INCOME DIVERSIFICATION OF RURAL HOUSEHOLDS IN NIGERIA: IMPLICATIONS FOR POVERTY REDUCTION

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A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN AGRICULTURAL AND APPLIED ECONOMICS OF SOKOINE UNIVERSITY OF AGRICULTURE. MOROGORO, TANZANIA.

2019

ABSTRACT

Income diversification is becoming the norm in developing countries and is regarded as a key factor in reducing the incidence of poverty especially among rural households. It is on this premise that this study focused on assessing how rural households in Nigeria diversify their income sources in relation to their poverty trajectories, using data from two waves of the Nigeria General Household Survey Panel (GHS- Panel) conducted by the National Bureau of Statistics in 2012/13 (wave 2) and in 2015/16 (wave 3). Specifically, this study identified and classified the various income diversification options of the households into two broad categories; (i) farm income and (ii) off-farm income. Results shows that the rural households earn a higher share of their total income from off-farm sources than from farm sources. The income earned from off-farm was positively and significantly influenced by covariates such as education level of household head, education level of other members of the household, the household size, the household assets and the total livestock units owned by the household. Findings of this study further showed that off-farm income has a positive relationship with agricultural intensification although this relationship is not significant. Also, the nexus between income diversification and poverty reduction in the study area is such that the incidence and depth of poverty (25%) experienced by the undiversified household is relatively higher than the depth of poverty (20%) experienced by the diversified households. The multidimensional poverty index (MPI) is also higher for households without off-farm than the MPI for households with off-farm income. This suggests that income diversification is a key factor in reducing the incidence of poverty among rural households in Nigeria. This study recommend as a policy measure that households should be encouraged to diversify their economy and transmit productivity gains from income diversification into the rural economy for the betterment of agriculture and for sustainable poverty reduction.

DECLARATION

I, Iraoya Augustine Okhale, do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted for degree award in any other Institution.

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The above declaration is confirmed by;

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Prof. A. C. Isinika Date

(Supervisor)

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ACKNOWLEDGEMENTS

I hereby express my utmost appreciation to God Almighty the fountain of wisdom, my fortress, my LORD and my redeemer for His mercies and grace that enabled me to complete this thesis successfully. “Being confident of this very thing, that He which hath begun a good work in you will perform it until the day of Jesus Christ” Philippians 1:6 (KJV).

I would like to express my sincere thanks to my erudite supervisor Prof. A. C. Isinika for her scholarly guide and support in making this thesis a success. Thanks to the entire staff members of DAEA. I am grateful to the following erudite scholars for their invaluable impact on my academics; Prof. T. E. Mafimisebi (Federal University of Technology Akure, Nigeria), Prof. Greg Hertzler (University of Western Australia, CSIRO), Prof. Haji Jema (Haramaya University), Dr. Mmatlou Kalaba (University of Pretoria), Prof. Willy-Marcel Ndayitwayeko, (University of Burundi) and Dr. Babatunde O. Abidoye (Yale School of Forestry and Environmental Studies, USA). I also appreciate the Bill and Melinda Gates Foundation (BMGF) and African Economic Research Consortium (AERC) for financing my studies at SUA and the University of Pretoria, South Africa. I am grateful to the Iraoya and Oloniyo dynasty for their love and care. Special thanks to my pastors and members of the Redeemed Christian Church of God, Nigeria and Tanzania Assemblies of God, BRT. Thanks to all my colleagues in SUA and other CMAAE universities.

Finally, my heartfelt appreciation goes to my wife Iraoya-Augustine Opeyemi Seun ‘Hephzibah’ for her priceless virtue, immense sacrifice, encouragement and immeasurable support all through my stay away from home on this academic journey. I deeply appreciate my son Iraoya-Augustine Eselikoghene Enoch Oluwademiladeogo for his understanding, love and support in making this study a success. God bless both of you greatly in Jesus Name.

DEDICATION

I dedicate this dissertation to God Almighty for His unfailing love and mercies in making this study a good success.

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LIST OF ABBREVIATIONS AND ACRONYMS

AERC	African Economic Research Consortium
AfDB	African Development Bank
CAADP	Comprehensive Africa Agriculture Development Program of the New Partnership for Africa’s Development
EA	Enumeration Areas
FE	Fixed Effects
FGT	Foster-Greere-Thorbecke poverty index
FHM	Farm Household Model
IDRC	International Development Research Centre
IHI	Inverse Herfindahl Index
IV	Instrumental Variable
LGA	Local Government Area
LSM-ISA	Living Standards Measurement Study - Integrated Surveys on Agriculture
MPI	Multidimensional Poverty Index
NBS	National Bureau of Statistics
NGHS	Nigeria General Household Survey
NISH	National Integrated Survey of Households
OPHI	Oxford Poverty and Human Development Initiative
PEP	Partnership for Economic Policy
RE	Random Effects
RIGA	Rural Income Generating Activities
SDG	Sustainable Development Goals
SSA	Sub-Saharan Africa
STAARS	Structural Transformation of African Agriculture and Rural Spaces
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

Almost two-thirds of the world's poor people living in the rural areas of low-income countries depend on subsistence agriculture and other natural resources for their livelihood (World Bank, 2015; Deng *et al*., 2017). Yet, agriculture in poor countries has low labour productivity compared to the rest of the economy, negligible trade flows and high employment relative to other sectors of the economy (Ssozi *et al.*, 2019; Herrendorf and Schoellman, 2015; Tombe, 2015).

Despite the numerous challenges (such as low access to and use of key inputs like fertilizer and improved seeds, and climate change) ravaging African farmers, agriculture is still a core feature of public policies aimed at stimulating and sustaining African rural development. The Comprehensive Africa Agriculture Development Program of the New Partnership for Africa's Development (CAADP) stated clearly that, "High and sustained rates of agricultural growth, largely driven by agricultural productivity growth, will be necessary if African countries are to accelerate poverty reduction" (CAADP 2006). However, studies have shown that as countries go through the process of structural transformation, agriculture gradually losses its dominance in terms of employment (Djurfeldt *et al.*, 2018), a shift of labour from agriculture to other more productive sectors ensues (Collier and Dercon, 2014; Amare and Shiferaw, 2017; Ma *et al.*, 2018) and the contribution of agriculture to overall growth in GDP per capita declines (Davis *et al.*, 2017). Hence, it is expected that African rural policies should reflect this development and policy makers should rethink regarding the practice of exclusive targeting of smallholder approach to poverty reduction (Collier and Dercon, 2014).

Although the agricultural sector boasts of high employment rate especially in Africa (including Nigeria) yet most of the poor households who depend on it for livelihood lack the resources and knowledge needed to benefit from new technologies or access to markets, which would increase the farmer's productivity and income (FAO, 2018). Actualization of The United Nations' Sustainable Development Goals (SDG) to end extreme poverty by 2030 is challenged especially in Nigeria as recent report by the World Poverty Clock (2018) (Fig. 1) shows that 86.9% of Nigerians now lives in extreme poverty, living on less than US $1.90 per day. This will likely worsen as Nigeria faces a population boom (World Poverty Clock, 2018).

It was on this note that the African Economic Research Consortium (AERC) with support from the International Development Research Centre (IDRC) of Canada, Partnership for Economic Policy (PEP), along with the African Development Bank (AfDB), Cornell University, and the World Bank launched the new "Structural Transformation of African Agriculture and Rural Spaces" (STAARS) programme in 2015 for high quality research and capacity building for agricultural transformation as a key to alleviate poverty in Africa (Amare and Shiferaw, 2017).

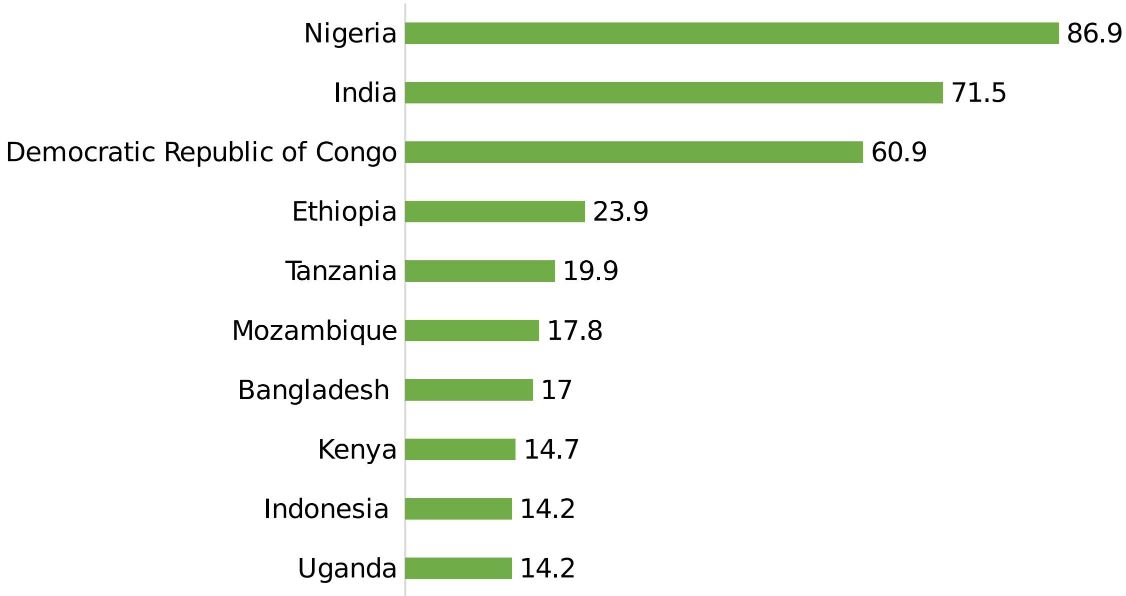

Figure 1: Number of people facing extreme poverty (millions) by countries

Source: World Poverty Clock Data (2018)

Moreover, high population growth in many sub-Saharan African (SSA), especially in rural areas, coupled with widespread deep-rooted poverty has reduced farm sizes, increased land size inequalities among smallholder farmers (Djurfeldt *et al.*, 2018) and encouraged growth through income diversification by rural households in a bid to improve rural incomes through poverty alleviation initiatives (Abdoulaye and Bekele, 2016). Thus, income diversification is becoming an increasingly key livelihood strategy for poor rural households in sub-Saharan Africa including Nigeria where the incidence of poverty is higher among the rural folk, (Msoo and Goodness, 2014; Alobo and Bignebat, 2017; Johny *et al.*, 2017). Empirical evidence from Nigeria (Figure 2) by Djido and Shiferaw, (2018) shows that 82% of rural households in Nigeria diversify their income sources, which underscores the importance of income diversification in the process of structural transformation. Income diversification is also an important strategy employed by households to reduce income variability, manage risks, cope with shocks and acquire farm inputs (Ellis, 2000; Wan *et al.*, 2016; Alobo and Bignebat, 2017).

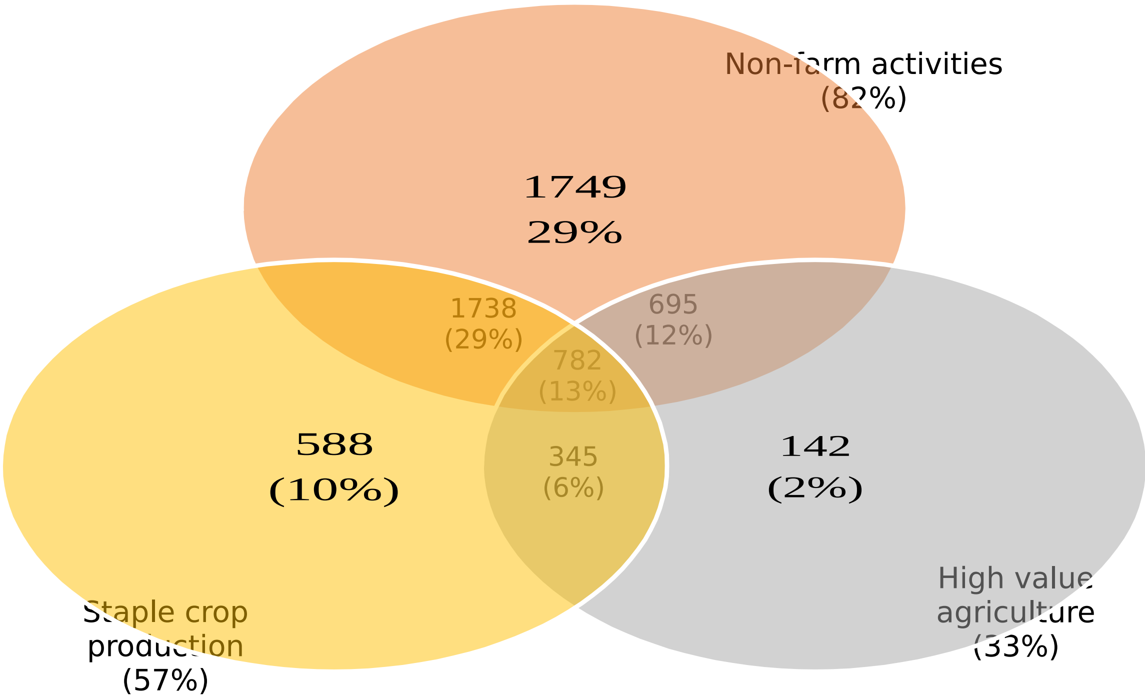

Figure 2: Venn diagram of rural household participation in staple crop, high value agriculture, and non-farm activities in Nigeria

Source: Adapted from Djido and Shiferaw (2018).

1.2 Problem Statement and Justification

The vast majority of Nigeria's rural households depend on the farm as their basic source of food and income are vulnerable to climatic conditions (FAO, 2015). They do not get enough to consume or to spend especially in the lean season. They are neither able to finance their children's education nor access health care and shelter from the meagre farm earnings (Osarfo *et al.*, 2016).

In order to achieve sustainable economic development in Nigeria in line with the Sustainable Development Goals (SDGs), agriculture must be transformed significantly, with rapid reduction in the number of people engaged in agriculture (Collier and Dercon, 2014; Amare and Shiferaw, 2017). Agriculture in Nigeria is at present characterized by poor smallholder farmers plagued by credit market failure, low yields, continuous lack of extensive rural infrastructure, stuck in a vicious cycle of poverty and limited farm commercialization (FAO, 2015).

Thus, income diversification is increasingly becoming a key livelihood strategy for poor rural households in Nigeria. However, there is a dearth of empirical studies, especially from Nigeria, to show how diversification has contributed to improving agricultural intensification and commercialization, leading to improved consumption, and ultimately poverty reduction (Alobo and Bignebat, 2017). One basic question is; does income diversification compete for farm labour and capital and thus reduce agricultural intensification, productivity and welfare? (Amare and Shiferaw, 2017).

The current study is motivated by the information gap found in the literature especially in most regional studies on income diversification in Sub-Saharan Africa. For example, Bryceson (2004) analyzed livelihoods, sustainability and poverty alleviation in six African countries; Malawi, Zimbabwe, Tanzania, Ethiopia, South Africa and Nigeria and reported that about 80% of rural households diversify their income sources, however these income sources were not clearly disaggregated nationally. Also, Nagler and Naude (2017) analyzed the prevalence and patterns of non-farm enterprises in six sub-Saharan African countries namely, Malawi, Ethiopia, Niger, Nigeria, Tanzania and Uganda using the World Bank’s Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA). The authors discovered that the push and pull factors of income diversification varied across the sampled countries. Hence there is a need for country specific studies to inform policy making and foster a balance between focusing on agriculture versus diversifying from agriculture as countries including Nigeria strive to use their scarce resources to meet the SDGs. This will avert the problem of “one size fits all policies”.

Furthermore, most of the country specific studies in this regard have used cross-sectional data and have often been limited to certain regions (Amanze *et al.*, 2017; Akpan *et al.*, 2016). Hence this study will seek to fill the knowledge gap regarding the effect of rural income diversification on poverty reduction, using nationally representative panel data, which takes into account the diversity of rural communities to elucidate the dynamics of income diversification and poverty reduction in Nigeria. The study will also contribute to a better understanding of the structural transformation process, standing out from previous studies by providing novel information on the nexus between income diversification and the livelihood trajectories ('hanging in'[1], 'stepping up'[2] and 'stepping out'[3]) (Dorward *et al*., 2009). This study is justified on the basis that understanding the role of income diversification of rural households is key to alleviating rural poverty in Nigeria and such understanding is crucial for designing effective rural development policies and programmes targeted at achieving 'zero hunger' as well as 'responsible consumption and production' by 2030.

1.3 Research Objectives

1.3.1 Overall objective

The overall objective of this study is to explore how rural households in Nigeria diversify their income sources in a nexus with their poverty trajectories.

1.3.2 Specific objectives

Specific objectives of the study are stated as to:

i. Analyse categories of diversification options among rural households in Nigeria

1 maintaining status quo and livelihoods
2 improving livelihoods and reinvesting in agricultural activities
3 changing livelihood activities and structures to more rewarding alternatives

ii. Assess the relationship between income diversification and expenses in agricultural intensification among rural households in Nigeria.

iii. Evaluate the impact of income diversification on poverty reduction of rural households in Nigeria.

1.4 Research Question and Hypotheses

The following research question and hypotheses are addressed in this study.

The research question for objective one is;

i. what are the main livelihood options of rural households in Nigeria?

Based on the other two specific objectives, two hypotheses were tested as follows;

With respect to specific objective number two, the null hypothesis states that; income diversification does not influence agricultural intensification

Mathematically this null and alternative hypotheses are presented as;

Ho: $X_D = X_{ND}$ ………………………………………………………………………. (1)

Hi: $X_D \neq X_{ND}$ ………………………………………………………………………... (2)

Where X_D = expenditure on agricultural intensification with off-farm income and X_{ND} = expenditure on agricultural intensification without off-farm income.

With respect to the third specific objective, the null hypothesis state that; income diversification does not contribute to poverty reduction while the alternative hypothesis states that; income diversification contributes to poverty reduction

Mathematically the two hypotheses are as presented below;

Ho: $P_{\alpha d} = P_{\alpha nd}$ …………………………………………………………. ……………. (3)

Hi: $P_{\alpha d} \neq P_{\alpha nd}$ …………………………………………………………………. (4)

Where $P_{\alpha d}$ = poverty status of rural households (incidence, gap and severity) that diversify their income (off-farm income) and $P_{\alpha nd}$ = poverty status of rural households that did not diversify their income.

1.5 Organisation of the Study

This dissertation comprises five chapters. The first chapter presents the background information for the study, covering the problem statement and justification of the study, objectives of the study, research questions and the study's hypotheses. In the second chapter, different empirical and theoretical studies on income diversification, agricultural intensification and poverty are critically reviewed to get a good understanding of the topic, identify methodological issues and clearly identify the research gap. The methodology used in this study is presented in chapter three while the results and discussions are presented in chapter four. The conclusion and recommendations of the study are presented in chapter five.

CHAPTER TWO

2.0 LITERATURE REVIEW

This chapter presents a comprehensive, contextualized and critical evaluation of previous scholarly writings on the dynamics of income diversification, agricultural input intensification and poverty that is relevant to our current study. We begin by clearly defining key terms and concepts used in the study, explore prior scholarly literature, identified clear research gap in order to rightly situate our work and add to existing knowledge in this field of study.

2.1 Theoretical Review

2.1.1 Basic concepts and definitions

Livelihood and income diversification

Livelihood diversification is defined as the "process by which rural families construct a diverse portfolio of activities and social support capabilities in their struggle for survival and in order to improve their standards of living" (Ellis, 1998). Income diversification on the other hand was defined by Escobal (2001) as "the process of switching from low-income crop produce to higher value crops, livestock and non-farm activities". Income diversification also refers to the process by which rural households increase their economic activities by allocating their productive assets to different income generating enterprises (Alobo and Bignebat, 2017). The differences between livelihood diversification and income diversification is that; livelihood diversification includes non-monetary activities as well as income earning activities, hence it is a broader concept than income diversification (Harris-Coble, 2017). An in-depth review of the literature shows that, among variables (income, assets and activities) used to analyze livelihood diversification, income variable stands out. Unlike assets which cannot be valued accurately in the presence of incomplete market and activities which do not truly reflect profitability, income gives a visible outcome of livelihood diversification and a clear interpretation as a welfare outcome (Harris-Coble, 2017; Alobo and Bignebat, 2017).

A wealth of information is found in the current literature on rural household diversification but with increasing inquiry into the drive of rural household income diversification. The drivers of diversification decision could be categorized broadly into two: necessity versus choice (Ellis, 2000). While diversification that is driven by necessity results from desperation and may lead the household to end up in a more vulnerable livelihood system, diversification may also stem from the voluntary decision of a household to pursue a wider scope of livelihood options. In this case, a household chooses to diversify not for survival *per see* but also for accumulation (Gautam and Adersen, 2016). However, going by this classification, it might be difficult to clearly identify those who diversify their livelihood for reason of desperation from those who diversify their livelihood by choice.

Rural households could also diversify their income in many ways and these options could be classified into three: (i) agricultural intensification (using productivity enhancing inputs, mixed cropping, and rearing different kinds of livestock), (ii) non-farm diversification (skill acquisition, self-employment and waged labour) and (iii) migration (Losch *et al*., 2012; Alobo and Bignebat, 2017; Batool *et al.*, 2017) depending on the economic opportunities and constraints they face. Invariably economic opportunities and constraints are geographically specific but only little attention has been given in the literature to the role of geography in determining rural household income strategies especially among Africans who have been termed “a late comer to the process of structural transformation” (Davis *et al.*, 2017). The geographic context will therefore make this study different from previous studies.

Agricultural Input Intensification

Agricultural input intensification refers to the increased use of modern inputs such as mineral fertilizer, hybrid seeds, pesticides and herbicide necessary for increasing agricultural productivity, food supply and farm earnings. Low use of agricultural inputs by some households leads to low agricultural productivity which consequently exacerbates chronic food insecurity and poverty status of rural households who depend on agriculture for food and income. The adoption of improved agricultural inputs and subsequent intensification of production systems over the past decades in sub-Saharan Africa has contributed to the reductions of food insecurity and poverty in the region (Kim *et al.*, 2018). The use of hybrid seeds do not only increase yield but also improve resistance to pests and diseases (Udondian and Robison, 2018), the use of pesticides reduces the incidence of harmful pests that could severely limit farm yield and it also reduces post-harvest losses (Kim *et al.*, 2018).

Poverty

“Don’t ask me what poverty is because you have met it outside my house. Look at the house and count the number of holes. Look at my utensils and the clothes that I am wearing. Look at everything and write what you see. What you see is poverty. —A poor man, Kenya 1997” (World Bank, 2005). Scholars give different definitions of poverty. The United Nations defined poverty as follow; “poverty is the inability of getting choices and opportunities, a violation of human dignity. It means lack of basic capacity to participate effectively in society. It also means not having enough to feed and clothe a family, not having a school or clinic to attend. Not having the land on which to grow one's food or a job to earn one's living, not having access to credit. It means insecurity, powerlessness, and exclusion of individuals, households, and communities. It means susceptibility to violence, and it often implies living in marginal or fragile environments, without access to clean water or sanitation".

It can then be deduced from the aforementioned that poverty is a multidimensional social phenomenon such that its definition and causes differs by age, gender, culture, and other factors. Poverty is not just the lack of one thing but lack of many interlocking factors that constitutes poor people's experiences and definitions of poverty (World Bank, 2005). Poverty has also been defined in terms of income poverty (UN, 1995), absolute poverty (World Bank, 2015) and relative poverty (UNESCO, 2017).

Income Poverty, Absolute Poverty and Relative Poverty

Income poverty is a situation in which a household's income is unable to meet a generally established threshold (UN, 1995). Income poverty is often measured with reference to the household and not the individual and it is adjusted for the number of persons that constitute the household. The income poverty indicator helps economists to identify households whose command over resources falls below the established threshold. Currently, the international threshold of extreme poverty is set at living on less than US$1.90 per day (World Bank, 2015).

The United Nations Educational, Scientific and Cultural Organization (UNESCO), (2017), defines absolute poverty as a measure of deficiency in relation to the amount of money necessary to meet basic human needs such as food, safe drinking water, sanitation facilities, health, education, information, clothing, and shelter. The concept of absolute poverty does not depend only on income but it also depends on access to human needs as listed above. However, this concept is limited because, apart from basic human needs, individuals also have other important cultural, social and political needs. In view of this, the World Bank defines poverty in absolute terms where extreme poverty is said to exist when a person is living on less than US$1.90 per day at 2011 purchasing power parity (2011 PPP). Meanwhile, moderate poverty is also define by the World Bank as living on less than $3.10 a day (World Bank, 2015). UNESCO (2017) defined poverty in relative terms where relative poverty defines the economic status of some members relative to other members of the same society. According to this definition, “people are poor if they fall below the prevailing standard of living in a given societal context”. Both concepts of absolute and relative poverty are criticized for their perceived exclusive focus on income and consumption since poverty is multidimensional. Hence, The United Nations in 2010 adopted a Multidimensional Poverty Index (MPI) covering health, education and standard of living (Alkire and Santos, 2014).

Poverty Measurement

Academic scholars are divided on the debate regarding national and international poverty measurement, in particular, there is no consensus about the best standard or approach to measure poverty given the fact that there is no single, universally accepted definition of the term. While some uphold approaches using the income poverty, others advocates that the best approach to poverty measurement should be multidimensional using the Multidimensional Poverty Index (MPI) (Ravallion 2011; Alkire and Santos, 2014; Wang *et al.*, 2016; Dotter and Klasen 2017; Burchi *et al.*, 2018, among others). The income poverty approach is based on the basic needs of an individual or a household and clearly account for the monetary or income aspect of poverty while the multidimensional poverty approach is based on basic capabilities and accounts for the non-monetary aspects of poverty (Wang *et al.*, 2016). Hence, the two major international standards widely adopted for measuring poverty are the World Bank's poverty line based on income level and the United Nations Development Programme Multidimensional Poverty Index (MPI) (Alkire and Santos, 2014).

Income-based measures of poverty are commonly used in measuring relative deprivation across the globe (Alkire and Santos, 2014). Although Alkire and Santos, (2014) debate that no single indicator such as income is able to accurately capture the multiple aspects that constitute poverty. Many scholars have nonetheless argued that the income-based measure of poverty encompasses education, health, food and non-food aspects and can adequately capture poverty in other dimensions despite aggregating welfare as a single monetary dimension (Dhongde and Haveman, 2014; Burchi *et al.*, 2018).

The Multidimensional Poverty Index (MPI) is a measure of multiple deprivations or acute global poverty developed by the Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the United Nations Development Programme's Human Development (Alkire and Santos, 2014; Wang *et al.*, 2016). The three dimensions identified by Alkire and Santos to be included in the MPI are health, education, and the standard of living. However, there is a divide among proponents of MPI. While some believe that multidimensional poverty is a complement to income poverty, focusing on the non-monetary aspect of poverty, others argue that income is a constituent of MPI in addition to other factors such as health and education (Wang *et al.*, 2016).

Furthermore, the concept of multidimensional poverty index has been widely debated by many scholars in the field of development research, challenging the conceptual and empirical merits of the MPI (Dotter and Klasen, 2017). For example, despite the inherent weaknesses of the income-based approach which assume an almost perfect correlation among dimensions of poverty, Burchi *et al.* (2018) argue that the MPI approach also invalidly assume zero correlation among dimensions of poverty such as health and education. This tends to suggest that there is a likelihood that some basic indicators of MPI such as the possession of a television correlates with access to electricity, which thus limits the validity of the results. Ravallion (2011) earlier argued that measuring the extent of poverty and informing policy decision should be based on a credible set of multiple indices covering all dimensions of poverty rather than a single multidimensional index. The MPI approach is also criticized in its choice of poverty dimensions and indicators which gives little attention to theoretical considerations and conceptual framework such as the concept of inequality of deprivations among the multidimensionally poor (Dotter and Klasen, 2017).

Alkire and Santos (2014) clearly maintain that the income-based approach and the multidimensional index approach are compliments whereby the MPI approach focuses on acute poverty while the income approach focuses on income poverty. However, the debate of whether the income-based approach should be complemented by the multidimensional approach in targeting poverty reduction policies as well as the 2030 global goals for sustainable development remains inconclusive (Burchi *et al.*, 2018). Hence, there is need to understand current poverty reduction policies such as the SDGs before choosing an appropriate approach.

The Sustainable Development Goals (SDGs)

The SDGs, otherwise known as the Global Goals or the 2030 Agenda for Sustainable Development, are a blueprint and a universal call for action to end poverty, attain zero hunger, protect the planet and ensure that all people enjoy peace and prosperity. Ending poverty is one of the 17 Sustainable Development Goals and target 1.2 of the SDGs focuses on reducing by half the proportion of children, women, and men living in poverty by 2030. However, the SDGs are interconnected such that the key to success on one will involve tackling issues more commonly associated with another (UN, 2015).

Figure 3: The sustainable development goals

Source: UN (2015)

Income Diversification and the Sustainable Development Goals (SDGs)

Poverty reduction and ending hunger by 2030 took preeminence in the global goals agreed upon by members of the United Nations in recognition of their key importance in human affairs. The need to prioritize addressing this challenge could also be seen from the World Bank estimates in 2015, which shows that 10% of the world's population lived on less than US$1.90 a day. Moreover, Sub-Saharan Africa is home to more than half of the extremely poor people in the world (Table 1) and most of these people who are living in extreme poverty, reside in rural areas, depending on agriculture as their primary source of livelihood (Harris-Coble, 2017). It is on this premise that FAO (2015) stated that the battle ground of ending hunger and poverty lies in the rural area where about 80% of the world's hungry and poor people reside.

Table 1: Top ten African countries with extreme poverty and SDG 1 status

Country	**Percentage of population in extreme poverty**	**SDG1 status**
Nigeria	86.9	Poverty rising
Democratic Republic of Congo	60.9	Poverty rising
Ethiopia	23.9	On track
Tanzania	19.9	Off track
Mozambique	17.8	Off track
Kenya	14.7	Off track
Uganda	14.2	Off track
South Africa	13.8	Off track
South Sudan	11.4	Poverty rising
Zambia	9.5	Poverty rising

Source: Adapted from World Poverty Clock Data (2018)

Table 1 shows that among the top ten African countries with extreme poverty, only Ethiopia is on track to meet the United Nations' SDG of ending extreme poverty by 2030. Eradicating hunger and lifting people out of poverty by 2030 could be achieved through a combination of pro-poor investments in sustainable agriculture, rural development and social protection (FAO, 2015). The conventional wisdom that "promoting smallholder agriculture in Africa will lead to growth and reduce poverty better than any other policy" was challenged by Collier and Dercon (2014) who argued that such conventional wisdom must be nested within an overall growth strategy that gives credence to the importance of agriculture but not prioritizing agriculture as the key sector. Moreover in the context of globalization where labour markets are integrated, it is indispensable that rural households diversify their economy and transmit productivity gains through income diversification into the rural economy for the betterment of agriculture and poverty reduction. This study assessed these income diversification and agriculture linkages using certain theoretical models.

2.1.2 Review of Theoretical Models

Analyzing income diversification strategies and its measurement

Income diversification strategies or pattern are analyzed by examining how multiple income generating activities make up the household income portfolio (Alobo and Bignebat 2017). Many approaches have been used in empirical studies to classify and measure sources of household income. For instance, Davis *et al.*, (2017) disaggregated household income into seven categories namely; (i) crop production; (ii) livestock production; (iii) agricultural wage employment, (iv) non-agricultural wage employment; (v) non-agricultural self-employment; (vi) transfer; and (vii) other. Also, Alobo and Bignebat (2017) classified household income into 10 categories namely; (i) crops, (ii) livestock, (iii) hunting, fishing and gathering (HFG), (iv) on-farm processing, (v) farm wage, (vi) nonfarm wage, (vii) nonfarm self-employment, (viii) remittances, (ix) transfers and (x) rents. These 10 categories were further aggregated into higher level groupings of farm income (categories one (i) through five (v)) and nonfarm income or non-agricultural sources (categories six (vi) through ten (x)). Furthermore, Sharma *et al.* (2015) broadly classified household income into farm and off-farm sources but with further classification within each broad category such that within off-farm, income is further sub-classified by source and labour involvement.

In addition to categorization of income sources, household income diversification is analyzed using different measurement or analytical tools such as the Herfindahl-Hirschman index, ‘The Berry’ index, the entropy measure of diversification, and the

Simpson Index (Batool *et al.*, 2017). Other indicators include the vector of income shares measurement (Sharma *et al.*, 2015; Alobo and Bignebat, 2017) and the Herfindahl-Simpson index (Djido and Shiferaw, 2018). There are no clearly defined distinguishing aspect of each of these index in empirical literature. However, Zhao and Barry (2013) carried out an analysis of the implications of different income diversification indexes on rural income diversification measures. The study found consistency among the income diversification measures and concluded that any one of the diversification indexes is acceptable in relevant studies.

The current study adopts the income share measurement complemented with a transformed Herfindahl Index known as the Inverse Herfindahl Index (IHI) to estimate income diversification strategies of rural households in Nigeria, which is consistent with Zhao and Barry (2013) and Alobo and Bignebat (2017). The Herfindahl index unlike other analytical approaches listed above, takes into account the number and distribution of income sources available, disaggregates diversification data, and provides a multidimensional perspective on diversification behaviour (Alobo and Bignebat, 2017). Moreover, the IHI has an outstanding advantage of not only estimating the number of household income sources but also estimates the contributions of each source of income to the total household income. The diversified household income could potentially influence rural economic growth, agriculture and poverty status of the rural households. We therefore need to understand the interaction between household income diversification, agricultural intensification in relation to poverty reduction in the farm households.

Analyzing the nexus between income diversification and agricultural intensification

Many approaches have been used in empirical studies to model the income diversification and agricultural intensification and the nexus between them. For example, Verkaart *et al.*

(2017) used the index of technology adoption, while Muraoka *et al.* (2015) used factor analysis. However, Ma *et al.* (2018) notes that agricultural intensification and income diversification could be influenced by unobservable factors such as farmers' attitude to income diversification, motivation and farmers' innate abilities such that ordinary least squares (OLS) regression methods cannot be used to model their relationship since they fail to account for endogeneity, and would lead to biased and inconsistent estimates (Wooldridge, 2016).

Amare and Shiferaw (2017) used Vella and Verbeek's two-step approach to estimate the impact of nonfarm income on agricultural intensification. Parameters of equation (5) were estimated in the first stage using a random effects Tobit,

$NF^*_{it} = \beta x X_{it} + \beta v V_{it} + \beta z Z_{it} + \beta c C_{it} + \theta_i + \varepsilon_{it}$,…………………………………………(5)

$$NF_{it} = \begin{cases} 1\, if NF ¿_{it} > 0 \\ . \\ 0\, otherwise \end{cases}$$

Where;

NF^*_{it}= latent variable representing nonfarm income,

X_{it}= vector of household characteristics such as education, age, gender, and household size;

Z_{it}= vector of wealth indicators such as land size, livestock, and non-land assets and

V_{it}= vector of risk variables, including observed weather conditions and shocks.

C_{it} = community-level characteristics such as percent of agricultural land within a 1 km buffer, access to public services, and access to infrastructure,

θ_i = unobserved heterogeneity in nonfarm income, and

ε_{it}= pure random component.

It is assumed that θi and εit are independently and normally distributed with zero mean and constant variance. Amare and Shiferaw (2017) further addressed the impact of income diversification on agricultural intensification using equation (6):

$Q_{it} = f\,(NF_{it};\beta) + \delta_T\, T_{it} + \eta_i + \gamma_{it}$ ……………………………………………………….(6)

Where;

Q_{it} = farm-level agricultural intensification indicator (represented by adoption of productivity-increasing inputs) for household *i* in period *t*,

NF_{it} = nonfarm income,

T_{it} = vector of other explanatory variables,

η_i = unobserved individual farm-level effect, and

γ_{it} = error term.

The coefficient estimates of T_{it} and their corresponding standard errors shows the estimate of the effect of income diversification on agricultural intensification

Following Amare and Shiferaw (2017) and Ma *et al.* (2018), this study analysed the interaction between income diversification and agricultural intensification using a two-stage estimation random effect Tobit model. The rationale for using the model is to account for the censured nature of the data and the need to control for the inherent unobserved heterogeneity using a correlated random effect procedure. Potential endogeneity of income diversification (off-farm income) will also be controlled by using a control function approach.

Apart from analyzing the interaction between income diversification and agricultural intensification, there is also a need to analyze the likely relationship between income diversification and poverty alleviation in the rural households.

Analyzing the correlation between income diversification and poverty alleviation

Non-farm income generated from income diversification plays a key role and contributes an increasing share in rural household income. Hence, income diversification has the potential of raising rural household income and reducing rural poverty (Ibrahim and Srinivasan, 2014). Imai *et al.* (2015) examined poverty and vulnerability-reducing effect of rural non-farm employment in Vietnam and India using a treatment effects model. Basically, a treatment effect model estimates poverty defined by household per capita consumption and covers households involved in the farm labour market only and households involved in both farm labour market and non-farm labour market. A treatment effect model has an advantage of explicitly estimating sample selection bias by using the results of a probit model, but the later established that it has many disadvantages or weaknesses, which according to Imai *et al.* (2015) include; (i) strong assumptions imposed on the distributions of the error terms; (ii) the coefficient estimates may be sensitive to choice of the explanatory variables and instruments; and (iii) the requisite valid instruments are difficult to find in non-experimental data.

Mat *et al.* (2012) used the Foster-Greere-Thorbecke (FGT) poverty index to examine the impact of non-farm income on poverty among agricultural household in rural Kedah, Malaysia. Ibrahim and Srinivasan (2014) used the FGT poverty measurement indices to examine the effect of off-farm income on rural poverty in Nigeria. Msinde *et al.* (2016) equally analyzed rural income poverty using the FGT poverty index and two stage least square (2SLS) regression. The preference of FGT poverty index in the studies presented above and many other studies is due to its ability to disaggregate the overall population into mutually exclusive subpopulations allowing for comparison of poverty between them (Ibrahim and Srinivasan, 2014). This study will build upon Mat *et al.,* (2012), Ibrahim and Srinivasan (2014) and Msinde *et al.* (2016) by using Foster-Greere-Thorbecke (hereafter FGT) poverty index and Alkire-Foster method of multidimensional poverty to analyze the effect of income diversification on poverty reduction of rural households in Nigeria.

2.2 Review of Empirical Literatures Related to Income Diversification

A shift of labour from agriculture to other more productive sectors is inevitable (Ma *et al.*, 2018) because income diversification signals agriculture gradually losing its dominance in terms of employment (Djurfeldt *et al.*, 2018) and suggests a decline in the relative importance of agriculture in rural areas of many developing countries like Nigeria. These are likely features of economic transformation (Collier and Dercon, 2014). However, growth in the rural non-farm economy cannot happen in isolation from agriculture (Davis *et al.*, 2017). Hence, there is a link between farm activities and income diversification such that outputs from one activity may serve as inputs for the other and promote investment in productivity-enhancing inputs (Msinde, 2016; Kousar and Abdulai, 2016).

Incentives for Income diversification

A critical review of the literature reveals that basically, there are two motives that drive income diversification (Alobo and Bignebat, 2017; Asfaw *et al.*, 2017). These are; income diversification due to “push factors” and income diversification due to “pull factors”. Income diversification necessitated by push factors is common with rural households facing relatively stagnant agricultural production, weather variations, crop failure, poor market access, market failure, and declining farm income (Ellis, 2000; Alobo and Bignebat, 2017; Asfaw *et al.*, 2017). Rural household often resort to this measure of income diversification due to lack of social insurance against agricultural production and market risks (Alobo and Bignebat, 2017).

Income diversification could be driven by “push factors” such as proximity to urban areas, improved infrastructure, better market access and commercialization. Through this motive, rural households strategically compliment their farm activities with off-farm activities, accumulate assets and consequently enjoy higher income (Alobo and Bignebat, 2017). Involvement in income diversification could also be driven by geographic location (Davis *et al.*, 2017), the level of human capital (Sharma *et al*., 2015), type of crop grown and social factors such as culture, age, religion, social position, associations, gender and liabilities (Alobo, 2015; Idris and Siwar, 2017). From a gender perspective, Alobo (2015) noted that women often embrace multiple livelihood options because they are more constrained in accessing land and other productive assets.

Income diversification in Nigeria

Although Nigeria’s rural economy is traditionally agrarian, only a minority of rural households derive income exclusively from farming. Djido and Shiferaw (2018) finds that 82% of rural households in Nigeria diversify their income sources and as much as 69% of the total rural household income in Nigeria is derived from non-farm income. The Nigerian rural households may have enough reasons to diversify their income. Firstly, factors such as inconsistent government policies, poor processing techniques, poor storage facilities, bad road networks and natural disasters which negatively impact on farmers’ productivity, drives income diversification in Nigeria (Msoo and Goodness, 2014). Secondly, Cooke and Jonathan (2016) argued that Nigerian farmers finds it very difficult to access quality agricultural inputs, such as seeds, pesticides, fertilizer and credit needed to scale up their farm operations. Thirdly, the Nigerian labour productivity per worker is about three times higher in the non-farm sector than the farm sector and the non-farm sector boast of higher average income than incomes from the farm sector (Djido and Shiferaw, 2018).

Moreover, given the prevalence of high risk associated with the rural Nigeria smallholder agriculture, the Nigeria rural households diversify their income sources to manage risks associated with agricultural production and imperfect market and as well ensure more rapid income growth. Exacerbating climatic conditions such as erratic rainfall, rising temperatures (Cooke and Jonathan, 2016), over grazing in the far north, desertification, incessant violent clashes between herdsmen and farmers and prevailing Boko Haram insurgency in the North-East (International Crisis Group, 2017) pushes poorer smallholder farmers to seek alternative incomes in the non-farm sector. Rural household income diversification in Nigeria could therefore have a potential correlation with agricultural intensification in the nation.

Agricultural Intensification in Nigeria

In Nigeria, agricultural intensification is also increasingly recognized as critical in the country’s agricultural policies and programmes. Different policies and programmes introduced by successive government were committed towards tackling the problem of low agricultural productivity in the country. For example in 2009, the Nigeria government introduce vision 2020 and in 2011, a new Nigeria government introduced the agricultural transformation agenda (ATA). Among the goals of the vision 2020 were to (i) achieve the adoption of improved varieties/species of seed and brood-stock by 50% of the farmers by 2015 and 75% by 2020, (ii) increase the size of irrigated land from current 1% of cultivable land to 10% of cultivable land by 2015 and to 25% by 2020 and (iii) to reduce the post-harvest loss of agricultural produce by an average of 50% in 2015 and 90% in 2020 (Olomola and Nwafor, 2018). Likewise, among the goals and targets of ATA was the Growth Enhancement Support Scheme (GESS) which was designed to improve farmers' access to modern agricultural inputs at subsidized prices, guarantee food security in the country and increase farmers' income. Olomola and Nwafor (2018) found that under the growth enhancement support scheme of ATA, Nigeria public spending on fertilizer subsidies increased from ₦13.30 billion (USD84.44 million) in 2012 to ₦82.38 billion (USD519.57 million) in 2014. Despite these laudable programmes and policies, low productivity remain the bane of agriculture in Nigeria.

Furthermore, the average fertilizer usage per hectare is still below the target, but the proportion of farm lands using fertilizer has improved from 38% in 2011 to 47% in 2016. Using evidence based on the Nigeria Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) in an attempt to analyze if increasing fertilizer use for maize production in SSA is a profitable proposition, Liverpool-Tasie *et al*. (2017) reported that fertilizer use in Nigeria is on the increase but there is limited profitability of fertilizer use especially in maize production due to high cost of transportation for fertilizer procurement and poor marginal yield. This challenge of agricultural intensification in Nigeria and indeed globally could be addressed through increased agricultural financing.

Income Diversification and Agricultural Intensification Nexus

The prospect of ending hunger and reducing poverty by 2030 became more difficult in recent years as investments in agriculture which are crucial to help improve the sector's productivity are fast declining. For example, the United Nation's 2018 progress report towards the SDGs shows that government expenditure in the agricultural sector declined from 0.38% in 2001 to 0.23% in 2016 globally and in Nigeria, agriculture's share in the total federal government expenditure declined from 3% to 1% in 2016 making a mockery of Nigeria's commitment to the Maputo declaration of committing 10% budgetary allocation to agriculture (Olomola and Nwafor, 2018). The need to urgently address this decline in agricultural investment cannot be overemphasized.

Empirical literature reveals that farmers finds it difficult to access institutional credit needed to induce their adoption of sustainable agricultural input intensification (Liverpool-Tasie, *et al.*, 2017), hence the agricultural sector remains underproductive, yield gaps and poverty keep increasing (Alobo, 2015). Faced with such idiosyncratic credit market failure, farmers tends to believe that income diversification holds the key to their liquidity, which is needed for investment in sustainable agricultural input diversification. Although the literature indicates mixed results regarding the nexus between income diversification and sustainable agricultural input intensification (Alobo, 2015; Kousar and Abdulai, 2016; Amare and Shiferaw, 2017; Ma *et al.*, 2018), based on evidence obtained from panel studies of agricultural transformation in nine sub-Saharan African countries, Djurfeldt, *et al.* (2011) (cited in Alobo, 2015), attribute the increased agricultural productivity recorded by smallholders in some regions to income diversification and agricultural input intensification.

Kousar and Abdulai (2016) show that income diversification induces increased investment in sustainable agricultural input intensification. Likewise, Ma *et al.* (2018) states that farmers' decisions to use farm machines are positively and significantly correlated with their income diversification status. In contrast, Amare and Shiferaw (2017) revealed an inverse relationship between income diversification and sustainable agricultural input intensification. Using several indicators such as joint use of modern inputs, use of inorganic fertilizer and crop-specific productivity measures, Amare and Shiferaw (2017) did not find a positive nor a significant link between income diversification and agricultural input intensification. Hence, building on this literature review, this study provides empirical evidence regarding the relationship between income diversification and agricultural input intensification in Nigeria and contribute to the needed information necessary in achieving SDGs 1, 2 and 12. Such empirical evidence is also needed for rural development and for designing pro-poor public policies in Nigeria in a bid to reduce the prevailing high rate of poverty in the nation (Ewubare and Okpani, 2018).

Nigeria's Poverty Status

The prevalence of poverty in Nigeria is sardonic given the abundant human and physical resources that the country is endowed with. For instance, Nigeria has high potential economic wealth in terms of natural resources and the high GDP growth (World Bank, 2014). It is further substantiated by the International Monetary Fund (IMF) (2018) (Fig. 4), Euromonitor International (2018) (Fig. 5), and by Djido and Shiferaw (2018) that Nigeria has the largest GDP in Africa. However, it is paradoxical that Nigeria is placed on the human development index (HDI) position at 157 out of the 189 countries on the HDI ranking in 2017. Ewubare and Okpani (2018) confirm this ranking when they argued that despite the nation's rapid economic growth and the numerous Nigeria government poverty alleviations programmes, poverty in Nigeria has reached an extreme high level. A recent report (Fig. 2) by the World poverty clock (2018) also placed Nigeria as leading the top ten African countries facing extreme poverty. The need to overcome this poverty trap could propel income diversification in the nation.

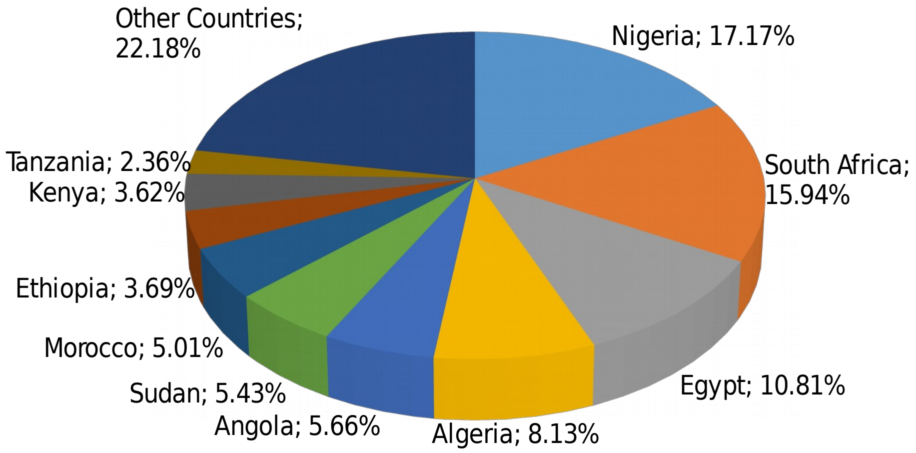

Figure 4: Growth in GDP (Nominal) of Africa 2017.

Source: IMF (2018)

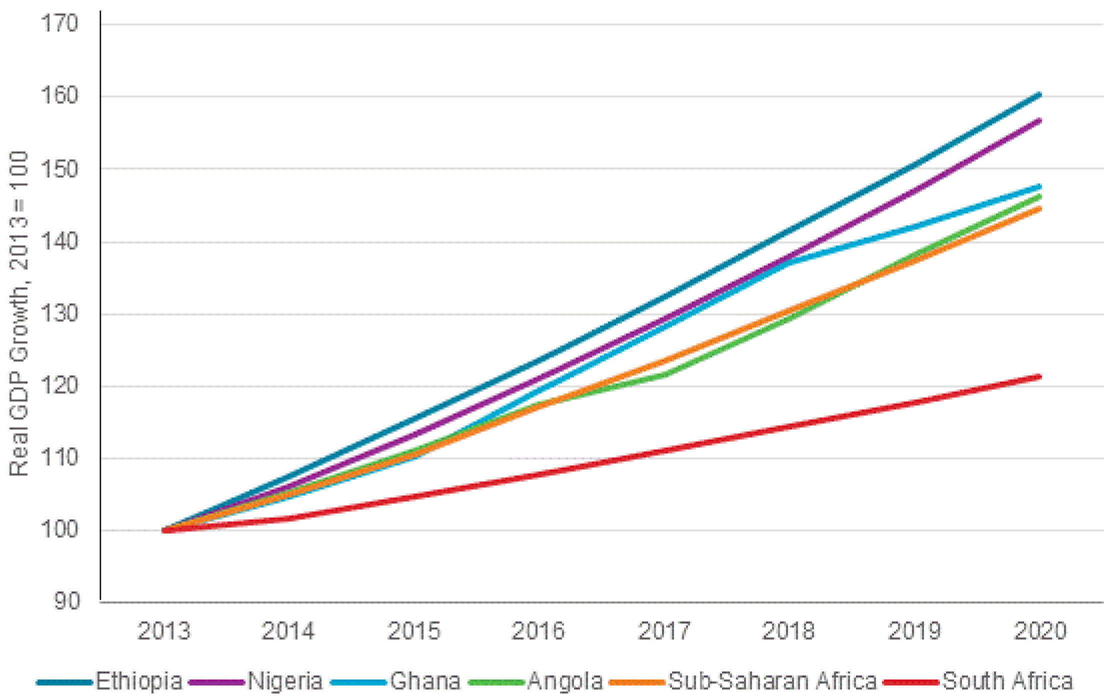

Figure 5: Real GDP growth in the Five Largest Sub-Saharan African Economies: 2013-2020

Source: Euromonitor International from national statistics/UN/OECD/IMF (2018)

Income Diversification and Poverty Nexus

A review of empirical studies concerning the interaction between income diversification of rural households and poverty reveals that although participation in non-farm activities has the potential to reduce poverty (Cunguara, 2011; Harris and Orr, 2014; Pingali, 2015; Batool *et al.*, 2017), it can also increase income inequality as the ability to diversify highly depends on the people's access to different types of assets such as physical, human, and social capital (Cunguara, 2011). As much as diversification provides additional source of income and employment while reducing poverty and improving the welfare of the rural poor, poorer households usually do not own enough liquid assets for investing in new activities and they do not have access to needed credit to invest in nonfarm activities. These barriers deters them from participating effectively in nonfarm activities in general (Pingali, 2015).

A common view shared by a number of empirical studies is that income diversification is important for poverty reduction. For example, Idris and Siwar (2017) analyzed the impact of non-farm income on poverty reduction in Malaysia, the findings shows that non-farm income induced poverty reduction by 69.12%, while the poverty gap and severity of poverty decreased by 79.64% and 82.86%, respectively. Etim and Edet (2016) examined the effect of income diversification on reducing poverty of rural households in Akwa Ibom State, Southern Nigeria, using Foster-Greer-Thorbecke (FGT) weighted poverty measure. The study revealed that poverty is inversely related to income diversification such that the incidence, gap and severity of poverty was lower for households with diverse income sources and higher for households with single income source. Furthermore, Ibrahim and Srinivasan, (2014) estimated the poverty measures (the incidence, depth and severity of poverty) employing the 2004 Nigeria's household data from the Rural Income Generating

Activities (RIGA) database and revealed that participation in the off-farm sector (either in self-employment or wage employment activities) have a positive impact on reducing rural poverty in Nigeria. These impact of income diversification on poverty reduction could also be understood in terms of the livelihood trajectories of the households.

Options for Livelihood Trajectories

The framework of livelihood aspirations and strategies of the poor developed by Dorward *et al*. (2009) shows that households aspire to maintain and/or advance their welfare basically by pursuing three of these livelihood trajectory. When households are "hanging in", it means that they are constrained to maintaining their welfare level and holding unto their productive asset in the face of adverse economic shocks (Tittonell, 2014). It is a negative coping strategy that traps households in a vicious cycle of poverty. "Stepping up" connotes that households are able to enhance the productivity of their assets, buffer risks through income diversification, accumulate assets, reinvest in improving agriculture (commercialization) and improve their welfare. Also, "Stepping Out" implies that households use the accumulated asset to diversify into non-farm activities that have different risk profile and higher returns. "Stepping out" do not necessary imply abandoning farming activities, rather it is a complement to agriculture based livelihood (Tittonell, 2014; Verkaart *et al.*, 2018). In this study, we focus on two of the trajectories which are "hanging in", and "stepping up" because we do not have sufficient data to analyze the other trajectory.

So keeping in view the alarming level of extreme poverty in Nigeria and the global goal of ending poverty by 2030, this study is designed to further explore the relationship between income diversification and poverty reduction in Nigeria in order to inform poverty reduction strategies for accelerated achievement of set targets. Moreover, to the best of our knowledge, previous research did not take a step further to show empirically if indeed the impact of income diversification on rural households translates to household's hanging in, stepping up, or stepping out in terms of their livelihood and poverty. This present study therefore fills that gap in literature.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Description of Study Area

Nigeria is located on the west coast of Africa, bordering Niger in the north, Chad in the northeast, Cameroon in the east, Benin in the west and by the Atlantic Ocean (Gulf of Guinea) in the south.

Nigeria occupies a land size of 923768km^2 (356669m^2), which extends between longitude 3"42'E to 14"11'E and latitude 3"10'N to 14"45'N. Nigeria comprises 36 states and the Federal capital territory (Abuja). The federation is divided into six geo-political zones namely; North Central, North East, North West, South West, South East, and South-South. Nigeria is also generally divided into the North and South region. The South is more urban while the North is more rural and with higher prevalence of poverty (Oseni and Winters, 2009).

3.2 Research Design

A longitudinal research design is adopted for this study. The panel data gotten from this design is well suited for this study because it accounts for individual-specific heterogeneity, has more data variations, gives more degrees of freedom and provides improved accuracy of econometric estimates (Wooldridge, 2016).

3.3 Sampling Procedure and Sample Size

A multi-stage stratified sampling procedure was used for the Nigeria General Household Panel Survey. This is based on a master sample referred to as the National Integrated Survey of Households (NISH). In the first stage, the National Bureau of Statistics (NBS) selected a master sample of enumeration areas (EAs) in each Local Government Area (LGA). This LGA master sample comprises 30 EAs that were selected with equal probability within each LGA of the 36 states of Nigeria, and 40 EAs that were selected in each LGA of Abuja (the federal capital territory). Hence, a sum of 23 310 EAs were selected from the 769 LGAs in 36 states of Nigeria and 6 LGAs in Abuja.

In the second stage, 2 220 EAs and then 10 households in each of the 2,220 EAs were selected systematically with equal probability for the general household survey (GHS). In the third stage, a subsample of the GHS which comprises of 500 sample EAs and 5 000 sample households were randomly allocated for the panel survey with probability proportional to size (PPS).

The urban and rural sectors are used as domains of estimation for most national household surveys in Nigeria including the NGHS-Panel (NBS, 2016). Hence this study is based on the rural sector data of the Nigeria General Household Survey Panel (GHS- Panel).

3.4 Data Source and Data Collection

This study uses data from two waves of the Nigeria General Household Survey Panel (GHS- Panel) conducted by the National Bureau of Statistics in 2012/13 (wave 2) and in 2015/16 (wave 3). The data was obtained through the World Bank LSMS-ISA website (http://www.worldbank.org/lsms-isa). The GHS-Panel is a product of partnership between the National Bureau of Statistics (NBS), the Federal Ministry of Agriculture and Rural Development (FMA&RD), the National Food Reserve Agency (NFRA), the Bill and Melinda Gates Foundation (BMGF), as well as with the World Bank (WB).

The Nigeria General Household Survey – Panel (NGHS-Panel) consists of 5,000 households from 500 enumeration areas. The NGHS-Panel captured information on; (i) farm and non-farm activities, (ii) household's human capital, (iii) household agricultural activities, (iv) other economic activities, and (v) access to services (Davis *et al.*, 2017; Amare and Shiferaw, 2017). The second wave of the GHS-Panel was carried out in two visits (post-planting visit in February – Apr 2011 and post-harvest visit in February – Apr 2013) and the third wave of the NGHS-Panel was also carried out in two visits (post-planting visit in September – November 2015 and post-harvest visit in February-April 2016). The NGHS-Panel is representative of both urban and rural areas but only the rural sample was used for this study. Also, the survey was sampled to be representative at the state level. In order to obtain nationally representative statistics from the NGHS-Panel data, the current study applied the sampling weights provided in the data set (NBS, 2016).

There was panel attrition of 8.4% due to the insecurity situation in the North-East Zone of Nigeria and other places. Also, sample restrictions were experienced due to missing data. The current study took necessary measures to address these data limitations. For example, household socio-demographic variables such as age, gender and education which were missing in one wave, were substituted for from other waves where the data were reported. Multiple imputation of missing data was also implemented in SPSS 20. Multiple imputation method helps to create predictions for each missing value, the imputation takes into account the uncertainty of missing values (the variance between the estimated values) and gives more accurate standard errors (Enders, 2017).

3.5 Data Processing

The data collected by structured questionnaires were coded, cleaned, recoded, aggregated, summarized and analyzed using the Statistical Package for Social Science (IBM SPSS 20) and STATA (Stata14) computer programs.

3.6 Theoretical Framework

This study is guided by the theory of the Farm Household Model (FHM). The FHM is a model in which rural households maximize utility over consumption and leisure time subject to time and budget constraints (Amare and Shiferaw, 2017; Weltin *et al.*, 2017), The farm household model encapsulates the farmers' objectives of attaining efficiency by allocating labour according to a comparison of marginal returns from farming and off-farm wages. The model reflects a farmer's objective of stabilizing erratic income associated with farming by mitigating risk with off-farm work and the simple objective of increasing the number of their farm enterprises (Weltin *et al.*, 2017). Given the inherent market failure in African rural economics including rural economies of Nigeria, the FHM is key to understanding the dynamics of rural household behaviour in Nigeria (Oseni and Winters, 2009).

The basic assumption of the FHM is that imperfect market conditions for product and factor markets makes the production and consumption decisions of farm households non-separable. Thus, households maximizes farm production function over agricultural labor supplied (*La*), purchased inputs (*K*), and fixed assets such as land (*X*) (Singh *et al.*, 1986) as follows;

$Q = q(La, K, X)$……………………………………………………………….………(7)

Where;

Q = farm output

La = agricultural labor supplied

K = purchased inputs

X = fixed assets such as land

The farm household optimization problem is to maximize utility function subject to time, liquidity, and income constraints. Thus, farm households in Nigeria like their peers worldwide, allocate their time between on-farm labour **La** = (La1, . . . , *La*m), off-farm employment **Ln** = (*Ln*1, . . . , *Ln*m) and leisure activities ***le*** = (*le*1, . . . , *lem*) subject to satisfying the time constraint:

$La + Ln + Le \leq T$…… ……………………………………………………………..(8)

Where;

La = agricultural labor supplied

Ln = off-farm employment

Le = leisure activities

T = Time constraint

In the presence of market imperfections, household expenditure on farm inputs (P_k), and hired labor is less than or equal the sum of exogenous income, savings (S) and income received from nonfarm work (ωLn):

$P_kK \leq S + \omega Ln.$ ………………………………………………………………(9)

Where,

P_k = price of farm input

K = farm input

S = savings

ω = wage rate

Ln = off-farm employment

The household is also faced with a budget constraint given as;

$C \leq P_q Q + PkK + \omega Ln + S$ ……………………………………………………... (10)

Where,

C = consumption expenditure

P_q = the price of farm output

Q = quantity of farm output

P_k = price of farm input

K = farm input

ω = market wage rate

Ln = off-farm employment

S = savings

Following derivations by Amare and Shiferaw, (2017) the first order condition for maximizing farm household utility conditioned on time constraint, liquidity constraint and income constraint (equation 10) will yield an equilibrium condition as follow;

$$P_q \frac{\partial q}{\partial L_a} = \frac{\frac{\partial q}{\partial L_e}}{\frac{\partial q}{\partial C}} = \frac{\square}{\square} = \left(1 + \frac{\square}{\square}\right) \quad \text{……………………………………………………(11)}$$

$$P_q \frac{\partial_q}{\partial_K} = P_K + \frac{\delta}{\square} P_K \quad \text{………………………………………………………………}$$

(12)

Where
μ = the marginal utility of leisure and

η = the marginal utility of consumption.

Other variables are as previously defined.

Equation (5) shows the relationship between the marginal rate of substitution, consumption, leisure and the shadow wage. In the presence of liquidity constraint ($\delta > 0$) faced by the farmers, the shadow wage will exceed the market wage by a factor equal to the shadow price of liquidity $\left(\frac{\square}{\square}\right)$ but in the absence of such liquidity constraint ($\delta = 0$), equation (11) becomes a reduced equation such that the marginal rate of substitution between consumption and leisure equals to the market wage rate and the farm shadow wage $\left(\frac{\square}{\square}\right)$ will be equal to the nonfarm wage (ω).

Furthermore, given incomplete credit market, equation (12) shows that for there to be an optimal input allocation, considering the budget constraint, the marginal value product from purchased input should be greater than the price of the input. Also, under liquidity constraint, the shadow value of purchased inputs will be greater than the price of the input as shown in equation 12, exceeding by the term $\left(\frac{\square}{\square}\right)P_K$. This means that less of those inputs will be used compared to the input combination at the global profit maximization.

Succinctly, Oseni and Winters, (2009) asserted that missing or imperfect market for input and output is inherent in rural Africa including rural Nigeria. Understanding the decisions of rural households in the presence of such market failure requires the use of a non-separable model such as the farm household model. Hence, this study builds on this standard farm household model in analysing the relationship between income diversification and agricultural intensification.

3.7 Theoretical Model

Building on the theoretical framework reviewed in section 3.6, some important econometric issues were considered in choosing an appropriate theoretical model for the relationship between income diversification and agricultural intensification. First, there is a potential endogeneity between off-farm income and agricultural intensification due to unobserved time-invariant heterogeneity. Secondly, there is a potential non-linear relationship between off-farm income and agricultural intensification. Thirdly, there is a potential censoring since not all the rural households in this study diversify their income nor invest in agricultural intensification (censored at zero). Moreover, the type of dataset which is a household panel data, was also considered. Hence, this study adopts the basic panel data model comprising fixed effect and random effect models and is justified on the premise that the outcome variable also depends on explanatory variables which are not observable but correlated with the observed explanatory variables (Amare and Shiferaw, 2017; Wooldridge, 2016; Biørn, 2016).

The functional forms of the fixed and random effect models are presented in equation (13) and (14) respectively;

$\gamma_{it} = (X_{it}^{'} \beta_i + u_{it})$ ……………………………………………………………………. (13)

$\gamma_{it} = (\square_i + X_{it}^{'} \beta_i + u_{it})$ ………………………………………………………..…….. (14)

¿ $u_{it} = \alpha_i + \varepsilon_{it} \, for \, i = 1, \ldots, N; t = 1, \ldots, T$

Where;

γ_{it} = the value of the dependent variable for the i^{th} case in the sample at the t^{th} time period.

$X_{it}^{'}$ = row vector of explanatory variables

β_i = column vector of individual-specific slope coefficients

u_{it} = fixed or random effect specific to individual (group) or time period

$\square_i$ = scalar of all other latent time-invariant variables that influence γ_{it}

α_i = unobserved individual effect or heterogeneity. This captures the impact of unobserved variables which are constant over time for a given individual, but which can vary between individuals; e.g. motivation (Jirata *et al*., 2014; Greene, 2011)

ε_{it} = idiosyncratic error. It captures the impact of unobserved variables which vary between individuals and over time; e.g. physical well-being

From equation (13) and (14), the obvious difference between the fixed effects and random effects panel data model is the absence of the term in the fixed effects model. Unlike the random effects model, the fixed effects model allows an arbitrary correlation between time-invariant individual effect $(\square_i)$ and other regressors $(X_{it}^{'})$ (Park, 2011; Wooldridge, 2016). The choice of either fixed effects or random effects model is still a subject of debate in empirical research (Wooldridge, 2016). However, researchers often apply both fixed effects and random effects and then test statistically, whether random individual effects are correlated with the explanatory variables or not by applying Hausman-Wu test (Wooldridge, 2016). The general idea is that one uses the random effects estimates except the Hausman-Wu (HW) test value is greater than the critical value (p-value < .05). Also, failure to reject the null hypothesis of the HW test implies that both the fixed effects and random effects estimates are sufficiently close such that it does not matter either of the estimates that is finally used.

After carrying out the Hausman-Wu test which shows that both the fixed and random effects model yield similar results, this study adopts the random effects model as the theoretical model for this analysis. This is also justified on the basis that the random effects model provides sufficient variance reduction compared to fixed effects model (Greene, 2011; Biørn, 2016).

The Random Effects Model

Starting with the basic pane data model as stated in equation (15);

$$\gamma_{it} = \left(X'_{it}\beta_i + \alpha_i + + \square_{it}\right) \qquad i = 1, \ldots, N; t = 1, \ldots, T \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(15)$$

Where the variables are as previously defined.

The different panel data models depend on the assumptions made about the individual specific effects (α_i). The random effects model assumes that the unobserved individual effects (α_i) are random variables that are not correlated with the explanatory variables;

$$\left(\alpha_i \vee X'_{it}\right) = 0 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots(16)$$

The random effect model also assumes that α_i has constant distribution across all “i" and no correlation between individual effect and the error term $\square_{it}$;

$$\alpha_i \, NIID\left(,\square^2_{\square}\right) \quad \text{and} \quad \square_{it} \, NIID\left(0,\square^2_{\square}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots.(17)$$

Thus the random effects model is written as;

$$\gamma_{it} = X'_{it}\beta_i + \square_{it} \qquad i = 1, \ldots, N; t = 1, \ldots, T \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(18)$$

Where $\square_{it} = \alpha_i + \square_{it}$. This is an error term consisting of two components namely; (i) α_i which does not vary over time and (ii) $\square_{it}$ which is uncorrelated with the individual effect over time (Jirata *et al*., 2014).

This form of $\square_{it}$ is often called an “error components model” and it shows why a random effect model is also called an error component model (Jirata *et al*., 2014; Greene, 2011; Park, 2011).

Let the component of variance be;

$$Cov = ¿\,\square_{it} \quad , \quad \square_{js}\,¿ = \left(\square_{it}, \square_{js}\right)$$

$$\left(\square_{it}, \square_{js}\right) = \square^2_{\square}$$

$$\square^2_{\square} = \square^2_{\square} + \square^2_{\square}\, if\ i = j \wedge t = s$$

$$\square^2_{\square} = \square^2_{\square}\, if\ i = j \wedge t\ s$$

$$\square^2_{\square} = 0\ if\ s, t \wedge i\ j$$

The variance structure of the errors or Ω matrix is;

$$Var\left(\square_{it}\right) = \square^2_{\square} I_T + \square^2_{\alpha} i_T i'_T$$

$$= \begin{bmatrix} \square^2_{\alpha} + \square^2_{\square} & \square^2_{\alpha} & \dots & \square^2_{\alpha} \\ \square^2_{\alpha} & \square^2_{\alpha} + \square^2_{\square} & \dots & \square^2_{\alpha} \\ \square^2_{\alpha} & \square^2_{\alpha} & \dots & \square^2_{\alpha} + \square^2_{\square} \end{bmatrix} = ¿ \quad \text{..........................(19)}$$

Where i_T is a T×1 column vector of 1s (ones). The form of in equation (19) gives the random effect structure of the random effects model. To overcome the inherent hetroscedaticity in the model, the random effect model is estimated using generalized least squares (GLS) method which helps in transforming a heteroscedasticity variance covariance matrix into a homoscedastic variance covariance matrix (Jirata *et al*., 2014; Greene, 2011).

3.8 Empirical Models and Analytical Techniques

The study employs the Inverse Herfindahl Index (IHI) in achieving objective one, Random Effects Tobit model and Random Effect Instrumental Variable model in achieving objective two, Foster-Greere-Thorbecke (FGT) index and Multidimensional Poverty Index (MPI) in achieving objective three.

3.8.1 Inverse Herfindahl Index Model (for Objective One)

The first objective of this study was to identify and analyse the various diversification options among rural households in Nigeria. This first objective is achieved by using a transformed Herfindahl Index known as the Inverse Herfindahl Index (IHI). This index allows for disaggregation of diversification data, it is sensitive to the range of components available (assets, activities or income sources) and hence gives a multidimensional perspective on diversification behaviour (Alobo and Bignebat, 2017).

Following Alobo and Bignebat, (2017), the Inverse Herfindahl Index (IHI) is specified as follows;

$$IHI = \frac{1}{Herfindahl\,index} = \frac{1}{\sum_{i=1}^{n} S_i^2} \quad \text{...} \quad (20)$$

Where,

S_i = the share of income source i in total income, while

n = the total number of income sources

For better understanding of this index, let y_{kh} be the income from source *k* in households *h*. Then household income Y_h is the sum of its components such that;

$$Y_h = \sum_{i=k}^{k} y_{kh} \,.. \quad \text{...} \quad (21)$$

The mean of the household income shares from source k (MS_k) is used to measure household income diversification while the Share of the k^{th} source in the mean income of the group of households is used to compare the relative share of mean income. The share of household income from income diversification is used to reflect the importance of nonfarm income in farm household's livelihood (Davis *et al.*, 2017; Alobo and Bignebat, 2017). The two variables are calculated as presented in equation (22) and (23).

$$MS_k = \frac{1}{n} \sum_{h=1}^{n} \frac{y_{kh}}{Y_h} \quad \text{...} \quad (22)$$

$$S_k = \frac{1}{\sum_{h=i}^{n} Y_h} \sum_{h=1}^{n} y_{kh} \quad \text{...} \quad (23)$$

The Inverse Herfindahl Index ranges from one (meaning that the household completely depends on a single income source) to as high as 10,000 (highly diversified). The index which is estimated using descriptive statistics such as mean, increases as the number of income sources for the household increases (Alobo and Bignebat, 2017).

3.8.2 Random Effect Tobit Model and Random Effect IV Model

Building on the theoretical model derivations in section 3.7, Park (2011) shows that a random effect model is a simple hierarchical linear model with a random intercept. It requires taking into account the censoring effects and correlations effects of the variables. Such estimation procedure is often called Tobit analysis (Biørn, 2016). Hence, random effect Tobit and random effect instrumental variable model is chosen as the empirical model to achieve the second objective of this study. The second objective of this study was to assess the relationship between income diversification and expenditure in agricultural intensification among rural households in Nigeria. The econometric basis for choosing the random effect Tobit model is to account for the censored nature of the data while the econometric basis for the random effect instrumental variable (IV) model is to control for the potential endogeneity of off-farm income. Moreover, the Tobit model is most appropriate to correct for the non-normality of the dependent variable because, there are some households with zero expenditure on agricultural intensification.

Based on the theoretical model, the general form for a left-censored Tobit model with panel data is as specified in equation (24);

$$\gamma_{it}^{*} = X_{it}^{'}\beta_i + \varepsilon_{it} \quad ; \qquad i = 1, \ldots, N ; t = 1, \ldots, T \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (24)$$

$$\gamma_{it} = \begin{cases} 1 \; if \; \gamma_{it}^{*} > 0 \\ . \\ 0 \; otherwise \end{cases}$$

γ_{it}^{*} = latent variable that is observed only when it is positive

$X_{it}^{'}$ = vector of explanatory variables such as education, age, gender, and household size

β_i = vector of estimable coefficients

ε_{it} = error term

N = number of groups (the number of households sampled)

T = number of the repeated observations for the households

γ_{it} = the dependent variable

The random effects Tobit model is derived by disintegrating the error term $\square_{it}$ into two parts;

$$\square_{it} = \alpha_i + \square_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(25)}$$

Where

$\square_{it}$ is as previously defined

α_i = random error term which does not vary over time and

$\square_{it}$ = disturbance term which is uncorrelated with the individual effect over time

The component of variance of the error terms is derived as already explained in the theoretical model. It is repeated as follow;

$$\overset{\square_{it}}{Cov = ¿} \quad , \quad \square_{js} ¿ = (\square_{it}, \square_{js})$$

$$(\square_{it}, \square_{js}) = \square_{\square}^{2}$$

$$\square_{\square}^{2} = \square_{\square}^{2} + \square_{\square}^{2} if\ i = j \wedge t = s$$

$$\square_{\square}^{2} = \square_{\square}^{2} if\ i = j \wedge t\ s$$

$$\square_{\square}^{2} = 0\ if\ s, t \wedge i\ j$$

The variance structure of the errors or Ω matrix is;

$$Var(\square_{it}) = \square_{\square}^{2} I_T + \square_{\alpha}^{2} i_T i'_T$$

$$= \begin{bmatrix} \square_{\alpha}^{2} + \square_{\square}^{2} & \square_{\alpha}^{2} & \ldots & \square_{\alpha}^{2} \\ \square_{\alpha}^{2} & \square_{\alpha}^{2} + \square_{\square}^{2} & \ldots & \square_{\alpha}^{2} \\ \square_{\alpha}^{2} & \square_{\alpha}^{2} & \ldots & \square_{\alpha}^{2} + \square_{\square}^{2} \end{bmatrix} = ¿ \qquad \ldots\ldots\ldots\ldots\ldots\ldots \text{(26)}$$

Following Amare and Shiferaw, (2017), the empirical random effect Tobit model for this study is specified as;

$$\gamma_{it}^{¿} = f(OF_{it}; \beta_i) + X'_{it} \beta_i + \alpha_i + \square_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(27)}$$

Where,

$y_{it}^{¿}$ = latent variable that is observed only when it is positive

OF_{it} = off-farm income,

β_i = vector of estimable coefficients

$X_{it}^{'}$ = vector of explanatory variables such as education, age, gender, and household size

α_i = random error term which does not vary over time and

❑$_{it}$ = disturbance term which is uncorrelated with the individual effect over time

The choice of the vector of explanatory variables X_{it} in the empirical model is based on a review of related theoretical works and empirical studies such as Msinde *et al.*, (2016). Amare and Shiferaw (2017), Weltin *et al.* (2017), Woldeyohanes *et al.* (2017), and *Ma et al.* (2018). These empirical studies revealed that there are specification issues that needs to be overcome in estimating the empirical model. This study carefully identified and addressed these specification issues in estimating equation (27). Firstly, there is a potential of endogenous relationship between off-farm income and agricultural intensification (Amare and Shiferaw, 2017; *Ma et al.*, 2018). This is attributed to inherent time-invariant individual effects and time-specific unobserved heterogeneity. These factors could correlate with other observable factors that influence sustainable agricultural intensification. Secondly, the component $f\ (NF_{it};\ \beta)$ in equation (27) has a potential non-linear relationship between household off-farm income and agricultural intensification. Thirdly, the issue of censored income is addressed since some households may have zero expenditure on agricultural intensification (censored at zero).

Estimation Technique

In order to address the above specification issues, there is need to account for the nature of the zero observations because it also affects the choice of an appropriate econometric model. Even though most households may be potential adopters of inputs for agricultural intensification, they may not be able to adopt such inputs due to financial constraints. In such a situation, the optimum choice for the household is a corner solution. Hence, a corner solution model such as Tobit is the most appropriate to apply (Woldeyohanes *et al.*, 2017).

Previous studies show that agricultural intensification and income diversification can be influenced by unobserved factors such as farmers' attitude to income diversification, motivation and farmers' innate abilities (Amare and Shiferaw, 2017; *Ma et al.*, 2018) such that we cannot use ordinary least squares (OLS) regression methods to model the relationship between income diversification and agricultural intensification. The OLS model fails to account for endogeneity, and would lead to biased and inconsistent coefficient estimates (Wooldridge, 2016). Given that the random effect assumption holds true, the study use Tobit model because it accounts for the variations (both within and between) among the variables of interest over time.

Instrumental variables estimation of the random effects model.

Given the linear model of the panel data from the theoretical model,

$$\gamma_{it} = X'_{it}\beta_i + \square_{it} + \square_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(28)$$

The random effects model assumes that the unobserved individual specific effects $(¿_{it})$ ¿ ,

are uncorrelated with the included regressors X $(¿¿it)$ ¿ , which is a shortcoming of the model (Greene, 2011). Taking deviations from group means in equation (28) above yields equation (29);

$$y_{it} - \acute{y}_i = \left(x_{it} - \acute{x}_i\right) + \square_{it} - \acute{\square}_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(29)$$

The transformation or deviations from group means removes from the random effects model the part of the disturbance that is correlated with the regressors. Hence, the group mean deviations can be used as instrumental variables for estimations.

Moreover, to control for the potential endogeneity of off-farm income, this study applies the control function approach (CFA) and to control for the unobserved heterogeneity of households with respect to off-farm income, the correlated random effects (CRE) is used. The control function approach involves using an instrumental variable (IV) in a reduced-form model but excluded from the structural model. This requires that the instrumental variable should be sufficiently correlated with the endogenous regressor but not with the error term (Wooldridge, 2016). The instrumental variable estimation procedure is a two stage process. Given a set of valid instruments, the parameters of interest are first estimated by regressing off-farm income on the valid instruments and all other covariates in the structural model. Secondly, residuals from the reduced form model are then included as additional covariate in the structural model (Woldeyohanes *et al.*, 2017). Also, the correlated random effects approach is used to include the vector of time-averaged explanatory variables in other to control for time invariant unobserved heterogeneity.

The control variables for this study includes household socio-demographics characteristics, and assets, which is consistent with Amare and Shiferaw (2017) and *Ma et al.* (2018). Specifically, the instrument for the off-farm income is access to electricity which most likely has a strong relationship with off-farm income but is likely not correlated with agricultural intensification and unobserved time varying shocks (such as drought) in the structural model.

Definition and measurement of variables

Table 2 presents the socio-demographic factors that are hypothesized to explain the dependent variable in this study, how they are measured and the *a-priori* expectations.

Table 2: Definition and measurement of variables used in analysis

Variable name		Definition and Unit	Expected signs
Income Source			
On-farm income	-	Total income from crops and livestock	+
Off-farm income	-	All cash income earned from agricultural wage employment, non-agricultural wage employment, self-employment, remittances, and income from any other source, measured in Naira	+
Household characteristics			
Household size	-	Actual number of household members	-
Gender HH head	-	Gender of household head (male = 1, female = 0)	+
Age HH head	-	Age of household head (years)	+
Educ. HH head	-	Education of household head (years)	+
Edu. Other	-	Mean years of schooling of household members (years)	+
Agri. Shocks	-	HH experienced agricultural shocks: drought and pests (yes = 1, no = 0)	-
Demog. Shocks	-	HH experienced demographic shocks (illness and death) (yes = 1, no = 0)	-
Ext service	-	HH gets extension service (yes = 1, no = 0)	+
Electricity	-	Access to electricity by household (yes = 1, no = 0)	
Tap Water	-	Access to tap water by household (yes = 1, no = 0)	
Wealth indicators			
Livestock	-	Livestock (measured in tropical livestock unit, TLU)	
Total asset	-	Value of total assets (Naira) per capita	
Farm size	-	Land holdings (hectares)	+
Soil fertility	-	1 if it is fertile soil, 0 otherwise	+
Irrigated farm size	-	% of farmland irrigated	+
Agricultural intensification	-	Average value of purchased inputs (fertilizer, agrochemical and improved seeds) use (naira) and use of machinery (naira)	+
Total Labour	-	Total value of both hired and family labour use (Naira)	+
Community characteristics			
Distance to market	-	Distance from household location to nearest major market (km)	+
Distance to town	-	Distance from household location to nearest urban center (km)	+
North Central	-	1 if household resides in North Central, 0 otherwise	
North East	-	1 if household resides in North East, 0 otherwise	
North West	-	1 if household resides in North West, 0 otherwise	
South-South	-	1 if household resides in South-South, 0 otherwise	
South East	-	1 if household resides in South East, 0 otherwise	
South West	-	1 if household resides in South West, 0 otherwise	

3.8.3 Foster-Greere-Thorbecke (hereafter FGT) Poverty Index

The final specific objective of this study was to evaluate the impact of income diversification on poverty reduction of rural households in Nigeria. The interaction between income diversification and poverty reduction is explored in this study from a monetary poverty perspective as well as a multidimensional poverty perspective. From the monetary or income poverty perspective, the study employs the concept of disaggregated population and measured three Foster-Greere-Thorbecke poverty indices; (i) poverty incidence, (ii) poverty depth and (iii) severity of poverty. Following Ibrahim and Srinivasan (2014) and Msinde *et al.* (2016), the general form of FGT poverty index is specified as presented in equation (30);

$$P_\alpha(y,z)=\frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (30)$$

Where:

P_α = poverty index

α = poverty aversion parameter

y_i = households total income per adult equivalent

z = the poverty line for the population

n = total number of households in a population (or sample)

q = number of poor households living under the poverty line (those with per capita income below Z)

$\frac{z-y_i}{z}$ = proportion shortfall in income below the poverty line.

The poverty aversion parameter (α) is a parameter that indicate sensitivity of the index to poverty. When $\alpha = 0$, then FGT is reduced to $P_0=\frac{q}{n}$, representing the headcount poverty index which measures the incidence of poverty and simply measures the proportion of the population that are poor or with per capita income below the poverty line (Tuyen, 2015; Msinde *et al.*, 2016).

When α= 1, then the FGT poverty measure represents the poverty gap index or the depth

of poverty $P\left(¿¿1\right)¿$. This is given as;

$$P_1 = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right)^1 \quad \text{………} (31)$$

P_1 measures the extent to which individuals fall below the poverty line or the poverty gap.

The poverty gap index shows the level of poverty and provides information about how far off the poor are from the defined poverty line (Tuyen, 2015).

When α= 2, the FGT class of poverty measure (P_2) is given as presented in equation (32) which is a measure of the severity of poverty.

$$P_2 = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right)^2 \quad \text{………} (32)$$

The poverty severity index averages the squares of the poverty gaps relative to the poverty line but also estimates the variation in income distribution among households that fall below the poverty line. The poverty severity index takes into account the distance separating the poor from the poverty line (the poverty gap) as well as the inequality among them (Tuyen, 2015). Furthermore, the study analyzes the likely poverty trajectory, assessing whether households change their livelihoods over time due to the livelihood options they choose. They who manage to improve but remain in agriculture are said to 'step up'. Those who improve their farming such that they are able to leave farming and invest elsewhere in higher return enterprises are said to 'step out'. The third category of farmers maintains the *status quo* due to various challenges. These are said to 'hang in' while those who fail to cope within agriculture are said to 'step down.' Exploring the type of experience facing the rural households will provide information to policy makers about the most appropriate households that should be targeted effectively in structural transformation policies and agricultural interventions.

3.2.4 Multidimensional Poverty Index (MPI)

This study also analyze and measured the dynamics of rural poverty by applying the Multidimensional Poverty Index (MPI) to integrate health, education, living standards and other indicators into the evaluation. Using this indicator is justified on the basis that no single indicator, such as income, is exclusively able to capture the multidimensional facets constituting poverty. Thus, this study applied the Alkire-Foster method of MPI to measure acute poverty of the rural households; (i) the incidence or proportion of households who experience multiple deprivations and (ii) the intensity of such deprivations within the households.

Step-By-Step Methodology of MPI

Building on the Foster-Greer-Thorbecke (FGT) poverty measure, Alkire and Foster (2011) methodology for computing MPI shows a flexible framework which can be adapted to different specifications. The step-by-step methodology of designing the MPI is explained in details in the appendices of this study but summarized according to Santos and Alkire, (2011) as follow; (i) define the data source e.g. General Household Survey Panel (GHS-Panel), (ii) choose the unit of analysis e.g. the household, (iii) choose the dimensions and indicators, (iv) choose the indicators' deprivation cut-offs (v) choose the indicators' weight; the three dimensions of the MPI are given equal weight such that each of the dimension takes a 1/3 weight and the indicators within each dimension also gets equal weight. (vi) choose the poverty cut-off to identify the poor; from the multidimensional poverty index perspective, an individual is considered MPI poor if they have a deprivation score greater than or equal to 1/3 of the weighted indicators. Hence, a weighted sum of deprivations is used to calculate the deprivation score of each individual such that the deprivation score lies between 0 and 1. An individual with a score of 0 is not deprived in any indicator. (vii) finally, compute the MPI.

The MPI is computed to show (i) the incidence or headcount ratio (H) representing the proportion of people within a given population who are MPI Poor and (ii) the mean intensity (A) of their poverty representing the mean proportion of weighted indicators in which the MPI poor people are deprived. The multidimensional headcount ratio (H) is expressed as presented in equation (33);

$$H=\frac{q}{n} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots$$

(33)

Where;

H = headcount ratio

q = the number of people who are multidimensionally poor and

n = the total population.

The average intensity of poverty (A) or the mean deprivation score of the MPI poor people is specified as presented in equation (34);

$$A=\frac{\sum_{i=1}^{n} c_i(K)}{q} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots..\cdots\cdots$$

(35)

Where;

A = average intensity of poverty

$c_i(K)$ = the censored deprivation score of individual *i* and

q = the number of people who are multidimensionally poor.

The MPI is thereafter calculated by multiplying the incidence of poverty by the average intensity across the poor;

$$MPI = H\ X\ A \qquad \text{…………………………………………………..…….. (36)}$$

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

The results and discussion of this research is based on comparison of two groups of rural households namely; (i) undiversified households and (ii) diversified households. The undiversified households are those households that depends solely on agricultural sources of income while the diversified households are those households who in addition to agricultural source of income, earns income from labour activity outside of the household's farm. The diversified households also include households in which any member of the household works outside the household's farm, owns and operates a nonfarm enterprise.

4.1 Descriptive Statistics of Socio-demographic Characteristics of Households

Table 3 presents descriptive statistics of continuous socio-demographic variables of the households used in estimations and Table 4 presents descriptive statistics of discrete socio-demographic variables of the households used in estimations. Summary statistics of key variables such as household size, education, mean investment in agricultural intensification, distance from household location to the market, access to electricity and use of irrigation were significantly different between household without off-farm income (undiversified) and households that earn off-farm income (diversified). The undiversified households have a mean of eight members, the household head has about eight years of schooling and other household members have about 10 years of formal education. However, the diversified households had a mean of seven members, the household head has about nine years of schooling and other household members have about 11 years of formal education. Moreover, the diversified household invested on average about ₦39824.15 on agricultural intensification while the undiversified households invest about ₦36019.09 on agricultural intensification. This difference of ₦3805.06 is statistically significant (P<0.05).

The diversified households differs significantly from the undiversified households in access to electricity (47% as against 38%) and use of irrigation (5% vs 2%). The discrete variables also shows that only 38% of the undiversified household have access to electricity and only 2% of the households use irrigation. Moreover, there is a significant difference in distance to market between the diversified and undiversified household (P<0.05). The community indicators of the two groups of households shows that with a relatively long distance to urban center (22.01km for the undiversified households and 22.87km for the diversified households) and long distance to input market (63.59km for the undiversified households and 67.73km for the diversified households), both household types are exposed to high transaction cost.

Table 3: Descriptive statistics

Continuous Variable	**Undiversified (n=2312)**		**Diversified (n=2469)**		**T-test**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	
Age HH head	52.77	14.54	52.27	14.31	1.18
Household size	7.63	3.71	7.24	3.56	3.75***
Educ. HH head	7.99	5.14	9.01	4.86	7.05***
Education of other household members	10.11	4.31	10.64	4.26	4.25***
Total Livestock Unit	33.70	161.02	40.14	171.49	1.34
Value of household assets (in Naira)	93534.86	305274.56	92773.69	211694.71	0.10
Agricultural	36019.09	53346.83	39824.15	51763.49	2.5**

Intensification (mean investment in Naira)					
Distance to town	22.01	17.46	22.87	17.48	1.70
Distance to market	63.59	46.01	67.73	46.72	3.08**

Computed from NGHS-panel data, 2013 and 2016

Coefficients are significant at *** $P < 0.01$, and at ** $P < 0.05$.

Table 4: Descriptive statistics (continued)

Discrete Variables	**Undiversified (n=2312)**		**Diversified (n=2469)**		**$\chi 2$ value**	**Df**	**Sig.**
	N	**%**	**n**	**%**			
Whether married					2.59	1	0.107
Yes	1824	78.89	1994	80.76			
No	488	21.11	475	19.24			
Gender					0.383	1	0.536
Male	1923	83.17	2070	83.84			
Female	389	16.83	399	16.16			
Shocks (drought and pests)					0.856	1	0.355
Yes	65	9.60	53	17.90			
No	2095	90.40	2027	82.10			
Extension					0.107	1	0.680
Yes	42	1.82	41	1.66			
No	2270	98.18	2428	98.34			
Electricity					43.121	1	0.000***
Yes	902	39	1160	47			
No	1410	61	1309	53			
Soil fertility					0.625	1	0.429
Poor	863	37.33	949	38.44			
Good	1449	62.67	1520	61.56			
Total	2312	100	2469	100			
Irrigation					24.584	1	0.000***
Yes	45	1.95	111	4.50			
No	2267	98.05	2358	95.50			

***, Coefficients are significant at $P < 0.01$

4.2 Income Diversification Options of Rural Households in Nigeria

This section explains the prevalence of rural household participation in different income generating activities as shown in Fig. 6 and Fig. 7. Figure 6 shows the engagement of rural households in the two major rural income generating activities while Fig. 7 presents the percentage of participating households that actually receives income from these activities. The results in Fig. 6 shows that a higher percentage (53% in 2012/13 and 56% in 2015/16) of rural households in Nigeria are engaged in agriculture as their primary occupation compared to a lower percentage engaged in off-farm as their primary occupation (47% in 2012/13 and 44% in 2015/16). This reflects the fact that agriculture remains a key labour employing sector in the economic portfolio of rural households. Further analysis in Fig. 7 shows that a lower percentage of the rural households actually earns income from agricultural sector. The result also shows that in 2012/13, 62% of the households earned income from agriculture while 76% earned income from off-farm. Also in 2015/16, 68% of the households earned income from agriculture while 86% earned income from off-farm. These figures support the debate that rural households are diversified in their income sources (Alobo and Bignebat, 2017; Davis *et al.*, 2017).

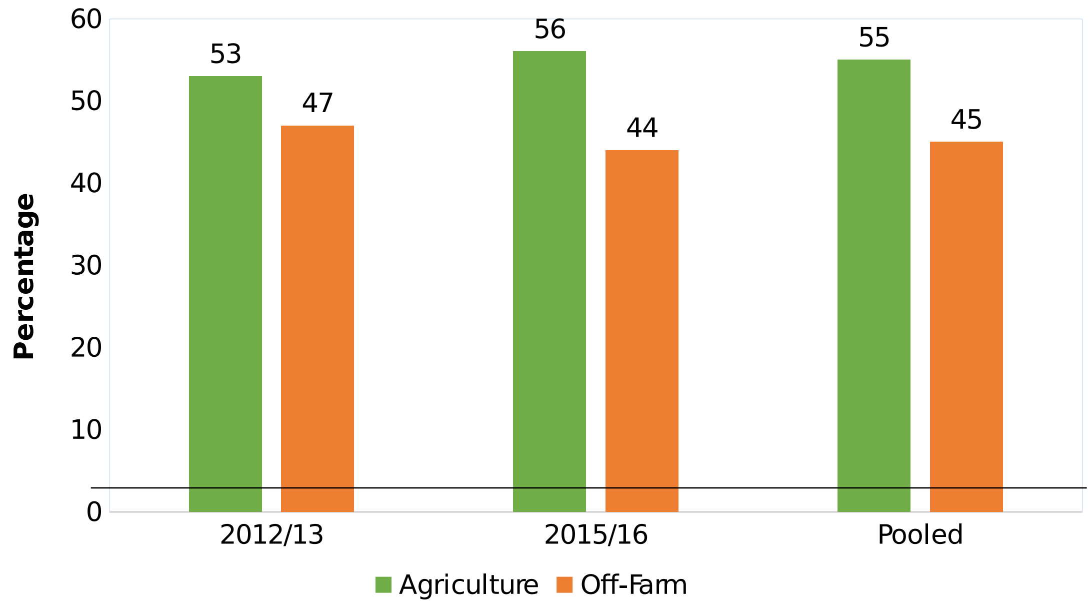

Figure 6: Rural households (%) engaged in agriculture and off-farm work

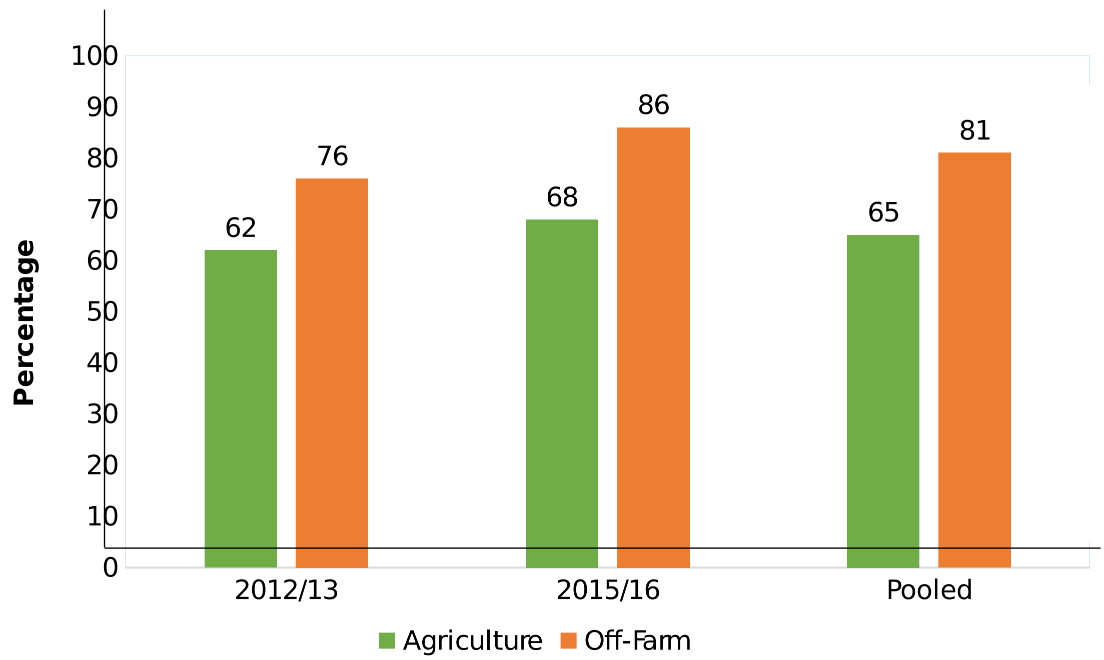

Figure 7: Rural households (%) earning income from Agriculture and Off-farm work

The economic portfolio of rural households could further be explored in terms of the diversification of their income earning activities. Based on data from the labour and nonfarm enterprise sections of the Nigeria General Household Survey – Panel (NGHS-Panel), this study classified households that meet the following criteria as diversified;

(i) provided that any member of the household is involved in a labour activity outside of the household's farm
(ii) given that any member of the household works outside the household's farm
(iii) that any member of the household owns and operates a nonfarm enterprise

In order to avoid complexity, this study simply classified the various income diversification options identified into two broad categories namely (i) farm income and (ii) off-farm income. Thereafter, the share of mean income is used to reflect the importance of each income source in the aggregate income of the rural households in Nigeria. Table 5 presents the household mean income, share of income and Inverse Herfindahl Index (IHI).

Table 5: Mean income, share of income and Inverse Herfindahl Index (IHI)

	Mean Income			**Share of Income**		
	2012/13	**2015/16**	**Average***	**2012/13**	**2015/16**	**Average***
Farm Income	88418.66	97969.32	93066.19	0.37	0.40	0.38
Off-Farm Income	148773.78	149253.78	149024.24	0.63	0.60	0.62
Total	**237192.15**	**247223.10**	**242090.43**	**1.00**	**1.00**	**1.00**
IHI				**0.86**	**2.72**	**1.79**

Survey weight applies. * Average for the two waves

The mean income from the off-farm sector as seen in Table 6 is considerably higher than the mean income from the farm sector in the two waves (2012/13 and 2015/16). Moreover, pooled analysis (average for the two waves) of the participating households shows that on average, the rural households earns about ₦93066.19 from farm income sources while they earn ₦149024.24 from off-farm income sources. Also, the share of farm income (38%) is lower than the share of off-farm income (62%) in the total household income as is the case for the two waves. This results substantiate previous findings by Oseni and

Winters (2009) and Djido and Shiferaw (2018) that rural households in Nigeria earn more income from off-farm than from farm sources. This could be a reflection of a gradual impact of the ongoing structural transformation of African agriculture and rural income portfolio (Amare and Shiferaw, 2017).

Furthermore, a higher engagement of rural households in agriculture (55% from Fig. 7), a lower mean income from agriculture (₦93066.19 Table 5) and a low share of farm income (38% from Table 6) relative to off-farm income suggests that subsistence mode of farming prevails in the rural households. However, the Inverse Herfindahl index (IHI) increases across the period of the NGHS-Panel with a value of 0.86 and 2.72 for 2012/13 and 2015/16 respectively. This also suggest that income diversification is increasing in Nigeria rural households.

4.3 Relationships between Income Diversification and Agricultural Intensification

4.3.1 Determinants of income diversification

In order to assess the relationship between income diversification and agricultural intensification among rural households in Nigeria, this study began by assessing the drive behind income diversification. This is done using a random effects Tobit model to analyse determinants of off-farm income engagement. Nine explanatory variables which were hypothesized from empirical literature to influence the level of rural household off-farm income are included in the Tobit model. The model statistics shows a probability χ^2 value of 0.001, which is highly significantly greater than zero ($P<0.05$). This implies that the model has a significant predictive ability and suitable for statistical inference.

As presented in Table 6, eight of these variables were found to have a positive statistically, significant influence on off-farm income. These variables include gender of the household head, education level of household head, education level of other members of the household, the household size, the household assets, access to electricity, demographic shocks experienced and distance to the nearest market (Table 6). The coefficient for distance to the nearest market had a negative sign but the influence on off-farm income is highly statistically significant. The coefficient for farm size was positive but not significant.

Table 6: Determinants of off-farm income

Variable	**Expected sign**	**Coefficient**	**Std. Error**	**P-value**
Age of household head (years)	_	-0.0002	0.0005	0.344
Gender	+	0.0431**	0.0188	0.011
Education of household head (years)	+	0.0277***	0.0063	0.000
Mean years of schooling of household members (years)	+	0.0064**	0.0027	0.008
Household size	+	0.0056**	0.0023	0.007
Farm size	+	0.0009	0.0027	0.371
Total livestock unit (TLU)	+	0.0063	0.0058	0.140
Assets	+	0.0052**	0.0025	0.018
Electricity	+	0.0274*	0.0141	0.026
Farm shocks	+	0.0218*	0.0121	0.035
Distance to market	-	-0.0169***	0.0052	0.000
Number of observations	113			
Wald chi2	21.60			
Prob > chi2	0.001			

Coefficients are significant at *** $P < 0.01$, ** $P < 0.05$, and * $P < 0.10$.

Furthermore, the results presented in Table 6 show that the age of the household head is negatively associated with off-farm income but it is not significant (P>0.05). Furthermore, gender of the household head, education level of the household head, education level of other members of the household as well as the household size all showed a positive and significant correlation ($P<0.05$) with income diversification. This implies that male headed households are more likely to diversify, it also depicts the fact that women are constrained in access to productive assets and comparative advantages in the labor market. Moreover, the positive and significant coefficient of education for the household head as well as for household members indicate that households with high level of education are more likely to diversify their income sources than those who are less educated. This finding is in line with previous empirical findings (Alobo and Bignebat, 2017; Amare and Shiferaw, 2017) and substantiates the fact that education allows households to overcome barriers to diversification and provides incentives for expansion of livelihood options both within and outside agriculture.

Furthermore, the farm size, the number of tropical livestock units owned by rural household, the value of the household assets, access to electricity and farm shocks experienced by the household indicate a positive and significant influence ($P<0.05$) on income diversification except for farm size that is not significant ($P>0.05$). However, distance to the main market shows a negative and significant relationship with household income diversification, implying that rural households further away from the nearest main market are relatively less likely to diversify their income sources. The positive association between farm shocks and off-farm income suggests that households who experience farm shocks such as drought and crop failure may be pushed into income diversification as a coping strategy while the significant association between assets and off-farm income implies that households with higher level of assets are more likely to diversify and that assets could be a barrier to involvement in off-farm income. These findings are in line with those by Amare and Shiferaw (2017) who established that off-farm income increases with household assets

4.3.2 Impact of off-farm income on agricultural intensification

Under *ceteris paribus* condition, this study hypothesized that off-farm income significantly affects investment in agricultural intensification. This hypothesis was examined by analyzing the association between off-farm income and agricultural intensification based on the household expenditure on agricultural intensification. The results of the analysis are presented in Table 7. In carrying out this analysis, potential endogeneity of off-farm income to agricultural intensification was controlled using access to electricity as an instrumental variable. Access to electricity directly affect off-farm engagement decisions but it does not directly affect agricultural intensification. After resolving the problem of endogeneity, the Hausman test was use to select the best estimation model choosing between Fixed Effects (FE) and Random Effects (RE) Instrumental Variable (IV) estimation model. The Random effects instrumental variable regression was chosen and applied in this analysis.

Table 7: Impact of off-farm income on agricultural intensification

Variable	Expected sign	Coefficient	Std. Error	P-value
LnOff-Farm Income	+	0.029	0.034	0.394
LnAge	-	-0.169	0.139	0.225
LnHousehold size	-	0.021	0.074	0.769
LnEducation of household head	+	0.345	0.078	0.000***
LnFarm size	+	0.076	0.039	0.052*
Soil quality	+	0.166	0.079	0.038**
Dependent Variable	LnAmount invested in agricultural intensification (₦)			
Number of observations	944			
R^2 (overall)	0.0411			
Wald chi2 (6)	38.50			
Prob > chi2	0.000			
sigma_u	0.774			
sigma_e	0.889			
Rho	0.743			

Computed from NGHS-panel data, 2013 and 2016

Coefficients are significant at *** $P < 0.01$, ** $P < 0.05$, and * $P < 0.10$.

The best fits model between the fixed and random effects was chosen by running a Hausman test. The null hypothesis of this test states that the preferred model is the random effects model while the alternate states otherwise. This test was carried out as follows; (i) the study ran a fixed effects model and saved the estimates, (ii) step one was followed by running a random effects model and save the estimates, (iii) the Hausman test was performed. The results of the Hausman test are presented in appendix 2, the P-value is 0.0694, meaning that it is not significant (P<0.05). This implies that the random effects IV is the best fits model. Therefore, the following discussion is based on the results of the random effects IV model.

The model estimates in Table 7 shows that the random effects model is statistically significant with a p-value of 0.000 which is less than a critical value of 0.050. Also, *rho* which represents the ratio of individual specific error variance to the total error variance is

0.743, which implies that the random effects model has a high goodness-of-fit and appropriate for statistical inferences. Results of the empirical analysis presented in Table 7 show that, the coefficient for the variable off-farm income is 0.029, meaning that a 1% increase in off-farm income increases expenditure on agricultural intensification by 0.029% *ceteris* paribus. This suggests that off-farm income has a positive relationship with agricultural intensification, but this relationship is not significant. The positive impact of off-farm income on agricultural intensification implies that as households diversify their income, they reinvest part of their off-farm income on their farms while most of the off-farm income goes to other household financing and consumption. Invariably, there is a tradeoff between income diversification and agriculture. This result is contrary to our stated hypothesis that off-farm income should have a significant impact on household expenditure in terms of agricultural intensification. Our finding is in line with empirical findings of other previous studies done by Amare and Shiferaw (2017) who also found a positive but insignificant impact of nonfarm income on input intensification. However, Oseni and Winters (2009) found that off-farm income had a positive and significant impact on the use of agricultural inputs in Nigeria, likewise, Babatunde (2012) found that off-farm income have a positive and significant impact on agricultural production in rural Nigeria.

Apart from off-farm income which is our key variable of interest, other socioeconomic factors are also seen to influence agricultural intensification. For example, the parameter estimate for the age of the household head is -0.169, which implies that holding all other variables constant, if the age of the household head increases by 1%, the level of agricultural intensification measured by amount invested in agricultural inputs and machinery would decrease by 0.169%. This negative and insignificant coefficient simply

imply that relative to older household, younger households are more likely to adopt agricultural intensification.

Contrary to *a-priori* expectation of a negative effect of household size on agricultural intensification, the parameter estimate for the household size is positive (0.021) but insignificant. This suggest that under *ceteris* paribus condition, an increase in the household size by 1% would increase the expenditure on agricultural intensification by 0.021%. This is probably because, households with more members in the sample are more likely to earn higher household income. The findings of this study also shows that an increase in the level of education of the household head by 1% would significantly increase the level of household expenditure on agricultural intensification by 0.345% at 1% level of significance, all other variables held constant. This suggests that relative to household heads with no formal education, educated household heads are more likely to engage in agricultural intensification.

Moreover, farm size and soil quality had a positive effect on variation in agricultural intensification. The coefficient for farm size is positive (0.076) implying that keeping all other variables constant, 1% increase in farm size leads to 0.076% increase in expenditure on agricultural intensification. Also, the coefficient for soil quality is positive (0.166) and significant at 5% level of significance. This implies that under the assumption of *ceteris paribus*, a unit increase in the soil quality would lead to 0.166% increase in household expenditure on agricultural intensification.

4.4 The Nexus between Income Diversification and Poverty Reduction

This study also set to test whether income diversification over-time contributed to poverty reduction *ceteris paribus*. This association between off-farm income and poverty reduction was tested using descriptive analytical tools whereby the poverty indices of the undiversified and diversified groups of households were compared using the income and multidimensional poverty indicators as measures of poverty.

4.4.1 Income measure of household poverty

Based on income perspective, this study assessed the dynamics of poverty among the rural households through the three Foster-Greer-Thorbecke (FGT) measures of poverty. These are; (i) incidence of poverty, (ii) poverty gap, and (iii) poverty severity. Results of the Foster-Greer-Thorbecke model presented in Table 8 shows that about 56% of rural households who depends solely on income from farm (undiversified) were observed to be below the poverty line and the international threshold of extreme poverty (set at living on less than US$1.90 per day PPP; World Bank, 2015) while about 44% of the diversified household were equally below the poverty line.

Moreover, the depth and severity of poverty were higher among the undiversified households. The depth of poverty experienced by the undiversified household (25%) is relatively higher than the depth of poverty experienced by the diversified households (20%). Also, the severity of poverty experienced by households without off-farm income is 18% compared to 14% severity of poverty experienced by the households with off-farm income.

Table 8: Foster-greer-thorbecke Poverty indices

	Undiversified	Diversified	t-value
Poverty headcount ratio	0.564	0.448	2.698**
	(0.117)	(0.074)	
Poverty gap index	0.252	0.207	0.378
	(0.162)	(0.043)	
Poverty severity index	0.189	0.147	1.826
	(0.056)	(0.033)	

Computed from NGHS-panel data, 2013 and 2016

Aside the income perspective, these dynamics of poverty among the rural households could also be explored from the multidimensional poverty perspective for a better understanding of the impact of income diversification on poverty reduction.

4.4.2 Multidimensional poverty indices of the rural households

In order to capture the non-money-metric dimensions that constitutes poverty, the estimated the multidimensional poverty indices of the rural households based on Alkire – Foster (AF) method. As stated earlier in the methodology, the MPI components are first computed to show; (i) the incidence or headcount ratio (H), representing the proportion of people within a given population that is MPI Poor, (ii) the mean intensity (A) of their poverty, representing the mean proportion of weighted indicators in which the MPI poor people are deprived. Based on the values of (H) and (A), the MPI is computed by multiplying the incidence of poverty (A) by the average intensity across the poor (H). These values were computed in this study and presented in Table 9.

Table 9 presents the estimated multidimensional poverty indices comprising headcount ratio of poverty (H), average intensity of poverty (A) and the multidimensional poverty index (MPI). Based on the thresholds of the AF method, a household is considered deprived in each indicator if their score falls below the threshold of the Alkire – Foster method (2014). Similar to the global MPI, the study used a poverty cross indicator cutoff to identify a household as MPI poor if the household has a deprivation score greater than or equal to one third of the weighted indicators.

Table 9: Multidimensional H, A and MPI for different deprivation cutoffs (k)

K	**H**			**A**			**MPI**		
	UNDV	**DV**	**t-value**	**UNDV**	**DV**	**t-value**	**UNDV**	**DV**	**t-value**
3	0.500	0.402	4.11**	0.729	0.702	1.25	0.351	0.293	2.59**
6	0.349	0.330	0.83	0.785	0.609	8.09**	0.274	0.201	3.58**
9	0.090	0.063	2.12**	0.978	0.952	2.93**	0.088	0.060	2.23**

Note: k = Deprivation cutoffs; UNDV = undiversified; DV = Diversified

Significant at ** $P < 0.05$

From Table 9, given that the households experienced deprivations at k=3, headcount ratio of poverty (H) is about 50% for farm income only households and 40% for households with off-farm income, indicating that a high proportion of the households were deprived in at least three indicators and implies a severe multidimensional poverty situation in the rural households. The average intensity of poverty (A; at k=3) is 73% for undiversified and 70% for diversified households and the difference is statistically significant (P<0.05). The percentage of the poor rural households (H) coupled with the share of deprivations in which the poor rural households are deprived (A) shows that multidimensional poverty index (MPI) of 29% is relatively lower for households with off-farm compared with 35% for households without off-farm income. It is also observed when tested for significance difference that the MPI of the diversified household differs significantly (P<0.05). The result also shows that MPI level changes with the number of indicators (k) such that MPI decreases as k increases. Thus as k increases, the percentage of the poor rural households

(H) is reducing, the intensity of poverty among the poor rural households is increasing and the estimated proportion of rural households that are MPI poor is reducing. This is consistent with previous empirical findings of Wang and Wang (2016) and Delalić *et al.* (2017).

4.4.3 Change in Livelihood Status (hanging in and stepping up)

Following the livelihood perspective of Dorward *et al*. (2009), this study further analyze the livelihood trajectory of the households to assess empirically if the impact of income diversification on rural households translates to their hanging in, or stepping up in agriculture and welfare. Results of this analysis as presented in Table 10 shows that irrespective of whether the households is diversified or undiversified, some households maintain the *status quo* by staying poor and maintaining subsistence agriculture, such households are said to be 'hanging in'. The rural households who manage to improve but remain in agriculture are said to be 'stepping up'.

Table 10: Livelihood trajectory of the rural households

	Undiversified	Diversified	t-value
Hanging in	0.56	0.45	4.60**
Stepping up	0.44	0.55	4.60**

Significant at ** $P < 0.05$

Table 10 shows that among those households that are hanging in and remaining in agriculture are 56% of households that are undiversified and 45% of the diversified households. The t-test shows that this difference is statistically significant (P<0.05). This implies that a higher proportion of the undiversified households are maintaining *status quo* and protecting livelihoods. It also implies that these households could not improve their livelihoods, constrained to maintaining their welfare level and holding unto their productive asset, probably due to adverse economic shocks. It is a negative coping strategy that traps households in a vicious cycle of poverty (Tittonell, 2014).

Furthermore, the stepping up cluster in Table 10 shows that 44% of the undiversified households and 55% of the diversified households improved their livelihood over time and re-investing in agriculture. Results of the t-test shows that this difference is statistically significant ($P<0.05$). This connotes that the stepping up households are able to enhance the productivity of their assets, buffer risks, accumulate assets, reinvest in improving agriculture (commercialization) and improve their welfare. However, a higher proportion of the stepping up households are those that are engaged in income diversification. This suggest that households who are diversified are more likely to stay out of the vicious cycle of poverty than households that are undiversified.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Although there is a growing wealth of literature that explore the determinants of income diversification but this study identified a gap in knowledge about the nexus between income diversification, agricultural intensification and poverty reduction especially in developing countries. This study has bridged the gap in knowledge by providing empirical findings based on the Nigerian general household panel data of 2012/13 and 2015/16.

The main objective of this study was to explore how rural households in Nigeria diversify their income sources in nexus with their poverty trajectories. This study classified the various income diversification options identified into two broad categories namely (i) farm income and (ii) off-farm income. Empirical findings of this study shows that Nigerian rural households diversify their income in many ways and these options could be classified into two broad categories namely (i) farm income and (ii) off-farm income. Findings of this study show that agriculture remains a key labour employing sector in the economic portfolio of rural households. However, a higher engagement of rural households in agriculture (55% from Fig. 7), a lower mean income from agriculture (₦93066.19 Table 6) and a low share of farm income (38% from Table 7) relative to off-farm income suggests that subsistence mode of farming prevails in the rural households and rural households in Nigeria earn more income from off-farm than from farm sources. Furthermore, the increasing Inverse Herfindahl Index (IHI) score of 0.86 for 2012/13 and 2.72 for 2015/16 implies that subsistence farming still exists in rural Nigeria but income diversification is increasing in Nigeria rural households.

Moreover, this study used Random Effects Instrumental Variable regression to assess the relationship between income diversification and agricultural intensification among rural households in Nigeria. The results shows that, there is a positive association between income diversification and agricultural intensification with a coefficient of 0.029 but this association is statistically insignificant.

Finally, the association between income diversification and poverty indices of the rural households was analysed from the income and multidimensional perspective. Results of the Foster-Greer-Thorbecke (FGT) model presented in Table 7 shows that about 56% of rural households who depends solely on income from farm (undiversified) were living below the poverty line of US$1.90 per day (World Bank, 2015) while about 44% of the diversified household were equally below the poverty line. The depth of poverty experienced by the undiversified household (25%) is relatively higher than the depth of poverty experienced by the diversified households (20%). Also, the severity of poverty experienced by households without off-farm income is 18% compared to 14% severity of poverty experienced by the households with off-farm income. Furthermore, the percentage of the poor rural households (H) coupled with the share of deprivations in which the poor rural households are deprived (A) shows that, the multidimensional poverty index (MPI) of 29% for households with off-farm is relatively lower compared with MPI of 35% for households without off-farm income. This implies that income diversification is a key factor in reducing the incidence of poverty among rural households in Nigeria.

5.2 Recommendations

Based on the findings of this study, the following recommendations are suggested for consideration by the government, policy makers and all other stakeholders concerned.

(i) The poverty transition matrix shows that the off-farm income contributes positively in reducing the poverty level of the rural households. Hence, there is need for greater public-private investment in the off-farm sector to boost the off-farm earnings of the rural households. Also, more rural households should be encouraged to engage in income diversification rather than an exclusive commitment to agriculture in other to reduce the incidence of poverty in the rural areas.

(ii) The empirical findings of this study reveals that community assets such as electricity correlates positively with income diversification but the MPI deprivation indices shows that about 55% of the rural households are deprived in access to electricity. It is recommended therefore, that Nigeria government and all other stakeholders concerned should step-up efforts at rural electrification and stabilize rural access to electricity.

(iii) Furthermore, in order to achieve the desired positive and significant impact of off-farm income on agricultural intensification and poverty reduction, complimentary policies capable of reducing the tradeoffs between income diversification and farming should likewise be promoted.

For further research, the complete three waves NGHS-Panel data could be analyzed, and compared on the bases of urban-rural differences. The determinants of MPI among the households could also be assessed.

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APPENDICES

Appendix 1: Step-By-Step Methodology of MPI

Building on the Foster-Greer-Thorbecke (FGT) poverty measure, Alkire and Foster (2011) methodology for computing MPI shows a flexible framework which can be adapted to different specifications. The step-by-step methodology of designing the MPI is discussed below following Santos and Alkire, (2011).

Step 1: Define the data source

This step requires that the data source should be clearly defined and that all the information for the unit of analysis are generated from the same survey. This is essential to show if the unit of analysis suffers multiple deprivations. This study uses information from the Nigeria General Household Survey Panel (GHS- Panel).

Step 2: Choose the unit of analysis

After defining the data source, the next thing to do is to specify the unit of analysis which can either be individual or household. This study uses the household as a unit of analysis which is in line with the global MPI.

Step 3: Choose the dimensions and indicators

Based on the human development index, the MPI uses ten indicators which are grouped into three dimensions. Although the process through which such an indicator is selected is important, but there is no rigid list of what should be included in the indicators.

Step 4: Choosing the indicators' deprivation cut-offs

The MPI specifies a deprivation cut-off (Z_i) for each indicator such that a person (i) is considered deprived if her score for that indicator (X_i) is below the cut-off ($X_i < Z_i$).

Step 5: Choose the indicators' weights

After selecting the indicators and their appropriate cut-off points, we define or assign weights to each indicator. The three dimensions of the MPI are given equal weight such that each of the dimension takes a 1/3 weight and the indicators within each dimension also gets equal weight. Therefore, each indicator within the health dimension is assign a weight of 1/6, indicators within the education dimension gets a weight of 1/6 and each indicator within the living standards dimension is assign a weight of 1/18 (which is 1/3 ÷ 6). Moreover, in cases where the number of indicators are less than 10, the weight of the indicators are adjusted in accordance with the same weighting principle above.

Step 6: Choose the poverty cut-off (to identify the poor)

The poverty cut-off is defined as the share of (weighted) deprivations a person must score in order for the individual to be considered poor (Santos and Alkire, 2011). From the multidimensional poverty index perspective, an individual is considered MPI poor if they have a deprivation score greater than or equal to 1/3 of the weighted indicators. Hence, a weighted sum of deprivations is used to calculate the deprivation score of each individual such that the deprivation score lies between 0 and 1. An individual with a score of 0 is not deprived in any indicator.

Step 7: Computing the MPI

The MPI is computed to show (i) the incidence or headcount ratio (H) representing the proportion of people within a given population who are MPI Poor and (ii) the mean intensity (A) of their poverty representing the mean proportion of weighted indicators in which the MPI poor people are deprived. The multidimensional headcount ratio (H) is expressed as presented in equation (37);

$$H = \frac{q}{n} \quad \text{..(37)}$$

Where;

H = headcount ratio

q = the number of people who are multidimensionally poor and

n = the total population.

The average intensity of poverty (A) or the mean deprivation score of the MPI poor people is specified as presented in equation (27);

$$A = \frac{\sum_{i=1}^{n} c_i(K)}{q} \quad \text{...}$$

(38)

Where;

A = average intensity of poverty

$c_i(K)$ = the censored deprivation score of individual *i* and

q = the number of people who are multidimensionally poor.

The MPI is thereafter calculated by multiplying the incidence of poverty by the average intensity across the poor;

$$MPI = H\ X\ A \quad \text{..(39)}$$

When a person is deprived in at least one third of the weighted indicators, they are identified as MPI poor. Table 11 shows the dimensions, indicators, deprivation cutoff points and weights of the MPI.

Table 11: The dimensions, indicators, deprivation cutoffs and weights of the MPI

Dimensions of poverty	**Indicators**	**Deprived if…**	**Weight**
Education	Years of Schooling	None of the household member have completed five years of schooling.	1/6
	Child School Attendance	Any school-aged child in the household is not attending school up to class 6.	1/6
Health	Child Mortality	Any child has died in the family.	1/6
	Nutrition	Any adult or child is malnourished.	1/6
Living Standards	Electricity	The household has no electricity.	1/18
	Improved Sanitation	The household's sanitation facility is not improved (according to MDG guidelines), or it is improved but shared with other households.	1/18
	Improved Drinking Water	The household does not have access to improved drinking water (according to MDG guidelines) or safe drinking water is more than a 30-minute walk from home, roundtrip.	1/18
	Flooring	The household has a dirt, sand or dung floor.	1/18
	Cooking Fuel	The household cooks with dung, wood or charcoal.	1/18
	Assets ownership	The household does not own more than one radio, TV, telephone, bike, motorbike or refrigerator and does not own a car or truck.	1/18

Source: Adapted from Alkire *et al.* (2014).

Appendix 2: Hausman specification test result for off- farm household income model

	Coefficients			
	(b) **Fixed**	**(B)** **Random**	**(b-B)** **Difference**	**sqrt(diag(V_b-V_B))** **S.E**
LnOff-Farm Income	0.039	0.029	0.01	0.034
LnAge	-0.236	-0.169	-0.067	0.078
LnHousehold size	0.345	0.021	0.324	0.212
LnEducation of household head	0.076	0.345	-0.269	0.135
LnFarm size	0.054	0.076	-0.022	0.0372
Soil quality	0.078	0.166	-0.088	0.079

b = consistent under Ho and Ha; obtained from xtivreg

B = inconsistent under Ha, efficient under Ho; obtained from xtivreg

Test: Ho: difference in coefficients not systematic

chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 11.69

Prob>chi2 = 0.0694