07 and 0.09 respectively. In 2019 there was fuzzy sets child MPI average of 0.10, 0.11, 0.10, 0.10, 0.11, 0.10, 0.10,0.10 and 0.10 in WC, EC, NC, FS, KZN, NW, GP, MPI and Limpopo, respectively. The combined dataset showed that the Western Cape had the lowest fuzzy sets child MPI average of 0.07. Eastern cape was on the lead with an average fuzzy sets' child MPI of 0.12 in the combined data. The Northern Cape, Gauteng and Limpopo provinces had the same fuzzy sets child MPI average of 0.08. It was also revealed that the Free State and North West province had an average fuzzy set child MPI of 0.09 and the KwaZulu-Natal and Mpumalanga had an average of 0.10 fuzzy sets child MPI in the combined data.

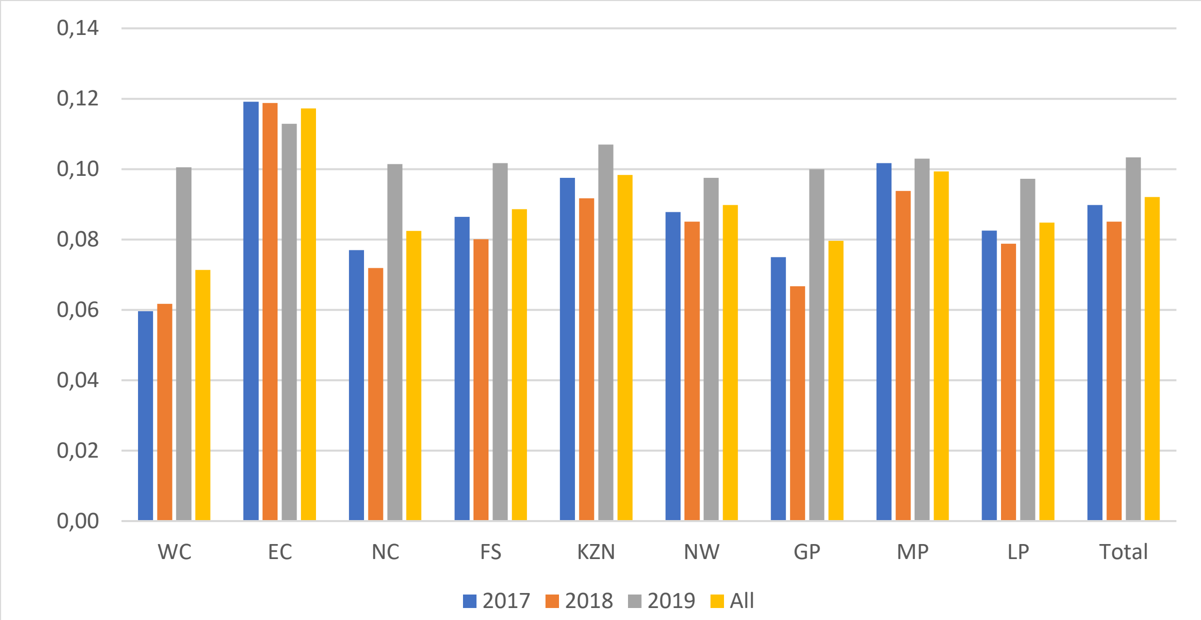

Figure 7.4: Average Fuzzy Set child MPI Across provinces in 2017, 2018, 2019 and all years

Source: Own Computation, 2022

7.11 AF Average Child MPI Across Child's Gender

The results presented in Figure 7.5 show the average child's Alkire-Foster MPI across gender in 2017, 2018, 2019 and all the years combined. The results of this study revealed that in 2017 dataset the AF child MPI average was the same between male and female children. It was further revealed that on the 2018 dataset, there was a slight difference of 0.01 between male (0.26) and female (0.25) children. It was revealed in this study that in 2019 dataset, male children had the slightly high average AF child MPI of 0.35 compared to female children with an average AF child MPI of 0.34. In the combined dataset, both male and female children had the same AF child MPI average. The results of this study are contrary to those of Omotoso and Koch (2018) who revealed that majority of female children are multidimensionally deprived compared to male children. Fransman and Yu (2018) also found that females were poorer compared to males. Furthermore, Dirksen and Alkire (2021) also revealed that female children are more MPI poor compared to male children. Their findings were explained by some cultural beliefs that male children are more important compared to female children as they will continue to bear the family names and, in some cultures, it is believed that male child should always be above their female counterparts.

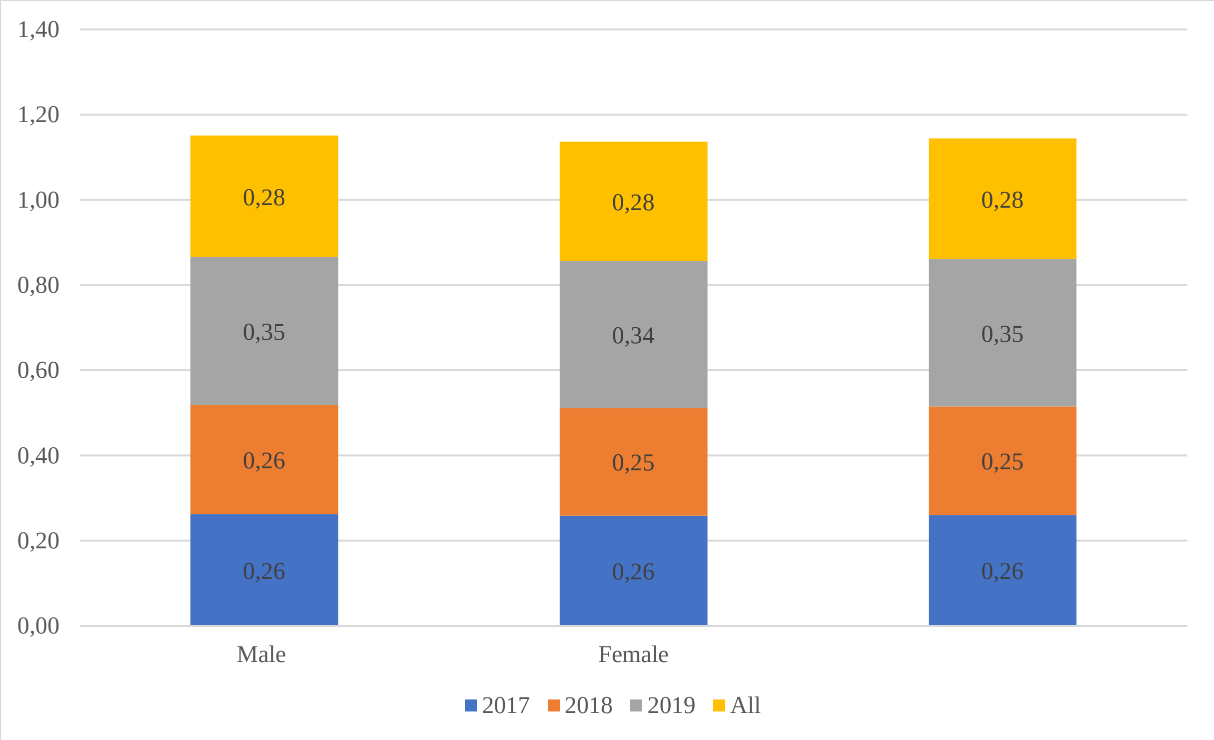

Figure 7.5. AF average child MPI across gender of a child

Source: Own Computation, 2022

7.12 Fuzzy Set Average Child MPI Across Gender of Child

The results presented in Figure 7.6 show the average Fuzzy Set child MPI across the gender of the children. The results of this study revealed that male children had an average fuzzy set child MPI of 0.09, 0.9, 0.10 and 0.09 in 2017, 2018, 2019 and combined data, respectively. The average Fuzzy Set child MPI of female children was similar to those of male children (0.09, 0.10, 0.09) in 2017, 2019 and combined data and slightly lower (0.08) in the 2018 dataset. These results generally revealed insignificant differences in the average fuzzy MPI across gender of the children.

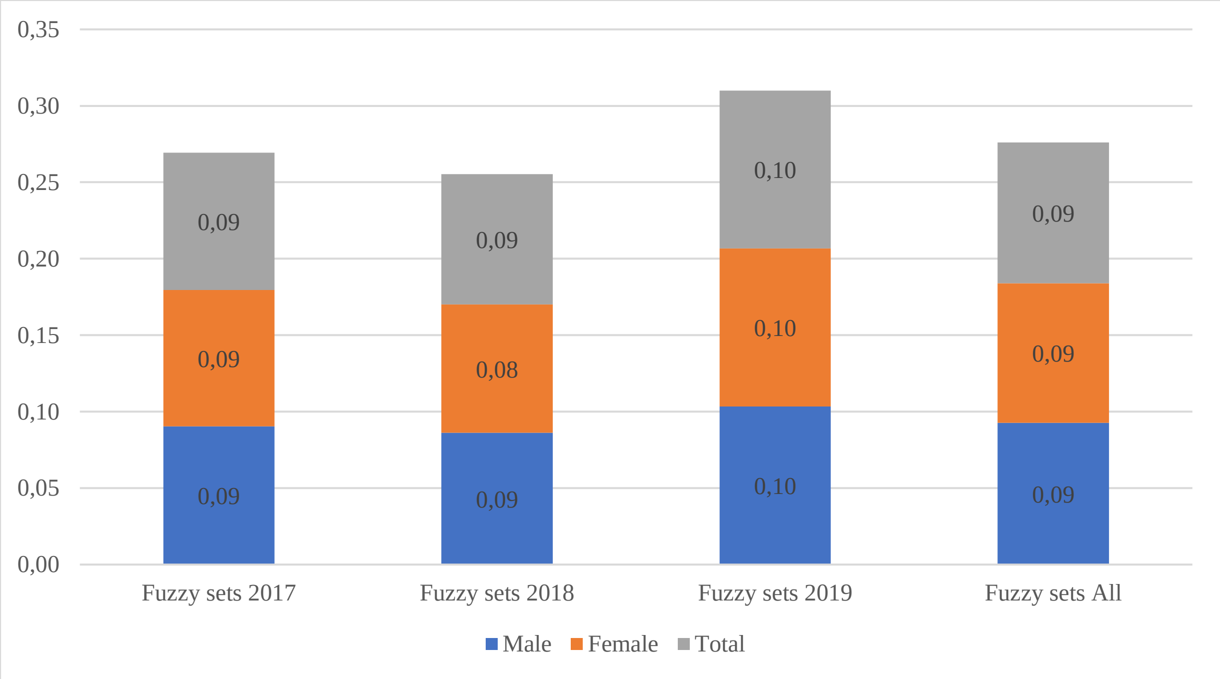

Figure 7.6. Fuzzy Set average child MPI across gender of child

Source: Own Computation, 2022

7.13 Average AF Child MPI Across the Child's Gender of the Households' Heads

The results presented in Figure 7.7 show the average AF child MPI across the gender of the household head. The results revealed that in 2017 dataset, male headed households had an AF child MPI average of 0.30 compared to 0.22 AF child MPI average for female headed household. In 2018 the average AF child MPI for male and female headed households slightly decreased to 0.29 and 0.21, respectively. The 2019 dataset show that the male and female headed households' average AF child MPI increased to 0.35 and 0.34, respectively. The combined data show that male headed households had an average AF child MPI of 0.31 compared to 0.25 of female headed households. These results generally revealed that based on gender of the households' heads, AF child's MPIs were lower among female headed house heads.

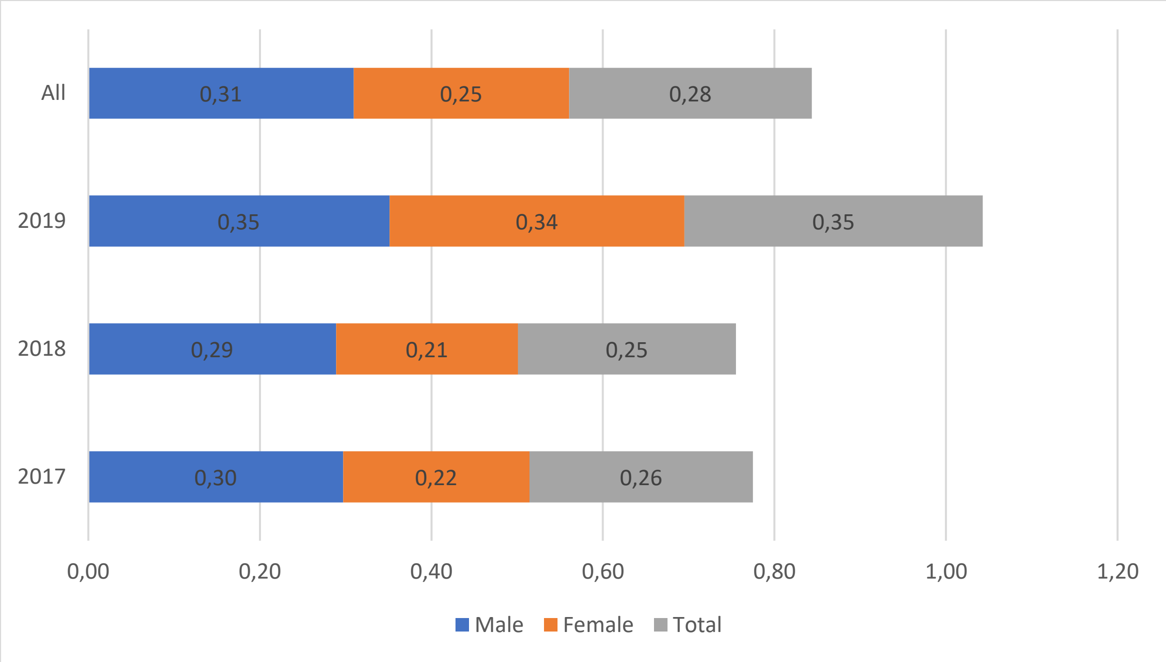

Figure 7.7: Average AF child MPI across the child's gender of the household head

Source: Own Computation, 2022

7.14 Average Fuzzy Set Child MPI Across the Gender of the Households' Heads

Figure 7.8 presents the Fuzzy Set child MPI across the gender of the household head. The results reveal that there was a slight difference between the male and female headed households' average Fuzzy Set child MPI. It is revealed that there was an average fuzzy set child MPI of 0.10 and 0.08 for male and female headed households, respectively in 2017. It is also revealed that there were 0.09 and 0.08 average Fuzzy Set child MPI for male and female headed households in 2018. In 2019, the male and female headed households' average Fuzzy Set child MPI increased to 0.11 and 0.10, respectively. The male headed households had slightly high (0.10) average Fuzzy Set child MPI compared to female headed households. These results revealed that the mean child's MPIs are not so different among male and female headed household heads.

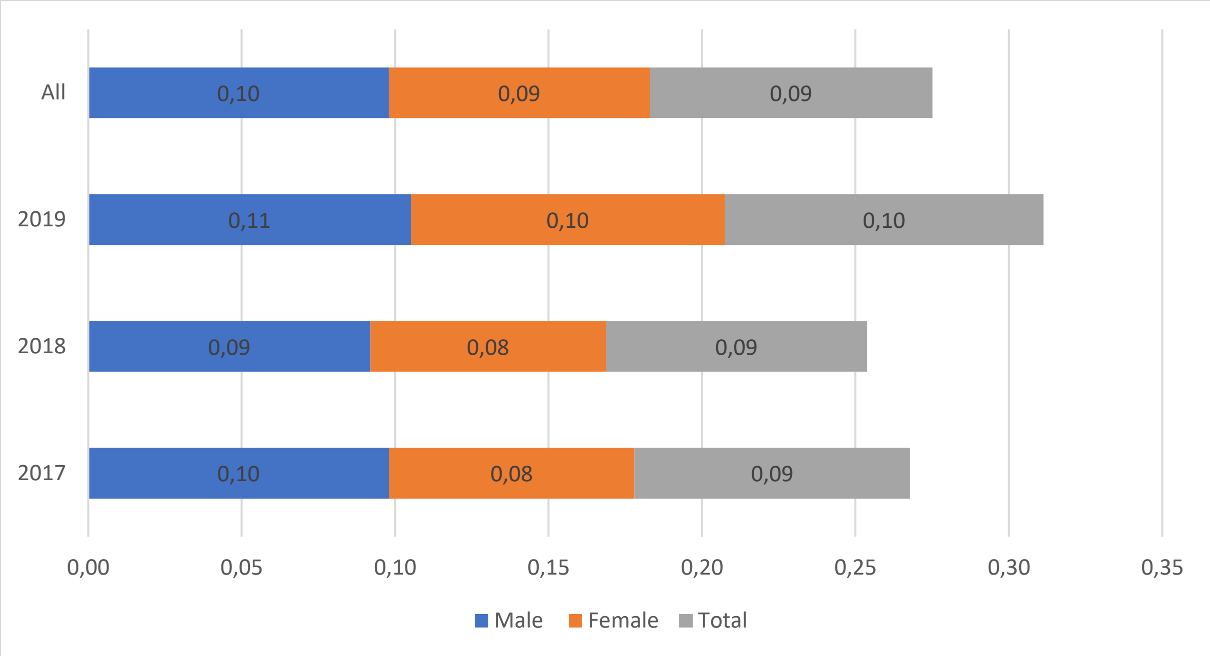

Figure 7.8 Average Fuzzy Set child MPI across the gender of the household head

Source: Own Computation, 2022

7.15 Average AF Child MPI Across Heads' Age Groups

The results presented in Figure 7.9 show the average AF child MPI across the age of the head. The results presented in this Figure show that the average AF child MPI for children with household heads that were <15 years old was 0.27, 0.27, 0.31 and 0.28 in 2017, 2018, 2019 and combined data, respectively. It was further revealed that the children with household heads who were 15<20 years, their average AF child MPI was 0.027,0.27, 0.33 and 0.29 in 2017, 2018, 2019 and combined data, respectively. The children with 20<25 years old household heads had an average AF child MPI of 0.26, 0.25, 0.36 and 0.29 in 2017, 2018, 2019 and combined data, respectively. It was further revealed that children with household heads of 25<30 years had an average AF child MPI of 0.26, 0.24, 0.34 and 0.28 in 2017, 2018, 2019 and combined data, respectively. The children with 30<35 years old household heads had 0.26, 0.24, 0.34 and 0.28 average AF child MPI. Children who were residing with household heads that were 35<40 their average AF child MPI is 0.26, 0.26, 0.38 and 0.29 in 2017, 2018, 2019 and combined data, respectively. Children who were residing with household heads that were 40<45 their average AF child MPI is 0.25, 0.25, 0.35 and 0.28 in 2017, 2018, 2019 and combined data, respectively. It was revealed that children residing with household heads that were 45<50 their average AF child MPI is 0.26, 0.25, 0.34 and 0.28 in 2017, 2018, 2019 and combined data, respectively. Those that were residing with 50<55 years old household heads their average AF child MPI is 0.25, 0.24, 0.36 and 0.28 in 2017, 2018, 2019 and combined data, respectively.

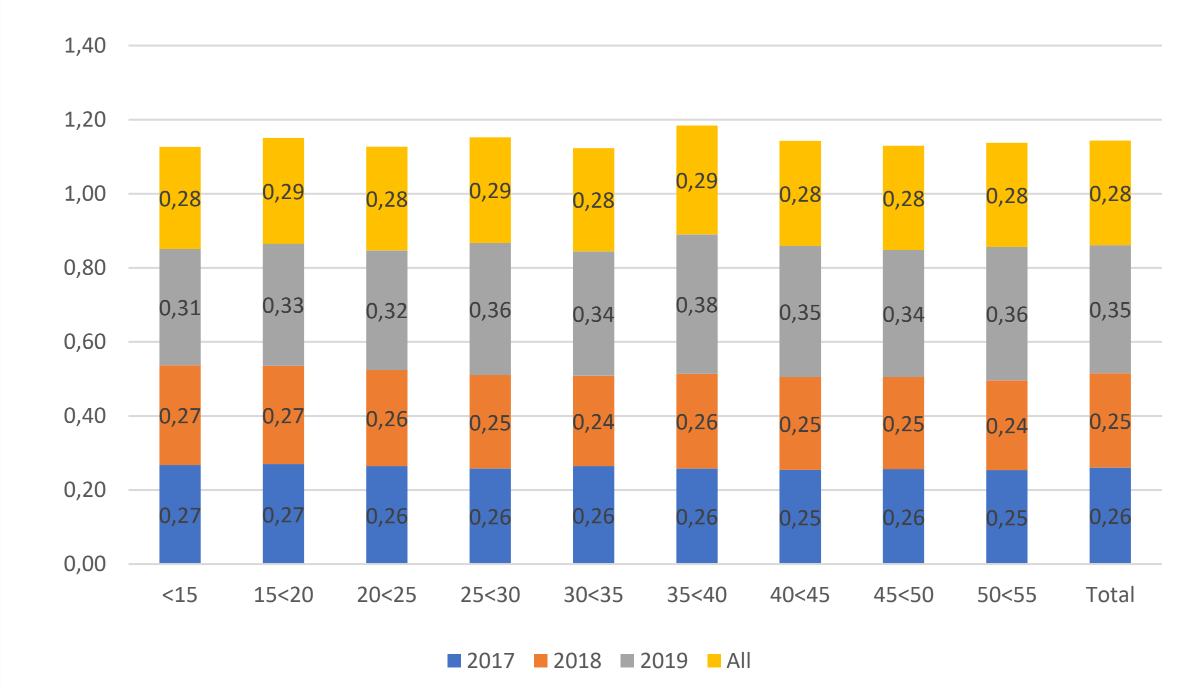

Figure 7.9. Average AF child MPI across head age groups

Source: Own Computation, 2022

7.1 6Average Fuzzy Child MPI Across Heads' Age Groups

Figure 7.10 presents the average Fuzzy Set child MPI across the head age group. The Figure revealed that in 2017 and the combined dataset, all the age groups had an average Fuzzy Set child MPI of 0.9. in the 2018 dataset, age groups 25-55 had a Fuzzy Set average of 0.8 and age groups 15-25 had Fuzzy Set child MPI average of 0.9. the 2019 dataset showed that age groups <15-25, 30<35 and 40-50 had a Fuzzy Set child MPI average of 0.10 while age groups 25<30, 35<40 and 50<55 had a Fuzzy Set child MPI of 0.11.

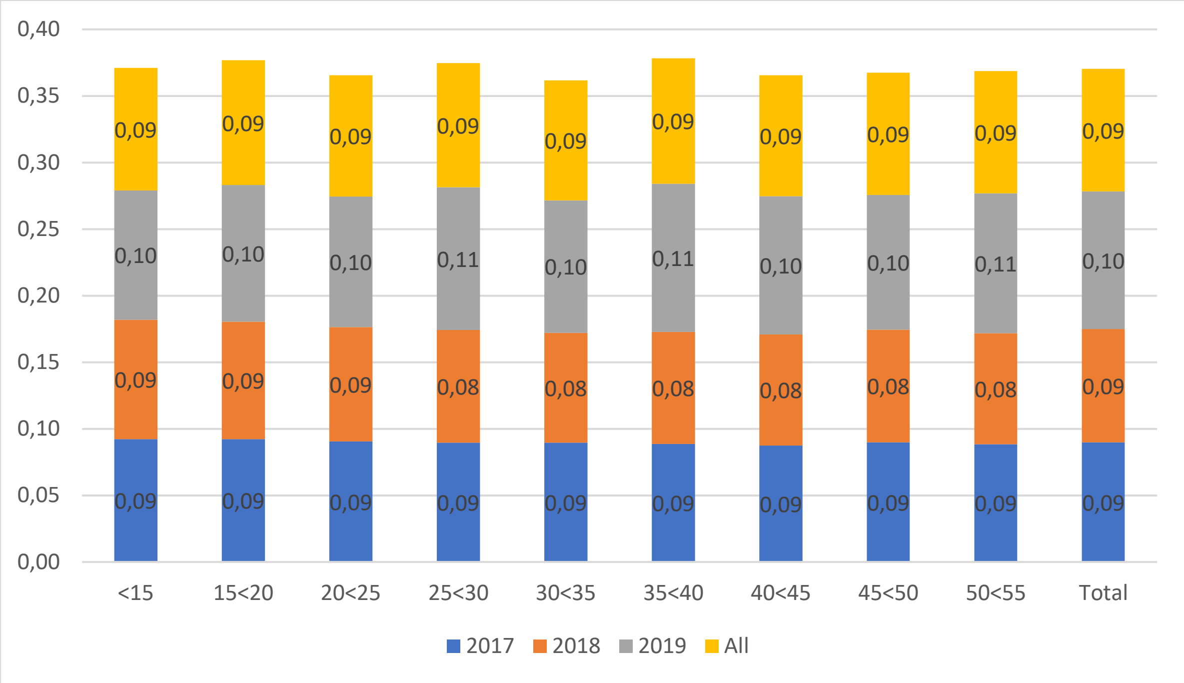

Figure 7.10. Average Fuzzy Set child MPI across head age groups

Source: Own Computation, 2022

7.17. Average AF Child MPI Across Population Groups

The results presented in Figure 7.10 show the average AF child MPI across the population group of a child. The results revealed that Black/African children had the highest AF child MPI average (0.30), followed by Coloured (0.20), Indian (0.12) and White (0.11) in the combined dataset. The results of this study further revealed that Black children had an average AF MPI of 0.28, 0.27 and 0.35 in 2017, 2018 and 2019 respectively. Coloured children had an average AF MPI of 0.15 in 2017, remained the same in 2018 (0.15) and increased to 0.34 in 2019. For Indian children, there was an AF MPI average of 0.03 in 2017, reduced to 0.02 in 2018 and increased to 0.32 in 2019. There was an average AF child MPI of 0.02, 0.01 and 0.32 for white children in 2017, 2018 and 2019, respectively.

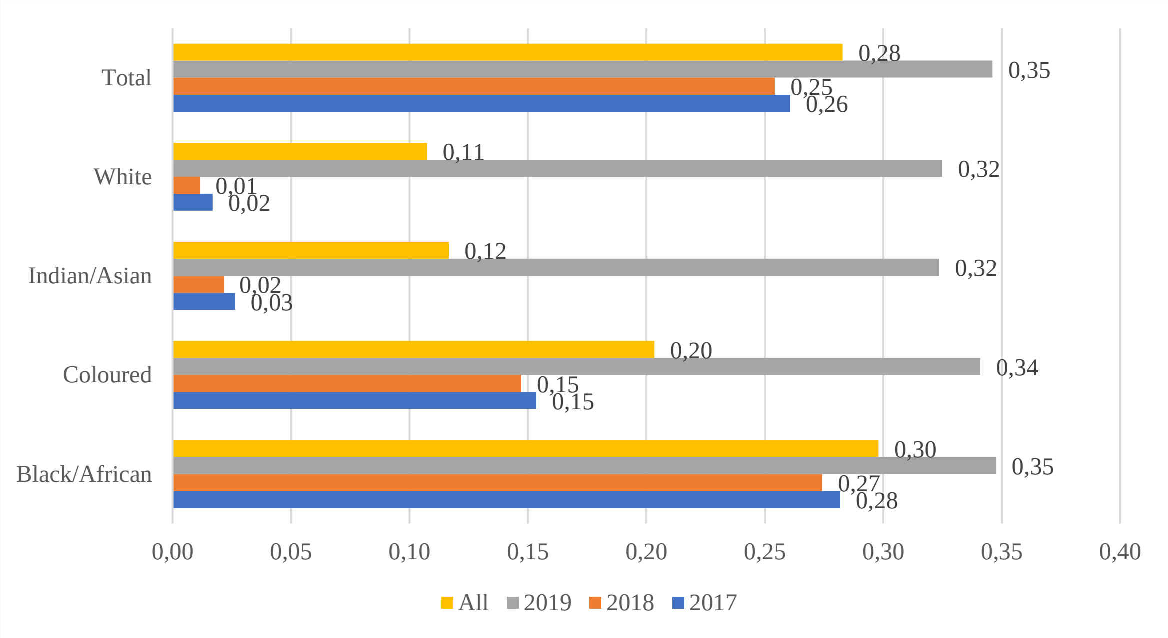

Figure 7.11. Average AF child MPI across population groups

Source: Own Computation, 2022

7.18 Average Fuzzy Set Child MPI Across Population Groups

Figure 7.9 presents the results on the average Fuzzy Set child MPI across different child population groups. The results show that Black children had an average fuzzy set child MPI of 0.10, 0.09, 0.10 and 0.10 in 2017, 2018, 2019 and combined years, respectively. It was also revealed that Coloured children had a fuzzy set child MPI of 0.06, 0.06, 0.10 and 0.07 in 2017, 2018, 2019 and combined years, respectively. The results of this study further revealed that there was a Fuzzy Set average of 0.04, 0.03, 0.10 and 0.05 in 2017, 2018, 2019 and combined years, respectively for Indian children. It was also revealed that White children had a fuzzy set child MPI average of 0.04, 0.04, 0.10 and 0.06 in 2017, 2018, 2019 and combined years, respectively.

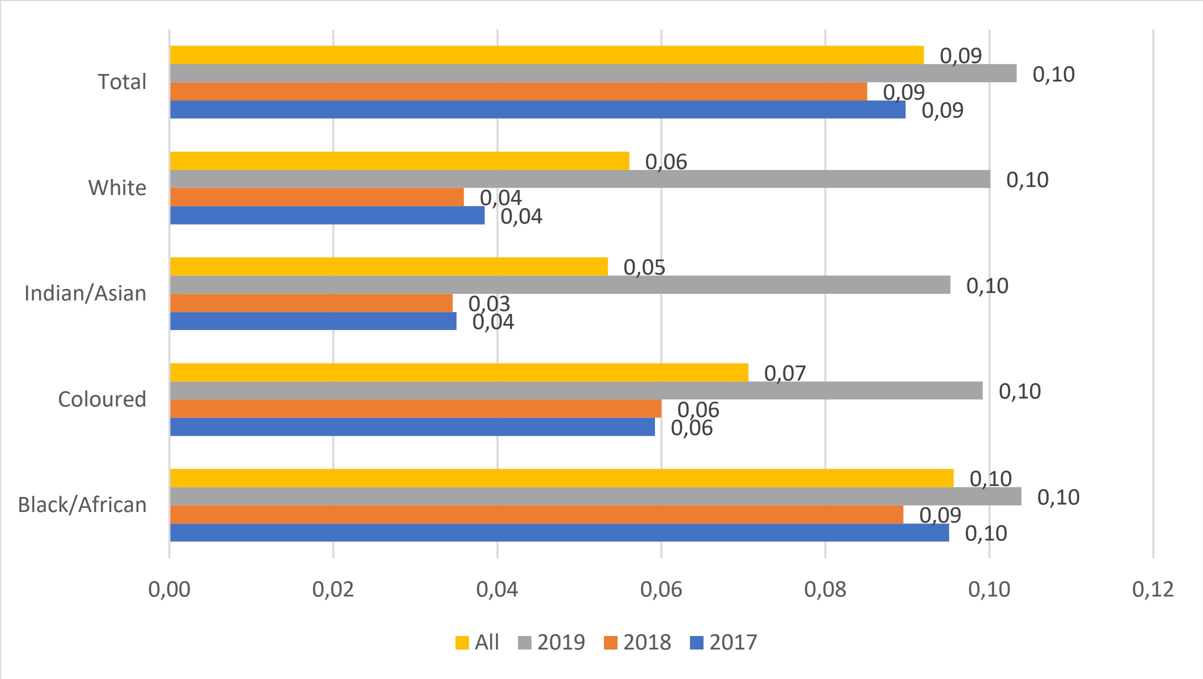

Figure 7.12. Average Fuzzy Set child MPI across population groups

Source: Own Computation, 2022

7.19 Average AF Child MPI Across Household Size

The average AF child MPI results are presented in figure 7.9. the results show that for children from <2 household members there was an AF child MPI average of 0.30, 0.28, 0.37 and 0.32 in 2017, 2018, 2019 and combined years, respectively. There was also an AF child MPI average of 0.23,0.23, 0.35 and 0.26 for children living with 2<4 members in a household in 2017, 2018, 2019 and combined years, respectively. It is further revealed that the AF child MPI averages of children with 4<6 members in a household were 0.25, 0.24, 0.35 and 0.27 in 2017, 2018, 2019 and combined years, respectively. Children residing in households with 6<9 members had an average AF child MPI of 0.28, 0.28, 0.35 and 0.31 in 2017, 2018, 2019 and combined years, respectively. Households with 9<11 members their children had 0.30, 0.29, 0.35 and 0.31 AF child MPI averages in in 2017, 2018, 2019 and combined years, respectively. Households with 11<13 members, their children had AF child MPI averages of 0.31, 0.26, 0.33 and 0.30 in 2017, 2018, 2019 and combined years, respectively. Children from households with members between 13<15 their children had an average AF child MPI of 0.34, 0.35, 0.34 and 0.34 in 2017, 2018, 2019 and combined years, respectively. There was an AF child MPI average of 0.34, 0.39, 0.35 and 0.36 for children in household with 15<17 members in 2017, 2018, 2019 and combined years, respectively. There was also an AF child MPI average of 0.32, 0.40, 0.35 and 0.35 for children with members between 17<19 in a household in 2017, 2018, 2019 and combined years, respectively. Households with ≥19 members their children had AF child MPI averages of 0.35, 0.40, 0.37 and 0.38 in 2017, 2018, 2019 and combined years, respectively.

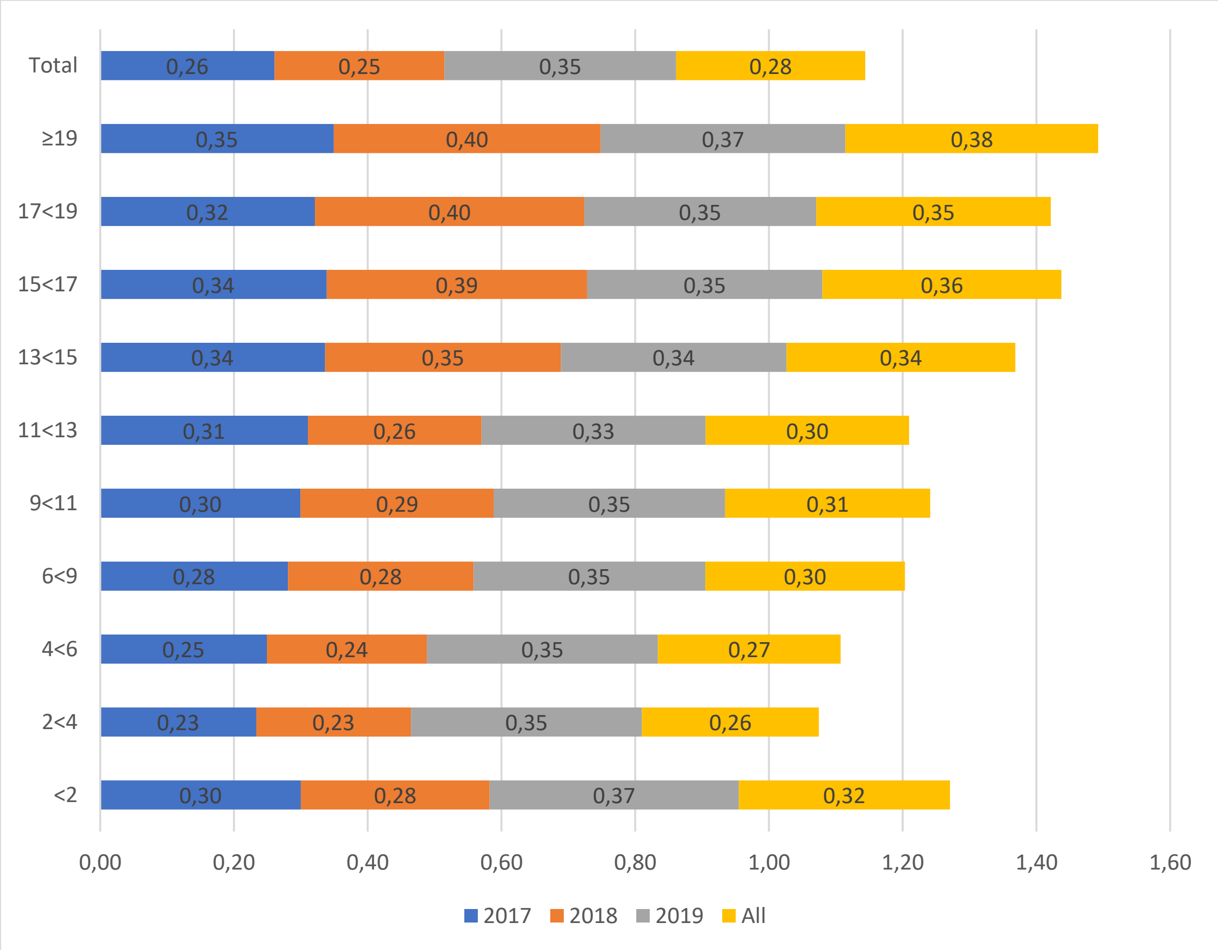

Figure 7.13. Average AF child MPI across household size

Source: Own Computation, 2022

7.20 Average Fuzzy Set child MPI across household size

The Fuzzy Set child MPI average results across household size have been presented in Figure 7.10. There were Fuzzy Set child MPI averages of 0.10, 0.09, 0.11 and 0.10 for children with <2 members in a household in 2017, 2018, 2019 and combined years, respectively. Children with 2<4 members in a household had Fuzzy Set MPI averages of 0.08, 0.08, 0.10 and 0.09 in 2017, 2018, 2019 and combined years, respectively. Children from households with 4<6 members had Fuzzy Set MPI averages of 0.09, 0.08, 0.10 and 0.09 in 2017, 2018, 2019 and combined years, respectively. Children that had between 6<9 members in a household had

Fuzzy Set MPI averages of 0.09, 0.09, 0.10 and 0.09 in 2017, 2018, 2019 and combined years, respectively. Children that had between 9<11 members in a household had Fuzzy Set MPI averages of 0.10, 0.09, 0.10 and 0.10 in 2017, 2018, 2019 and combined years, respectively. Children that had between 11<13 members in a household had Fuzzy Set MPI averages of 0.10, 0.08, 0.10 and 0.09 in 2017, 2018, 2019 and combined years, respectively. Children that had between 13<15 13 members in a household had Fuzzy Set MPI averages of 0.11, 0.12, 0.10 and 0.12 in 2017, 2018, 2019 and combined years, respectively. There were Fuzzy Set MPI averages of 0.12, 0.13, 0.10 and 0.12 for children with 15<17 members in a household. It was also revealed that children with 17<19 members had Fuzzy Set MPI averages of 0.13, 0.11, 0.10 and 0.11 in 2017, 2018, 2019 and combined years, respectively. The results also show that children with ≥19 members in a household had Fuzzy Set MPI averages of 0.09, 0.12, 0.10 and 0.11 in 2017, 2018, 2019 and combined years, respectively.

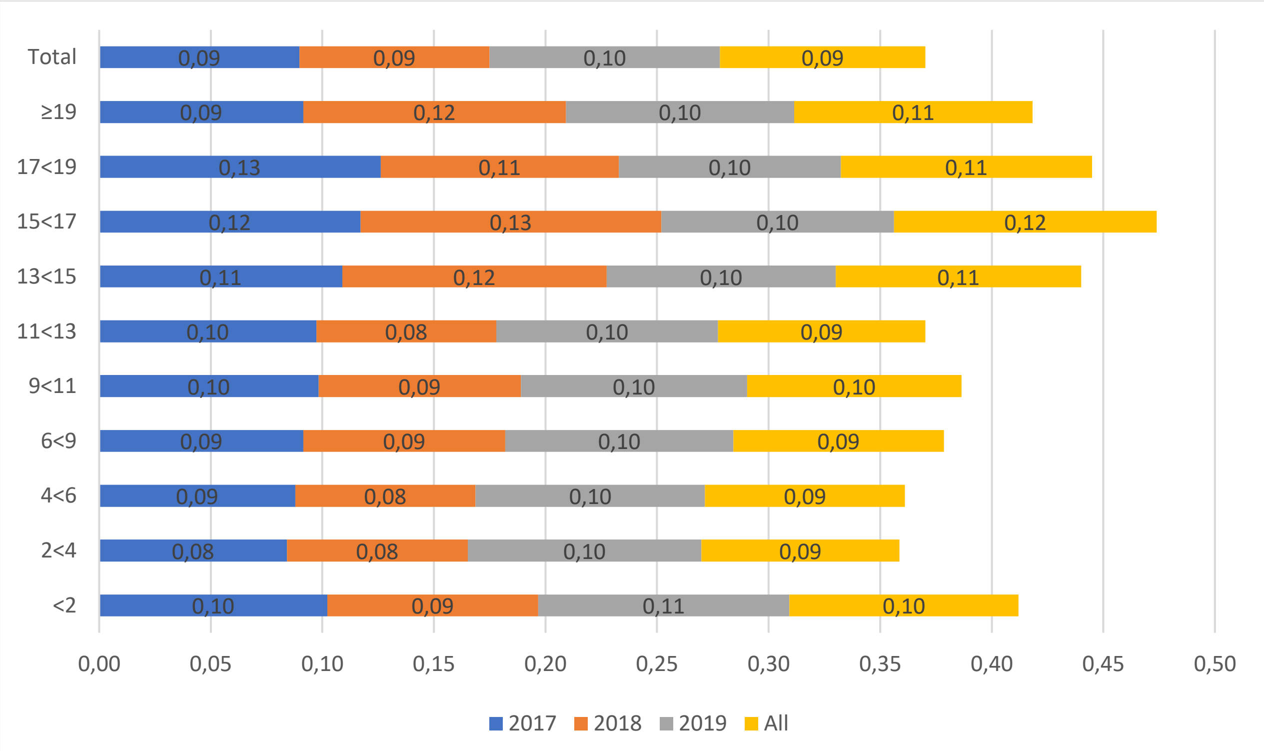

Figure 7.14. Average Fuzzy Set child MPI across household size

Source: Own Computation, 2022

7.21 Average AF Child's MPI Across Geography Type

The AF child MPI averages across different geography types that children reside in are presented in Figure 7.11. the results show that children in traditional areas and farms had the highest AF MPI averages. It is revealed that there were AF averages of 0.19, 0.19, 0.34 and 0.23 for children residing in urban areas. The results of this study further revealed that children in traditional areas had AF MPI average of 0.34 in 2017, remained the same in 2018, increased to 0.36 in 2019 and in combined data set was 0.34. it is also revealed that children in farms had AF MPI average of 0.33 in 2017, remained the same (0.33) in 2018 and increased to 0.37 in 2019 and was 0.34 in the combined data.

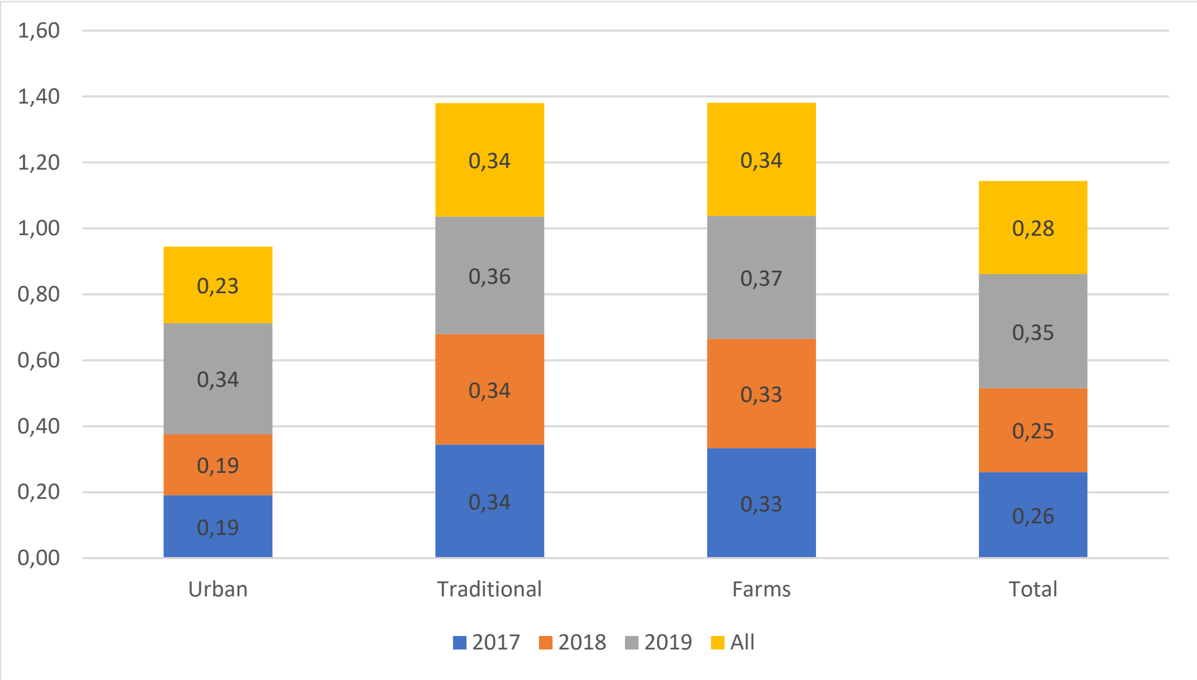

Figure 7.15. Average AF child MPI across geography type

Source: Own Computation, 2022

7.22 Average Fuzzy Set Child MPI Across Geography Type

Figure 7.21 presents the results on the Fuzzy Set MPI averages across the child's geography type. The results revealed that in 2017, children residing in farms had the highest Fuzzy Set MPI average of 0.12, followed by children in the traditional areas (0.11) and children in the urban areas had the lowest Fuzzy Set MPI average of 0.07. In 2018 dataset, the findings show that children residing in farms had the highest Fuzzy Set MPI average of 0.11, followed by children in the traditional areas (0.10) and urban areas (0.07). The 2019 dataset show the Fuzzy Set MPI averages of 0.12, 0.11 and 0.10 for children residing in farms, traditional areas and urban areas, respectively. The combined data shows the Fuzzy Set averages of 0.12, 0.11 and 0.08 for children residing in farms, traditional areas, and urban areas, respectively.

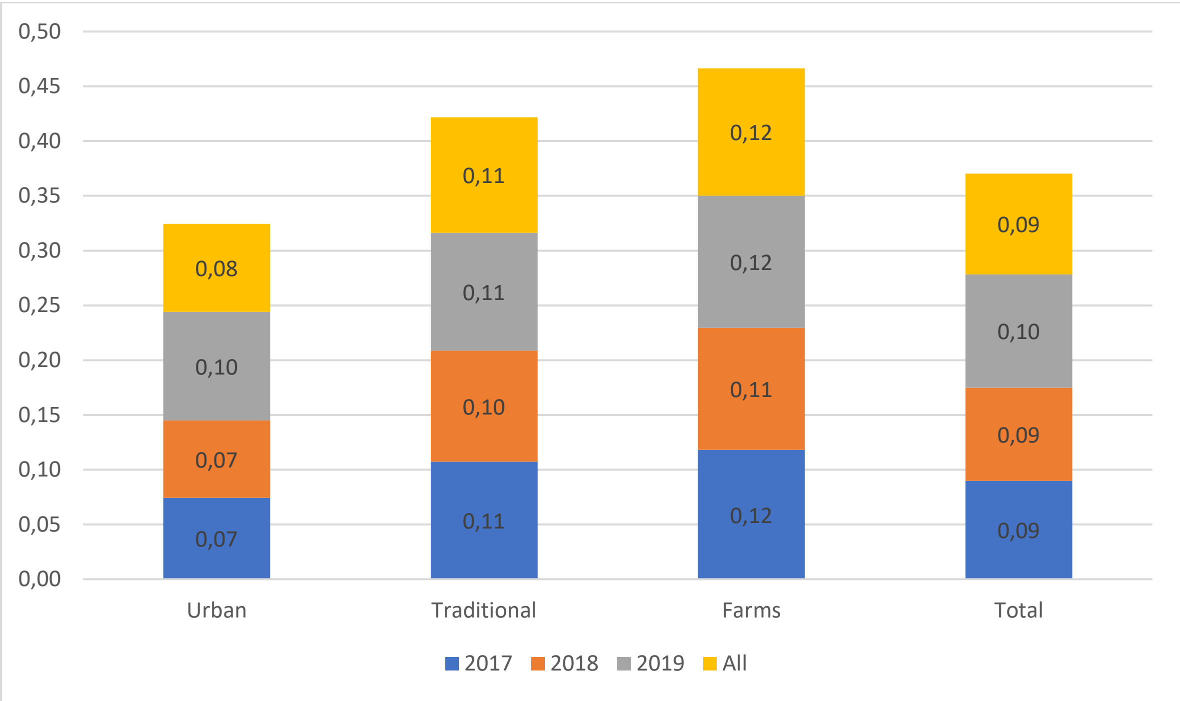

Figure 7.16. Average Fuzzy Set child MPI across geography type

Source: Own Computation, 2022

7.23 Decomposition of MPI into Its Absolute and Relative Contributions

The Alkire-Foster MPI approach carries the advantage of being able to decompose it across different groups and characteristics. Decomposition of multidimensional poverty index is essential for identifying those that are deprived the most in specific areas so that policy makers can correctly put in place relevant strategies to tackle poverty developmental problem. Table 7.4 presents the results on the decomposition of child MPI by looking at different provinces in the country, different population groups, the household head gender as well as the geography type across three different years and all the years combined. The results of this study revealed children in the KwaZulu-Natal as the poorest province with a constant MPI of 0.06 in 2017, 2018, 2019 and combined years, respectively. This province was followed by the Eastern cape with a constant MPI of 0.05 in 2017, 2018 and combined data and MPI of 0.04 in 2019. The western cape and the Northern cape provinces were revealed to be the lowest contributors to the overall child MPI. The results of this study are in line with those of Omotoso and Koch who also revealed the KwaZulu-Natal and Eastern cape provinces to have the highest proportion of multidimensionally deprived children. The Western Cape and Free State had an

MPI of 0.01 in 2017 and 2018 and MPI of 0.02 in 2019 and combined data. The results also show that the Northern Cape had a constant MPI of 0.01 in 2017, 2018, 2019 and combined years. The results of this study also revealed that the North West province had a constant MPI of 0.02 in 2017, 2018, 2019 and combined years. The Gauteng province had an MPI of 0.03 in 2017, 0.03 in 2018, 0.05 in 2019 and 0.04 in combined data. Mpumalanga had an MPI of 0.03 in 2017, 2018, 2019 and combined years. Children in Limpopo had an MPI of 0.04 in 2017, 2018 and combined data and MPI of 0.03 in 2019.

Regarding the population group, the results of this study revealed that Black/Africans contributed the most to overall MPI, followed by the Coloureds, Whites and Indians/Asians were revealed to be the least contributors to child MPI across the years. The results presented in table 7.5. show that Blacks/Africans had an MPI of 0.089, 0.085, 0.088 and 0.262 with a relative and absolute contribution of 94%, 95%, 88% and 92% in 2017, 2018, 2019 and all the years combined, respectively. Coloured were revealed to have an MPI of 0.005, 0.004, 0.008 and 0.017 with a relative and absolute contribution of 5%, 5%, 8% and 6% in 2017, 2018, 2019 and all the years combined, respectively. The results of this study are similar to those of Omotoso and Koch (2018) who also revealed that being Black significantly contributed to child MPI in the two periods that they were observing. This might be the results of the previous disadvantage that the Blacks/African and Coloured have i.e., apartheid effects.

The findings of this study also revealed that male headed households were contributing more to poverty compared to female headed households across the years. It was revealed that children from male headed households had a declining MPI of 0.058, 0.056, 0.054 and 0.168 in 2017, 2018, 2019 and all the years combined, respectively. The male headed households contributed 62%, 62%, 54% and 59% to child MPI in 2017, 2018, 2019 and all the years combined, respectively. The findings of this study are contrary to those of Rogan (2016) and Megbowon (2018) who found out that female headed households significantly contributed more to multidimensional poverty compared to their male counterparts.

Regarding the geography type, traditional areas were found to be contributing more to child MPI compared to urban areas and farms. The findings of this study revealed that children residing in traditional areas had an MPI of 0.053, 0.050, 0.042 and 0.145 with a contribution of 55%, 56%, 42% and 51% in 2017, 2018, 2019 and all the years combined, respectively. Children in urban areas has an MPI of 0.037, 0.035, 0.054 and 0.126 with a contribution of 40%, 40%, 55% and 45% in 2017, 2018, 2019 and all the years combined, respectively. The results of this study are contrary to those of Omotoso and Koch who found out that children residing in urban areas were poorer compared to those in urban areas. The findings of this study offer ideas on geography types to focus on for interventions/implementations when addressing the issue of welfare. Megbowon (2018) also revealed same results and noted that this could be because of the larger number of people in urban areas. These people might be going to urban areas in search of employment or education opportunities.

Table 7.5: Decomposition of MPI and its absolute and relative contribution across child's province, population group, household head gender

	2017		2018		2019		All	
	N	MPI	N	MPI	N	MPI	N	MPI
Province								
Western Cape	772	0.01	775	0.01	1282	0.02	2829	0.02
Eastern Cape	3082	0.05	2882	0.05	2744	0.04	8708	0.05
Northern Cape	673	0.01	671	0.01	880	0.01	2224	0.01
Free State	930	0.01	908	0.01	1071	0.02	2909	0.02
KwaZulu-Natal	3750	0.06	3569	0.06	3707	0.06	11026	0.06
North West	1086	0.02	1014	0.02	1158	0.02	3258	0.02
Gauteng	2030	0.03	1993	0.03	3532	0.05	7555	0.04
Mpumalanga	1822	0.03	1712	0.03	1746	0.03	5280	0.03
Limpopo	2541	0.04	2442	0.04	1945	0.03	6928	0.04
Population group								
Black/African	15767	0.26	15153	0.24	15914	0.25	46834	0.26
Coloured	869	0.00	780	0.01	1442	0.02	3091	0.02
Indian/Asian	18	0.00	14	0.00	190	0.00	222	0.00
White	32	0.00	19	0.00	519	0.01	570	0.00
Head gender								
Male	10268	0.16	9913	0.16	9721	0.15	29902	0.17
Female	6418	0.10	6053	0.10	8344	0.13	20815	0.11
Geography type								
Urban	6741	0.10	6398	0.10	9910	0.15	23049	0.13
Traditional	9253	0.15	8904	0.14	7570	0.12	25727	0.15
Farms	692	0.01	664	0.01	585	0.01	1941	0.01
Total	16686	0.26	15966	0.25	18065	0.28	50717	0.28

Source: Own Computation, 2022

When it comes to multidimensional poverty, the most important thing is to correctly identify those who are mostly deprived in specific areas so that these people who are identified as MPI poor can be targeted in those areas for implementing the suitable poverty alleviation strategies. According to Alkire et al. (2015) we need to compute a multidimensional poverty degree to meet the requirements of being able to breakdown dimensions so that we can analyse compositions of MPI. Figure 7.17. presents the decomposition finding across different dimensions or indicators. the findings revealed that the assets contribute the most to the AF child MPI by 46.92%, followed by telecommunications (18.78%) and Nutrition (8.92%). Megbowon (2018) mentioned that when a household owns more assets, the chances of them being multidimensionally poor are low. He further mentioned that this is because of the economic advantage that the assets have, and they are basis for social prestige. When a household lacks assets, it means they do not have anything to turn into cash or to turn into credit security when times are bad or faced with uncertainties (Anderson, 2012). These assets

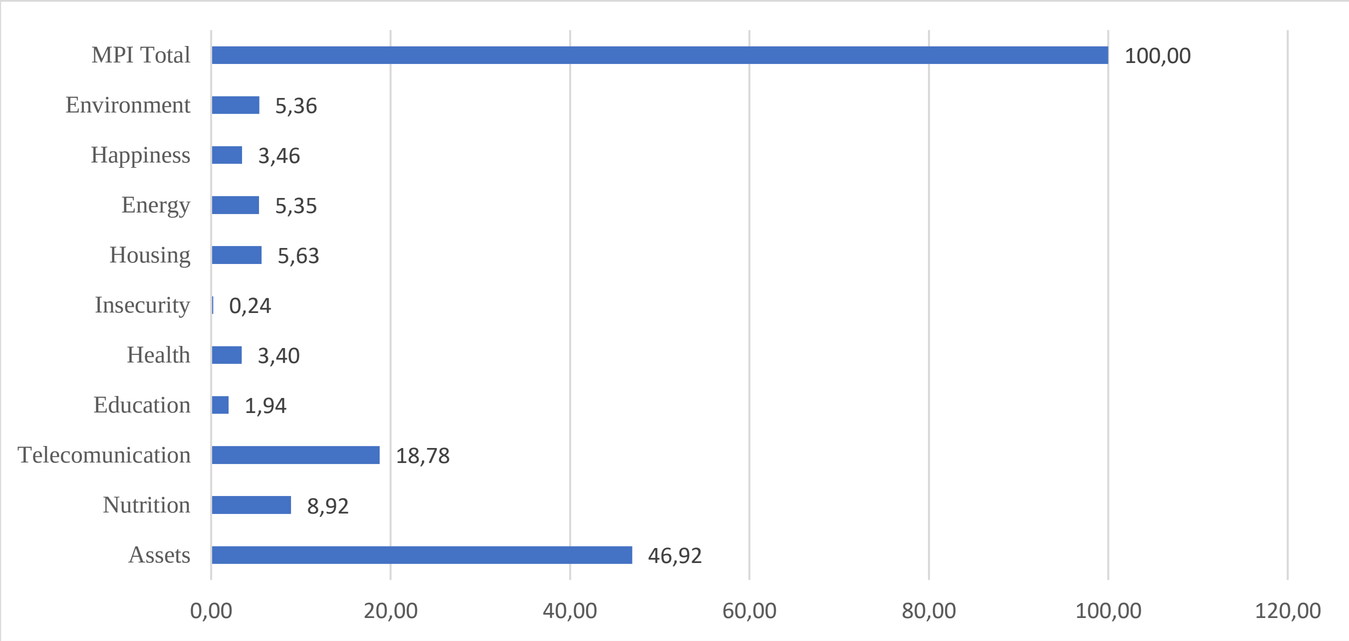

Figure 7.17. Decomposition of AF child MPI Dimensions

Source: Own Computation, 2022

can help the households to accumulate income from renting them out. Lacking assets also puts households at risk/threat of being unable to escape poverty causing generational poverty (Carter and Barret, 2006). It is evident from these studies that assets are a collection of wealth. According to Kiprono (2021) children that do not have access to important information via media are likely to be poor. A study conducted by Pradhan et al. (2022) revealed nutrition to be the largest contributor to multidimensional poverty. Other contributors to the overall AF child MPI are housing (5.63%) slightly different from environment (5.36%) and energy (5.35%). Suppa (2015) used indicators of housing to capture the behaviour of having a roof over your head and having privacy. Suppa further mentioned that housing contributes to healthy living conditions and the results computed revealed that housing contributed relatively more to multidimensional poverty. According to Kahn and Kahn (2009) environmental hazards that are harmful to human beings are cause by the disposal of hazardous and junk residues. Pérez-Cirera et al. (undated) computed main practices of disposing refuse and confirmed whether household practiced direct harmful waste disposal methods. Happ (2021) mentioned that energy falls under basic commodities. She further mentioned that those without energy are deprived the opportunity to be study, play or do anything after the sunsets. Happiness contributed 3.46% to the overall MPI. It was then followed by health (3.40%), education

(1.94%) and insecurity (0.24%). There are positive correlations between MPI and lack of happiness.

CHAPTER EIGHT

CORRELATES OF CHILD'S MULTIDIMENSIONAL WELFARE INDICATORS

8.1. Introduction

The results presented in this chapter address the third objective of this study which seeks to analyse the determinants of child's multidimensional welfare indicators. The results were obtained by regressing the computed children's Alkire-Foster and fuzzy MPI as the dependent variables (separately) against the children's selected characteristics using Tobit model.

8.2. Determinants of Child Multidimensional Welfare Using Tobit Regression

8.2.1 Diagnostic Indicators for Estimated Models and Test for Multicollinearity

The Tobit regression results for Alkire-Foster MPI and fuzzy MPI are presented in Table 8.1 and Table 8.2, respectively. Multicollinearity among the analysed variables was scrutinized. This was done by computing the variance inflation factor (VIF) statistics. The mean VIF for the independent variables were 3.76, 3.49, 2.92 and 3.42 for 2017, 2018, 2019 and all the years combined, respectively. These results show that the models did not suffer from serious problem of multicollinearity. The models also produced good fits for the data given the statistical significance of the Likelihood Ratio Chi Square ($p<0.01$). Hypothesis one is hereby rejected.

8.2.2 Disability Factors Influencing MPI

Table 8.1 shows the effects of some disability variables such as child's being unable to see, walk, hear, take care of self, remember things and communicating on MPI. The t statistics revealed that inability to see, walk, take care of yourself, and communicate significantly affected Alkire-Foster and Fuzzy Set MPI in some of the results. The parameters of being unable to see did not show statistical significance in 2017 ($p>0.10$). However, the estimated parameters for 2018, 2019 and combined dataset showed statistical significance ($p<0.01$ and $p<0.05$). These results imply that children who had eyesight problems had their AF MPI decreased by 3.52e-07, 1.66e-07 and 2.38e-07 in 2018, 2019 and combined dataset, respectively. When comparing these results to the fuzzy MPI results in Table 8.2, it revealed similar results to the AF MPI. The results showed statistical significance ($p<0.01$ and $p<0.10$) for children experiencing eyesight problems. The Fuzzy Set MPI results imply that children who experienced eyesight problems had their Fuzzy Set MPI decreased by 0.0073, 0.0086, 0.0023 and 0.0067 in 2017, 2018, 2019 and combined dataset, respectively. The parameters of hearing impairment in Table 8.1 did not show statistical significance ($p>0.10$) in 2017, 2018 and 2019. However, the combined data parameters showed statistical significance ($P<0.10$). These results imply that children who were suffering from hearing impairment had their AF MPI decreased by 5.08e-08 in combined dataset. The results presented in Table 8.2 show that hearing impairment parameters in 2019 were not significant. However, the estimated parameters were significant in 2017, 2018 and combined dataset. The results in Table 8.2 imply that children who had hearing impairments had their Fuzzy Set MPI decreased by 0.0091, 0.0115 and 0.0089 in 2017, 2018 and combined dataset, respectively. Investigations on poverty and disability have gained momentum and this is influenced by the work done by Sen on the capability approach. White et al. (2017) examined multidimensional poverty among the native- and foreign-born in the United States and considered the disability aspect. Their results are contrary to the results of this study since they found out that people with disabilities were likely to be multiply deprived. Moreover, numerous studies conducted on poverty and disability found out that disabled people are more likely to be poor compared to people without disabilities (Brucker et al., 2015, Pinilla-Roncancio, 2018, Banks et al. 2021, DeBeaudrap et al. 2020). Banks et al. (2021) found that multidimensional poverty was related to an individual having a functioning limitation that affects cognition and self-care.

The results in Table 8.1 revealed that there was no statistical significance in for children who were unable to walk in 2018, 2019 and combined dataset, respectively. However, in 2017 datasets there was statistical significance ($p<0.05$) of the estimated parameters. These results mean that children who were unable to walk had their AF MPI chances being increased by 3.33 e-07 in 2017. Table 8.2 results also revealed a statistical significance ($p<0.01$) for the parameters of children who were unable to walk. These results imply that children who were unable to walk had their Fuzzy Set MPI increased by 0.0253, 0.0145 and 0.0140 in 2017, 2018 and combined dataset, respectively. However, there was no statistical significance for the estimated parameters in 2019. The parameters of forgetfulness in Table 8.2 did not show statistical significance in all the years. Table 8.2 revealed the same results as those of Table 8.2, that is, there was no statistical significance for the estimated parameters for all the years. The results on Table 8.1 show that there was no statistical significance for children who were not able to care for themselves in 2017 and 2019. However, the 2018 and combined datasets showed a statistical significance ($p<0.05$, $p<0.01$). This implies that children who were not able to care for themselves had their AF MPI increased by 1.64 e-07 and 9.83 e-08 in 2017 and combined dataset, respectively. The results in Table 8.2 did not show statistical significance in all the years. Regarding communication impairment the results presented in Table 8.1 show that even though the 2017 and 2019 parameters were insignificant, the estimated parameters in 2018 and combined datasets showed a statistical significance ($p<0.01$). This means that children who were suffering from some form of communication impairment had their AF MPI increased by 3.54 e-07 and 2.04 e-07 in 2018 and combined dataset, respectively. The results in Table 8.2 revealed the same results as those in Table 8.1. The parameters of communication impairment did not show statistical significance in 2017 and 2019. However, the estimated parameters for 2018 and combined dataset were statistically significant ($p<0.01$). These results imply that children who were suffering from some form of communication impairment had their Fuzzy Set MPI increased by 0.0008 and 0.0070 in 2018 and combined dataset, respectively. These results are in line with those of Mitra et al. (2011) who revealed that people with disabilities were found to be multidimensionally poor compared to people without disabilities. They further mentioned that disabled people had four times higher chances of being multidimensionally poor compared to people without disabilities. UNICEF (2007) mentioned that people with disabilities are affected by poverty because it lowers household income due to their needs and these disabled people are unable to work, resulting in them being depending on others. It was further stipulated by Opoku et al (2017) that even though disabled people do not depend on anyone, that is, are employed, they are more likely to be underemployed due to their capabilities or underpaid which results in reducing their per capita income. Endusei et al. (2017) on assessing the impact and uses of the disability common fund among persons with disabilities in Kumasi Metropolis in Ghana, found out that some people living with disability can depend on the generosity of family members or the community, however, there is lack of formal government support. Grut et al (2012) in South Africa found out that there are unique challenges faced by disabled people in accessing the health care services.

Mutwali and Ross (2019) found out that In South Africa, disabled people have poor pohysical access to health care facilities in terms of not being covered under any medical aid scheme, using public facilities and taking longer time to reach the health care facilities compared to those without disabilities. According to a study conducted by Mkabile and Swartz (2020) in the WC, it was revealed that caregivers and parents of children living with disabilities could not utilize intellectual disability service because of financial challenges, community stigmatization.

Table 8.1 Tobit Regression Estimates of the Determinants of Children's Alkire-Foster MPI

AF child MPI	2017		2018		2019		All	
	Coefficient	t stat	Coefficient	t stat	Coefficient	t stat	Coefficient	t stat
Seeing	-1.25e-07	-1.25	-3.52e-07	-3.41***	-1.66e-07	-2.00**	-2.38e-07	-4.02***
Hearing	1.49e-07	1.11	-2.16e-08	-0.15	-8.69e-08	-0.78	-5.08e-08	-0.64*
Walking	3.33e-07	2.24**	1.37e-07	0.88	4.87e-08	0.42	1.44e-07	1.66
Remembering	-6.21e-08	-0.54	2.03e-09	0.02	-2.62e-08	-0.28	-2.57e-08	-0.38
Selfcare	6.24e-08	0.93	1.64e-07	2.44**	1.10e-09	0.02	9.83e-08	2.49***
Communication	-1.31e-07	-0.97	3.54e-07	2.56***	2.79e-08	0.28	2.04e-07	2.68***
Province								
Eastern Cape	6.64e-07	9.12*	5.26e-07	7.12*	-6.34e-08	-0.93	4.63e-07	8.45
Northern Cape	8.93e-08	1.05	-6.32e-10	-0.01	-2.37e-07	-3.09*	3.78e-08	0.74
Free State	-3.96e-08	-0.47	-1.05e-07	-1.23	-2.32e-07	-2.96*	-6.65e-08	-1.30
KwaZulu-Natal	3.98e-07	5.49*	5.24e-08	0.72	-1.56e-07	-2.31*	1.78e-07	4.07
North West	1.74e-07	2.04*	-5.54e-08	-0.64	-4.58e-07	-5.86	-9.84e-09	-0.19
Gauteng	-2.55e-07	-3.69*	-3.91e-07	-5.64*	-8.91e-08	-1.38	-2.03e-07	-4.85
Mpumalanga	3.88e-07	4.84*	1.37e-08	0.17	-2.65e-07	-3.60	1.28e-07	2.65
Limpopo	-3.64e-07	-4.65*	-5.76e-07	-7.31*	-4.87e-07	-6.57	-4.51e-07	-9.45
Child gender	-6.83e-08	-2.39	-4.24e-08	-1.45	-2.97e-08	-1.15	-5.54e-08	-3.20
Child age	-9.71e-09	-2.05	-1.17e-08	-2.42	1.92e-08	4.55	2.57e-09	0.90
Population group								
Coloured	-8.10e-07	-2.77	-9.29e-07	-4.23	-3.50e-08	-0.59	-6.26e-07	-16.12
Indian/Asian	-1.26e-06	-8.35	-1.20e-06	-7.90	-1.36e-07	-1.07	-9.56e-07	-8.77
White	-8.41e-07	-8.67	-9.36e-07	-9.17	-1.14e-07	-1.41	-7.24e-07	-12.77
Son or daughter	6.14e-07	15.07	5.57e-07	13.48	1.05e-07	3.03	4.39e-07	18.49
Father alive	-1.20e-07	-3.46	-1.19e-07	-3.39	1.30e-08	0.45	-8.34e-08	-4.08
Father part of household	-3.17e-07	-8.04	-3.21e-07	-8.01	-6.69e-08	-1.96	-2.69e-07	-11.58
Mother alive	-2.00e-08	-0.35	-1.46e-07	-2.50	1.95e-08	0.40	-7.20e-08	-2.11
Mother part of household	-1.20e-07	-3.01	-1.20e-07	-2.98	-1.11e-07	-3.17	-1.32e-07	-5.59
Domestic worker service	1.18e-06	16.89	1.31e-06	18.25	4.18e-07	8.22	1.11e-06	28.86

Table 8.1 Tobit Regression Estimates of the Determinants of Children's Alkire-Foster MPI Cont.

Household size	9.92e-09	1.67	3.32e-08	5.55	-1.28e-08	-2.76	2.60e-08	7.77
Geography type								
Traditional	1.05e-06	25.73	1.14e-06	27.55	2.96e-07	8.66	8.56e-07	36.01
Farms	1.38e-06	17.00	1.53e-06	18.28	5.30e-07	6.88	1.19e-06	23.74
Salaries/wages commission	-8.70e-07	-6.00	-9.08e-07	-6.81	-1.02e-07	-3.77	-7.98e-07	-41.59
Income from business	-6.22e-07	-4.43	-6.87e-07	-5.32	-1.45e-08	-0.40	-4.48e-07	-17.54
Remittances	-3.38e-07	-8.79	-4.24e-07	-0.89	1.57e-08	0.43	-3.40e-07	-14.60
Pensions	-1.01e-06	-1.34	-9.55e-07	-1.09	-4.62e-08	-0.53	-8.68e-07	-16.13
Grants	9.00e-07	14.78	7.93e-07	12.64	-4.06e-08	-1.30	5.93e-07	22.18
Social grants	-7.34e-07	-5.01	-6.27e-07	-2.60	-1.98e-07	-6.26	-6.69e-07	-28.23
Sales of farming products/service	-1.16e-07	-1.23	-2.73e-07	-2.90	-2.05e-08	-0.23	-1.29e-07	-2.25
Other income sources	-5.44e-07	-5.06	-4.82e-07	-4.00	-1.26e-08	-0.13	-4.84e-07	-7.15
Backyard garden	2.94e-07	7.35	2.92e-07	7.14	-4.24e-08	-1.28	3.33e-07	14.47
School garden	8.30e-07	1.80	-4.65e-07	-1.02	4.61e-07	1.45	4.47e-07	1.78
Communal garden	-3.64e-08	-0.13	5.36e-07	2.23	1.74e-07	0.91	4.24e-07	2.93
_Cons	2.20e-06	14.80	2.21e-06	14.64	4.67e-06	38.63	2.80e-06	33.31
Var (e,mpi)	5.29e-12		5.35e-12		3.43e-12		5.37e-12	
LR Chi2	9969.90		9230.63		577.61		17448.17	
Prob Chi2	0.0000		0.0000		0.0000		0.0000	
Pseudo R2	-0.0169		-0.0161		-0.0012		-0.0106	
Log Likelihood	299666.44		291533.92		242348.05		828736.54	
Mean VIF	3.76		3.49		2.92		3.42	

Source: Own Computation, 2022. NB ***, ** and * implies statistically significant at 1%, 5% and 10% levels of significance, respectively

8.2.3 Provincial and Geographical Factors Influencing MPI

Tables 8.1 and 8.2 also present the results on provincial and geographical factors influencing child MPI. The parameters of the Eastern Cape province did not show statistical significance in 2019 in the AF model. However, the estimated parameters for 2017, 2018 and combined dataset showed statistical significance ($p<0.10$). This implies that when compared with children from Western Cape and holding other variables constant, children from the Eastern Cape had their AF MPI increased by 6.64e-07, 5.26e-07 and 4.63e-07 in 2017, 2018 and combined dataset, respectively. The Eastern Cape parameters in Table 8.2 showed a statistical significance ($p<0.01$) in the Fuzzy Set model for 2017, 2018, 2019 and combined dataset. These results imply that when compared to children from Western Cape and holding other variables constant, children from the Eastern Cape had their Fuzzy Set MPI increased by 0.0248, 0.0264, 0.0048 and 0.0206 in 2017, 2018, 2019 and combined dataset, respectively. These results are related to those of Mosasane and Oyekale (2021) who reveled that the people from the Eastern Cape were one of the top respondents to be multidimensionally poor. Megbowon (2018) mentioned that although the South African government has made progress in alleviating poverty since the official end of apartheid in 1994, there is still existance of poverty in the province. Moreover, the EC province is the most poverty striken province in SA. According to Noble et al. (2014) people in the EC province are the largest receiving grants and have the highest rates of deprivations.

Table 8.1 shows that Northern Cape parameters did not show statistical significance ($p>0.10$) in 2017, 2018 and combined dataset. However, the estimated parameters for 2019 showed statistical significance ($p<0.10$). These results imply that compared to children from the Western Cape and holding other variables constant, children in the Northern Cape had their AF MPI lower by average of 2.37e-07 in 2019. The parameters of Free State in Table 8.1 did not show statistical significance in 2017, 2018 and combined data. However, the estimated parameters showed statistical significance ($p<0.10$) in 2019. The results of this study are also related to those of Mosasane and Oyekale (2021) who also found out that the Northern Cape province respondents had their MPI reduced when compared to the WC. These results awre in line with those of Ndlovu (2010) who also revealed that the NC province was one of the provinces that experienced a significant decline in poverty.

These results imply that when comparing children from the Free State to children from the Western Cape and holding other variables constant, children from Free State had their AF MPI lower by average of 2.32e-07 in 2019. The Free State parameters in Table 8.2 did were insignificant in 2018, 2019 and combined dataset. However, in 2017, the estimated parameters showed statistical significance ($p<0.10$). These results imply that compared to children from the Western Cape, children from Free State had their Fuzzy Set MPI higher by average of 0.0042. These results are in line with those of Jackson (2021) who conducted a study on the multidimensional poverty index of South Africa and found the Free State province to have increased MPI.

The parameters of KwaZulu-Natal in Table 8.1 did not show statistical significance in 2019. However, the estimated parameters in 2017, 2018 and combined dataset showed statistical significance ($p<0.10$). These results imply that when compared to children from the Western Cape and holding other variables constant, children from KwaZulu-Natal province had their AF MPI higher by average of 3.98e-07 and 1.78e-07 in 2017 and combined dataset and their AF MPI was lower by average of 2.31e-07 in 2019. The results in Table 8.2 showed that KwaZulu-Natal parameters in 2017, 2018 and combined dataset were not significant. However, in 2019 the estimated parameters showed statistical significance ($p<0.10$). These results imply that in 2019 children from KZN had their Fuzzy Set MPI lower by average of 1.88 compared to children in Western Cape province. Mosasane and Oyeakle (2021) and Jackson (2021) who analyzed multidimensional poverty in SA also found the results that are related to one of this study which is the KZN province respondents had their MPI increased.

The North West province parameter in 2019 and combined dataset did not show statistical significance ($p>0.10$). However, in 2017 and 2019 the estimated parameters show statistical significance ($p<0.10$). The results in Table 8.1 imply that when compared to children from the Western Cape and holding other variables constant, children from the NW province had their AF MPI higher by average of 1.74e-07 in 2017 and lower by average of 4.58e-07 in 2019. The North west parameters in Table 8.2 for 2017 and 2018 were not significant and 2019 and combined dataset showed statistical significance ($p<0.05$). The results in Table 8.2 imply that when compared to children from the Western Cape province and holding other variables constant, children in the North West province had their Fuzzy Set MPI lower by average of 0.0101 and 0.0030 in 2019 and combined data, respectively. These results are related to those of Fransman and Yu (2019) who revealed that people from the NW province had their MPI increased.

Gauteng parameters did not show statistical significance in 2019. However, the estimated parameters showed statistical significance in 2017, 2017 and combined dataset ($p<0.10$). The results in Table 8.1 imply that when compared to children from the Western Cape and holding other variables constant, children from Gauteng province had their AF MPI lower by 2.55 e-07, 3.91 e-07 and 2.03 e-07 in 2017, 2018 and combined dataset, respectively. Fransman and Yu (2019) also revealed the findings that are similar to the one of this study where respondents from Gauteng and WC provinces had their MPI reduced. The Gauteng parameters in Table 8.2 did not show statistical significance in 2019 and combined dataset. However, in 2017 and 2018 the estimated parameters showed statistical significance ($p<0.01$). The results in Table 8.2 imply that when compared to children from Western Cape and holding other variables constant, children fro Gauteng had their Fuzzy Set MPI higher by average of 0.0047 and lower by average of 0.0047 in 2017 and 2018, respectively. Jackson (2021) also found Gauteng respondents to have increased MPI.

The parameter of Mpumalanga did not show statistical significance in 2018. However, the estimated parameters for 2017, 2019 and combined dataset showed statistical significance. The results in Table 8.1 imply that when compared to children from the Western Cape and holding other variables constant, children from Mpumalanga had their AF MPI increased by average of 3.88 e-07 and 1.28 e-07 in 2017 and combined dataset and lower by 3.60 e-07 in 2019. Mpumalanga parameters in Table 8.2 did not show statistical significance for 2018. However, the estimated parameters showed statistical significance ($p<0.01$, $p<0.05$). The results presented in Table 8.2 imply that when compared to children from Western Cape and holding other variables constant, children from Mpumalanga had their Fuzzy Set MPI increased by average of 0.0076 and 0.0024 in 2017 and combined datasets and lower by 0.0062 in 2019. The Limpopo parameters showed statistical significance ($p<0.10$). These results are related to those of Mosasane and Oyekale (2021) who compared WC to MP and found out that the MP repondents had their MPI increased.

The results in Table 8.1 imply that when compared to children in the Western Cape and holding other variables constant, children from Limpopo province had their AF MPI lower by average of 3.64 e-07, 5.76 e-07, 4.87 e-07 and 4.51 e-07 in 2017, 2018, 2019 and combined dataset, respectively. These results are related to those of Jackson (2021) who also revealed that the Limpopo province respondents had their MPI increased.

Regarding the geographic type in which children reside in, the results in Table 8.1 showed statistical significance ($p<0.10$) for children residing in traditional areas for 2017, 2018, 2019 and combined dataset. The results presented in Table 8.1 showed that when compared to children from urban areas and holding other variables constant, children from traditional areas had their AF MPI higher by average of 1.05 e-06, 1.14 e-06, 2.96 e-07 and 8.56 e-07 in 2017, 2018, 2019 and combined dataset, respectively. When observing the results presented in Table 8.2, parameters for children from traditional areas showed statistical significance ($p<0.01$). The results in Table 8.2 imply that when compared to children from urban areas and holding other variables constant, children from traditional areas had their Fuzzy Set MPI higher by average of 0.0194, 0.0172, 0.0010 and 0.0163 in 2017, 2018, 2019 and combined data, respectively. Cheteni et al. (2019) also found out that people residing in traditional areas are likely to be poor. Lilenstein et al. (2018) also found out that poverty rates in traditional areas were far higher in traditional areas compared to urban areas.

The farms parameters showed statistical significance ($p<0.10$) in 2017, 2018, 2019 and combined data. The results presented in Table 8.1 imply that compared to children in urban areas and holding other variables constant, children from farms had their AF MPI higher by average of 1.38 e-06, 1.53 e-06, 5.30 e-07 and 1.19 e-06 in 2017, 2018, 2019 and combined data, respectively. In Table 8.2 farms parameters showed statistical significance ($p<0.01$). The results imply that when compared to children from urban areas and holding other variables constant, children from farms had their Fuzzy Set MPI higher by average of 0.0377, 0.0351, 0.0225 and 0.0329 in 2017, 2018, 2019 and combined data, respectively. These results are in line with those of the UNICEF (2020) which also revealed that children from rural areas had higher rates of poverty compared to those in urban areas.

8.2.4 Racial Factors Influencing MPI

The results on racial factors influencing child MPI are presented in Table 8.1 (AF MPI) and Table 8.2 (Fuzzy Set MPI). The Coloured parameters in Table 8.1 did not show statistical significance for 2019. However, the estimated parameters showed statistical significance ($p<0.10$) in 2017, 2018 and combined data. The results presented in Table 8.1 imply that when compared to Black/African children, Coloured children had their AF MPI lower by average of 8.10 e-07, 9.29 e-07 and 6.26 e-07 in 2017, 2018 and combined data, respectively. The Coloured parameters in Table 8.2 showed statistical significance ($p<0.01$) for 2017, 2018, 2019 and combined data. These results imply that when compared to Black/African children and holding other variables constant, Coloured children had their Fuzzy Set MPI lower by average of 0.0203, 0.0176, 0.0028 and 0.0144 in 2017, 2018, 2019 and combined data, respectively.

The Indian/Asian parameters did not show statistical significance ($p>0.10$) in Table 8.1. However, the estimated parameters for 2017, 2018 and combined dataset were significant ($p<0.10$). The results presented in Table 8.1 imply that when compared to Black/African children and holding other variables constant, Indian/Asian children had their AF MPI lower by average of 1.26 e-06, 1.20 e-06, 1.36 e-07 and 9.56 e-07 in 2017, 2018, 2019 and combined data, respectively. The Indian/Asian parameters in Table 8.2 did not show statistical significance in 2019. However, for 2017, 2018 and combined dataset for 2017, 2018 and combined dataset, the estimated parameters showed statistical significance ($p<0.01$). The results presented in Table 8.2 imply that when compared to Black/African children and holding other variables constant, Indian/Asian children had their Fuzzy Set MPI lower by average of 0.0230, 0.0202 and 0.0171 in 2017, 2018 and combined data, respectively. The White parameters did not show statistical significance in 2019. However, the estimated parameters showed statistical significance ($p<0.01$) in Table 8.1 for 2017, 2018 and combined data. The results imply that when compared to Black/African children and holding other variables constant, White children had their AF MPI lower by average of 8.41 e-07, 9.36 e-07 and 7.24 e-07 in 2017, 2018 and combined data, respectively. The White parameters in Table 8.2 also did not show statistical significance for 2019. However, the estimated parameter showed statistical significance ($p<0.01$) for 2017, 2018, 2019 and combined data. The results in Table 8.2 imply that compared to Black/African children and holding other variables constant, White children had their Fuzzy Set MPI lower by average of 0.0165, 0.0163, 0.0009 and 0.0126 in 2017, 2018, 2019 and combined data, respectively. The results of this study are related to those of the Stats SA (2021) that revealed that Black children had increased MPI compared to other population groups. Timæus et al (2013) also revealed that because of the previledged backgroung that Coloured, Indian and White children have enable them to start school in time and get employment opportunities.

8.2.5 Maternal and Paternal Factors Influencing MPI

Parental factors influencing MPI results are presented in Table 8.1 (AF MPI) and Table 8.2 (Fuzzy Set MPI). The son/daughter parameters showed statistical significance for 2017, 2018, 2019 and combined data. The results in Table 8.1 imply that non-biological children in the household had their AF MPI increased by 6.14 e-07, 5.57 e-07, 1.05 e-07 and 4.39 e-07 in 2017, 2018, 2019 and combined data, respectively. The son/daughter parameters in Table 8.2 showed statistical significance for 2017, 2018, 2019 and combined data. The results imply that non-biological children in the household had their Fuzzy Set MPI increased by 0.0130, 0.0103, 0.0040 and 0.0090 in 2017, 2018, 2019 and combined data, respectively. The father alive parameters did not show statistical significance in 2019. However, the estimated parameters for 2017, 2018 and combined dataset showed statistical significance ($p<0.01$). The results presented in Table 8.1 imply that children who their fathers were alive had their AF MPI being reduced by 1.20 e-07, 1.19 e-07 and 8.34 e-08 in 2017, 2018, 2019 and combined data, respectively. in Table 8.2 the father alive parameters in 2019 did not show statistical significance ($p>0.10$). However, the estimated parameters in 2017, 2018 and combined dataset showed statistical significance ($P< 0.05$, $p<0.01$). The results in Table 8.2 imply that children who their father was alive had their Fuzzy Set MPI reduced by 0.0020, 0.0017 and 0.0013 in 2017, 2018 and combined data, respectively.

The father part of the household parameters showed statistical significance in 2017, 2018, 2019 and combined data. The results in Table 8.1 imply that children who their father were part of the household had their AF MPI reduced by 3.17 e-07, 3.21 e-07, 6.69 e-08 and 2.69 e-07 in 2017, 2018, 2019 and combined data, respectively. The father part of the household parameters in Table 8.2 also showed statistical significance in 2017, 2018, 2019 and combined data. The results imply that children who were residing in the same household as their fathers had their Fuzzy Set MPI reduced by 0.0066, 0.0068, 0.0017 and 0.0055 in 2017, 2018, 2019 and combined data, respectively. the mother alive parameters did not show statistical significance ($p>0.10$) in 2017 and 2019. However, the estimated parameters for 2018 and combined dataset showed statistical significance ($p<0.01$). The results in Table 8.1 imply that children who their mothers were alive ah their AF MPI reduced by 1.46 e-07 and 7.20 e-08 in 2018 and combined dataset, respectively. In Table 8.2 the mother alive parameters did not show statistical significance in 2017, 2018, 2019 and combined data. The mother part of the household parameters in Table 8.1 showed statistical significance ($p<0.01$) in 2017, 2018, 2019 and combined data. The results imply that children who were reding in the same households as their mothers had their AF MPI reduced by 1.20 e-07, 1.20 e-07, 1.11 e-07 and 1.32 e-07 in 2017, 2018, 2019 and combined data, respectively. in Table 8.2 the mother part of the household parameters showed statistical significance ($p<0.01$). These results imply that children who were residing in the same household as their mothers had their Fuzzy Set MPI reduced by 0.0033, 0.0027, 0.0017 and 0.0028 in 2017, 2018, 2019 and combined data, respectively. The results are related to those of the UNICEF (2020) which also revealed that children with a mother or father alive have reduced chances of being multiply deprived.

8.2.6 Households' Socioeconomic and Demographic Factors Influencing MPI

In Table 8.1 child gender parameters did not show statistical significance ($p>0.10$) for 2018 and 2019. However, the estimated parameters showed statistical significance ($p<0.01$) for 2017 and combined dataset. The results imply that male children had their AF MPI reduced by 6.83 e-08 and 5.54 e-08 in 2017 and combined dataset, respectively. Table 8.2 child gender parameters did not show statistical significance for 2019. However, the estimated parameters showed statistical significance ($p<0.10$, $p<0.01$) in 2017, 2018 and combined dataset, respectively. These results imply that male children had their Fuzzy Set MPI reduced by 0.0014, 0.0020 and 0.0013 in 2017, 2018 and combined data, respectively. These results are related to those of Agyire-Tettey (2021) who looked at multidimensional child poverty in Ghana and found out that male children had their MPI reduced.

The results presented in Table 8.1 show child age parameters, The child age parameters did not show statistical significance in combined dataset. However, the estimated parameters showed statistical significance ($p<0.01$) for 2017, 2018 and 2019. These results imply that as a child add one year into their live, they will have their AF MPI reduced by 9.71 e-09, 1.17 e-08, 1.92 e-08 and 2.57 e-08 in 2017, 2018, 2019 and combined data, respectively. The child age parameters in Table 8.2 did not show statistical significance ($p>0.10$) in 2017. However, the estimated parameters showed statistical significance($p<0.01$) in 2018, 2019 and combined data, respectively. These results imply that when a child add one years in their lives, they will have their Fuzzy Set MPI increased by 0.0002, 0.0001 and 0.0002 in 2018, 2019 and combined data, respectively. These results are related ot those of Aboaba et al. (2019) who found out that age had a negative relationship with poverty.

The domestic worker services parameter showed statistical significance in 2017, 2018, 2019 and combined data. The results in Table 8.1 imply that children with domestic worker services in a household had their AF MPI increased by 1.18 e-06, 1.31 e-06, 4.18 e-07 and 1.11 e-06 in 2017, 2018, 2019 and combined data, respectively. In Table 8.2 domestic worker services showed statistical significance ($p<0.01$) in 2017, 2018, 2019 and combined data. These results imply that children who had domestic worker services had their Fuzzy Set MPI increased by 0.0178, 0.0197, 0.0050 and 0.0162 in 2017, 2018, 2019 and combined data, respectively. These results might be associated with the circumstance that having to pay the worker(s) reduces the household purchasing power or per capita income.

The household size parameters in Table 8.1 showed statistical significance in 2017, 2018, 2019 and combined data. These results imply that as a household adds one additional member their children will have an AF MPI increased by 9.92 e-08, 3.32 e-08 and 2.60 e-08 in 2017, 2018 and combined dataset, respectively and reduced by 1.28 e-08 in 2019. Table 8.2 household size parameters also showed statistical significance in 2017, 2018, 2019 and combined data. These results imply that when a household adds one additional member, their child will have an increased Fuzzy Set MPI of 0.0004, 0.0007 and 0.0003 in 2017, 2018 and combined dataset, respectively and reduced by 0.00058 in 2019 dataset. The results of this study are related to those of Makhalima (2020) who also revealed that the larger the household size, the more likely a child will become poor.

Income is a significant measure of wellbeing. The salaries/wages commission parameters showed statistical significance in 2017, 2018, 2019 and combined data. These in Table 8.1 results imply that children from household that were receiving salaries/wages commission had their AF reduced by 8.70 e-07, 9.08 e-07, 1.02 e-07 and 7.98 e-07 in 2017, 2018, 2019 and combined data, respectively. Table 8.2 salaries/wages commission parameters revealed statistical significance ($p<0.01$). these results imply that children from households earning salaries/wages commission had their Fuzzy Set MPI reduced by 0.0168, 0.0159, 9.87 and 0.0132 in 2017, 2018, 2019 and combined data, respectively. The income from business parameters in Table 8.1 did not show statistical significance in 2019 ($p>0.10$). However, the estimated parameters showed statistical significance ($p<0.01$) in 2012, 2018 and combined dataset. These results imply that children from households that were earning income from businesses had their AF MPI reduced by 6.22 e-07, 6.87 e-07 and 4.48 e-07 in 2017, 2018 and combined data, respectively. in Table 8.2 the income from business parameters also did not show statistical significance in 2019. However, the estimated parameters were significant ($p<0.01$) in 2017, 2018 and combined dataset. These results imply that children from households that were earning income from business had their Fuzzy Set MPI reduced by 0.0102, 0.0098 and 0.0067 in 2017, 2018 and combined data, respectively. The remittances parameters in Table 8.1 did not show statistical significance in 2019. However, for 2017, 2018 and combined dataset the estimated parameters showed statistical significance ($p<0.01$). These results imply that children from households that were receiving remittances had their AF MPI reduced by 3.38 e-07, 4.24 e-07 and 3.40 e-07 in 2017, 2018 and combined data, respectively. the remittances parameters in Table 8.2 also did not show statistical significance for 2019. However, the estimated parameters showed statistical significance ($p<0.01$) for 2017, 2018 and combined dataset. These results imply that children from households receiving remittances had their Fuzzy Set MPI reduced by 0.0063, 0.0117 and 0.0074 in 2017, 2018 and combined data, respectively. The pensions parameters in Table 8.1 did not show statistical significance for 2019. However, the estimated parameters showed statistical significance ($p<0.01$) for 2017, 2018 and combined dataset. The results presented in Table 8.1 imply that children from households that were receiving pensions had their AF MPI reduced by 1.01 e-07, 9.55 e-07 and 8.68 e-07 in 2017, 2018 and combined data, respectively. In Table 8.2 the pensions parameters also did not show statistical significance in 2019 ($p>0.10$). However, for 2017, 2018 and combined dataset the estimated parameters were statistically significant ($p<0.01$). The results imply that children from households that were receiving pensions had their Fuzzy Set MPI reduced by 0.0166, 0.0122 and 0.0123 in 2017, 2018 and combined data, respectively. These eresults are related to those of Aboaba et al. (2019) and Ashagidigbi et al. (2020) who revealed that people earning income had their poverty declining.

The grants parameters did not show statistical significance in 2019. However, the estimated parameters for 2017, 2018 and combined dataset were statistically significant ($p<0.01$). The results in Table 8.1 imply that children from households that were receiving grants had their AF MPI increased by 9.00 e-07, 7.93 e-07 and 5.93 e-07 in 2017, 2018 and combined data, respectively. Table 8.2 grants parameters also did not show statistical significance. However, the estimated parameters showed statistical significance for 2017, 2018 and combined dataset. These results imply that children from household that were receiving grants had their Fuzzy Set MPI increased by 0.0135, 0.0100 and 0.0082 in 2017, 2018 and combined data, respectively. These results might be associated to the circumtance that the social security grants money is not enough to be able to provide for their basic needs.

The social grants parameters were statistically significant ($p<0.01$) in 2017, 2018, 2019 and combined data. The results imply that children from households that were receiving social grants had their AF MPI reduced by 7.34 e-07, 6.27 e-07, 1.98 e-07 and 6.69 e-07 in 2017, 2018, 2019 and combined data, respectively. The results in Table 8.2 also showed social grants parameters to be statistically significant ($p<0.01$) in 2017, 2018, 2019 and combined data. These results imply that children from households that were receiving social grant s had their Fuzzy Set MPI reduced by 0.0072, 0.0062, 0.0034 and 0.0078 in 2017, 2018, 2019 and combined data, respectively. The sales of farming- products/services parameters were insignificant in 2017 and 2019. However, the estimated parameters were statistically significant ($p<0.01$) for 2018 and combined dataset. These results imply that children from households that had sales of farming products/services had their AF MPI reduced by 2.7 e-073 and 1.29 e-07 in 2018 and combined data, respectively. in Table 8.2 the sales of farming products/services also did not show statistical significance ($p>0.10$) for 2017, 2019 and combined dataset. However, the estimated parameters showed statistical significance for 2018. The results imply that children from households with sales of farming products/services had their Fuzzy Set MPI reduced by 0.0040 in 2018. Other income sources parameters in Table 8.1 were insignificant for 2019 and combined dataset. However, the estimated parameters were statistically significant ($p<0.01$) for 2017 and 2018. These results imply that children from households with other income sources had their AF MPI reduced by 5.44 e-07 and 4.82 e-07 in 2017 and 2018, respectively. in Table 8.2 the other income sources parameters did not show statistical significance for 2019. However, the estimated parameters for 2017, 2018 and combined dataset showed statistical significance ($p<0.01$). These results imply that children from households that had other income sources had their Fuzzy Set MPI reduced by 0.0136, 0.0117 and 0.0104 in 2017, 2018 and combined data, respectively. The results on income sources across child households are related to those of Makhalima (2020) on determinants of child poverty in SA who revealed that children from households that are earning some form of income, their children are less likely to be poor.

Table 8.1 backyard garden parameters were statistically insignificant. However, the 2017, 2018 and combined dataset parameters were statistically significant ($p<0.01$). these results imply that children who had backyard gardens had their AF MPI increased by 2.94 e-07, 2.92 e-07 and 3.33 e-07 in 2017, 2018 and combined data, respectively. In Table 8.2, backyard garden parameters were statistically significant ($p<0.01$). These results imply that children who had backyard gardens had their Fuzzy Set MPI increased by 0.0033, 0.0051 and 0.0045 in 2017, 2018 and combined data, respectively and reduced by 0.0010 in 2019. The school garden parameters in Table 8.1 did not show statistical significance for 2018 and 2019. However, the estimated parameters showed statistical significance for 2017 and combined data. These results imply that children who had school gardens had their AF MPI increased by 8.30 e-07 and 4.47 e-07 in 2017 and combined data, respectively. The school garden parameters in Table 8.2 did not show statistical significance in 2017, 2018, 2019 and combined data. The communal garden parameters in Table 8.1 did not show statistical significance for 2017 and 2019. However, the estimated parameters showed statistical significance ($p<0.01$) for 2018 and combined dataset. These results imply that children who had communal gardens had their AF MPI increased by 5.36 e-07 and 4.24 e-07 in 2018 and combined dataset, respectively. The communal garden parameters in Table 8.2 did not show statistical significance in 2017, 2018, 2019 and combined data. The results found in this study are related to those of Heshmati and Rashidghalam (2019) who revealed that respondents who had vegetable gardens had their MPIs reduced.

Table 8.2: Tobit regression estimates of Determinants of child Multidimensional using Fuzzy Set child MPI

Fuzzy Set MPI	2017		2018		2019		All	
	Coefficient	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**t**
Seeing	-.0073022	-2.75	-.0086242	-3.43	-.00228	-1.69**	-.0066532	-4.87
Hearing	-0091434	-2.57	-.0114884	-3.37	-.0028822	-1.58	-.0088978	-4.84
Walking	.0252517	6.39	.0145403	3.84	.0012512	0.66	.0140006	7.01
Remembering	-.000708	-0.23	.0023394	0.81	.0011235	0.74	.0010815	0.70
Selfcare	-0008482	-0.48	.0006076	0.37	-.0008106	-0.88	-.0001335	-0.15
Communication	.0006573	0.18	.0137393	4.08	.0013062	0.81	.0070299	4.00
Province								
Eastern Cape	.0248389	12.84	.0264059	14.69	.0048414	4.35	.0206468	20.19
Northern Cape	.0014356	0.63	-.0026745	-1.28	-.0020934	-1.67***	.0001118	0.09
Free State	.0042065	1.87	-.0009178	-0.44	-.0018955	-1.49	.0014728	1.24
KwaZulu-Natal	.0031287	1.62	-.0007209	-0.41	-.0020651	-1.88	.001355	1.34
North West	-0009077	-0.40	-.0025412	-1.20	-.0100601	-7.91***	-.0030277	-2.54
Gauteng	.0047408	2.59	-.0046546	-2.76	-.0014435	-1.38	.0003102	0.32
Mpumalanga	.0076159	3.57	.001684	0.85	-.0062167	-5.19***	.0023788	2.13
Limpopo	-0183106	-8.80	-.0183952	-9.58	-.0132063	-8.94***	-.0166835	-15.16
Child gender	-0014452	-1.90	-.0020171	-2.84	.0000565	0.13	-.0012768	-3.20
Child age	.0000292	0.23	.0001985	1.70	.0001	1.46***	.0001763	2.69
Population group								
Coloured	-0202795	-2.03	-.0175984	-1.07	-.0028171	-2.92	-.014365	-16.02
Indian/Asian	-0229819	-5.75	-.020208	-5.44	-.0030835	-1.49	-.0170639	-8.33
White	-0165271	-6.41	-.0163398	-6.57	.0008902	0.68	-.0125679	-9.61
Son or daughter	.0129675	11.98	.0102966	8.24	.0040134	7.13***	.0089661	16.35
Father alive	-0020069	-2.17	-.0017023	-1.99	.0000779	0.17	-.001284	-2.73
Father part of	-0065834	-6.29	-.0067903	-6.96	-.0017297	-3.11**	-.0055422	-8.32
Mother alive	-0002473	-0.16	-.000374	-0.26	-.0004402	-0.55	-.0007202	-0.91

Table 8.2: Tobit regression estimates of Determinants of child Multidimensional using Fuzzy Set child MP Cont.

Fuzzy Set MPI	**2017**		**2018**		**2019**		**All**	
	Coefficient	**T**	**Coefficient**	**T**	**Coefficient**	**T**	**Coefficient**	**T**
Mother part of	-0032717	-3.10	-.0026706	-2.72	-.001669	-2.94***	-.0027707	-5.07
Domestic worker	.0177513	9.53	.019743	11.29	.0049648	6.00***	.0161904	18.17
Household size	.0003639	2.31	.0006518	4.47	-.0005844	-7.74***	.0003206	4.15
Geography type								
Traditional	.0194576	17.97	.0171641	17.01	.0099847	17.94***	.0162547	29.64
Farms	.0376979	17.43	.0351203	17.18	.0224555	17.90***	.0329452	28.54
Salaries/wages	-0167699	-18.88	-.0159475	-19.34	9.87e-06	0.02***	-.013228	-29.88
Income from	-0101663	-8.87	-.0097914	-8.97	-.0007	-1.18	-.0067374	-11.43
Remittances	-.006251	-6.12	-.0116865	-12.32	-.0003376	-0.57	-.0074095	-13.77
Pensions	-0165893	-7.00	-.0122369	-5.84	.0000366	0.03	-.0123112	-9.91
Grants	.0135227	8.36	.0100014	6.55	-.0003095	-0.61	.0082174	13.32
Social grants	-.007248	-5.58	-.0062136	-5.13	-.0034429	-6.68***	-.0078366	-14.33
Sales of farming	.0032249	1.28	-.0039603	-1.73	-.0014037	-0.97	-.0005268	-0.40
Other income	-.013648	-4.77	-.0116736	-3.98	-.0015816	-0.96	-.01041	-6.66
Backyard garden	.0032535	3.06	.0050556	5.08	-.0009863	-1.83	.0045344	8.54
School garden	.0101509	0.83	-.0136609	-1.23	.000708	0.14	.0007339	0.13
Communal garden	.0013081	0.18	.0055933	0.95	.0012999	0.42	.0041525	1.24
_Cons	.0633597	16.05	.0611379	16.65	.101859	51.73***	.0722852	37.25
Var (e.fuzzy)	.0037351		.0031751		.0009088		.0028579	
Lr Chi2	4782.99		5003.19		1397.27		10739.76	
Prob Chi2 (39)	0.0000		0.0000		0.0000		0.0000	
Pseudo R2	-0.0719		-0.0730		-0.0166		-0.0522	
Log Likelihood	35660.461		36758.085		42846.714		108275.93	
Mean VIF	3.76		3.49		2.92		3.42	

Source: Own Computation, 2022. NB ***, ** and * implies statistically significant at 1%, 5% and 10% levels of significance, respectively

CHAPTER NINE

FOOD INTAKES AND DETERMINANTS OF UNDER-5 HEALTH OUTCOMES

9.1. Introduction

This chapter addresses the fourth objective of this study which is to analyse the effect of food intakes on the health outcomes of under-5 children. The chapter starts by looking at the demographic characteristics of children. Moreover, the chapter looks at the factors that affect the children's health outcomes categorising them under 0-5months, 6-23 months and 24-59 months, respectively.

9.2 Children's Demographic Characteristics

Table 9.1 presents the results of the distribution of children among the provinces. The Table shows that 4.81% of the 0-5, 6.18% of the 6-23 and 6.80% of the 24-59 months old children resided in the Western Cape province. The Eastern Cape accounted for 12.03% of the 0-5, 14.32% of the 6-23, and 12.30% of the 24-59 months old children. The Table further shows that the Northern Cape province contributed 9.09% of the 0-5, 7.37% of the 6-23, and 7.84% of the 24-59 months old children. Free State accounted for 10.43% of the 0-5, 7.81% of the 6-23 and 9.52% of the 24-59 months old children. KwaZulu-Natal province accounted for 17.11% of the 0-5, 16.16% of the 6-23, and 15.19% of the 24-59 months old children. Moreover, North West province accounted for 9.63% of the 0-5, 10.30% of the 6-23, and 11.92% of the 24-59 months old children. The Gauteng province had 10.43% of the 0-5, 10.09% of the 6-23, and 10.23% of the 24-59 months old children. The results also revealed that Mpumalanga accounted for 12.30% of the 0-5, 13.45% of the 6-23 and 13.28% of the 24-59 months old children. The children from the Limpopo province accounted for 14.17% of the 0-5, 14.32% of the 6-23, and 12.90% of the 24-59 months old children.

Figure 9.1 presents the percentage distribution of the children's selected demographic characteristics. It shows that a higher proportion of the children resided in rural areas. Specifically, 47.00% of the 0-5, 48.00% of the 6-23 and 46.00% of the 24-59 months old children resided in rural areas. The Figure further shows that 63.00% of the 0-5, 45.00% of the 6-23 and 45.00% of the 24-59 months old children were living in households where toilets were being shared. In addition, 89.00% of the 0-5 months old children were discharged at the same time with their mothers after birth. This can be compared with 90.00% for the 6-23 and 73.00% for the 24-59 months old children. Figure 1 further reveals that majority of under-5 children were not health insured. Specifically, only 5.00% of the 0-5 months and 6-23 months, and 6% of the 24-59 months old children were covered by health insurance.

The children with working mothers were 22.00% for the 0-5, 25.00% for the 6-23 months, and 33.00% for the 24-59 months old children.

Table 9.1: Percentage Distribution of the Children Based on Their Province of Residence

Province	0-5 months	6-23 Months	24-59 Months
Western Cape	4.81	6.18	6.80
Eastern Cape	12.03	14.32	12.30
Northern Cape	9.09	7.38	7.84
Free State	10.43	7.81	9.53
KwaZulu-Natal	17.11	16.16	15.19
North West	9.63	10.30	11.92
Gauteng	10.43	10.09	10.23
Mpumalanga	12.30	13.45	13.28
Limpopo	14.17	14.32	12.90

Source: Own Computation, 2022

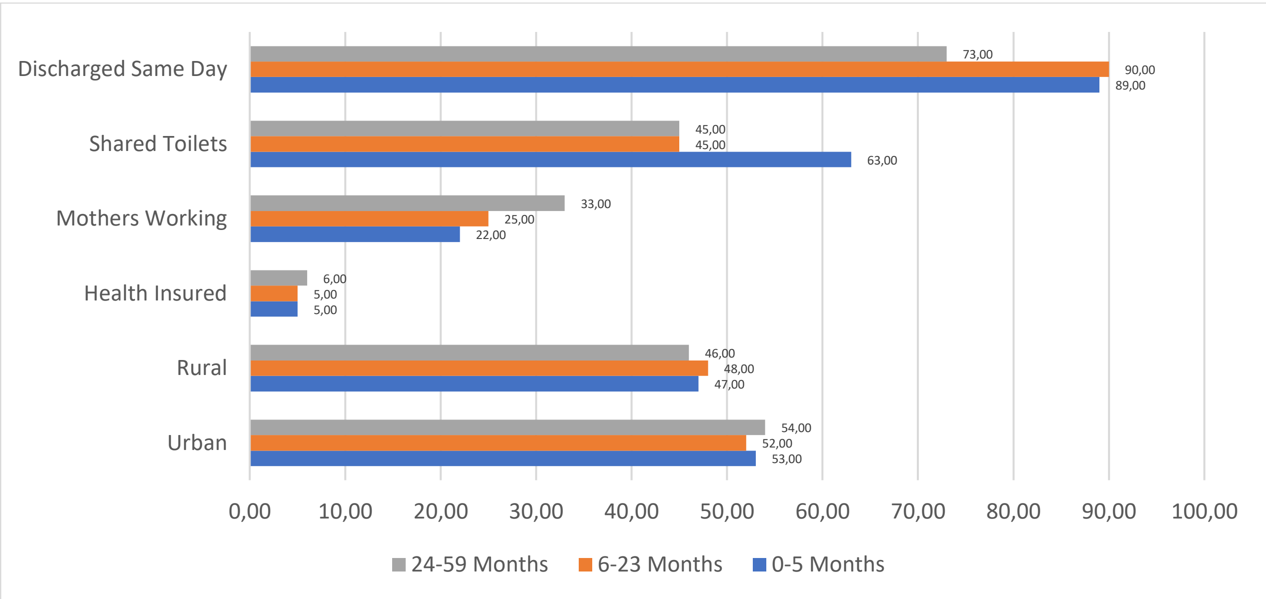

Figure 9.1: Distribution of Children's Selected Variables Across Their Ages

Source: Own Computation, 2022

9.3 Distribution of Children's Food Intake Patterns

The results in Figure 9.2 revealed that 71.93%, 40.24% and 1.25% of the 0-5, 6-23 and 24-59 old children were breastfed, respectively. It also revealed that 3.48% of the 0-5 months old children were drinking juice, which can be compared to 32.32% of the 6-23 months and 3.81% of the 24-59 months old children. The children who were consuming coke constituted 0.53% of the 0-5, 15.62% of the 6-23, and 1.47% of the 24-59 months old. The Figure further shows that 1.34% of the 0-5 months old children, 25.05% of the 6-23 months old children and 2.61% of the 24-59 months old children were consuming butter. In addition, chocolates were consumed by 0.53% of the 0-5, 31.78% of the 6-23 and 3.27% of the 24-59 months old children. Snacks were consumed by 0.80% of the 0-5 months, 38.61% of the 6-23, and 4.25% of the 24-59 months old children. Grain, roots, and tubers were consumed by 25.40% of the 0-5, 81.78% of the 6-23, and 10.34% of 24-59 months old children. The results also showed that legumes and nuts were consumed by 0.8% of the 0-5, 14.53% of the 6-23 and 1.52% of the 24-59 months old children. Flesh foods were consumed by 0.80% of the 0-5, 44.03% of the 6-23, and 4.35% of the 24-59 months old children. Eggs were also by 2.14% of the 0-5, 36.98% of the 6-23, and 4.84% of the 24-59% old children. Vitamin A rich fruits and vegetables were consumed by 3.21% of the 0-5, 38.94% of the 6-23, and 3.87% of the 24-59 months old children. On consumption of dairy milk, about 38.77% of the 0-5, 64.32% of the 6-23 and 8.87% of the 24-59 months old children answered in the affirmative. Fruits and vegetables were consumed by 2.41% of 0-5, 44.36% of 6-23 months and 4.41% of 24-59 children.

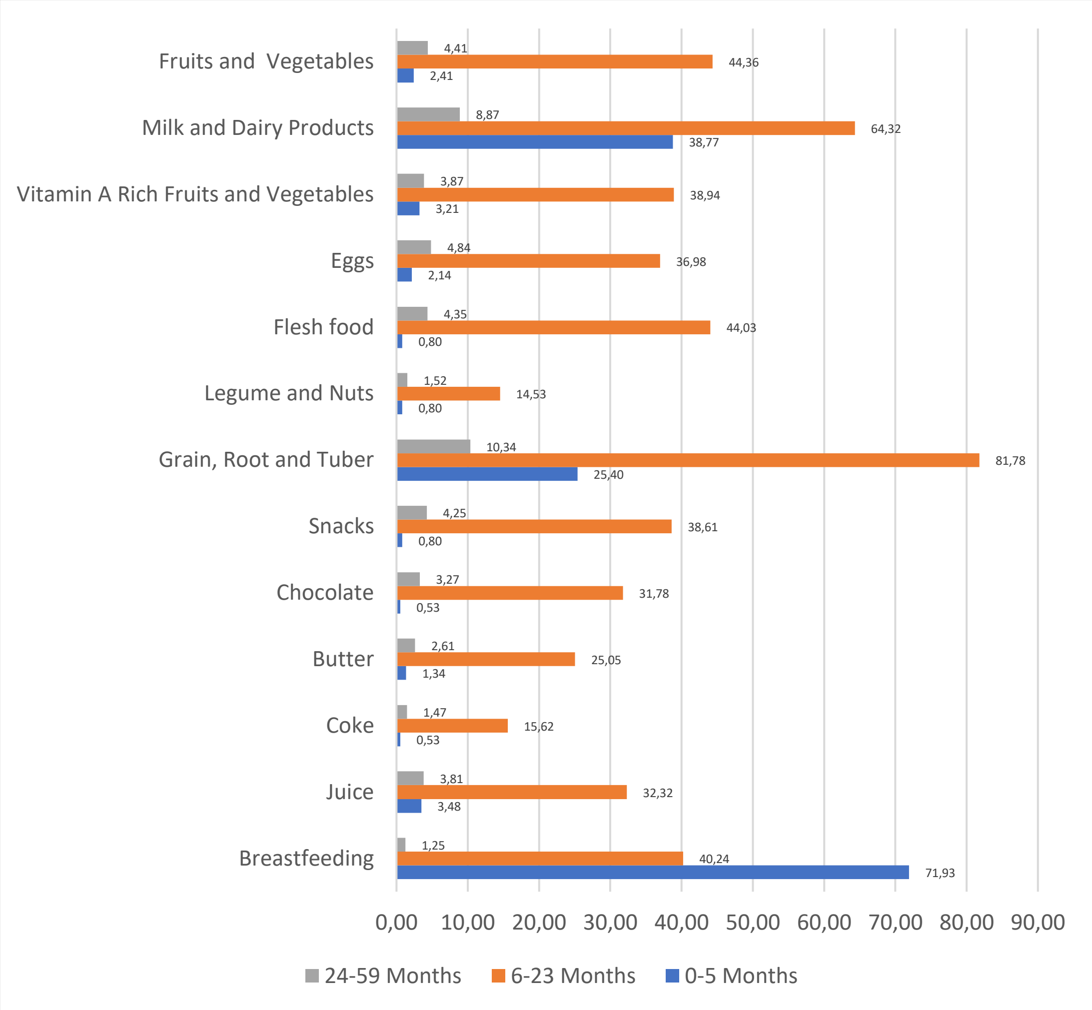

Figure 9.2: Distribution of Food Products Consumed by the Children Across Their Age Groups
Source: Own Computation, 2022

9.4 Distribution of Health Outcomes among the Children

Figure 9.3 presents the results of height-for-age, weight-for-age and weight-for-height among under-5 children. The results revealed that among the 0-5, 26.00% were stunted, compared to 24.00% and 22.00% of the 6-23- and 24-59 months old children, respectively. Regarding wasting, the figure shows that 53.00% of the 24-59 were wasted. Moreover, 30.00% of the 0-5 were wasted. Underweight was most prevalent among the 6-23 (26%), compared to the 0-5 (25.00%) and the 24-59 (21.00%).

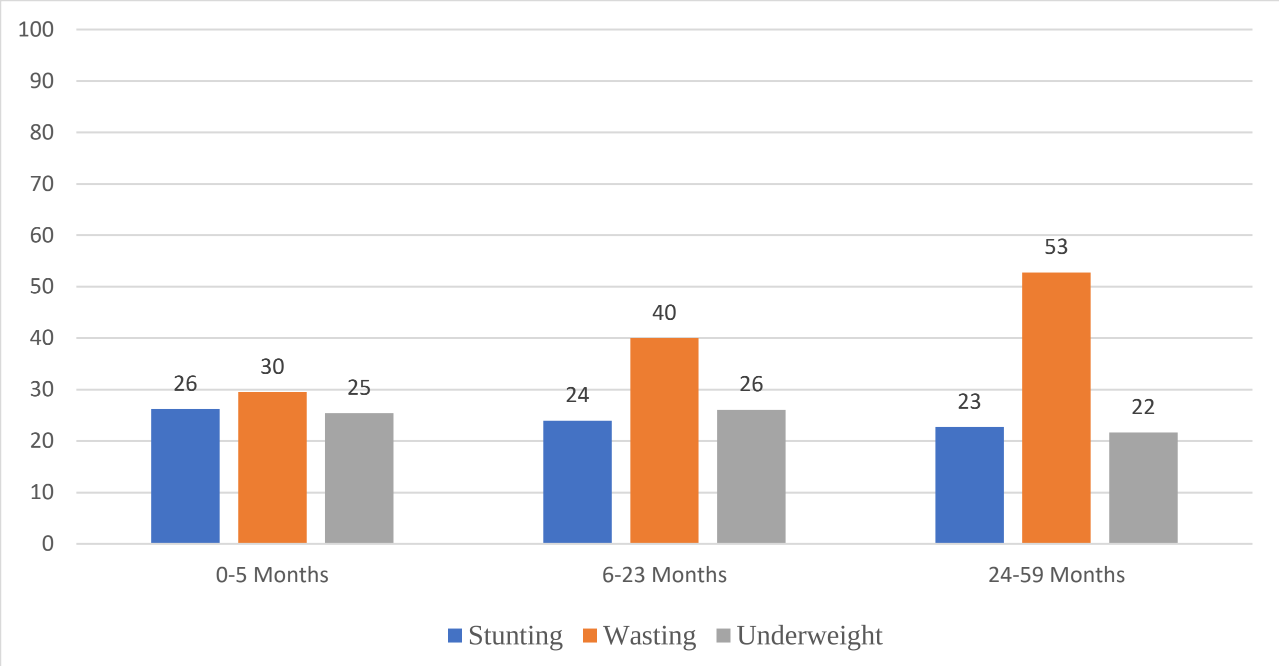

Figure 9.3: Percentage Distribution of Children's Health Outcomes

Source: Own Computation, 2022

9.5 Determinants of Child's Health Outcomes (0-5 months)

9.5.1 Determinants of stunting among 0-5 children

Table 9.2 presents the results of logistic regression for the 0-5 months old children. In the stunting model, being discharged from the hospital after birth at the same time with the mother is statistically significant ($p<0.05$). This implies that children who were discharged at the same time as their mothers from hospital after birth had 90% lower chance of being stunted. This may be associated with the advantages that comes with being discharged with the mother like getting better and enough sleep, having decreased chances of exposure to infections and access to breast milk (Jones et al. 2021). It is also an indication that children who were not discharged at the same time with the mother may have development some infections or possess some medical conditions that require some close monitoring and treatments by healthcare workers.

The parameter of gender in the stunting model is also statistically significant ($p<0.05$). This implies that a boy child possessed 82% less chance of being stunted. The results of this study are in line with those of Sapkota and Gurung (2009) who also revealed that boys were less likely to be stunted compared to their female counterparts. However, these results are contrary to those of Lesiapeto et al. (2010), Khan et al (2019) and Blankenship et al (2020) who their results revealed that boys are likely to become stunted compared to girls. These results may be because more attention is given to boys since it was noticed that they are vulnerable to being stunted. The parameter of having medical insurance in the stunting model is also statistically significant ($p<0.01$). This shows that the children with medical insurance were 34.5 times more likely to be stunted. These results show unexpected outcome as numerous studies discovered that having medical insurance decreases the probability of being stunted (Nshakira-Rukundo et al. 2020, Chen and Chu, 2019). Under the provincial parameters, the Western Cape was taken as the reference group. The results revealed that a child has 19.7 higher chances of being stunted when residing in the Northern Cape province, 42.9 higher chances when in Free-State and 70.5 higher chances when in Gauteng province. These results are in line with the provincial results obtained by Sambu (2019) which showed that stunting was highest in the Gauteng and Free State provinces.

Regarding the shared toilet, it was revealed that there are 1.43 higher chances of being stunted when a child resides in a household where toilets are shared with other households. This is supported by a statement made by Omotayo (2018) who mentioned that sharing a toilet is dangerous as it can make children susceptible to some infectious diseases that may lead to poor health. It was also revealed that there are 0.0001% lower chances of being stunted when as the wealth index increased. The findings are in line with those of Habyarimana et al. (2016) who revealed that the wealth indicator statistically and significantly affects the height-for-age of a child. They also revealed that a child born within a poor family has 1.543 (p-value=0.0079) higher chances of being stunted than a child born into a rich family. The parameter of the number of children in a household also shows statistical significance. This implies that children's chance of stunting increases 1.7 times as the number of household members increases by one. The results can be supported by that of Raj et al. (2016) who found that when a child has more siblings, his or her odds of being stunted increases. This may be caused by having to share food and other family resources with others.

9.5.2 Determinants of wasting among 0-5 children

Looking at the incidence of wasting in children between 0-5 months, the results revealed that there are 77% lower chances of being wasted when a child consumes dairy milk. This is in contrast with a few authors who mentioned that babies between 0-5 months cannot digest dairy milk as completely and easily as they can on breast milk or formula. It was also revealed that there are 0.002% less chance of wasted as the birth weight increases by 1kg. This is in line with Abbas (2021) who found out that children with low birth weight had the highest odds of being moderately wasted and severely wasted and both (stunted and wasted) compared to those with normal birth weight. The change of wasting increased by 1.5 times as the number of people in a child's household increases by one. This may be because of having to share the food with others.

9.5.3 Determinants of underweight among 0-5 children

The model for underweight among 0-5 children reveals that only one parameter is statistically significant at 5% level. The result showed that children that were consuming milk and other dairy products had about 33% less chance of being underweight. These results are related to those of Nguyen et al. (2018) who looked at consumption of dairy per day and mentioned that it was related to a lower risk of a child being underweight when they had ≥2 dairy consumptions per day.

Table 9.2: Logistic regression results on the determinants of health outcomes among 0-5 months old children

Variables	Stunting		Wasting		Underweight	
	Odds ratio	Prob.	Odds ratio	Prob.	Odds ratio	Prob.
Breastfeeding	3.3140	0.328	.5704	0.482	.9595	0.963
Juice	1		1		1	
Coke	1		1		1	
Butter	1		1		1	
Chocolate	1		1		1	
Snacks	1		1		1	
Grains, roots and tubers	0.3069	0.228	0.8251	0.780	1.8285	0.395
Legume and Nuts	1		1		1	
Flesh Foods	1		1		1	
Eggs	1		1		1	
Vitamin A Rich Fruits and Vegetables	1		1		1	
Milk and Dairy Products	.6705	0.560	.2318***	0.042	.1812***	0.022
Fruits and Vegetables	1		1		1	
Discharged same time	0.0995**	0.033	.3418	0.248	.4702	0.437
Male Child	0.1757**	0.017	.8311	0.724	1.1859	0.752
Health Insured	34.5326***	0.006	2.6147	0.287	.7367	0.757
Employed	.3678	0.321	.5969	0.508	1.2530	0.765
Province						
Western Cape	1		1		1	
Eastern Cape	1.712677	0.701	.6294225	0.652	2.1939	0.474
Northern Cape	19.7004**	0.048	1.954087	0.532	2.0710	0.496
Free State	42.8978**	0.015	.8712062	0.899	1.7079	0.622
KwaZulu-Natal	8.1362	0.109	.7974298	0.811	1.1868	0.872
North West	1.378446	0.836	.9058559	0.924	.9994	1.000
Gauteng	70.41668**	0.011	1.081626	0.948	1.6989	0.654
Mpumalanga	4.9613	0.250	1.325627	0.772	.3988	0.487
Limpopo	1		1		1	
Urban residence	.3277536	0.154	.7106066	0.605	1.8840	0.349
Shared Toilet	1.430398**	0.043	.9262917	0.663	.9036	0.560
Birth Weight	.9991683	0.111	.9982169***	0.001	.9994	0.190
Wealth Index	.9999919**	0.045	1.000001	0.759	1.0000	0.482
Number of Living Children	1.672854**	0.045	1.549363*	0.062	1.3708	0.201
Constant	6.722703	0.438	315.6557**	0.009	1.2265	0.922
LR Chi2 (19)	41.57		26.55		21.68	
Prob> Chi2	0.0020		0.1156		0.3006	

Source: Own Computation, 2022

9.6 Determinants of Child's Health Outcomes (6-23 months)

9.6.1 Determinants of stunting among 6-23 children

The parameter of breastfeeding in the stunting model shows statistical significance ($p<0.05$). Therefore, the 6-23 months old children who were being breastfed were about 50% less likely to be wasted. This may be supported by Muldiasman et al. (2018) who stated that when children are breastfed, the chance of consuming contaminated river water which is a health risk is reduced and as a result the chances of stunting are also reduced. Another significant variable is the consumption of dairy milk. it was revealed that children who consumed dairy milk have 0.54 (46%) lower chances of being stunted. This is in line with the findings of Nguyen et al. (2018) who found out that children who drink between 1 and 2 cups of dairy milk per day have lower chances of being stunted.

The results also revealed that there are 2.12 higher chances of being stunted when a child is a boy. These results are in line with those of Ali et al. (2017) and Khan et al (2019) who also revealed that male children had higher chances of being stunted compared to their female counterparts. There are 80% lower chances of being stunted when residing in the Eastern Cape province, 90% lower chances of being stunted when residing in Mpumalanga and 80% lower chances of being stunted when residing in Limpopo province. There is also a 90% lower chances of being stunted as the birthweight increases by 1kg. This is what was also shown by an analysis performed by Aryastami (2017) that babies born with low birth weight had 1.7 higher chances of being stunted.

According to Abuya et al. (2012), maternal education is one of the strong predictors of child stunting. They further mentioned that when a mother has formal education, they are well-informed and knowledgeable on how to prevent their children from stunting or reduce the degree of stunting when it occurs. This study found that a child has 15% lower chances of being stunted as the mother's years of education increase.

9.6.2 Determinants of wasting among 6-23 children

The results pertaining to wasting of children between 6-23 months revealed that there are 4.45 lower chances of being wasted when a child reside in an urban area. These results are in line with those of Kang et al (2018) and Banerjee et al (2021) who revealed that compared to children in rural areas, children from urban areas had better nutritional status. There are 66% lower chances of being wasted when a child resides in a household where a toilet is shared. This might be because the toilet is shared within a household and not with other households and the facilities are always clean. Sinha et al. (2018) also mentioned that sharing a toilet facility was one of the predictors on child health outcomes. The parameter of the number of living children is statistically significant ($p<0.10$). It implies that as the number of living children increased, the likelihood of being wasted increased by 1.21 times. These results might be associated with siblings not acquiring the required nutrients since they must share everything.

9.6.3 Determinants of underweight among 6-23 months old children

The logistic regression results of the determinants of underweight among children between 6-23 months are also presented in Table 9.3. The results showed that a child who consumes snacks has 54% less chances of being underweight. This may be because of the nutritional benefits that come with consumption of snacks by children. Adequate intake of snacks may assist children in achieving optimal nutrition and reducing the future risks of having malnutrition related diseases. Although the results were unexpected, it was revealed that there are 2.14 higher chances of being underweight when a child consumes Vitamin A rich fruits and vegetables. These results are contrary to those of Khamis et al. (2019) and Ali et al. (2017) who found that children consuming foods that are rich in Vitamin A had lower chances of being underweight. These unexpected results may be associated with Semba et al. (2010) who mentioned that children who eat Vitamin A rich foods and still underweight might not have met their recommended Vitamin A recommended nutrient intake. It was also revealed that there were 47% less chance of being underweight when consuming other fruits and vegetables. These results might be associated with those of Abedi et al. (2015) who found that when children consume fruits and vegetables, they had lesser chances of being underweight. Abedi et al. (2015) further mentioned that for growth and immunity children must be given Vitamin A since its deficiency is a major contributor to morbidity as well as mortality caused by infections.

Taking the Western Cape as the reference, it was revealed that a child has 4.9, 7.3, 11.6 and 8.3 higher chances of being underweight when they reside in Kwazulu-Natal, North West, Gauteng and Limpopo province, respectively. These results are partially in line with those of Bomela (2007) who found that NW and LP provinces had higher numbers of underweight children. For NW, KZN and LP children might underweight because the provinces are mainly rural, and they lack favourable socioeconomic conditions for their wellbeing. The results further showed that there is 0.001% less chance of being underweight as the birthweight increases. These results might be associated with those of Abbas (2021) who found that children born with low birth weight were more vulnerable to diseases and death and usually remain undernourished i.e., stunted, wasted or underweight. Therefore, being born with normal weight can promote a steady growth among children that are between 6 and 24 months old.

In addition, as the years of education of mothers increase, there are about 14% less chance of the child being underweight. These results are in line with those of Chowdhury et al (2018) and Amaha and Woldeamanuel (2021) who also revealed that maternal education is related with less odds of a child being underweight. In addition, as the number of living children increased, the chance of being underweight increased by 1.24 times. This might also be associated with the reality that children/siblings must share everything no matter how small.

Table 9.3: Logistic regression results on the determinants of health outcomes among 6-23 months old children

Variables	Stunting		Wasting		Underweight	
	Odds ratio	Prob.	Odds ratio	Prob.	Odds ratio	Prob.
Breastfeeding	.5023752**	0.048	1.068158	0.835	1.003893	0.989
Juice	.6400079	0.255	.8444891	0.637	.7620801	0.417
Coke	2.036153	0.130	.4758325	0.131	1.732858	0.194
Butter	1.843024	0.128	.7799912	0.555	1.676474	0.169
Chocolate	.5064923	0.147	1.075986	0.871	.79268	0.570
Snacks	1.010695	0.978	1.133181	0.740	.4589209**	0.031
Grain root butter	.9443287	0.912	2.336927	0.124	.566646	0.229
Legume nuts	.6745825	0.384	.5355993	0.249	.8845436	0.773
Flesh Food	1.616194	0.198	.9456239	0.871	.9614585	0.904
Eggs	1.818373	0.143	.8430372	0.655	1.287051	0.487
Vitamin A fruits and Vegetables	.9037949	0.778	1.506165	0.229	2.146273**	0.021
Dairy milk	.5398531*	0.097	1.011624	0.975	.9958864	0.990
Fruit and vegs	.7791818	0.557	.6964072	0.351	.5293496*	0.086
Discharged same time	.4748338	0.133	1.852625	0.290	.4914547	0.123
Male Child	2.124126**	0.022	1.25842	0.451	1.421462	0.213
Insure	.3406844	0.148	1.866893	0.288	.7680542	0.642
Employed	.5309229	0.156	.8973614	0.781	.648471	0.238
Province						
Eastern Cape	.1614862**	0.033	.6793543	0.646	1.68034	0.584
Northern Cape	.3672246	0.281	1.634067	0.575	1.936677	0.510
Free State	.2267327*	0.100	.2839879	0.185	4.17631	0.136
KwaZulu-Natal	.4787845	0.355	.6215011	0.557	4.915409*	0.081
North West	.4385713	0.325	1.540794	0.604	7.293592**	0.033
Gauteng	.3928989	0.267	1.138924	0.873	11.64865***	0.009
Mpumalanga	.0832281***	0.007	1.141557	0.870	2.852512	0.263
Limpopo	.1538693**	0.030	2.481726	0.282	8.32523***	0.025

Table 9.3: Logistic regression results on the determinants of health outcomes among 6-23 months old children Cont.

Urban resident	.9553079	0.907	2.383453**	0.026	1.396262	0.348
Share toilet	1.324033	0.209	.3363851**	0.028	.7717952	0.322
Birth weight	.9991847***	0.001	.9997153	0.237	.9989964**	0.000
Years of education	.8467096**	0.015	1.047457	0.532	.8530023**	0.014
Number of living children	1.157689	0.216	1.212506*	0.084	1.243141**	0.039
Constant	118.053***	0.001	.0639443*	0.066	27.13578**	0.021
LR Chi2 (30)	66.28***		46.33**		77.84***	
Prob> chi2	0.00002		0.0289		0.0000	

Source: Own Computation, 2022

9.7 Determinants of Child Health Outcomes (24-59 months)

9.7.1 Determinants of stunting among children (24-59 months)

The results in Table 9.4 showed that among 24-59 months old children, consumption of legumes and nuts decreased the chances of stunting by about 95%. These results are in line with those of Jager et al. (2019) who found out that nutrient intake was greater among children consuming legumes compared to those who are not consuming them. The results of this study are also in line with that of Esfarjani et al. (2013) who also found that consumption of legumes is associated with lower odds of being stunted among children.

There is also a significant relationship between stunting and consumption of fruit and vegetables $p<0.01$). The results revealed that there is 35.5 higher chance of being stunted when a child consumes fruit and vegetables. These results are in line with those of Aguayo et al. (2016) who also found that consumption of fruits and vegetables is associated with stunting among children. Aguayo et al. (2016) further mentioned that this is due to lower feeding frequency.

There is 2.4 higher chance of being stunted when residing in Free-State. These results are in line with those of Pilditch (2020) who also revealed that stunting was prevalent in the Free State province. It was also revealed that there were 2.0 chances of being stunted when residing in KwaZulu-Natal province. The same findings were revealed by Kaldenbach et al. (2022) who also found out that stunting was prevalent in KZN.

9.7.2 Determinants of wasting among children (24-59 months)

Wasting in children between 24-59 months showed 0.1 lower chances of being wasted when a child consumes coke. This may be because sugar in liquid form has higher chances of increasing weight compared to sugar in solid form (Zhang et al. 2020). A child has 0.6 lower chances of being wasted when discharged from hospital after birth at the same time as the mother. The results also revealed that a child whose mother is employed has 0.6 lower chances of being wasted. Eshete et al. (017) discovered that wasting was 8.8% on children whose mothers were employed and 10.8% on children with unemployed mothers. A child with higher birth weight was revealed to have 1.0 lower chances of being wasted.

The results showed that a child who resided in urban areas had 45% less chances of being stunted ($p<0.05$). these results are in line with those of Kang et al (2018) and Banerjee et al (2021) who revealed that compared to children in rural areas, children from urban areas had better nutritional status. These results may be associated with the favourable socioeconomic conditions that urban children find themselves in where they can eat all the foods that are able to meet their daily nutrient intake requirements.

The results also revealed that as the level of education increases, the child had 8.04% lower chances of being stunted ($p<0.01$). These results are in line with those of Torlesse et al. (2016) and Makoka and Masibo (2015) who found out that the chances of a child being stunted decrease with the increase in level of education. The results revealed that a child born with normal birth weight had 0 07% less chances of being stunted ($p<0.05$). these results are connected to those of Aryastami et al. (2017) who also found out that stunting is associated with low birth weight.

9.7.3 Determinants of underweight among children (24-59 months)

In children between 24-59 months, there are 0.74% lower chances of a child being underweight when a child resides in Kwazulu-Natal. In addition, as the birthweight of children 24-59 months increased, there is a 0.001% less chance of being underweight. This can be supported by a study conducted by Machira and Chirwa (2020) who revealed that smaller weight of a child after birth had effect to increase the chances of a child being underweight.

Table 9.4: Logistic regression results on the determinants of health outcomes among 24-59 months old children

Variables	**Stunting**		**Wasting**		**Underweight**	
	Odds ratio	**Prob.**	**Odds ratio**	**Prob.**	**Odds ratio**	**Prob.**
Breastfeeding	2.293652	0.359	.3358598	0.209	1	
Juice	3.690067	0.161	2.710825	0.184	1.984602	0.368
Coke	.1499971	0.239	.101689*	0.074	.6864827	0.779
Butter	.1753146	0.247	.4775615	0.481	.1445648	0.157
Chocolate	4.076256	0.270	3.957579	0.238	2.410542	0.504
Snacks	.8431144	0.874	3.218528	0.165	.6527344	0.648
Grain root butter	.6025108	0.406	.8704046	0.794	1.503973	0.470
Legume nuts	.0465216*	0.075	3.163403	0.339	9.439491	0.102
Flesh Food	.7801657	0.832	.5867988	0.587	.3933085	0.437
Eggs	2.537133	0.297	.421022	0.254	1.080492	0.934
Vitamin A fruit and vegs	.2246237	0.248	.712193	0.758	1.855268	0.521
Dairy milk	.3758221	0.146	.6704037	0.451	.7588815	0.662
Fruit and vegs	35.54581***	0.007	.7603154	0.784	.9106652	0.950
Discharged same time	.6672119	0.165	.6111399*	0.069	1.015341	0.961
Child sex	1.110506	0.636	.9048962	0.589	.8660059	0.523
Insure	.6521581	0.351	1.003752	0.991	1.118831	0.780
Employed	.9319601	0.784	.6163411**	0.022	.4074569***	0.002

Table 9.4: Logistic regression results on the determinants of health outcomes among 24-59 months old children Cont.

Province						
Western Cape	1					
Eastern Cape	1.221556	0.636	.9606352	0.942	.5364279	0.338
Northern Cape	.9352999	0.906	1.597261	0.407	.4274945	0.212
Free State	2.37071*	0.071	.9967917	0.995	.4218572	0.181
KwaZulu-Natal	1.95833*	0.094	.6716626	0.463	.2638713**	0.045
North West	1.300151	0.547	1.288545	0.643	.7844198	0.704
Gauteng	1.660212	0.332	1.712195	0.340	.4973842	0.297
Mpumalanga	.9488754	0.900	1.522341	0.434	.492183	0.265
Limpopo	1	Empty	1.735716	0.322	.8850001	0.850
Urban resident	.5494565**	0.029	.71447	0.124	1.042637	0.877
Share toilet	.8369505	0.121	.9040554	0.153	.8899123	0.242
Birth weight	.9992555***	0.000	.9988529***	0.000	.9989747***	0.000
Years of education	.9195928**	0.044	.9472984	0.162	.9734561	0.537
Number of living children	1.057085	0.504	1.064185	0.413	1.076154	0.396
Constant	7.872721**	0.019	109.6853***	0.000	15.4628	0.013
LR Chi2 (29)	68.75***		100.10***		66.06***	
Prob > Chi2	0.0000		0.0000		0.0001	

Source: Own Computation, 2022

CHAPTER TEN

MULTIDIMENSIONAL PRO-POOR GROWTH MEASUREMENT

10.1 Introduction

The results presented in this chapter address the last (fifth) objective of this study, which is to examine the pro-poorness of growth in child's multidimensional welfare indicators. The study applied three approaches to analyse pro-poor growth based on the relative and absolute measures that had been proposed in the literature. The first is Growth Incidence Curve (GIC) that was proposed by Ravallion and Chen (2003) and represents the absolute measure of pro-poor growth. The other two approaches, which represent relative measure of pro-poor growth are Pro-Poor Growth Index (PPGI) that was proposed by Kakwani and Pernia (2000), and the Poverty Equivalent Growth Rate (PEGR) that was proposed by Kakwani and Son (2002). The GICs were drawn by the computed percentiles of the multidimensional poverty indices (MPI) based on the Alkire-Foster (AF) and fuzzy set approaches. However, to compute the PPGI and PEGR, a poverty line needs to be specified. Therefore, the computed MPI from the AF and fuzzy set were transformed into multidimensional wealth index (MWI) by deducting each of the percentile average values from one (1). Conventionally, a poverty line of one was used for AF welfare indicator, while 0.90797 was used for fuzzy set. The 0.90797 was obtained by deducting the average fuzzy MPI for all the respondents from one. Generally, hypothesis three is to be rejected for pro-poor conclusion. In this chapter, the results for the absolute and relative measures of pro-poor growth are going to be systematically presented across the periods that were studied, provinces, geography types and population groups.

10.2 Absolute and Relative Measures of Pro-Poor Growth Between 2017 and 2019

Figures 10.1 and 10.2 show the Growth Incidence Curves (GICs) for fuzzy MPI for the 2017-2018 and 2018-2019 periods, respectively. The curves show that in the 2017-2018 and 2018-2019 periods, the people on the higher percentiles, who are the poorest in the population had their poverty growth rates being lower than the overall average for the population. More specifically, the average growth rate of fuzzy MPI was 0.25 in each of the years. The GICs lie above this value until one reaches the 60^{th} percentiles. Moreover, Figures 10.3 and 10.4 show the AF MPI GICs for the 2017-2018 and 2018-2019 periods, respectively. The results indicate that while Figure 10.3 did not give any indication of pro-poor growth, Figure 10.4 reveals some form of pro-poor growth since growths in poverty among the poorest were lower than the overall average. In absolute term and depending on the approach that had been used to compute the MPI, poor children may have benefitted from the proceeds of growth in the national economy between 2017 and 2019. These benefits may have accrued from some programmes and interventions such as social grants, school feeding, healthcare service delivery, and schooling. Although several factor can promote pro-poor growth within an economy, the growth pathway in South Africa has been recently affected by several external shocks. Specifically, the World Bank (2018) projected a 1.3% growth rate for the South Africa's GDP in 2017. The expected growth will increase to 1.4% in 2018, 1.8% in 2019 and 1.9% in 2020.

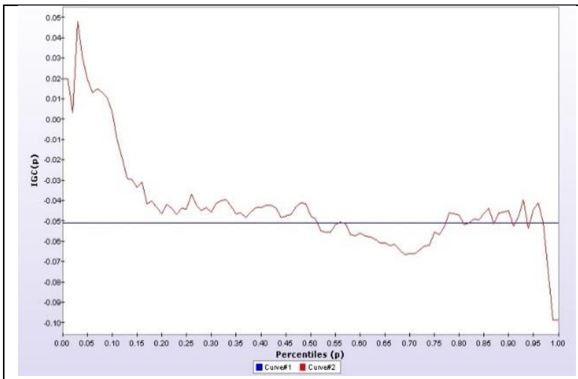

Figure 10.1: Child's Fuzzy sets Multidimensional Growth Incidence Curve in South Africa (2017-2018)

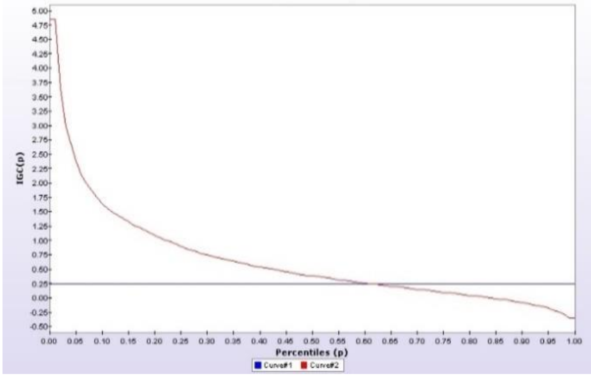

Figure 10.2: Child's Fuzzy sets Multidimensional Growth Incidence Curve in South Africa (2018-2019)

Source: Own Computation, 2022

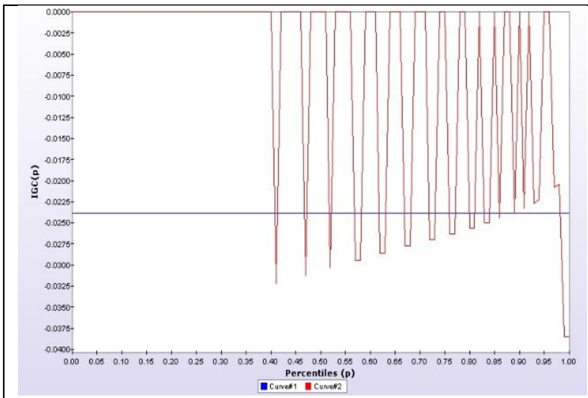

Figure 10.3: Child's Alkire-Foster MPI Growth Incidence Curve in South Africa (2017-2018)

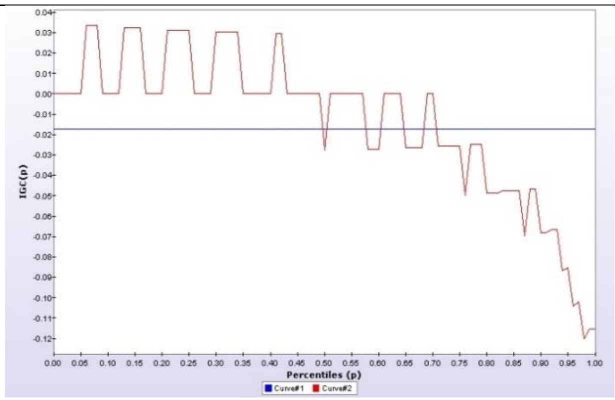

Figure 10.4: Child's Alkire-Foster MPI Growth Incidence Curve in South Africa (2018-2019)

Source: Own Computation, 2022

Table 10.1 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the Alkire-Foster and fuzzy set approaches between 2017 and 2019. The Table shows that the AF PPGI for incidence, depth and severity were 8801162.09, 1.15 and 0.83, respectively for 2017-2018 while those for fuzzy set were 1.33, 1.84 and 2.56. These results imply that growth was pro-poor for multidimensional poverty incidence and depth in the two approaches because the computed PPGI are greater than one. Moreover, based on PPGI for poverty severity in AF approach was not pro-poor, while that for fuzzy set was pro-poor. The results presented in Table 10.1 also showed the AF and fuzzy set child's Poverty Equivalent Growth Rates (PEGRs) over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.008 for 2017-2018, while that for fuzzy set was 0.005. The AF PEGRs over the period of 2017-2018 for poverty incidence, depth and severity were 73959.34, 0.009 and 0.007, respectively, while those for fuzzy set were 0.006, 0.009 and 0.012. These results imply that AF and fuzzy set MWIs were pro-poor for poverty incidence and depth, while fuzzy set MPI showed pro-poorness for poverty severity.

The Table further showed that over the period of 2018-2019, the AF PPGIs were 0.66667, 0.654235 and 0.375569 for poverty incidence, depth, and severity, respectively which can be compared with 1.714286, 0.002528 and 0.927928 for fuzzy set. These results imply that with AF and fuzzy set approaches, growth was not pro-poor over the period based on poverty depth and severity. However, the results imply that the poverty incidence shows pro-poorness under the fuzzy set approach. The AF multidimensional wealth growth rate was 0.12292 for 2018-2019, while that for fuzzy set was 0.021379. The results also showed that over the period of 2018-2019 the AF PEGRs were 0.08194, 0.08042 and 0.04616 for incidence, depth, and severity wealth index, respectively, while fuzzy set had 0.036650, 0.000054 and 0.019338. These results also imply the same conclusion as given above for PPGI with poverty incidence under fuzzy set, being pro-poor in 2018-2019.

Table 10.1. PPGI and PEGRs Multidimensional Wealth Index Growth Rates Across the Years

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.008403	8801162	73959.35	0.004537	1.333333	0.006568
Depth	0.008403	1.153848	0.009696	0.004537	1.842612	0.009076
Severity	0.008403	0.833007	0.007000	0.004537	2.562582	0.012623
2018-2019						
Incidence	0.12292	0.666667	0.08194	0.021379	1.714286	0.036650
Depth	0.12292	0.654235	0.08042	0.021379	0.002528	0.000054
Severity	0.12292	0.375569	0.04616	0.021379	0.927928	0.019838

Source: Own Computation, 2022

10.3 Absolute and Relative Measures of Pro-Poor Growth Across the Provinces

10.3.1 Multidimensional Pro-Poor Growth in Western Cape

Due to limitations in the number of respondents, the GIC graphs for the Western Cape AF MPI for 2018-2019 could not be drawn. Figure 10.5 shows the distribution of the AF MPI for Western Cape province over the period of 2017-2018. The Figure shows that the AF MPI growth rates were higher than the average growth for the whole population. These results imply that growth was not pro-poor. Figures 10.6. and 10.7 show the GICs for fuzzy set MPI for 2017-2018 and 2018-2019 periods, respectively. Figure 10.6 shows that from the 3rd to the 76th percentiles, average growth rates of fuzzy set MPI were lower than the average growth for the whole population. However, beyond the 76th percentile, the fuzzy set MPI growth rates were higher than the average growth for the whole population. On the other hand, Figure 10.7 shows that from the 1st percentile until the 63 percentiles, the fuzzy set MPI growth rates were higher than the average growth for the whole population. However, beyond the 63rd percentile, the Figure shows that the fuzzy set MPI growth rates were lower than the average growth for the whole population. These results imply that between 2017-2018, some poor children in the Western Cape benefited from growth. However, the poorest among this province did benefit from growth. Additionally, between 2018-2019 the poorest among poor children in Western Cape derived some benefits from growth.

Table 10.2 shows the relative measures of pro-poor growth using some indices of multidimensional wealth that were computed with AF and fuzzy set approaches between 2017 and 2019 for Western Cape. The Table shows that the AF PPGI for incidence, depth, and severity were 19173961.343, 1.618132 and 0.878545, respectively for 2017-2018, while those for fuzzy set were 1.500000, 0.502492 and 1.081381. These results imply that growth was pro-poor for multidimensional poverty for incidence and depth under the AF indicator, and pro-poor for incidence and severity under the fuzzy Set approach because the computed PPGIs are greater than 1.

The results presented in Table 10.2 also showed the AF and fuzzy set child's PEGRs for Western Cape over the 2017-2018 period. The AF multidimensional wealth growth rate was 0.068518 for 2017-2018, while that of fuzzy set was 0.010668. The AF PEGRs over the period of 2017-2018 in Western Cape for poverty incidence, depth, and severity were 1313761.6162, 0.110871 and 0.006196, respectively, while those for fuzzy set were 0.0016002, 0.005360 and 0.011536. These results imply that the AF MWIs were pro-poor for poverty incidence and depth while the fuzzy set MWI showed pro-poorness for poverty incidence and severity. The Table further shows that in the Western Cape over the period of 2018-2019, the AF PPGIs were 0.819672, 0.652292 and 0.425943 for poverty incidence, depth, and severity, respectively, which can be compared with no observation, 0.110084 and 0.139813 for fuzzy set. These results imply that with the AF and fuzzy set approaches, growth was not pro-poor in the Western Cape over the period of 2018-2019 based on poverty incidence, depth, and severity. The AF multidimensional wealth growth rate was 0.2325324 for 2018-2019, while that of fuzzy set was 0.668922. The results also showed that the AF PEGRs for 2018-2019 were 0.190600, 0.151679 and 0.099045 for incidence, depth, and severity wealth index, respectively, while fuzzy set had no observations, 0.073638 and 0.093524. These results imply the same conclusion as given above for AF and fuzzy set PPGI.

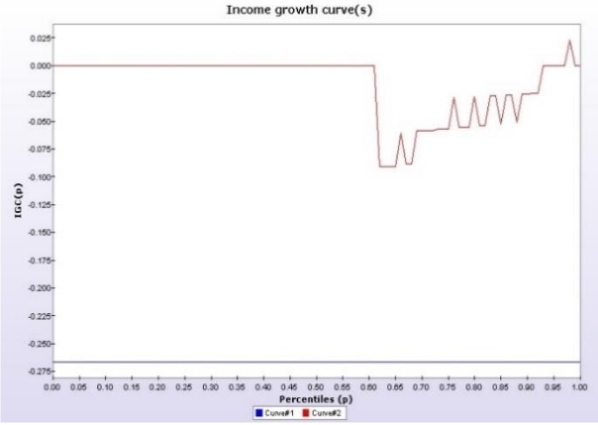

Figure 10.5: Child's Alkire-Foster MPI Growth Incidence Curve in Western Cape (2017-2018)

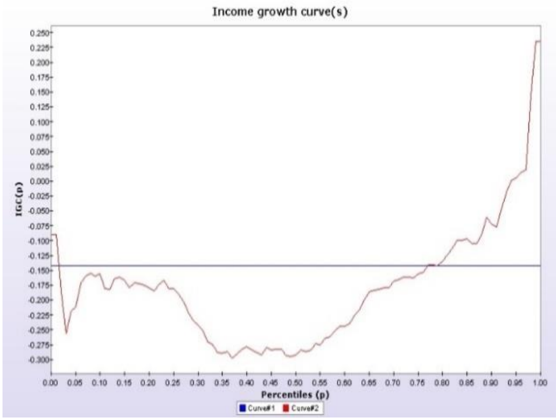

Figure 10.6: Child's Fuzzy Set MPI Growth Incidence Curve in Western Cape (2017-2018)

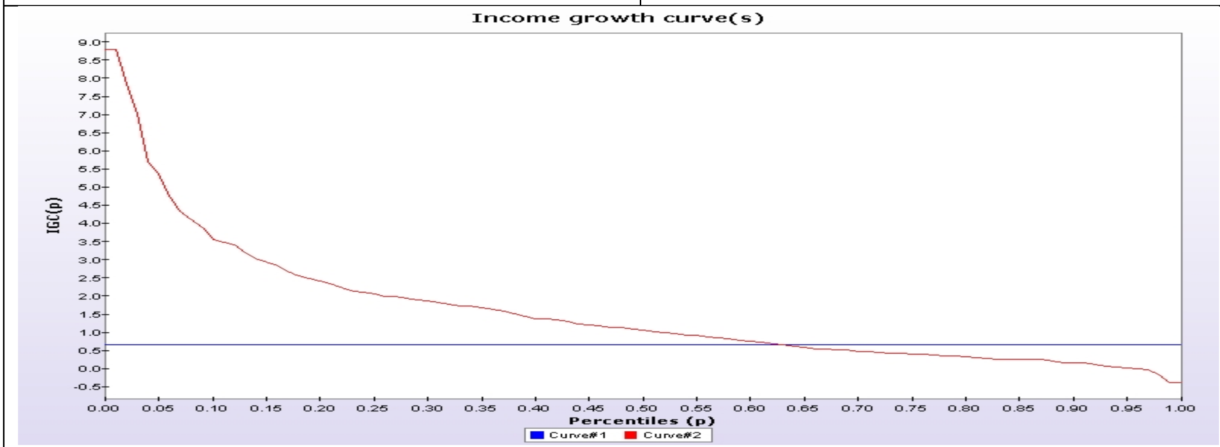

Figure 10.7: Child's Fuzzy Set MPI Growth Incidence Curve in Western Cape (2018-2019)

Source: Own Computation, 2022

Table 10.2. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Western Cape

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.068518	19173961.343	1313761.6162	0.010668	1.500000	0.016002
Depth	0.068518	1.618132	0.110871	0.010668	0.502492	0.005360
Severity	0.068518	0.878545		0.010668	1.081381	0.011536
2018-2019						
Incidence	0.232532	0.819672	0.190600	0.668922	-	-
Depth	0.232532	0.652292	0.151679	0.668922	0.110084	0.073638
Severity	0.232532	0.425943	0.099045	0.668922	0.139813	0.093524

Source: Own Computation, 2022

10.3.2 Multidimensional Pro-poor Growth in Eastern Cape Province.

The GIC graph for AF MPI for 2018-2019 could not be drawn due to limitations in the number of respondents. Figure 10.8 shows the GIC for AF MPI for 2017-2018 period. The curve shows that the 2017-2018 children in Eastern Cape between the first percentile and 25th percentile had AF MPI average growth rates that were higher than the average growth for the whole population. The figure also shows that AF MPI growth rates between 26th and 95th percentiles were fluctuating above and below the average growth rate for the whole population. However, beyond the 95th percentile, the AF MPI average growth rates were lower than the average growth for the whole population. Figures 10.9 and 10.10 show the GICs for fuzzy set MPI for 2017-2018 and 2018-2019 periods, respectively. The curves show that in the 2017-2018 and 2018-2019 periods, children on higher percentiles, that is, the poorest had their poverty growth rated being lower than the overall average for the population. It evident from the AF and fuzzy set graphs that the poorest children among the poor in the Eastern Cape province benefited a bit from growth.

Table 10.3 shows the relative measures of pro-poor growth using indices of multidimensional wealth computed with AF and fuzzy set approaches between 2017 and 2019. The Table shows that the AF PPGIs for incidence, depth, and severity were 0.000000, 0.8448883 and 0.002756, respectively, for 2017-2018, while those for fuzzy set were 1.000000, 1.672172 and 4.180428. These results indicate that while the AF PPGI did not give any indication of pro-poor growth, the fuzzy set PPGI reveals that growth was pro-poor since all the values were greater than 1. The results presented in Table 10.3 also showed the AF and fuzzy set PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.003262 for 2017-2018, while that of fuzzy set was 0.003944. The AF PEGRs over the period of 2017-2017 for poverty incidence, depth, and severity were 0.000000, 0.002756 and 0.003452, respectively, while that of fuzzy set were 0.003944, 0.006595 and 0.016489.

These results imply the same conclusion as given above for AF and fuzzy set PPGI. The Table further shows that over the period of 2018-2019, the AF PPGIs were 0.523810, 0.639250 and 0.057452 for incidence, depth, and severity, respectively, which can be compared with 3.333333, 5.126368 and 7.691747 for fuzzy set. These results imply that wealth growth was not pro-poor for the AF approach based on the incidence, depth, and severity while the fuzzy set approach showed growth to be pro-poor based on incidence, depth, and severity. The AF multidimensional wealth growth rate for the 2018-2019 period was 0.039687 compared to 0.005584 for the fuzzy set. The results also showed that over the period of 2018-2019 the AF PEGRs were 0.020788, 0.025370 and 0.002280 for poverty incidence, depth, and severity, respectively, which can be compared to 0.036650, 0.000054 and 0.019838 for fuzzy set. These results imply that even though the AF approach did not give any indication of pro-poor growth, the fuzzy sets showed multidimensional wealth growth to be pro-poor based on poverty incidence, depth, and severity.

Different conclusions were consistently reached from the AF and fuzzy PPGI and PEGR analytical approaches. This also underscores the fact that pro-poor growth measurement using the multidimensional approach is highly sensitive to the adopted methodology. However, based on the fuzzy set results, it was found that there had been pro-poor growth among children's households in the Eastern Cape province. Although Eastern Cape is largely reckoned as the poorest province in South Africa, the fuzzy set finding is in support of the Eastern Cape's Socio-Economic Consultative Council (ECSECC) (2016) report that indicated reduction in poverty incidence from 63.6% in 1996 and to 43.4% in 2014.

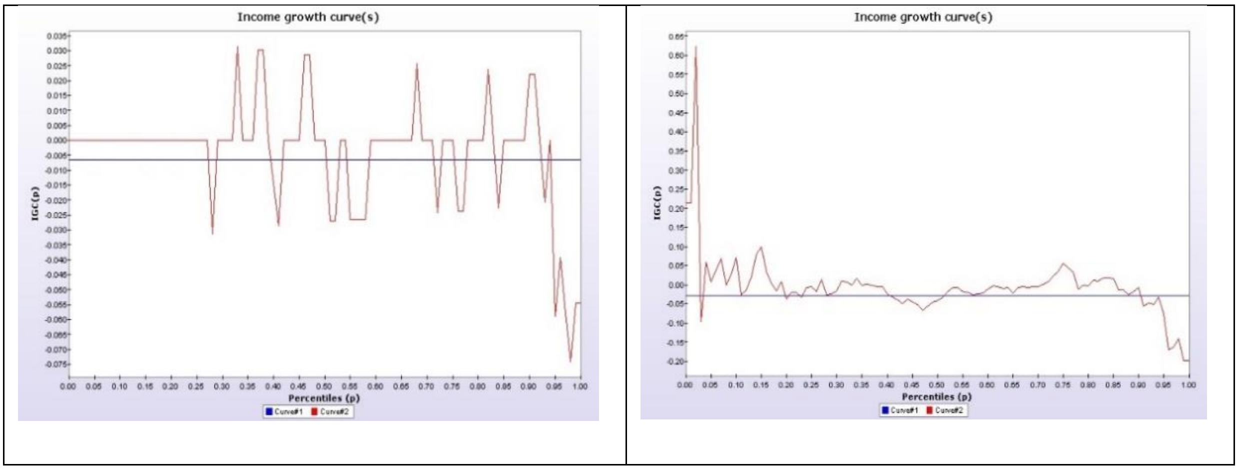

Figure 10.8: Child's Alkire-Foster MPI Growth Incidence Curve in Eastern Cape (2017-2018)

Figure 10.9: Child's Fuzzy Set MPI Growth Incidence Curve in Eastern Cape (2017-2018)

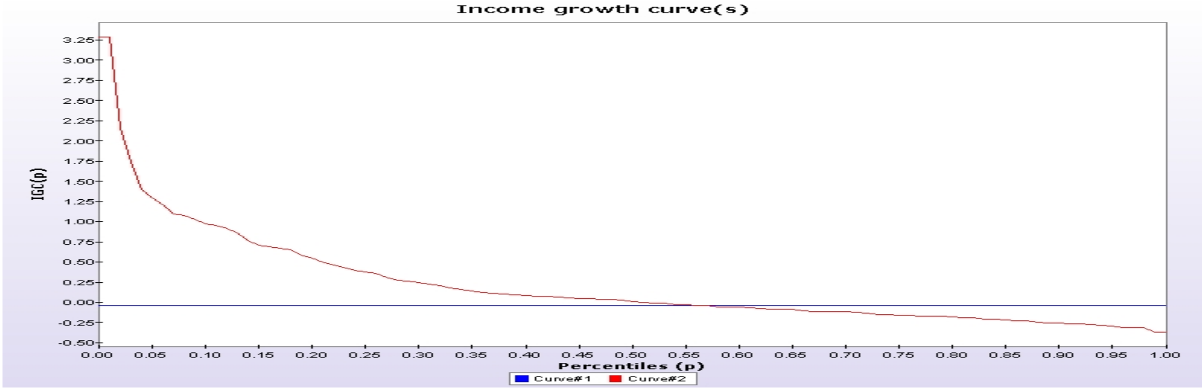

Figure 10.10: Child's Fuzzy Set MPI Growth Incidence Curve in Eastern Cape (2018-2019)

Source: Own Computation, 2022

Table 10.3. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in EC

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.003262	0.0000000	0.000000	0.003944	1.000000	0.003944
Depth	0.003262	0.8448883	0.002756	0.003944	1.672172	0.006595
Severity	0.003262	0.002756	0.003452	0.003944	4.180428	0.016489
2018-2019						
Incidence	0.039687	0.523810	0.020788	0.005584	3.333333	0.018612
Depth	0.039687	0.639250	0.025370	0.005584	5.126368	0.028623
Severity	0.039687	0.057452	0.002280	0.005584	7.691747	0.042947

Source: Own Computation, 2022

10.3.3. Multidimensional Pro-poor Growth in Northern Cape Province

Due to limitations on the number of respondents, the GIC graphs for AF MPI 2017-2018 and 2018-2019 could not be drawn. Figures 10.11 and 10.12 show the GIC of the fuzzy set MPI for Northern Cape province over the period of 2017-2018 and 2018-2019, respectively. The curves showed that children on the higher percentiles, who were the poorest of poor children in the population, had their poverty growth rates being lower than the overall average for the population. Figure 10.11 shows that beyond the first percentile, the fuzzy set average growth rate was lower than the overall average growth rate for the population, while Figure 10.12 shows that beyond the 55th percentile the average growth rate was lower than the average growth rate for the population. These figures show that there was some form of pro-poor growth, that is, poor children benefited from wealth growth. Table 10.4

shows the relative measures of pro-poor growth over the period of 2017-2018 and 2018-2019. The table shows that the AF PPGI for incidence, depth, and severity were 0.063830, 0.782329 and 0.367108, respectively, for 2017-2018, which can be compared to 2.3883730.353871, 6.018253 and 9.886047 for fuzzy set. These results imply that growth was not pro-poor for AF multidimensional poverty incidence, depth, and severity, while the fuzzy set poverty incidence, depth, and severity were pro-poor. The results presented in Table 10.4 also showed the AF and fuzzy set PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.0010529, which can be compared to 0.001638 for fuzzy set for 2017-2018. The AF PEGRs over the period of 2017-2018 were 0.0000672, 0.008237 and 0.003865 for multidimensional poverty incidence, depth, and severity, respectively, while those for fuzzy set were 39115.51, 0.0099856 and 0.016191. These results also imply the same conclusion as given above for PPGI. The table further showed that over the period of 2018-2019, the AF PPGIs were 0.704545, 0.662005 and 0.414561 for multidimensional poverty incidence, depth, and severity, which can be compared to 1.000000, 0.648151 and 0.400434 for fuzzy set. These results indicate that growth was not pro-poor the AF approach based on multidimensional poverty incidence, depth, and severity, while those of the fuzzy set indicate that growth was pro-poor over the period of 2018-2019 based on multidimensional poverty incidence, depth, and severity. The table showed that over the period of 2018-2019, the AF multidimensional wealth growth rate was 0.153803 which can be compared to 0.032006 of the fuzzy set. The results also showed that over the period of 2018-2019, the AF PEGRs were 0.108361, 0.101818 and 0.063760 for multidimensional incidence, depth, and severity, respectively, which can be compared to 0.032006, 0.020745 and 0.012816 for fuzzy set. These results also imply the same conclusion as given above for PPGI with poverty incidence, depth, and severity not being pro-poor for the AF approach while being pro-poor under the fuzzy set approach.

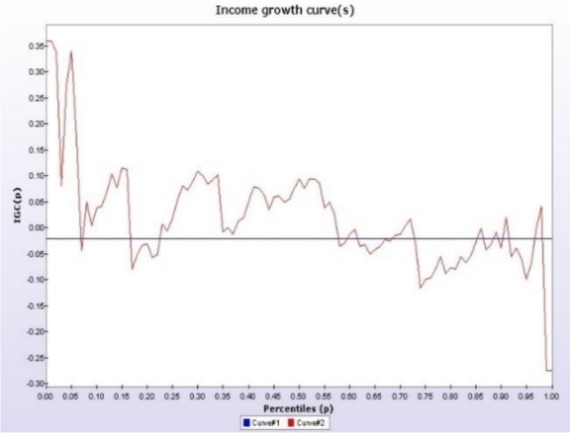

Figure 10.11: Child's Fuzzy Set MPI Growth Incidence Curve in Northern Cape (2017-2018)

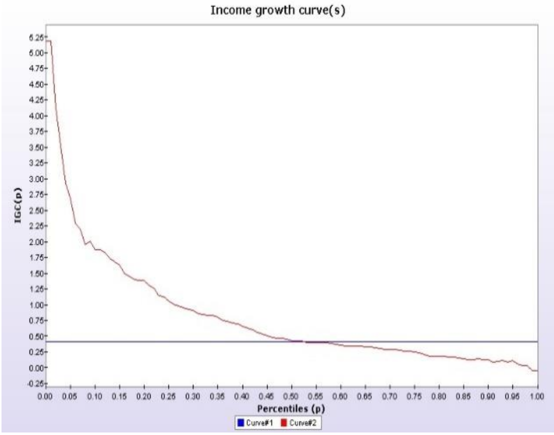

Figure 10.12: Child's Fuzzy Set MPI Growth Incidence Curve in Northern Cape (2018-2019)

Source: Own Computation, 2022

Table 10.4: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Northern Cape

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.010529	0.063830	0.000672	0.001638	23883730.353871	39115.51
Depth	0.010529	0.782329	0.008237	0.001638	6.018253	0.0099856
Severity	0.010529	0.367108	0.003865	0.001638	9.886047	0.016191
2018-2019						
Incidence	0.153803	0.704545	0.108361	0.032006	1.000000	0.032006
Depth	0.153803	0.662005	0.101818	0.032006	0.648151	0.020745
Severity	0.153803	0.414561	0.063760	0.032006	0.400434	0.012816

Source: Own Computation, 2022

10.3.4. Multidimensional Pro-poor Growth in Free State Province.

Due to limitations in the number of respondents, the GIC graphs for 2018-2019 AF MPI could not be drawn. Figure 10.13 shows the GIC of AF MPI for FS province over the period of 2017-2018. The figure shows that the average growth rates for the 42nd percentile was zero. However, between the 42nd and 57th percentiles, the average growth rates of AF MPI were higher than the average growth for the whole population. Between 57th and 94th percentiles, the average growth rates of AF MPI were below the average growth for the whole population. Beyond the 98th percentile, the AF average growth was higher than the average growth for thew hole population. It is evident from the curve that some of the poorest children in the FS benefited from growth. Figures 10.14 and 10.15 showed the GICs for the 2017-2018 and 2018-2019 fuzzy set MPI. The curves show that in the 2017-2018 and 2018-2019 periods, children beyond 56th percentile (AF) and 60th percentile (fuzzy set), had their poverty growth rates being lower than the overall average growth for the whole population. These results indicate that there was some form of pro-poor growth in poverty among the poorest children.

Table 10.5 shows the relative measures of pro-poor growth using the AF and fuzzy set indices over the period of 2017-2018 and 2018-2019. The table shows that the AF PPGIs for incidence, depth, and severity were 0.000000, 1.262088 and 1.304241, respectively for 2017-2018, which can be compared to 1.777778, 2.049359 and 2.129897 for fuzzy set. These results imply that growth was pro-poor based on multidimensional poverty depth and severity for AF approach and incidence, depth, and severity for fuzzy set approach. The AF multidimensional wealth growth rate was 0.036085, while that of fuzzy set was 0.038242. The table further showed that over the period of 2017-2018, the AF PEGRs were 0.000000, 0.045542 and 0.047063 for poverty incidence, depth, and severity, which can be compared to 0.067987, 0.07873 and 0.081453 for fuzzy set. These results imply that the AF MWIs were pro-poor for poverty depth and severity2, while the fuzzy set MWI showed pro-poorness for poverty incidence depth and severity. The results presented in Table 10.5 also showed that over the period of 2018-2019, the AF PPGIs were 0.641026, 0.662560 and 0.426104 for multidimensional poverty incidence, depth, and severity, which can be compared to 1.714286, 0.201632 and 0.539586 for fuzzy set. These results imply that with the AF approach, growth was not pro-poor based on incidence, depth, and severity. The fuzzy set approach also did not show pro-poorness of growth for depth and severity. However, the results indicate that poverty incidence shows pro-poorness under the fuzzy set approach. The AF multidimensional wealth growth rate was 0.133798 for 2018-2019, while that for fuzzy set was 0.024541. the results also showed that over the 2018-2019 period the AF PEGRs were 0.085768, 0.088649 and 0.057012 for incidence, depth, and severity wealth index, respectively, which can be compared with 0.042076, 0.004948 and 0.013242 for fuzzy set. These results also imply the same conclusion as given above for PPGI with poverty incidence under fuzzy sets being pro-poor in 2018-2019.

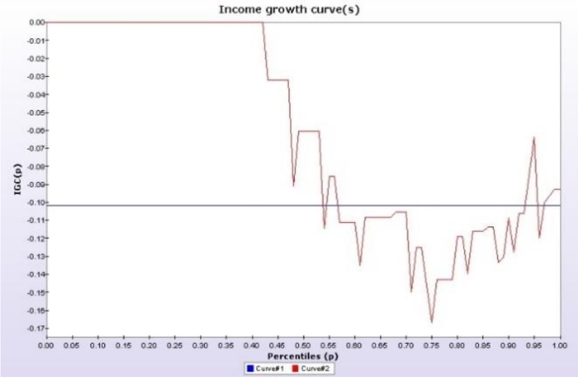

Figure 10.13: Child's Alkire-Foster MPI Growth Incidence Curve in Free State (2017-2018)

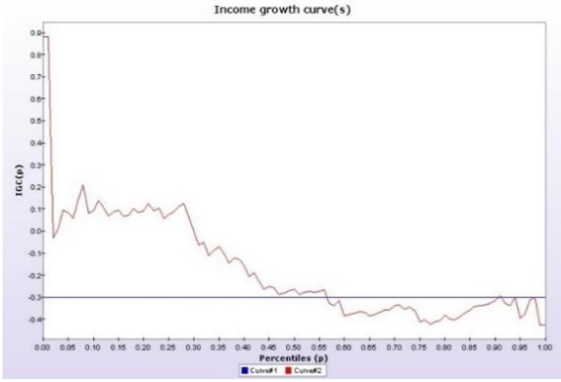

Figure 10.14: Child's Fuzzy Set MPI Growth Incidence Curve in Free State (2017-2018)

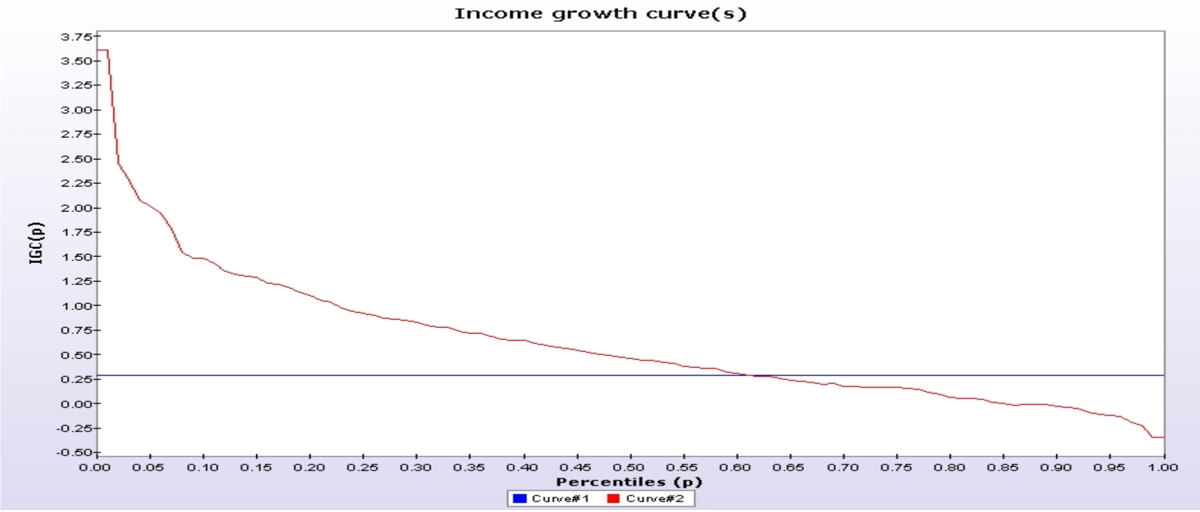

Figure 10.15: Child's Fuzzy Set MPI Growth Incidence Curve in Free State (2018-2019)

Source: Own Computation, 2022

Table 10.5: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in FS

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.036085	0.000000	0.000000	0.038242	1.777778	0.067987
Depth	0.036085	1.262088	0.045542	0.038242	2.049359	0.078373
Severity	0.036085	1.304241	0.047063	0.038242	2.129897	0.081453
2018-2019						
Incidence	0.133798	0.641026	0.085768	0.024541	1.714286	0.042070
Depth	0.133798	0.662560	0.088649	0.024541	0.201632	0.004948
Severity	0.133798	0.426104	0.057012	0.024541	0.539586	0.013242

Source: Own Computation, 2022

10.3.5. Multidimensional Por-poor Growth in KwaZulu-Natal Province

Due to limitations in the number of respondents, the GIC curves for AF MPI 2017-2018 and 2018-2019 and those for fuzzy sets MPI for 2018-2019 could not be drawn. Figure 10.16 shows the GIC for fuzzy sets MPI over the period of 2017-2018 for the KZN province. The Figure shows that the first 57^{th} percentiles the average growths rates of fuzzy sets MPI were higher than the average growth for the whole population. Beyond the 57^{th} percentile, the average growth rate for fuzzy sets MPI were lower than the average growth for the population. These results indicate that the poorest among the poor children in KZN province benefited a bit from growth.

Table 10.6 further shows the relative measures of pro-poor growth using the AF and fuzzy sets multidimensional wealth indices over the period of KZN in 2017-2018 and 2018-2019. The table shows that the AF PPGI for incidence, depth and severity were 2056976.682785, 0.942678 and 0.5997754, respectively which can be compared to 1.250000, 1.358935 and 1.175815. These results imply that growth was pro-poor for multidimensional poverty incidence (AF) and multidimensional incidence, depth and severity (fuzzy sets). However, these results also indicate that growth was not pro-poor for multidimensional poverty depth and severity under the AF approach.

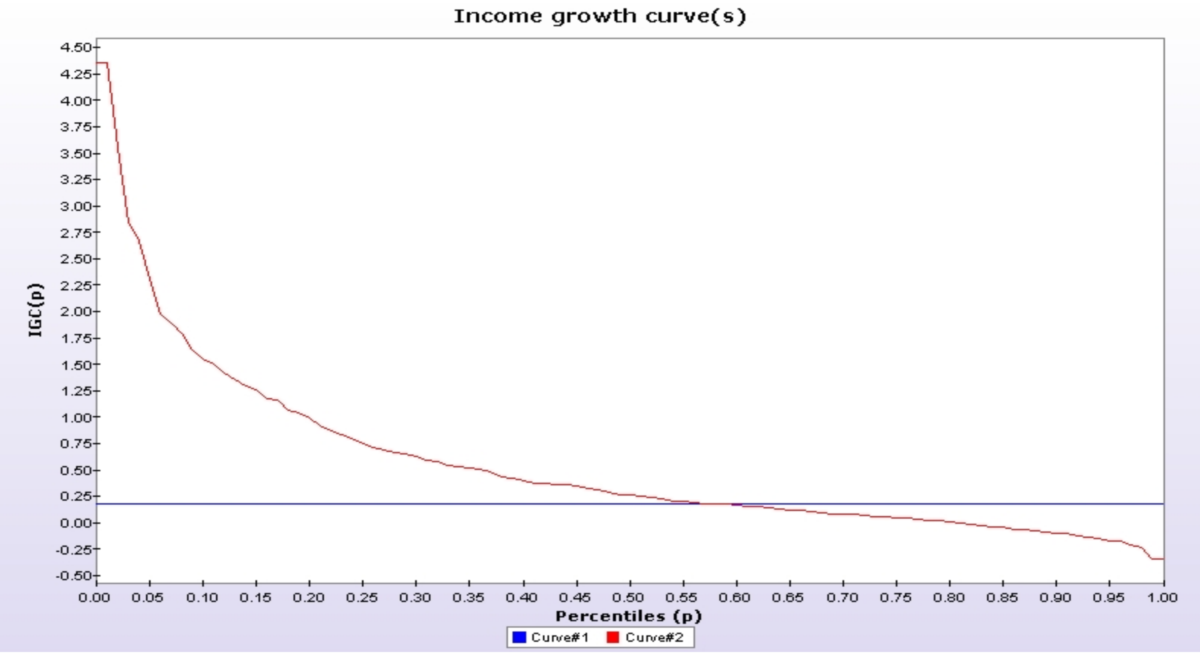

Figure 10.16: Child's Fuzzy Set MPI Growth Incidence Curve in Kwa-Zulu Natal (2017-2018)

Source: Own Computation, 2022

The result presented in Table 10.6 also showed the AF and fuzzy sets PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate was 0. 015193 for 2017-2018 which can be compared to 0.005489 of fuzzy sets. The AF PEGRs over the period of 2017-2018 for poverty incidence, depth and severity were 31251.039071, 0.014322 and 0.009081 respectively, while those of fuzzy sets were 0.006862, 0.0047460 and 0.006455. These results imply that the fuzzy sets MWIs were pro-poor for poverty incidence, depth and severity, while AF MWIs showed pro-poorness for poverty incidence. However, the AF MWI showed no indications of pro-poorness for depth and severity. The table further showed that over the period of 2018-2019 in KZN, the AF PPGIs were 0.629630, 0.643915 and 0.316809 for poverty incidence, depth and severity, respectively, which can be compared to 1.818182, 0.039636 and 0.931128 for fuzzy sets. Although these results give no indication of pro-poor growth under the AF approach, the fuzzy sets approach showed growth to be pro-poor based on multidimensional poverty incidence. However, based on multidimensional poverty depth and severity the AF MPI showed no indication of pro-poor growth. The AF multidimensional wealth growth rate over the period of 2018-2019 was (KZN) 0.086169 while that of fuzzy sets was 0.018342. The results also showed that the AF PEGRs over the period of 2018-2019 for multidimensional poverty incidence, depth and severity were (KZN) 0.054254, 0.055485 and 0.02799, respectively, while of fuzzy sets were 0.033348, 0.000727 and 0.017078. These results imply the same conclusion as given above for PPGI with multidimensional poverty incidence under fuzzy sets being pro-poor in 2018-2019.

Table 10.6. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Kwa-Zulu Natal

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.015193	2056976.682785	31251.039071	0.005489	1.250000	0.006862
Depth	0.015193	0.942678	0.014322	0.005489	1.358935	0.007460
Severity	0.015193	0.5997754	0.009081	0.005489	1.175815	0.006455
2018-2019						
Incidence	0.086169	0.629630	0.054254	0.018342	1.818182	0.033348
Depth	0.086169	0.643912	0.055485	0.018342	0.039636	0.000727
Severity	0.086169	0.316809	0.027299	0.018342	0.931128	0.017078

Source: Own Computation, 2022

10.3.6. Multidimensional Pro-poor Growth in North West Province

The GIC curve for North West over the period of 2018-2019 could not be drawn due to limitations in the number of respondents. Figure 10.17 shows the AF GIC curve for North West over the period of 2017-2918. The figure shows that in all percentiles, the growth rate of AF MPI was higher than the average growth for the population. These results imply that poor children in the NW province did not benefit from growth. Figures 10.18 and 10.19 show the GICs for fuzzy sets MPI for the 2017-2018 and 2018-2019 periods, respectively. Figure 10.18 shows that the average growth rates of fuzzy sets MPI between 1-13, 34-40, 65-94 and beyond 97th percentile the fuzzy sets MPI were higher than the average growth for the whole population. However, the growth rate for the fuzzy sets MPI between 13-34, 40-65 and 94-97 were lower than the average growth for the whole population. On the other hand, figure 10.19 showed that in the first 57th percentiles, the fuzzy sets MPI were higher than the average growth for the population. However, beyond 57th percentile, the fuzzy sets MPI growth rates were lower than the average growth for the whole population. These results indicate that there was some form of pro-poor growth since growths in poverty among poor children were lower than the overall average.

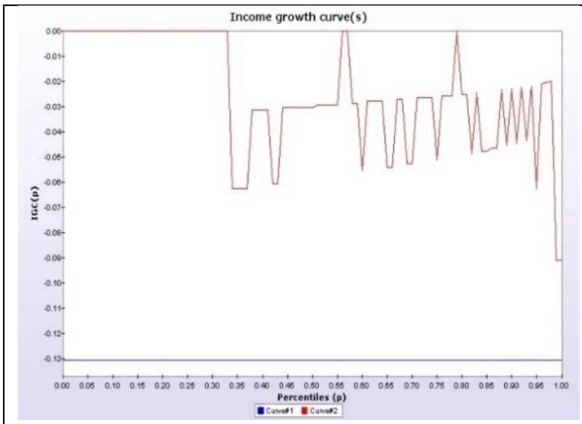

Figure 10.17: Child's Alkire Foster MPI Growth Incidence Curve in North West (2017-2018)

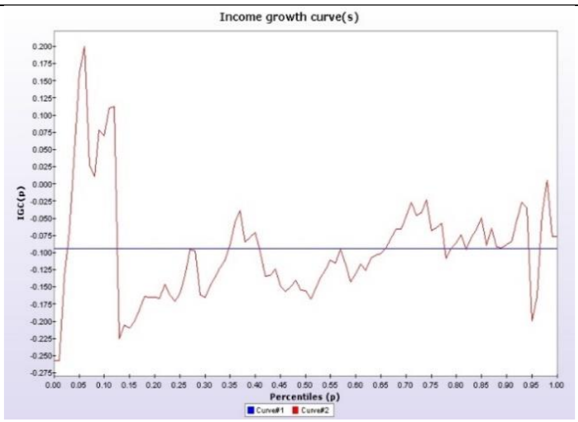

Figure 10.18: Child's Fuzzy Set MPI Growth Incidence Curve in North West (2017-2018)

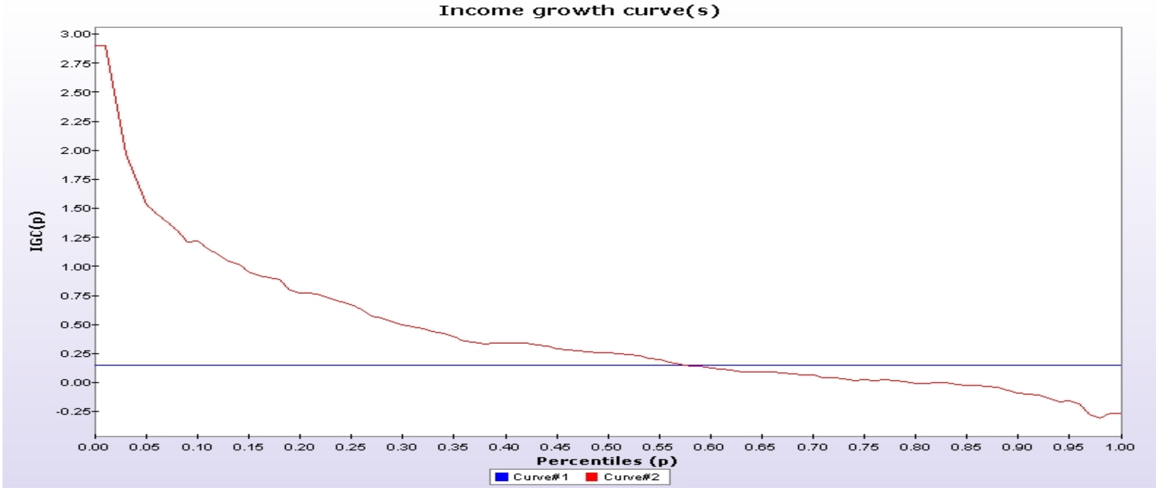

Figure 10.19: Child's Fuzzy Set MPI Growth Incidence Curve in North West (2018-2019)

Source: Own Computation, 2022

Table 10.7. shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy sets approaches over the period of 2017-2018 and 2018-2019. The table shows that the AF PPGIs in NW for poverty incidence, depth and severity over the period of 2017-2018 were 150994958.062619, 0.965714 and 0.582912, respectively, while those of the fuzzy sets were 2.333333, 1.269560 and 1.589634. These results indicate that while the depth and severity for AF approach did not give any indication of pro-poor growth, the incidence for the approach showed that growth was pro-poor. Moreover, the fuzzy sets approach showed that growth was pro-poor for multidimensional incidence, depth and severity.

Table 10.7: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in North West

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.0582855	150994958.062619	8800766.1305	0.009655	2.333333	0.022528
Depth	0.058285	0.965714	0.056287	0.009655	1.269560	0.012257
Severity	0.058285	0.582912	0.033975	0.009655	1.589634	0.015348
2018-2019						
Incidence	0.083751	0.545455	0.045682	0.014073	1.444444	0.020328
Depth	0.083751	0.670330	0.056140	0.014073	0.451220	0.006350
Severity	0.083751	0.335294	0.028081	0.014073	1.416142	0.019930

Source: Own Computation, 2022

The results presented in Table 10.7 also showed the AF and fuzzy set child's PEGRs in the North West province over the period of 2017-2018. The AF wealth growth rate in NW province over the period of 2017-2018 was 0.0582855 which can be compared to 0.009655 of the fuzzy set. The AF

PEGRs for incidence, depth and severity were 8800766.1305, 0.056287 and 0.033975, respectively, while those of the fuzzy set were 0.0225281, 0.012257 and 0.015348. These results imply that the AF MWIs were pro-poor for poverty incidence while fuzzy set MWIs were pro-poor for poverty incidence, depth and severity. However, the AF MWIs did not show pro-poorness for poverty depth and severity. The table further showed that in the NW province over the period of 2018-2019, the AF PPGIs were 0.545455, 0.670330 and 0.335294 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 1.444444, 0.451220 and 1.416142. These results imply that with the AF approach, growth was not pro-poor over the period of 2018-2019 based on poverty incidence, depth and severity. These results also imply that with the fuzzy set approach, growth was not pro-poor based on poverty depth. However, the results also imply that the poverty incidence and severity show pro-poorness under the fuzzy set approach.

In the North West over the period of 2018-2019, the AF multidimensional wealth growth rate was 0.083751 while that of the fuzzy set was 0.014073. The results also showed that over the period of 2018-2019, the AF PEGRs were 0.045682, 0.056140 and 0.028081 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 0.0203281< 0.006350 and 0.019930. These results also imply the same conclusion as given above for PPGI with poverty incidence and severity under fuzzy set being pro-poor in 2018-2019.

10.3.7. Multidimensional Pro-poor Growth in Gauteng Province

Due to limitation in the number of respondents, the 2018-2019 AF GIC graph for GP could not be drawn. Figure 10.20 shows the GIC for Gauteng over the period of 2017-2018. This figure did not give any indication of pro-poor growth since the AF growth rates were higher than the average growth for the whole population in all percentiles. Figures 10.21 and 10.22show the GICs for fuzzy set MPI in Gauteng over the period of 2017-2018 and 2018-2019 periods, respectively. Figure 10.21 shows that from the first 85 percentiles, the fuzzy set MPI growth rates were higher that the average growth rate for the whole population. Beyond the 85th percentile, fuzzy set MPI growth rates were lower than the average growth for the whole population. Figure 10.22 shows that in the first 68 percentiles, the fuzzy set MPI growth rates were higher than the average growth for the whole population. Beyond the 68th percentile, the fuzzy set MPI growth rates were lower than the average growth rates for the whole population. These results imply that the poorest among poor children in the Gauteng province benefited a little from growth.

Source: Own Computation, 2022

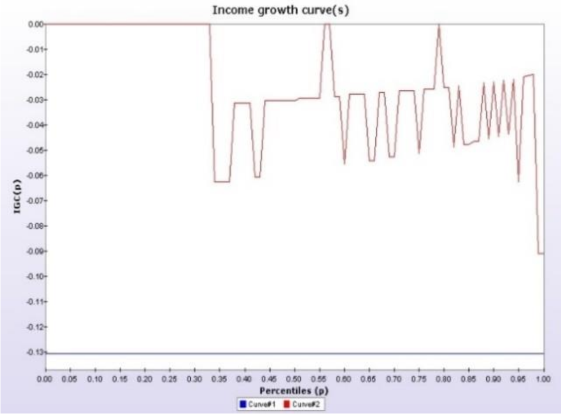

Figure 10.20: Child's Alkire Foster MPI Growth Incidence Curve in Gauteng (2017-2018)

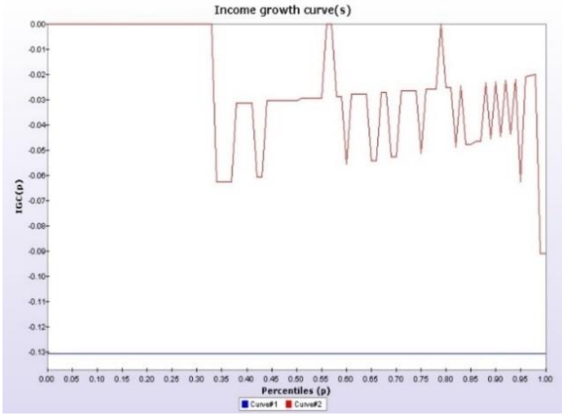

Figure 10.21: Child's Fuzzy MPI Growth Incidence Curve in Gauteng (2017-2018)

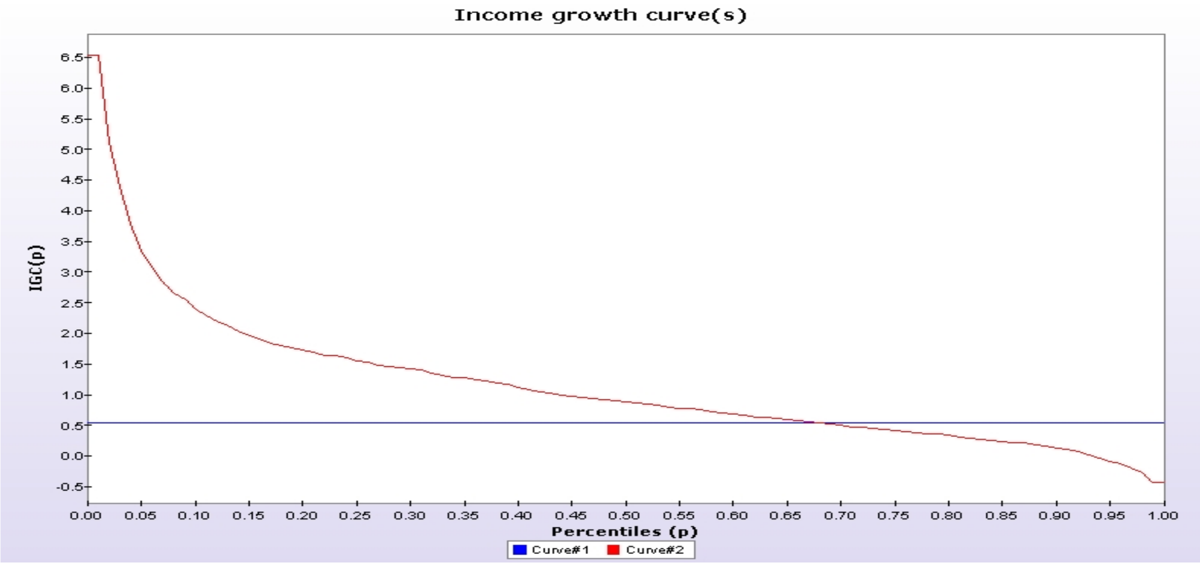

Figure 10.22: Child's Fuzzy MPI Growth Incidence Curve in Gauteng (2018-2019)

Table 10.8 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches over the period of 2017-2018 and 2018-2019 the table shows that the AF PPGIs for poverty incidence, depth and severity over the period of 2017-2018 were 89478504.66628, 1.725961 and 1.272407, respectively, while those of the fuzzy set were 1.090909, 3.209457 and 4.963200. these results imply that growth was pro-poor for multidimensional poverty incidence, depth and severity in the two approaches (PPGI>1). The results presented in Table 10.8 also showed the AF and fuzzy set child's PEGRs over the period od 2017-2018. The AF multidimensional wealth growth rate was 0.0467933 in Gauteng over the period of 2017-2018 which can be compared to 0.031311 of the fuzzy set. The AF PEGRs for incidence, depth and severity were 4186928.002823, 0.080762 and 0.059539, respectively in 2017-2018 while those of fuzzy set were0.034157, 0.100491 and 0.155402. These results imply that the AF and fuzzy set MWIs were pro-poor for multidimensional poverty incidence, depth and severity in 2017-2018. The table further showed that in Gauteng over the period of 2018-2019, the AF PPGIs for multidimensional poverty incidence, depth and severity were 0.789474, 0.657121 and 0.434549, respectively, while those of the Fuzzy sets were 1.458333, 0.017274 and 0.414673. These results imply that the AF MPI did not show any indication of pro-poor growth based on poverty incidence, depth, and severity, while the fuzzy set was not pro-poor based on poverty depth and severity. These results also imply that growth was pro-poor based on the poverty incidence for fuzzy set approach.

Table 10.8. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in GP

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.0467933	89478504.666628	4186928.002823	0.031311	1.090909	0.034157
Depth	0.046793	1.725961	0.080762	0.031311	3.209457	0.100491
Severity	0.046793	1.272407	0.059539	0.031311	4.963200	0.155402
2018-2019						
Incidence	0.214750	0.789474	0.169539	0.037690	1.458333	0.054964
Depth	0.214750	0.657121	0.141117	0.037690	0.017274	0.017274
Severity	0.214750	0.434549	0.093319	0.037690	0.414673	0.015629

Source: Own Computation, 2022

10.3.8. Multidimensional Pro-poor Growth in Mpumalanga Province

The GIC graphs for AF MPI 2017-2018 and 2018-2019 could not be drawn due to limitations in the number of respondents. Figures 10.23 and 10.24 show the GIC graphs for fuzzy set MPI for MP over the period of 2017-2018 and 2018-2019, respectively. Figure 10.23 did not give any indication of pro-poor growth, while Figure 10.24 reveals some form of pro-poor growth since growth between 7-10, 17-29, 56-83 and 93-98 percentiles show average growth rates of fuzzy set MPI to be lower than the average growth rate for the whole population.

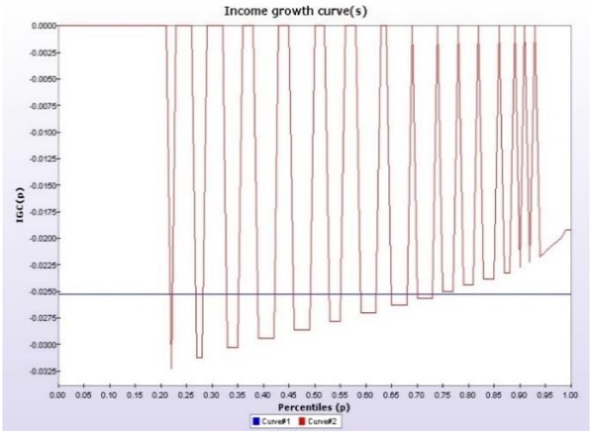

Figure 10.23: Child’s Fuzzy MPI Growth Incidence Curve in Mpumalanga (2017-2018)

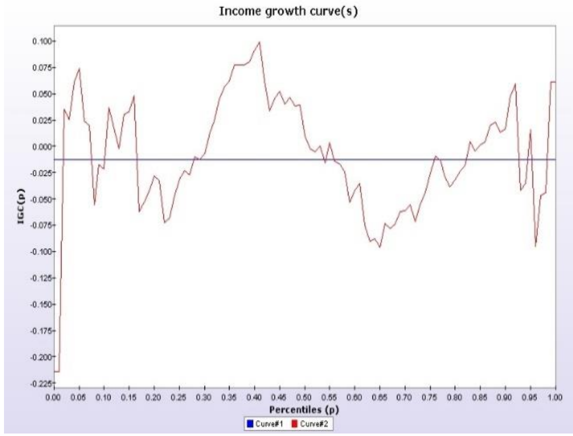

Figure 10.24: Child’s Fuzzy MPI Growth Incidence Curve in Mpumalanga (2018-2019)

Source: Own Computation, 2022

Table 10.9 shows the relative measures of PPG using some indices of multidimensional wealth computed with the AF and fuzzy set approaches over the period of 2017-2018 and 2018-2019. The table shows that the AF PPGIs for poverty incidence, depth and severity were 0.035714, 0.707847 and 0.707847, respectively, over the period of 2017-2018, while those of the fuzzy set were 2.000000, 3.294856 and 2.248909. These results imply than in Mpumalanga province, growth was not pro poor for poverty incidence, depth and severity under the AF approach. However, the fuzzy set approach showed growth to be pro-poor based on poverty incidence, depth and severity over the period of 2017-2018. The results presented in Table 10.9 also showed the AF and fuzzy set child’s PEGRs over the period of 2017-2018 in MP. The AF multidimensional wealth growth rate over the period of 2017-2018 was 0.0077007 for poverty incidence, depth and severity, respectively, while that of fuzzy set was 0.001252. The AF PEGRs over the period of 2017-2018 were 0.000250, 0.004960 and 0.004960 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 0.002505, 0.004126 and 0.002816. These results imply the same conclusion as given above for PPGI with poverty incidence, depth and severity under fuzzy set being pro-poor in 2017-2018. The Table further showed that over the period of 2018-2019, the AF PPGIs for MP were 0.555556, 0.653458 and 0.328380 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 2.500000, 0.746306 and 2.225628. These results imply that with the AF approach, growth was not pro-poor for poverty incidence, depth and severity. These results also imply that with the fuzzy set approach, growth was not pro-poor for poverty depth. However, growth was pro-poor for poverty incidence and severity. The AF multidimensional wealth growth rate for 2018-2019 was 0.076839 while that of the fuzzy set was 0.001537. The results also showed that over the period of 2018-2019, the AF PEGRs were 0.042688, 0.050211 and 0.025232 for poverty incidence, depth and severity, respectively, which can be compared to 0.028843, 0.008610 and 0.0225678 for fuzzy set. These results imply the same conclusion as given above for PPGI with poverty incidence and severity under fuzzy set being pro-poor in 2018-2019.

Table 10.9. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Mpumalanga

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.007007	0.035714	0.000250	0.001252	2.000000	0.002505
Depth	0.007007	0.707847	0.004960	0.001252	3.294856	0.004126
Severity	0.007007	0.707847	0.004960	0.001252	2.248909	0.002816
2018-2019						
Incidence	0.076839	0.555556	0.042688	0.001537	2.500000	0.028843
Depth	0.076839	0.653458	0.050211	0.011537	0.746306	0.008610
Severity	0.076839	0.328380	0.025232	0.011537	2.225628	0.025678

Source: Own Computation, 2022

10.3.9. Multidimensional Pro-poor Growth in Limpopo Province

Due to limitations in the number of respondents, the GIC graphs for AF MPI in 2017-2018 and 2018-2019 and those of fuzzy set MPI in 2017-2018 could not be drawn. Figure 10.25 shows the GIC graph for Limpopo province over the period of 2018-2019. The figure shows that in the first 63 percentiles, the average growth rates for fuzzy set MPI were higher than the average growth for the whole population. Beyond the 63rd percentile, the growth rate of fuzzy set MPI were lower than the average growth for the whole population. These results imply that the poorest among poor children in LP benefited a little from growth.

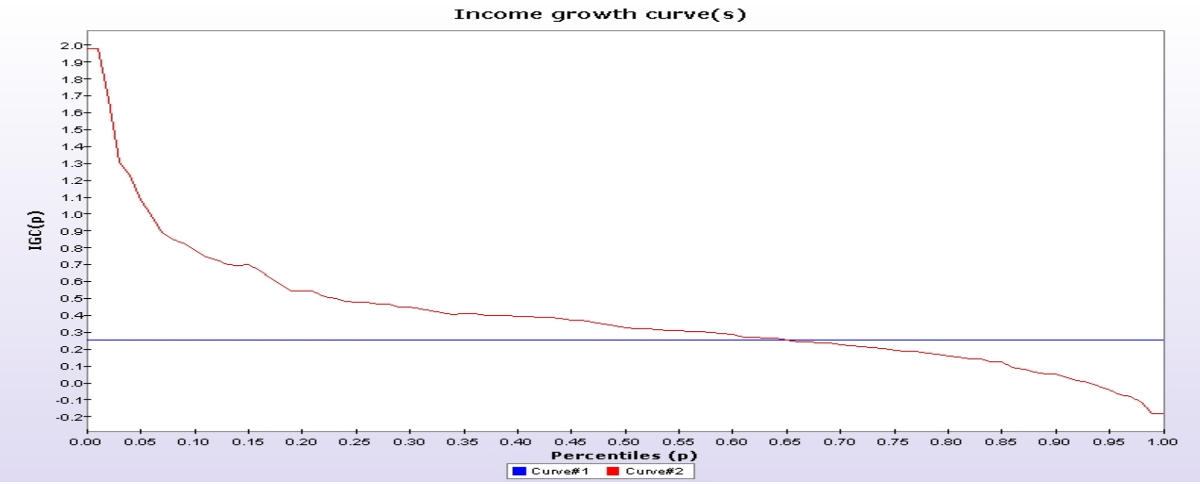

Figure 10.25: Child's Fuzzy MPI Growth Incidence Curve in Limpopo (2018-2019)

Source: Own Computation, 2022

Table 10.10 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches between 2017 and 2019. The table shows the AF PPGIs for incidence, depth and severity were 0.200000, 0.726274 and 0.108501, respectively, for 2017-2018 while those fuzzy set were 1.833333, 3.142059 and 3.941465. These results imply that growth was pro-poor for poverty incidence, depth and severity in the fuzzy set approach. However, based on PPGI for poverty incidence, depth and severity in AF approach, growth was not pro-poor.

Table 10.10. PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Limpopo

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.018305	0.200000	0.003661	0.011500	1.833333	0.021083
Depth	0.018305	0.726274	0.013294	0.011500	3.142059	0.036133
Severity	0.018305	0.108501	0.001986	0.011500	3.941465	0.045326
2018-2019						
Incidence	0.084212	0.500000	0.042106	0.021479	1.238095	0.026593
Depth	0.084212	0.665113	0.056011	0.021479	0.580883	0.012477
Severity	-0.084212	0.0445966	-0.037556	0.021479	0.000284	0.000006

Source: Own Computation, 2022

The results presented in Table 10.10 also showed the AF and fuzzy set child's PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.018305 for LP in 2017-2018, while that of fuzzy set was 0.011500. The AF PEGRs over the period of 2017-2018 for poverty incidence, depth and severity were 0.003661, 0.013294 and 0.001986, respectively, while those of fuzzy set were 0.021083, 0.036133 and 0.045326. These results imply the same conclusion as given above for PPGI with poverty incidence, depth and severity under fuzzy set being pro-poor in 2017-2018.

The Table further showed that over the period of 2018-2019, the AF PPGIs for poverty incidence, depth and severity in LP were 0.500000, 0.665113 and 0.044596, respectively, while those of the fuzzy set were 1.238095, 0.580883 and 0.000284. These results imply that growth was pro-poor for multidimensional poverty incidence in the fuzzy set approach. Moreover, based on PPGI for poverty incidence, depth and severity in the AF approach and poverty depth and severity in the fuzzy set approach, growth was not pro-poor. The AF multidimensional wealth growth rate for LP was 0.084212 for 2018-2019, while that of the fuzzy set was 0.021479. These results also show that over the period of 2018-2019 the AF PEGRs were 0.042106, 0.056011 and 0.037556 for incidence, depth and severity, respectively, while those of the fuzzy set were 0.026593, 0.012477 and 0.000006. These results imply that with poverty incidence under the fuzzy set, growth was pro-poor in 2018-2019.

10.4. Absolute and Relative Measures of Pro-poor Growth Across Geography Type

10.4.1. Multidimensional pro-poor growth in urban areas

The 2018-2019 AF MPI GIC graph could not be drawn limitations in the number of respondents. Figure 10.26 shows that across all percentiles, the average growth rate of the AF MPI was higher than the average growth for the whole population. These results imply that under the AF MPI, growth was not pro-poor in urban areas in 2017-2018. Figures 10.27 and 10.28 show the GICs for fuzzy set MPI for 2017-2018 and 2018-2019 periods, respectively. The curves show that in the 2017-2018 and 2018-2019, children on the higher percentiles, who were the poorest in the population had their poverty growth rates being lower than the average growth for the whole population. More specifically, the average growth rate for fuzzy set MPI was 0.050 for 2017-2018 and 0.5 for 2018-2019. The GIC in Figure 10.27 show fuzzy set MPI for 2017-2018 where the first percentiles were higher than the average growth for the whole population, while beyond the 75th percentile, average growth rates of fuzzy set were lower than the average growth for the whole population. Figure 10.28 shows that the first 65 percentiles, average growth rates of fuzzy set were higher the average growth for the whole population. Beyond the 65th percentile, average growth rates of fuzzy set were lower than the average growth rate for the whole population. It is evident from the graphs that the poorest among poor children in urban areas benefited a little from growth.

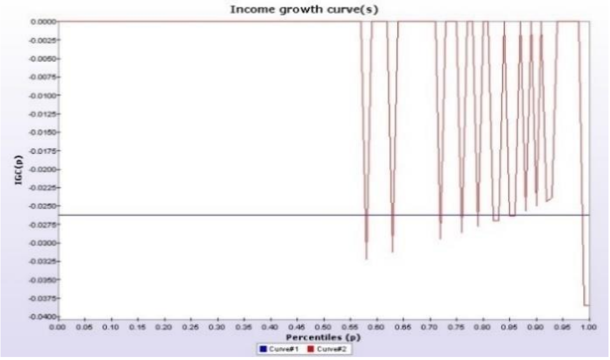

Figure 10.26: Child's Alkire-Foster MPI Growth Incidence Curve in Urban Areas (2017-2018)

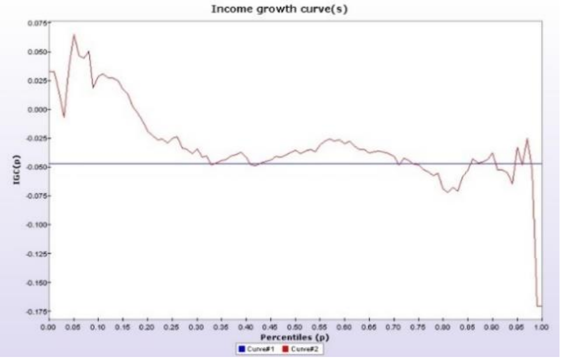

Figure 10.27: Child's Fuzzy MPI Growth Incidence Curve in Urban Areas (2017-2018)

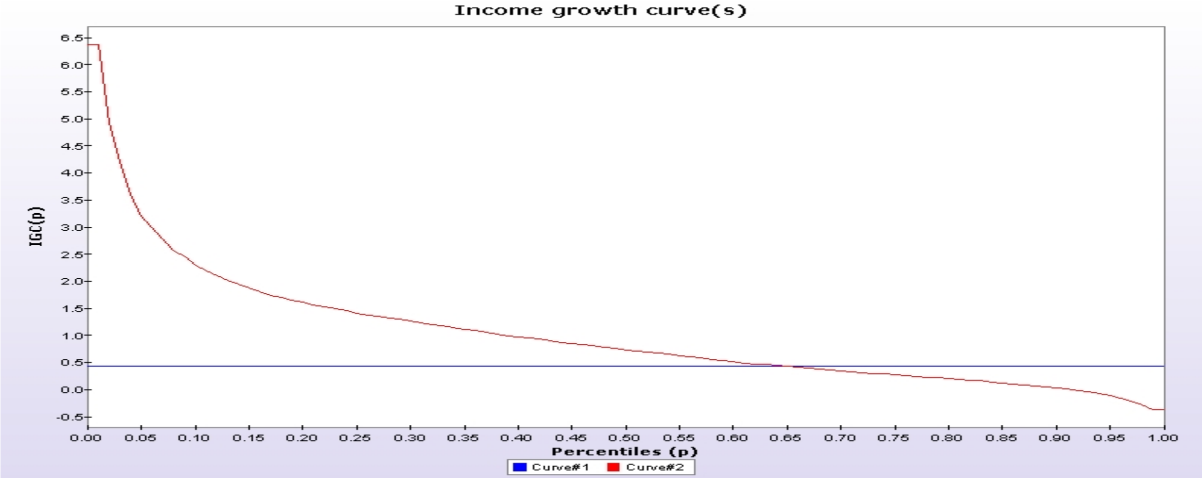

Figure 10.28: Child's Fuzzy MPI Growth Incidence Curve in Urban Areas (2018-2019)

Source: Own Computation, 2022

Table 10.11 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches between 2017 and 2019. The Tables shows that the AF PPGIs for poverty incidence, depth and severity in urban areas were 5835553.279788, 1.680176 and 1.080088, respectively, while those of the fuzzy set were 1.500000, 2.711152 and 4.825332. These results imply that growth was pro-poor for poverty incidence, depth and severity in the two approaches (PPGI>1). The results presented in Table 10.11 also showed the AF and fuzzy set child's PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.006169 for 2017-2018 while that of the fuzzy set was 0.003672. The AF PEGRs for 2017-2018 were 36002.179812, 0.010366 and 0.006664 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 0.005509, 0.009956 and 0.017720. These results imply that growth was pro-poor for poverty incidence, depth and severity in the AF and fuzzy set approaches over the period of 2017-2018. Table 10.11 further showed that over the period of 2018-2019, the AF PPGIs were 0.750000, 0.661450 and 0.426908 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 1.450000, 0.295845 0.463329. These results imply that growth was not pro-poor for poverty depth and severity in the two approaches. Moreover, based on PPGI for poverty incidence in AF approach growth was not pro-poor, while those for fuzzy set was pro-poor in 2018-2019. The AF multidimensional wealth growth rate in urban areas was 0.188037 for 2018-2019 while that of the fuzzy set was 0.032387. The results also show that over the 2018-2019 period, the AF PEGRs were 0.141027, 0.124377 and 0.080237 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 0.046962, 0.009582 and 0.015006. These results also imply the same conclusion as given earlier for PPGI with poverty incidence under fuzzy set being pro-poor in 2018-2019.

Table 10.11: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Urban areas

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.006169	5835553.279788	36002.179812	0.003672	1.500000	0.005509
Depth	0.006169	1.680176	0.010366	0.003672	2.711152	0.009956
Severity	0.006169	1.080088	0.006664	0.003672	4.825332	0.017720
2018-2019						
Incidence	0.188037	0.750000	0.141027	0.032387	1.450000	0.046962
Depth	0.188037	0.661450	0.124377	0.032387	0.295845	0.009582
Severity	0.188037	0.426708	0.080237	0.032387	0.463329	0.015006

Source: Own Computation, 2022

10.4.2. Multidimensional Pro-poor Growth in Traditional Areas

Due to limitation in the number of respondents, the GIC graph for 2018-2019 AF MPI could not be drawn. Figure 10.29 shows the GIC for AF MPI in 2017-2018. The curve shows that the AF MPI growth rate was higher than the average growth for the whole population. The average growth rate was 0.05. Figures 10.30 and 10.31 show the GICs for the 2017-2018 and 2018-2019 periods, respectively. The curves show some form of pro-poor growth because growth among some of the poor children was lower than the average growth for the whole population. More specifically, Figure 10.30 showed that between 1-25, 80-92 and beyond 98th percentiles, the fuzzy set MPI growth rates were higher than the average growth rate for the whole population. However, the figure also showed that between 25-80 and 92-97, the fuzzy set growth rates were lower than the average growth rate for the whole population. Figure 10.31 showed that in the first 64 percentiles, fuzzy set MPI growth rates were higher than the average growth rate for the whole population and beyond the 64th percentile, the fuzzy set MPI growth rates were lower than the average growth for the whole population.

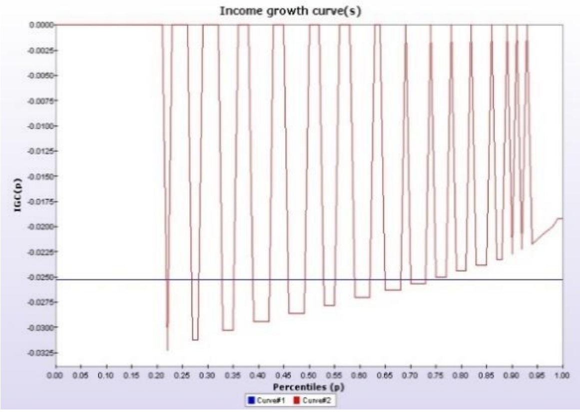

Figure 10.29: Child's Alkire-Foster MPI Growth Incidence Curve in Traditional Areas (2017-2018)

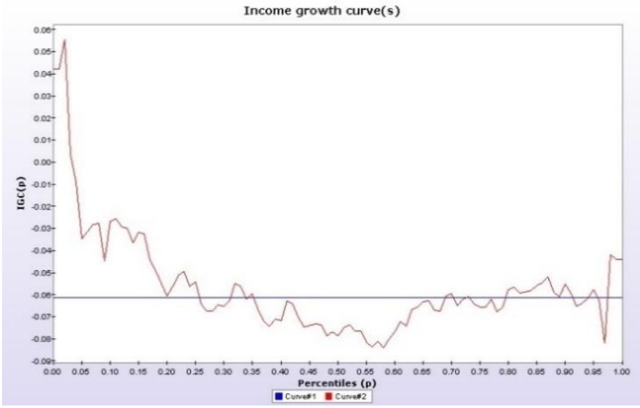

Figure 10.30: Child's Fuzzy MPI Growth Incidence Curve in Traditional Areas (2018-2019) Fuzzy Traditional 2017-2018

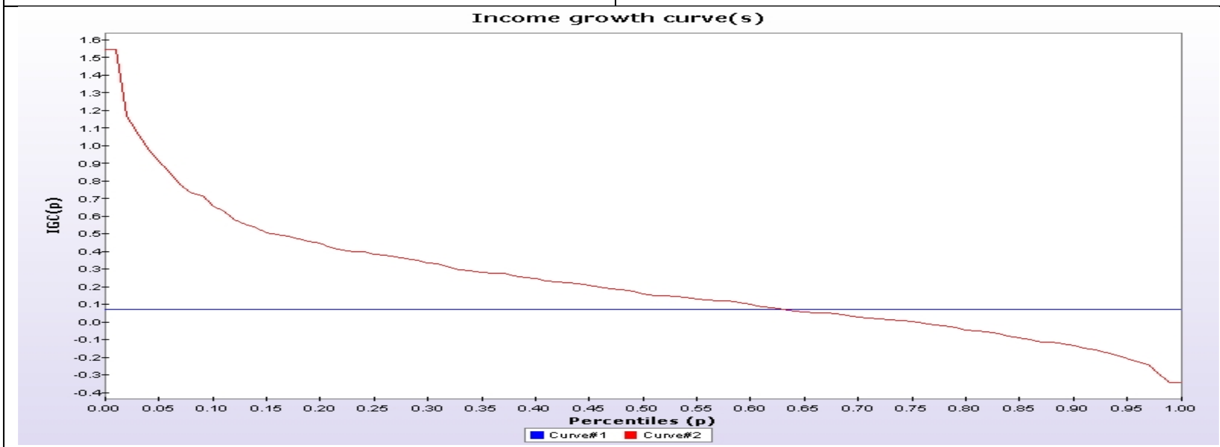

Figure 10.31: Child's Alkire-Foster MPI Growth Incidence Curve in Traditional Areas (2018-2019)

Source: Own Computation, 2022

Table 10.12 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches between 2017 and 2019. The table shows that the AF PPGIs for poverty incidence, depth and severity for traditional areas were 3273603.102912, 0.793725 and 0.637298, respectively, for 2017-2018, while those of the fuzzy set were 1.200000, 1.425627 and 1.657539. These results imply that growth was pro-poor for poverty incidence in the

AF approach and poverty incidence, depth and severity in the fuzzy set approach. Moreover, based on the PPGI for poverty depth and severity in the AF approach, growth was not pro-poor (PPGI<1). The results presented in Table 10.12 also showed the AF and fuzzy set child's PEGRs over the period of 2017-2018. The AF multidimensional wealth growth rate for 2017-2018 in traditional areas was 0.013182, while that of the fuzzy set was 0.007340. The AF PEGRs for poverty incidence, depth and severity were 43153.803897, 0.010463 and 0.008401 for 2017-2018, respectively, which can be compared to 0.008808, 0.010464 and 0.012166 for fuzzy set. These results imply the same conclusion given above for PPGI with poverty incidence under the AF approach and poverty incidence, depth and severity under the fuzzy set approach being pro-poor in 2017-2018. Table 10.12 further show that over the 2018-2019 period the AF PPGIs in traditional areas were 0.411765, 0.643245 and 0.227845 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 3.000000, 0.877714 and 2.991740 for fuzzy set. These results imply that growth was not pro-poor for poverty incidence, depth and severity in the AF approach. These results also imply that based on PPGI for poverty depth in fuzzy set, growth was not pro-poor, while poverty incidence and severity under fuzzy set was pro-poor. The multidimensional wealth growth rate in traditional areas was 0.033361 over the period of 2018-2019 while that of fuzzy set was 0.008207. The AF PEGRs over the period of 2018-2019 in traditional areas were 0.013737, 0.021459 and 0.007601 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 0.024620, 0.007203 and 0.024452. These results imply the same conclusion as given earlier for PPGI with poverty incidence and severity under the fuzzy set being pro-poor in 2018-2019 in traditional areas.

Table 10.12: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Traditional areas

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.013182	3273603.102912	43153.803897	0.007340	1.200000	0.008808
Depth	0.013182	0.793725	0.010463	0.007340	1.425627	0.010464
Severity	0.013182	0.637298	0.008401	0.007340	1.657539	0.012166
2018-2019						
Incidence	0.033361	0.411765	0.013737	0.008207	3.000000	0.024620
Depth	0.033361	0.643245	0.021459	0.008207	0.877714	0.007203
Severity	0.033361	0.227845	0.007601	0.008207	2.991740	0.024552

Source: Own Computation, 2022

10.4.3. Multidimensional pro-poor growth in farm households

The GICs for farms in 2017-2018 and 2018-2019 AF MPI and those for 2017-2018 and 2018-2019 fuzzy set MPI could not be drawn due to limitations in the number of respondents. Table 10.13 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the A and fuzzy set approaches for 2017-2018 and 2018-2019. The table shows that that the child's AF PPGIs for poverty incidence, depth and severity in farms were 0.000000, 0.0873049 and 0.866946, respectively, in 2017-2018, while those of the fuzzy set had no observations. These results imply that growth was not pro-poor for poverty incidence, depth, and severity in the AF approach. The results presented in Table 10.13 also showed the child's PEGRs for 2017-2018. The AF multidimensional wealth growth rate in farms was 0.005830 while those of the fuzzy set had no observations. The results also indicated that while there are no observations for fuzzy set in farms over the period of 2017-2018, the AF PEGRs for poverty incidence, depth and severity were 0.000000, 0.005090 and 0.005055, respectively. These results imply that poverty incidence, depth and severity were not pro-poor under the AF approach. The table further showed over the period of 2018-2019, the AF PPGIs in farms were 0.652174, 0.624931 and 0.189556 for poverty incidence, depth, and severity, respectively, while those of the fuzzy set were 5.000000, 0.585188 and 1.8871660. These results imply that growth was not pro-poor for poverty incidence, depth, and severity under the AF approach. Moreover, based on PPGI for poverty depth, growth was not pro-poor under fuzzy set, while for poverty incidence and severity growth was pro-poor.

Table 10.13: PPGI and PEGRs Multidimensional Wealth Index Growth Rates in Farm Households

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.005830	0.000000	0.000000	-	-	-
Depth	0.005830	0.873049	0.005090	-	-	-
Severity	0.005830	0.866946	0.005055	-	-	-
2018-2019						
Incidence	0.067572	0.652174	0.044069	0.011632	5.000000	0.058162
Depth	0.067572	0.624931	0.042228	0.011632	0.585188	0.006807
Severity	0.067572	0.189556	0.012809	0.011632	1.871660	0.021772

Source: Own Computation, 2022

The AF multidimensional wealth growth rate was 0.067572 for 2018-2019 while that of the fuzzy set was 0.011632. The AF child's PEGRs for poverty incidence, depth and severity were 0.044069, 0.042228 and 0.012809, respectively, while those of the fuzzy set were 0.058162, 0.006807 and 0.021772. These results imply the same conclusion as given above for PPGI with poverty incidence and severity under the fuzzy set being pro-poor in 2018-2019.

10.5. Absolute and Relative Measures of Pro-Poor Growth Across Child's Population Group

10.5.1. Multidimensional Pro-poor Growth among Black/African Children

The AF and fuzzy set MPI GICs for 2017-2018 and 2018-2019 could not be drawn due to limitations on the number of respondents. Table 10.14 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches between 2017 and 2019. The Table shows that over the period of 2017-2018, the AF PPGIs for Black/African children 89478482.666817, 1.040771 and 0.781002 for poverty incidence, depth and severity, respectively, while those of the fuzzy set were 1.333333, 1.670443 and 2.266603. These results imply that growth was pro-poor for poverty incidence and depth for the two approaches. However, based on the PPGI for poverty severity in the AF approach, growth was not pro-poor, while that of the fuzzy set was pro-poor.

Table 10.14: PPGI and PEGRs Multidimensional Wealth Index Growth Rates for Blacks/Africans

Pro-poor	Growth Rate	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.009734	89478482.666817	871005.078659	0.005793	1.333333	0.007724
Depth	0.009734	1.040771	0.010131	0.005793	1.670443	0.009677
Severity	0.009734	0.781002	0.007602	0.005793	2.266603	0.013130
2018-2019						
Incidence	0.105279	0.645161	0.067922	0.017942	1.833333	0.032895
Depth	0.105279	00.649018	0.068328	0.017942	0.124930	0.002242
Severity	0.105279	0.358760	0.037770	0.017942	1.214189	0.021786

Source: Own Computation, 2022

The results presented in Table 10.14 also showed the AF and fuzzy set Black/African child's PEGRs over the period of 2017-2018. The AF multidimensional wealth growth that for Black/African children was 0.009734 for 2017-2018 while that of the fuzzy set was 0.005793. The PEGRs for Black/African children were 871005.078659, 0.010131 and 0.007602 for poverty incidence, depth, and severity, respectively, over the 2017-2018 period while those of fuzzy set were 0.032895, 0.002242 and 0.021786. These results imply the poverty incidence and depth for the two approaches were pro-poor and poverty severity under fuzzy set was pro-poor in 2017-2018, while that of the AF approach was not pro-poor. The Table further showed that over the period of 2018-2019, the AF PPGIs for Black/African children were 0.641561, 0.649018 and 0.358760 for poverty incidence, depth, and severity, respectively while those of the fuzzy set were 1.833333, 0.124930 and 1.214189. These results imply that growth was not pro-poor for poverty incidence, depth, and severity under the AF approach. Moreover, based on the PPGI for poverty depth in the fuzzy set approach, growth was not pro-poor, while PPGI for poverty incidence and severity were pro-poor in 2018-2019. The table also showed the child's AF and fuzzy set PEGRs over the period of 2018-2019. The AF multidimensional wealth growth rate was 0.105279 in 2018-2019 while that of the fuzzy set was 0.017942. The child's AF PEGRs were 0.067922, 0.068328 and 0.037770 for poverty incidence, depth, and severity, respectively, while those of the fuzzy set were 0.032895, 0.0022442 and 0.021786. These results also imply the same conclusion as given earlier for PPGI with poverty incidence and severity under fuzzy set being pro-poor in 2018-2019.

10.5.2. Multidimensional Pro-poor Growth among Coloured Respondents

Due to limitations in the number of respondents, only the fuzzy set MPI GIC graph could be drawn. Figure 10.32 shows that between 3-4 and 18-90 percentiles, average growth rates for fuzzy set MPI were lower than the average growth for the whole population. These results indicate some form of pro-poor growth since growths in poverty among some poor children was lower than the overall average growth.

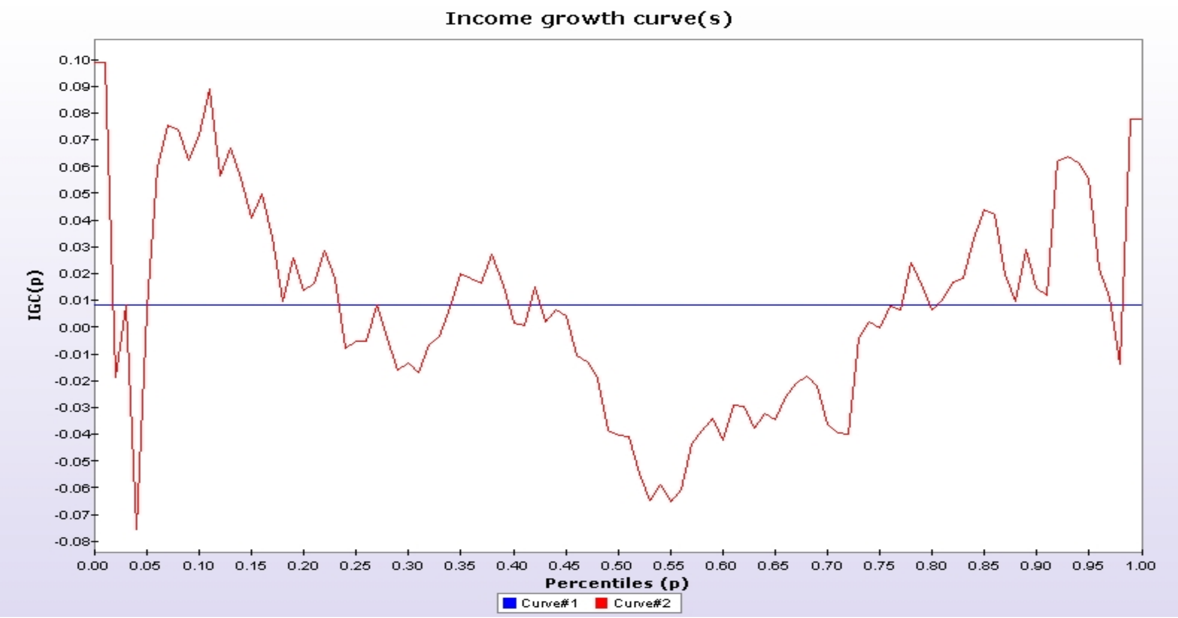

Figure 10.32: Child's Fuzzy Set MPI Growth Incidence Curve among Coloured (2017-2018)

Source: Own Computation, 2022

Table 10.15 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set and approached between 2017 and 2019. The table shows that the AF PPGIs for poverty incidence, depth and severity were 13421773.554998, 2.167936 and

0.917241 for 2017-2018, respectively, while those of the fuzzy set were 0.000000, 9.229339 and 14.385523. These results imply that growth was pro-poor for poverty depth in the two approaches. Based on the PPGI for poverty incidence under fuzzy set approach, growth was not pro-poor, while that for AF was pro-poor. Moreover, the PPGI for poverty severity was not pro-poor in the AF approach, while that of the fuzzy set was pro-poor. Table 10.15 also showed the AF and fuzzy set child's PEGRs for Coloured children over the period of 2017-2018. The AF multidimensional wealth growth rate was 0.007860 while that of the fuzzy set was 0.000505. The AF PEGRs for poverty incidence, depth and severity were 2105489.476311, 0.017039 and 0.007209, respectively, while those of the fuzzy set were 0.000000, 0.004658 and 0.007261. These results also imply the same conclusion as given above for PPGI with poverty incidence and depth under the AF approach and poverty depth and severity under fuzzy set being pro-poor in 2017-2018. The table further showed that over the period of 2018-2019, the AF PPGIs for Coloured children were 0.806452, 0.658009 and 0.435759 for poverty incidence, depth and severity, respectively, for 2018-2019 while those of the fuzzy set were 1.409091, 0.554959 and 0.064350. These results imply that growth was not pro-poor for poverty depth and severity in the two approaches. Based on the PPGI for poverty incidence under the AF approach, growth was not pro-poor while under the fuzzy set was pro-poor.

Table 10.15: PPGI and PEGRs Multidimensional Wealth Index Growth Rates for Coloureds

Pro-poor	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	0.007860	13421773.554998	2105489.476311	0.000505	0.000000	0.000000
Depth	0.007860	2.167936	0.017039	0.000505	9.229339	0.004658
Severity	0.007860	0.917241	0.007209	0.000505	14.385523	0.007261
2018-2019						
Incidence	0.229530	0.806452	0.185104	0.042517	1.409091	0.059911
Depth	0.229530	0.658009	0.151032	0.042517	0.554957	0.023595
Severity	0.229530	0.435759	0.100020	0.042517	0.064350	0.002736

Source: Own Computation, 2022

The AF multidimensional wealth growth rate was 0.229530 in 2018-2019 while that of the fuzzy set was 0.042517 for Coloured children. The AF PEGRs for poverty incidence, depth and severity were 0.185104, 0.151032 and 0.100020, respectively, for 2018-2019 while those of the fuzzy set were 0.059911, 0.023595 and 0.002736. These results imply that the AF and fuzzy set MWIs were not pro-poor for poverty depth and severity and the fuzzy set MWI was pro-poor for poverty incidence while the AF MWI was not.

10.5.3 Multidimensional Pro-poor Growth among White Respondents

The AF and fuzzy set MPI GICs for 2018-2019 and 2017-2018, respectively, could not be drawn due to limitations in the number of respondents. Figure 10.33 shows the GIC for AF MPI for White children over the period of 2017-2018. The figure shows that the average growth of the AF MPI was 0.00 in 2017-2018. The average growth rate for AF MPI were higher than the average growth for the whole population. These results imply that in 2017-2018, White children did not benefit from growth. Figure 10.34 shows that the fuzzy set MPI average growth rate was 1.8 in 2018-2019. The figure also shows that in the first 65 percentiles, the fuzzy set MPI growth rates were higher than the average growth for the whole population. These results imply that the poorest among poor White children benefited a bit from growth in multidimensional wealth.

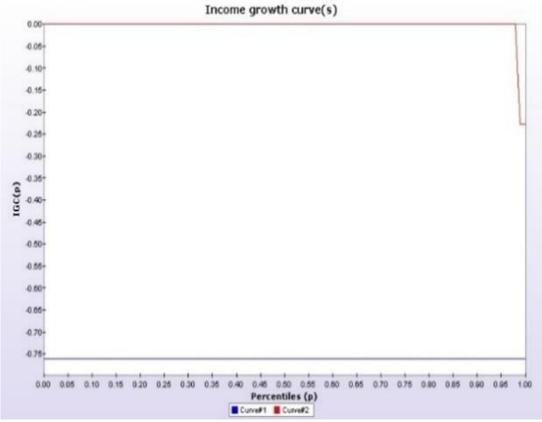

Figure 10.33: Child's Alkire-Foster MPI Growth Incidence Curve for the White (2017-2018)

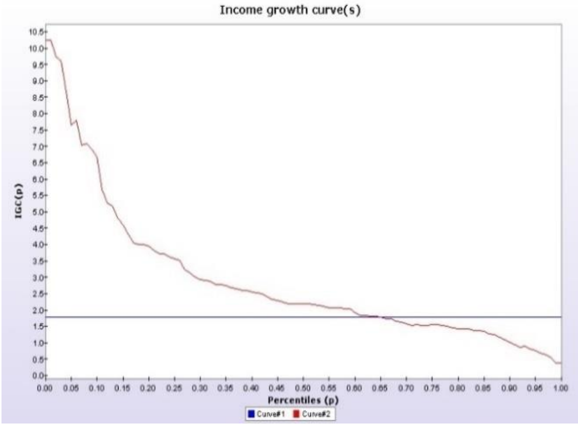

Figure 10.34: Child's Fuzzy Set MPI Growth Incidence Curve for the White (2018-2019)

Source: Own Computation, 2022

Table 10.16 shows the relative measures of pro-poor growth using some indices of multidimensional wealth computed with the AF and fuzzy set approaches over the period of 2017-2018 and 2018-2019. The table shows that the AF PPGIs for poverty incidence, depth and severity for White children had no observations, 24.656582 and 13.017822 for 2017-2018, respectively, while those of the fuzzy set were 0.000000, 30.378717 and 27.826928. These results imply that growth was pro-poor for multidimensional poverty incidence and depth in the two approaches (PPGI>1). The results also indicate that there were no AF MPI observations, the fuzzy set child's PPGI for poverty incidence was not pro-poor. The results presented in Table 10.16 also showed the AF and fuzzy set child's PEGRs over the 2017-2018 periods. The AF multidimensional wealth growth rate was 0.012180 for

2017-2018 while that of the fuzzy set was 0.003133. The AF PEGRs for poverty incidence, depth and severity were no observations, 0.300317 and 0.158557, respectively, which can be compared to 0.000000, 0.095175 and 0.687181 for fuzzy set. These results imply that on PEGR for poverty incidence, depth and severity, growth was pro-poor in the two approaches. The table further showed that over the period of 2018-2019, the AF PPGIs were no observations, 0.695915 and 0.603566 for poverty incidence, depth and severity, respectively for 2018-2019, while those of the fuzzy set were 1.111111, 1.332989 and 1320170. These results imply that in 2018-2019, the AF PPGIs for poverty incidence, depth and severity were not pro-poor while those of the fuzzy set were pro-poor. The AF multidimensional wealth growth rate was 0.301448 in 2018-2019 while that of the fuzzy set was 0.061129. The AF PEGRs for poverty incidence, depth and severity were no observations, 0.209783 and 0.181944, respectively in 2018-2019, while those of the fuzzy set were 0.0679211, 0.081484 and 0.80700. These results also imply the same conclusion as given above for PPGI with poverty incidence, depth and severity under fuzzy set being pro-poor in 2018-2019.

Table 10.16: PPGI and PEGRs Multidimensional Wealth Index Growth Rates for Whites

Pro-poor indices	Growth	PPGI	PEGR	Growth	PPGI	PEGR
2017-2018	Alkire-Foster MWI			Fuzzy MWI		
Incidence	-	-	-	0.003133	0.000000	0.000000
Depth	0.012180	24.656582	0.300317	0.003133	30.378717	0.095175
Severity	0.012180	13.017822	0.158557	0.003133	27.826928	0.087181
2018-2019						
Incidence	-	-	-	0.061129	1.111111	0.067921
Depth	0.301448	0.695915	0.209783	0.0661129	1.332989	0.081484
Severity	0.301448	0.603566	0.181944	0.061129	1.320170	0.80700

Source: Own Computation, 2022

10.6 Discussion on Pro-Poor Growth Results

The results of pro-poor growth using the PPGI and PEGR are not the same across the nationally aggregated data, provinces, sector of residence and population group. More specifically, the at the national level, the fuzzy set results consistently showed pro-poorness in the 2017/2018. Although there are many economic policies that could have promoted pro-poor growth or its absence, the South African case can be viewed from different perspectives. The results can be related to the growth rates of 1.3% and 1.4% that were recorded in South Africa in the 2017 and 2018 fiscal years, respectively (Statistics South Africa, 2017 & 2018).

In some previous studies, the drivers of economic growth in South Africa were found to be government expenditures (Leshoro, 2017), money supply (Dingela & Khobai, 2017), renewable energy consumption (Shakouri & Khoshnevis Yazdi, 2017; Sunde, 2018), expansionary fiscal policies to stimulate gross capital formation and employment opportunities (Pasara & Garidzirai, 2020). The role of the informal sector in promoting pro-poor growth can also be emphasized. This is a critical issue given that government's operational modality and economic policies can affect households' welfare through the performance of the informal sector. More importantly, therefore, an economy with strong linkage between the formal and informal sectors can witness significant growth among the poorest segment of the population. Specifically, the poor people who are resident in slums and those affected by survival shocks due to rural-urban migration depend on the informal economy (Mahadea & Zogli, 2018). Also, the informal sector bridges the gaps between the formal economic policies' inability to promote employment opportunities, safety nets and social protection, adequate capital inflows, and human capital formation and development (Etim and Daramola, 2020).

Furthermore, in some previous studies, the pro-poorness of economic growth in South Africa, using the unidimensional poverty measure had been analyzed. Duclos and Verdier-Chouchane (2010) analyzed pro-poor growth in South Africa and found that in 1995, the national Gini was 0.62 while Western Cape, KwaZulu Natal, Gauteng and Mpumalanga recorded significant increases in Gini-coefficient between 1995 and 2005. In addition, between 1995 and 2005, urban Gini coefficient increased from 0.55 to 0.65 respectively, while a slight decline in rural inequality from 0.58 to 0.53 was recorded. In addition, growth was not found to be pro-poor due to rising inequality. In some other studies, a study of non-income indicators of poverty in Benin using the Multiple Correspondence Analysis (MCA) reveals that poverty declined between 2006 and 2011 and had been generally pro-poor.

At the provincial level, the PPGI and PEGR results largely infer pro-poor growth in the all the provinces over the periods using the fuzzy set approach. Although different policy scenario may have contributed to these findings, the interplay of urbanization and informal economy in some provinces may have led to poverty reduction. Specifically, it should be noted that Western Cape and Gauteng are among the highly developed and urbanized provinces in South Africa. Specifically, there have been some job creation activities to facilitate poverty reduction in the Western Cape province. A very good example of these initiatives is the "Western Cape's Provincial Department of Environmental Affairs and Development Planning (DEADP) Working for Energy (W4E) Programme" which was implemented in accordance with the Western Cape Government's Provincial Strategic Plan (2014-2019). This initiative seeks to provide job opportunities and promote environmental resilience and sustainability (Western Cape Government [WCG], 2014). Dladla (2020) submitted that the programme made significant impact on poverty reduction by facilitating generation of employment opportunities among the youth.

In addition, tourism is another factor that can be unilaterally considered as a driver of local economy for significant poverty alleviation. It is important to note that Western Cape, Mpumalanga, Limpopo, KZN, and Northern Cape present significant opportunities for tourism. However, vulnerability to droughts in some of these provinces not only affect the farming businesses but have significant impacts on the tourism sector (Dube et al., 2020). Although tourism is highly concentrated in some specific places in the Western Cape and other associated provinces, government's efforts to spread the benefits accruing from tourism has not been so successful because of some institutional constraints. Development of domestic tourism promises to facilitate reduction in poverty and inequality across South Africa (Cornelissen, 2005). Ferreira (2007) also advocated for a conscientious identification of cultural heritage in every town for the promotion of tourism and poverty reduction.

Furthermore, the South African government had been international applauded for the design and implementation of functioning social protection programmes for children and other vulnerable groups. Therefore, in many provinces, social grants constitute a significant portion of households' income sources. Specifically, in Eastern Cape, social grants remain the most effective poverty reduction instrument that has been used by government (Ngumbela, 2021). However, although development of community tourism holds some prospects for poverty alleviation in Eastern Cape and some other provinces (Setokoe, 2021), this aspect of rural livelihood is yet to be fully developed.

At the national level, the number of grant holders have increased from 11.312 million as at the end of April in 2020 to 11.450 million at the end of March in 2021 (Parliament, 2021). At the provincial level, the number of grant holders increased from 2655831 in 2012 (Ngumbela, 2021) to about 2801000 in 2019 in Eastern Cape (Statista, 2022). Moreover, between April 2020 and March 2021, Gauteng, Limpopo and Kwa-Zulu Natal had the highest increase in the number of social grant recipients with 40961, 30554, and 22038 people respectively.

It should also be emphasized that some other poverty reduction measures in some provinces include promotion of employment opportunities, quality education, entrepreneurial skill development, health care services, and social capital development (Ngumbela, 2021). In addition, the role of agriculture in poverty reduction in some province cannot be over-emphasized. In a study by Ndhleve et al. (2017)

emphasized the positive impacts of agricultural spending and investment promotion for poverty alleviation in the Eastern Cape province. Similarly, provinces like the North West, Limpopo, and Mpumalanga have significant agricultural production potentials, which if utilized can promote pro-poor growth.

CHAPTER ELEVEN

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

11.1. Introduction

This chapter presents the summary of the major findings, conclusions and policy recommendations to address poverty among South African children. It also highlights some directions for future studies.

11.2. Summary of Major Findings

This thesis fulfilled five specific objectives. The analyses that were carried out brought some major findings, which are summarized in this section. It was found that there are different magnitude of deprivations by children's households in the ninety one (91) selected welfare indicators. Assets such as motor vehicle, swimming pool, DSTV subscription, AC, computer/laptop, dish washing machine, security services, home theatre and solar geyser were owned by a very small proportion of the sampled children's households. However, on nutrition/hunger, the results showed that majority of the children did not skip/cut meals while many lacked telecommunication gadgets.

Also, majority of South African children had parents who were alive, although many of them were not residing with their fathers. It was also evident from the results that majority of the households had between 4-9 members. Most of the South African children were from urban areas, and majority were supported by social grants. Majority of the sampled children were not covered under any medical insurance and the many of them reported an excellent/good health. Regarding education, it is evident that almost all children of pre-school and school age were attending ECDs and education institutions. It is also evident from the results of this study that the majority of sampled children did not have any injuries related to bicycle, crime, abuse, among others. It is evident that majority of sampled children were residing in improved dwelling type, had improved wall, floor and roof material, were drinking from improved drinking water source and were residing in households that were not over-populated. It was also revealed that majority of the sampled children had access to electricity. However, the majority were also using unimproved source of energy such as paraffin, coal, animal dung, candles for cooking/heating/space heating/lighting. Even though the results show that majority of children were affected by land degradation, they were not affected by littering, water/air pollution and excessive noise.

Regarding the number of deprivations experienced by children in different provinces, it is evident that the majority experienced 30<40 deprivations for 2017 and 2018 while the 2019 majority experienced 40<50 number of deprivations. The Limpopo province was revealed to be the province with the majority deprived in those deprivations, followed by KZN province. It is evident that male-headed households were deprived in most of the deprivations compared to their female counterparts. The study also showed that older household heads were deprived in majority (40<50) of the number of deprivations. It is evident from the results of this study that households with 11-19 members had the highest number of deprivations. It can also be concluded that Black/African children had the largest number of deprivations compared to other population groups. Children from traditional areas also had the highest number of deprivations.

When it comes to decomposing the child's MPI across their characteristics, it is evident from the results that KwaZulu-Natal and Eastern Cape provinces contributed more to MPI compared to other provinces. It is also evident that Black/African children and children from traditional areas contributed the most to MPI. Assets, telecommunications as well as nutrition/hunger were the top three dimensions that contributed the most to MPI. Compared to children in the WC, children from Northern Cape, Free-State and Gauteng provinces had higher chances of being stunted. Children who were born within a poor family, had larger number of children in a household, resided in an urban area and consumes vitamin fruit and vegetables showed to have higher chances of being stunted/wasted or underweight. When comparing children from other provinces to children from the WC, it is evident that children from EC, KZN, NW and MP had increased AF and fuzzy set MPIs. However, children from NC, FS and GP had reduced AF and fuzzy set MPIs. It is also evident that when compared to Black/African children, all population groups had their AF and fuzzy set MPIs reduced. Moreover, compared to children from urban areas, children from traditional areas and farms had their AF and fuzzy set MPI increased. Children who had mother/father alive and residing in the same household had their AF and fuzzy set MPIs reduced. Male children also had their AF and fuzzy set MPIs reduced. It is also evident from the results of this study that as a child gets older, their AF and fuzzy set MPIs were reduced. Children who had domestic worker services, increasing number of household members had their AF and fuzzy set MPIs increased. It was also indicated that except for children who received grants, children who or their heads received salaries/wage commission, remittance, pensions, and social grants had their AF and fuzzy set MPI reduced. Children who were born within a poor family, had larger number of children in a household, resided in an urban area and consumes vitamin fruit and vegetables showed to have higher chances of being stunted/wasted or underweight. Regarding multidimensional pro-poor growth, it is evident from the results of this study that the child's PPGIs and PEGRs were pro-poor for 2017-2018 period. It can also be concluded that over the period of 2017-2018, the child's PPGIs and PEGRs were pro-poor for the WC, FS, GP, urban areas, Black/African children, Coloured and White children in all approaches, while the PPGIs and PEGRs that were only pro-poor under the fuzzy set approach over the 2017-2018 period were NC, KZN, NW, MP, LP, and traditional areas. Over the period of 2018-2019, the AF and fuzzy set approached showed that the child's PPGIs and PEGRs were not pro-poor. Children from the WC, FS, KZN, GP, LP, urban areas, and Coloured children were revealed to not have benefited from growth in the AF and fuzzy set approaches. However, over the 2018-2019 period children from the EC, NC, NW, MP, traditional areas, farms, Blacks/African and White children had their PPGIs and PEGRs pro-poor under the fuzzy set approach. In brief, majority of the children from different provinces, geography type and population groups had their fuzzy set PPGIs and PEGRs pro-poor, while most of their AF PPGIs and PEGRs were not pro-poor.

11.3. Conclusions

Although South Africa officially and legislatively subscribes to the SDGs, a proper understanding of the dimension of poverty is a fundamental prerequisite to register progress in achieving many of the SDGs. More importantly, being the pride and future of South Africa, the welfare of children occupies a central place in policy discourse, whether locally, nationally or internationally. The growing concern on the role of economic growth on poverty alleviation through a drastic reduction in inequality remains a policy related issue on which this study is built. This also forms an indisputable justification for this study. The analyses that were carried out in this thesis have revealed the dimension of multidimensional poverty among South African children. The notion of future sustainable economic development in South Africa is therefore brought to light, given the prime place that is occupied by child welfare.

This study has highlighted the dimension of multidimensional deprivation among South African children using the Alkire-Foster and fuzzy set approaches. There are some critical highlights of provincial, racial and sectoral differences among the children's multidimensional poverty index (MPI). More importantly, several households' demographic and socio-economic variables had some significant influences on children's multidimensional poverty. In addition, the incidences of stunting, wasting, and underweight among South Africa under-5 children had been unfolded with some important policy inclined correlates. Therefore, the realm of marginal reforms to address poverty among South Africa children has been unfolded, given the critically of some explored explanatory variables like gender, age, province of residence, geography type, income, income sources, diasbility and race. An evaluation of the pro-poorness of multidimensional wealth index using reduction efforts by the government also reveals the sensitivity of obtained results to the selected approach and poverty measures. More importantly, between 2017 and 2018, growth in multiidmensional wealth was largely pro-poor, but largely non pro-poor between 2018 and 2019.

11.4. Recommendations

This study analyzed the child’s multidimensional welfare and pro-poor growth in SA using the 2017, 2018 and 2019 GHS datasets. Regarding access to telecommunications, it is evident for the results that majority of the sampled children and their households did not have access to different kinds of telecommunications. The SA Government and the private sector must come with strategies that can enable access to telecommunications by the poor. This can be done by installing free wi-fi routers for those that are deemed poor. Majority of sampled children were not covered under any medical health insurance. This calls for redressing of the medical services and programmes offered by the Government. The Limpopo province was revealed to be the province with the majority deprived in those deprivations, followed by KZN province. When it comes to decomposing the child’s MPI across their characteristics, it is evident from the results that KwaZulu-Natal and Eastern Cape provinces contributed more to MPI compared to other provinces. Compared to children in the WC, children from Northern Cape, Free-State and Gauteng provinces had higher chances of being stunted. When comparing children from other provinces to children from the WC, it is evident that children from EC, KZN, NW and MP had increased AF and Fuzzy Sets MPIs. Children from the WC, FS, KZN, GP, LP, urban areas, and Coloured children were revealed to not have benefited from growth in the AF and Fuzzy Sets approaches.

The Government needs to critically come with a strategy of targeting specific provinces on their current programmes and policies to safeguard the achievement of the MDGs as well as SDGs. It is evident that male-headed households were deprived in most of the deprivations compared to their female counterparts. The on-going efforts of SA Government for empowering women are commendable since that has shown a positive effect on their livelihoods. However, it is also important for Government also empower men to avoid having men who cannot provide for their families and some form of inequality between the genders. The study also showed that older household heads were deprived in majority (40<50) of the number of deprivations. The current Government effort for providing for the elderly (old-age grant) shows to be having a little impact in the elderly’s lives. However, this study shows that people between 40 and 50 years of age were the most deprived. Therefore, it is critical for the Government to consider including people from 50 years of age on their current poverty intervention programmes. It is evident from the results of this study that households with 11-19 members had the highest number of deprivations. There are government awareness programmes that educate women and girl children of child-bearing age about family planning; however, the programmes show to have little impact on the number of children born. It is critical for the Government to redress these programmes and to ensure that the reach all the poor people especially those in traditional areas, farms as well as Blacks/Africans and Coloureds.

It can also be concluded that Black/African children had the largest number of deprivations compared to other population groups. It is also evident that Black/African children and children from traditional areas contributed the most to MPI. It is very critical for the Government to consider how they are going to specifically target people/children who are Black and from traditional areas and farms in their current policies and programmes to achieve some of the MDGs and SDGs. Assets, telecommunications as well as nutrition/hunger were the top three dimensions that contributed the most to MPI. It is also evident that when compared to Black/African children, all population groups had their AF and Fuzzy Sets MPIs reduced. Moreover, compared to children from urban areas, children from traditional areas and farms had their AF and Fuzzy Sets MPI increased. It was also indicated that children who received grants had their AF and Fuzzy Sets MPI increased.

Even though growth was pro-poor in 2017-2018, the period of 2018-2019 showed that the AF and Fuzzy Sets approached on child's PPGIs and PEGRs were not pro-poor. This shows that the Government's interventions to address this issue has low impact on the lives of the poor. Government programmes and policies that were put in place to address the problem of pro-poor growth need to be redressed since the results show that in 2018-2019 the rich were benefiting more than the non-rich from growth.

11.5 Limitations of the Study

This study had several limitations. The main limitation of this study was the inability to collect primary data due to financial constraints. The data that was used had missing information on important factors that can influence the MPI status of children. The information includes maternal education level. The secondary data also had some limitations, that is, some variables, did not have responses. More specifically, the 2019 dataset had missing number of respondents. This led to the GIC graphs of some observed variables being unable to be drawn. GHS was not able to capture information on nutrition and anthropometric data. Information across the years was not the same.

11.6. Recommendations for further study

Although this study provides a comparison of the results that were obtained from Alkire-Foster and fuzzy set approaches, other composite approaches for the analysis of multidimensional poverty among South African children can be explored. These include PCA, MCA and other methods that had been advanced by some scholars. Although one-third of the selected attributes was used as the poverty line, it will also be interesting if studies can explore the sensitivity of MPI to changes in the cut-off points like selection of one-quarter or one-half. In addition, there is also a possibility of changing the poverty line for the PPGI and PEGR, to evaluate the sensitivity of obtained results to the conclusions reached.

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