Multidimensional Poverty, Inequality, Vulnerability to Poverty, and Production Factor Risks in Ethiopia

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School of Graduate Studies

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Declaration

I, Getu Tigre, hereby declare to the School of Graduate Studies of Addis Ababa University, College of Business and Economics, Department of Economics that, this dissertation entitled "Multidimensional Poverty, Inequality, Vulnerability to Poverty, and Production Factor Risks in Ethiopia" is a product of my original research work. It was not submitted, in full or part, for the attainment of any academic degree elsewhere. To the best of my knowledge, I have fully acknowledged the materials and pieces of information used in the study. The reporting procedures do comply with the expected standards and regulation of the University.

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Acronyms

AF	Alkire Foster
BMI	Body Mass Index
CA	Cluster Analysis
CSA	Central Statistical Agency
DHS	Demographic and Health Survey
EA	Enumeration Area
EDHS	Ethiopian Demographic and Health Survey
EEA	Ethiopian Economic Association
ERHS	Ethiopian Rural Household Survey
EIAP	Eligible Individual Account Plan
FA	Factor Analysis
FGLS	Feasible Generalized Least Square
FGT	Foster, Greer and Thorbecks
GDP	Gross Domestic Product
GE	Generalized Entropy
GTP-I	The first Growth and Transformation Plan
GTP-II	The Second Growth and Transformation Plan
HCES	Household Consumption and Expenditure Survey
HDI	Human Development Index
HGC	Highest Grade Completed
HIES	Household Income and Expenditure Survey
HIS2	The Second Integrated Household Survey
HPI	Human Poverty Index
JIBS	Jonkoping International Business School
JU	Jonkoping University
LCA	Latent Class Analysis
LSMII	Living Standard Multidimensional Inequality Index
MCA	Multiple Correspondence Analysis
MDGs	Millennium Development Goals
MDI	Multidimensional Inequality
MII	Multidimensional inequality index
MoFED	Ministry of Finance and Economic Development
MPI	Multidimensional Poverty Index
MVP	Marginal Value Product
NGO	None Governmental Organization
OECD	Organization for Economic Co-operation and Development.
OLS	Ordinary Least Square
OPHI	Oxford Poverty and Human Development Initiative
PASDEP	Plan for Accelerated and Sustainable Development to End Poverty
PCA	Principle Component Analysis
RTS	Return to Scale
SDGs	Sustainable Development Goals
SEM	Structural Equation Model

SNN	South Nations and Nationalities
SSA	Sub-Saharan Africa
SWF	Social Welfare Function
TFC	Total Factor Cost
TVP	Total Value Product
UN	United Nation
UNDP	United Nation Development Program
VE	Variance Elasticity
VEP	Vulnerability as Expected Poverty
VER	Vulnerability as Uninsured Exposure to Risk
VEU	Vulnerability as Low Expected Utility
WHO	World Health Organization
WIDE	World Inequality Database on Education

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Chapter 1: Introduction and Summary of the Thesis

Abstract

Measures of income or consumption expenditure-based poverty provide incomplete information and guidelines for addressing poverty. Applying the Alkire-Foster method of a multidimensional poverty analysis using Ethiopian Demographic and Health Survey in this thesis shows that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular. Multidimensional poverty has been decreasing moderately over time, but still large proportions of the population live under multidimensional poverty. Households that are poor at any given point in time may differ from those who are vulnerable to poverty and there should be a distinction between poverty prevention (vulnerability) and poverty alleviation programs. The distribution of vulnerability across different segments of the population is different from the distribution of poverty. Interventions and programs that are targeted at reducing the level of vulnerability in the population therefore need to be targeted differently from those aimed at poverty alleviation. There are also distributional concerns of well-being indicators. Consumption inequalities are higher in urban than in rural areas in the country. Considerable differences in regional consumption inequalities are observed between different regions. Inequalities in the multidimensional indicators decrease over the wealth quintiles while living standard contributes the most to multidimensional inequalities. Reducing inequalities between socioeconomic groups will have a greater impact on reducing poverty than reducing inequalities within groups as between group elasticity is greater than within group elasticity. Parents' education has a positive impact on children's education, and educated children have a positive effect on reducing intergenerational inequalities. In rural Ethiopia, production and generation of wealth is highly associated with agricultural productivity and risks in the sector. Risks are inherent in agricultural production. A stochastic production function to estimate variability (risks) indicates that fertilizer and labor are risk decreasing inputs while land is risk increasing input. The more farmers diversify their crops, the less is the yield variability or risks. The risk decreasing/increasing effects of these farm inputs vary by location. Considering risk is important for managing farm risks and thus ensuring food security.

Keywords: Multidimensional poverty, vulnerability, inequality, input risks

JEL Classification Codes: I32, I38, D63

Brief Summary of the Thesis

This thesis analyzes multidimensional poverty, vulnerability to poverty, inequality, and input risks using demographic and health surveys and household income, consumption, and expenditure data for 2016. This thesis is organized into five chapters. The first chapter gives the introduction and summary of the thesis and provides the general background including poverty and vulnerability to poverty. It also does a theoretical review of the nexus between growth, poverty, and inequality. This chapter also shows that nexus between poverty, vulnerability to poverty, risks, and inequalities and highlights how the four chapters of the thesis are inter-related. It also presents the statement of the problem, the objectives of the thesis, the data, and the methodological approaches used. It also provides a summary of the chapters and highlights the contributions and policy implications of the study.

The first essay (Chapter 2) examines multidimensional poverty and its dynamics in Ethiopia over the period 2000-16. It gives the extent of multidimensional poverty in Ethiopia and discusses the determinants of multidimensional poverty that have been identified. The most recent study on multidimensional poverty using an equal weight approach is by OPHI (2017) which used a similar set of indicators and analyzed multidimensional poverty in a country and in its regions. The main contribution of this thesis is that it uses the factor weight approach which considers the correlation between the indicators. One strong assumption of the Alkire-Foster (AF) dual cut-off approach is using fixed poverty cut-offs. In response to this strong assumption, the thesis uses a sensitivity analysis for changes in poverty cut-offs. The analysis shows that the proportion of multidimensional poor was less sensitive to downward as opposed to upward revisions in the poverty cut-offs. We also did a sensitivity analysis for the weighting system, where the headcount and the multidimensional poverty index (MPI) were different when equal weights and factor analysis weights were used showing that MPI is sensitive to the weights attached to the indicators. This chapter was published as 'Multidimensional Poverty and its Dynamics in Ethiopia,' in Heshmati and Yoon (2018).

A poverty analysis is an ex-post measure of households' well-being. For policy purposes, what really matters is the likelihood of households or individuals falling into poverty in the near future (vulnerability to poverty). The second essay (Chapter 3) focuses on unidimensional and multidimensional vulnerability to poverty. It assesses the extent of vulnerability to poverty in Ethiopia, and examines the determinants of vulnerability to poverty, and provides theoretical and empirical evidence. Its revised version was published as 'Vulnerability to Poverty in Ethiopia,' in Nilsson and Heshmati (2019).

The third essay (Chapter 4) discusses multidimensional inequalities in Ethiopia. Before estimating the multidimensional inequality index, it is very important to estimate inequalities of each multidimensional inequality indicator. Hence, we estimated inequalities in health and living standard indicators so that the readers have a clear picture of the distribution of multidimensional poverty's indicators before estimating the multidimensional inequality index (MII). Then, using a multistage multidimensional inequality analysis the chapter examines the existing inequalities in Ethiopia. Our results show that even though multidimensional poverty was high, multidimensional inequality was quite low in Ethiopia. In this chapter inequalities in the various dimensions of multidimensional inequality are also estimated. Living standards contribute the most to multidimensional inequalities and the inequalities in multidimensional indicators decrease over the wealth quintiles. Parents' education has a positive impact on children's education and educated children have a positive intergenerational inequality reducing effects.

The fourth essay (Chapter 5) studies the risks of agricultural inputs to smallholder farmers in rural Ethiopia using farm household surveys covering the period 1995-2015. It uses the stochastic production function to estimate variabilities (risks) in agricultural inputs. The variance or risk estimation results show that inputs like fertilizers are risk decreasing inputs while labor and land are risk increasing inputs. The risk decreasing/increasing effects of these farm inputs vary across regions. Considering agricultural risks is important for national agriculture risk management and food security efforts.

The rest of this chapter is organized as follows. Section 1 discusses the background of the study including poverty and vulnerability to poverty in Ethiopia; the nexus between poverty, vulnerability to poverty, inequality, and input risks; statement of the problem; and the objectives of the thesis. It also reviews related literature. Section 2 discusses the data and the methodology used in each chapter in detail. Section 3 presents the summary and conclusion of the thesis; it summarizes the findings of each chapter and draws conclusions based on these findings.

1.1 Background of the Study

Ethiopia is the fastest growing economy in Africa. Currently the country's main challenges are poverty reduction and sustaining its economic growth. Ethiopia has designed and implemented a series of poverty reduction programs and strategies. The Sustainable Development and Poverty Reduction Program, the Plan for Accelerated and Sustained Development to End Poverty and the First Growth and Transformation Plan are some of the programs that it has implemented so far. Ethiopia experienced an average growth rate of 10.3 percent from 2007 to 2017 and is aiming at reaching the lower-middle-income status by 2025 (MoFED, 2015). The country is also implementing the second Growth and Transformation Plan (GTP II) which will run till 2019-20. Ethiopia aims to expand its physical infrastructure through public investments and transforming its economy into one that is dominated by the manufacturing sector.

However, though it has achieved economic growth over the past ten years, like the other African countries Ethiopia too still has a high poverty rate. Poverty rates in other African countries show that about 50 percent of the African population is poor (Fosu, 2008) and the poverty headcount ranges from 32 to 78 percent. In Ethiopia agriculture, construction, and the services sectors accounted for most of the growth and national poverty decreased from 30 percent to 24 percent from 2011 to 2016. The monetary poverty line is used to assess the poverty status of households; however, there are arguments against using this poverty line in measuring poverty because the monetary measure ignores many overlapping deprivations faced by people living in poverty. In literature, there is increasing agreement about the importance of poverty measures to reflect the multidimensional nature of poverty (Alkire and Sumner, 2013; Maasoumi et al., 2015).

In most developing countries, poverty reduction policies focus on people or households that are currently poor and ignore those who are likely to become poor. Poverty analyses have shown detailed profiles of the poor to understand the incidence or depth of poverty. But poverty to a large extent is a stochastic phenomenon as poor households today may or may not be poor tomorrow and non-poor households today may become poor in the near future because of some adverse shock. A poverty analysis is an ex-post measure of households' well-being which does not measure households' vulnerability to poverty. For the purposes of formulating policy, the most important measure is vulnerability to poverty. The most effective way of ensuring households' economic well-being is preventing them from falling into poverty. Vulnerability to poverty is essential for poverty reduction efforts. Therefore, policies designed to reduce poverty should consider those households which are vulnerable to poverty along with poor households. Poverty and vulnerability to poverty are closely related concepts and poverty reduction strategies need to consider not just poverty alleviation but also poverty prevention. In Ethiopia, expected poverty (vulnerability) is much higher than the point in time estimates of poverty (Fekadu, 2013; Negassa et al., 2014). Hence, vulnerability to poverty has to be of concern in Ethiopia. This research studied vulnerability to poverty both from a unidimensional and a multidimensional perspective and provides a detailed account of vulnerability to poverty in Ethiopia.

Many developing countries' economies are growing; economic growth is essential for improving the living standards of the people and it also helps in reducing poverty and vulnerability to poverty. Income distribution determines the impact of poverty reduction on growth and there are considerable variations in this among sub-Saharan African (SSA) countries (Fosu, 2008). Equitable distribution of income, resources, and wealth increases the rate at which growth can reduce poverty. According to Fentaw et al., (2016), in 2015 the urban consumption Gini coefficient which was 0.334 is less than the national Gini coefficient of 2010-11 (0.371). It is very important to consider inequalities along with growth and poverty reduction efforts in a country to make growth sustainable and ensuring that everyone enjoys the fruits of economic growth.

Ethiopia is fundamentally an agrarian country and agriculture which dominated by subsistence agriculture is predominantly rain-fed. Risk is inherent in subsistence agricultural production leading to vulnerabilities because of uninsured exposure to different risks (Guan et al., 2017; Sarker et al., 2016) as weather conditions change; prices at the time of harvest could drop; fertilizer application may not be on time; and government policy can change overnight forcing farmers to take decisions under risky conditions. These risk factors that affect farmers' decisions cannot be predicted with complete certainty (Kahan, 2008). Further, households are exposed to only a few risk coping strategies such as social insurance programs related to crop failures, unemployment, and sickness. In many developing countries insurance markets are not well developed and production risks play a critical role in use of farm inputs (Dercon et al., 2007). Some of the risk factors like changes in weather conditions are beyond the control of the farmers but they can control the others if they are aware of them. There are tools available to farmers to manage production risks (Chuku and Okoye, 2009) as they can use optimal farm input levels to reduce farm production risks thus increasing their farms' efficiency (Ligeon et al., 2013).

1.1.1 Poverty and Vulnerability to Poverty

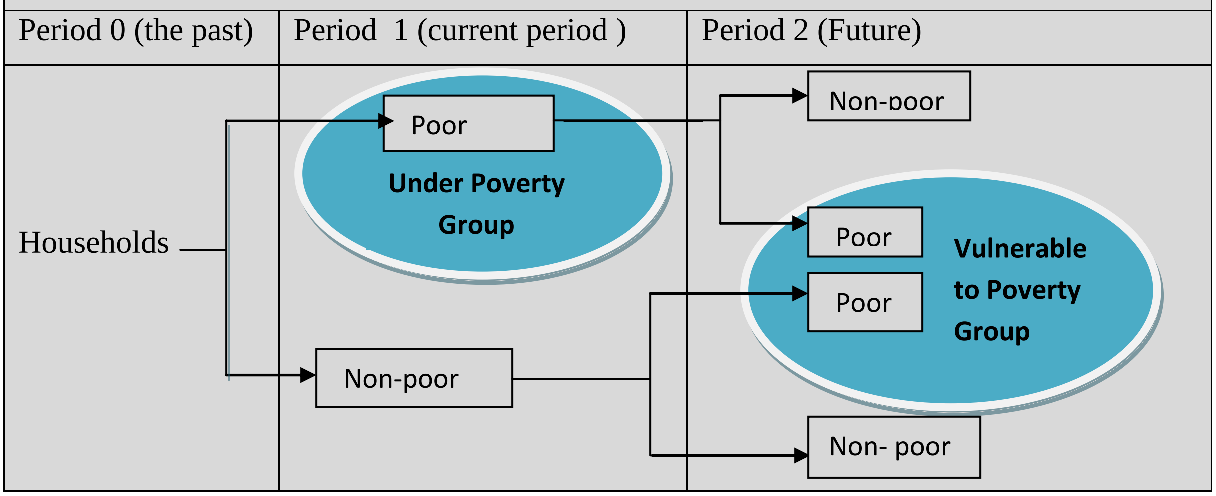
Ethiopia had an average annual economic growth rate of 11 percent from 2005-06 to 2009-10, with annual per capita income growth of 8 percent. As a result, absolute poverty and food insecurity declined by around 10 percent during this period (MoFED, 2010). However, despite this economic growth it still had severe poverty which was also more pervasive (MoFED, 2008). The Ethiopian economy is characterized by traditional, rain-fed, and subsistence farming which is extremely vulnerable to many shocks. Hence, people suffer from extreme poverty and are vulnerable to poverty. There is high poverty prevalence in rural Ethiopia and according to Bogale et al., (2005) nearly 40 percent of the sample households lived below the poverty line in 2000. These authors also argued that rural poverty was strongly linked to entitlement failures such as lack of household resource endowments of crucial farming assets such as land and oxen. Hence, there was a need to analyze and understand conceptual and methodological issues of poverty and vulnerability to poverty (Baulch and Hoddinot, 2000).

Poverty can be viewed as income poverty but there are other dimensions which determine the well-being of the people. Following a multidimensional approach is more comprehensive as it gives a holistic picture of the extent and depth of poverty and vulnerability to poverty in developing countries. The notion of poverty is described and measured in different ways by different institutions and indicators of poverty also differ based on the type of poverty (unidimensional or multidimensional) and the number of indictors included. Poverty is the state of being without the basic necessities of daily living which can be measured based on a particular threshold (poverty line). For some, poverty is subjective and relative and can be viewed or assessed relative to the society in which a household lives. Poverty is not only deprivation of material resources but also a violation of human rights, feelings of powerlessness, and insecurities.

Poverty is a description and measure of current poverty status of households or society; in contrast vulnerability to poverty gives a forward-looking perspective on what might happen if the households are exposed to a certain hazard (Cannon et al., 2003). Vulnerability is more difficult to measure and monitor than poverty. The linkages between vulnerability and poverty (Figure 1.1) have been a subject of discussion based on the objectives of the studies that consider them. Vulnerability is usually considered as a part of poverty. Some authors see vulnerability as one aspect which can lead to poverty or hinder people from escaping poverty. The inclusion of vulnerability in analyses of poverty has resulted in poverty not only being measured as income poverty, but also being measured within the framework of well-being which takes a comprehensive view of the livelihood of the people. Prowse (2003) explains the poverty-vulnerability linkage and discusses the mutually reinforcing nature of poverty and vulnerability to poverty. Vulnerability is generated by multiple processes (Eriksen et al., 2007). First, vulnerability represents poor people's exposure to risks that are much broader than simply being a threat to their lives or lack of secure well-being. Second, vulnerability is people's capacity to cope with and adapt to these risks. Third, vulnerability includes personal, social, and environmental characteristics that exacerbate or reduce risks and limit households' adaptive capacities.

Some authors claim that we can view vulnerability to poverty as risk and/or social and political factors which are important for understanding the link between poverty and vulnerability. The risks highlight transient poverty. Poorer and disadvantaged groups are exposed to different kinds of risks or disasters and have fewer resources to cope with them. The poorer people also have low political and social positions in society and hence have a smaller role to play in the social and political conditions in the country. Being poor reduce households' risk coping capacities and reduce their social and political participation; hence, the poor are more vulnerable to poverty than the rich.

Figure 1.1. Households in poverty and vulnerable to poverty groups in different periods (periods 1 and 2)



Source: Author's interpretation.

Vulnerability to poverty is described as the reasons for people or households' entering poverty or chronic poverty. Vulnerable to poverty focuses on the transient poor and does not focus on those already in poverty (chronically poor). In Sri Lanka, the degree of instability in financial assets and vulnerability to externalities forces the poor to remain poor for long periods implying that vulnerability to shocks is a major reason for chronic poverty in the country (Tudawe, 2002). However, Okidi and Mugambe (2002) argue that vulnerability to shocks is not just a reason for being in poverty but that it is also a symptom of poverty. This is also highlighted by Baulch et al., (2000) who state that households with greater endowments and greater returns but which are vulnerable to shocks are likely to be poor. Their study focuses attention on the mutually reinforcing nature of poverty and vulnerability to poverty.

1.1.2 Inequalities in Ethiopia

One of the Sustainable Development Goals (SDGs) is reducing income inequalities as economic inequality is increasing within countries (Milanovic, 2013). Measuring income inequalities and other welfare indicators has been an area of great interest for statisticians and economists (Idrees and Ahmad, 2017). Authors have also emphasized the causes and consequences of inequalities in developed and developing countries (Alvaredo and Gasparini, 2015). In recent years, there has also been an interest and a debate around exploring the types, size, and economic implications of income inequalities and their impact on poverty reduction and economic growth (Bakare, 2012). In the 18^{th} century, inequality measures like range and mean deviation were used for measuring income inequalities while some specific inequality measures were proposed in the 19^{th} century. Following these inequality measures, Dalton (1920) linked inequality to economic welfare and from there started the idea of having normative inequality measures.

Kuznets (1955) proposed an inverted U-shaped relationship between a country's level of income growth and its level of inequality. According to him, growth led to an increase in income inequalities in the initial stages but at the last stage of economic development inequalities decreased. Most people in developing countries live in rural areas and are engaged in traditional agriculture which is less productive and therefore provides lesser incomes. Since the industrial sectors are located in urban areas, rural people migrate to urban areas looking for better jobs and finally inequalities decrease. Piketty (2014) supports Kuznets' idea and clarifies that during the initial stages of economic development only the minority benefits from the new wealth creation but later inequalities automatically decrease as a larger proportion of the population participates in the fruits of economic growth. Fekadu (2009) studied inequality using cross-sectional data and supports Kuznets' curve because he found that initially inequalities increased but they decreased as the country's economic growth increased. Studies such as those by Bourguignon (2003) do not agree with the Kuznets' inverted U-curve and argue that there is no systematic relationship between inequalities first increasing and then decreasing because of economic growth. Even if there is a relationship, it is country specific. Studies have also challenged the Kuznets' curve maintaining that it fails to hold when several Latin American countries are not included in the analysis (Palma, 2011).

Existing literature stresses the importance of the multidimensionality of well-being in measuring inequalities (Lugo, 2007; Weymark, 2006). Different indices of inequalities measuring the degree of heterogeneity of well-being exist. Recently interest in multidimensional inequality has grown and studies are looking at multiple dimensions of well-being simultaneously by considering how these attributes differ across households. In its inequality analysis the World Bank (2013) stated that in Ethiopia, economic growth was accompanied by an increase in urban inequalities; however, the inequality coefficient remained stable in the rural areas of the country. Woldehanna et al, (2008) showed that there was a significant increase in urban inequalities in Ethiopia while inequalities remain unchanged in the rural areas. Their research also showed that in rural Ethiopia consumption increased and this increase led to a reduction in headcount poverty; however, the effect of economic growth on poverty reduction differed among the regions.

1.1.3 The Growth, Poverty, and Inequality Nexus

The relationship between growth, poverty, and inequality has been one of the most controversial topics in development economics (Shorrocks et al., 2004). The debate on the correlation between growth, poverty, and inequality has a long history and goes back to Ricardo and Malthus (Maasoumi et al., 2013). According to Maasoumi et al. (2013) while some believe that economic growth benefits the poor and reduces the incidence of poverty others consider growth as ultimately detrimental to the poor; some others hold a position between these two extremes. Bourguignon (2003) and Marinko and Romina (2016) stated that variables of poverty, inequality, and growth interact with each other. The very essence of economic growth is improving the living conditions and welfare of the population. However, the link between growth and welfare gains and the link between growth, poverty, and inequality is not always clear. Growth is the central issue in development economics and it is the main driver of poverty reduction. Growth has to be sustainable and inclusive to be able to deliver the best outcomes including poverty reduction. Inclusive growth requires addressing poverty and inequalities both. It also requires drawing clear relationships between growth, poverty, and inequality. According to Bourguignon (2004) a change in poverty is a function of growth, redistribution, and a change in the distribution of incomes. He adds that growth affects income distribution in different ways. First, there are changes in income because of growth (growth effect) and second there are changes in relative income (distribution effect).

The positive correlation between economic growth and poverty reduction has been observed by many authors in different countries (Maasoumi et al., 2013; Marinko et al., 2016; Ravallion, 2001; Sachs, 2005). According to Maasoumi et al. (2013) there is an inverse relationship between growth and poverty and its empirical application in Iran confirmed an inverse association between the two. However, there is no general consensus among economists on this issue because the impact of economic growth on poverty reduction depends on income distribution. Economic growth benefits the rich more than the poor as the rich save and invests more than the poor, implying that a higher degree of initial inequalities result in higher aggregate savings, capital accumulation, and growth. Hence, economic growth results in an increase in inequalities. However, if economic growth benefits the poor more than the rich, then economic growth will result in a decrease in income inequalities. Therefore, the relationship between economic growth and income distribution is critical for poverty reduction. The importance of growth and inequality in poverty reduction has also been growing (Ali et al., 2000; Easterly, 2000; Fosu, 2008). Studies have documented that economic growth is a pre-requisite for poverty reduction efforts but the initial level of inequalities and how these inequalities change over time are the primary factors which determine why there are different rates of poverty reduction at a given rate of growth (Alexander, 2015). Poverty has been hypothesized to negatively affect growth through under-investments in human capital (education and health) and physical capital leading to lower growth. These under-investments are a result of lack of resources (poverty). This argues for looking at poverty as one factor which may hinder economic growth.

Ostry et al., (2014) argue that there is some consensus in literature that inequalities affect growth as they tend to reduce growth's pace and durability. However, there is no general and clear consensus on the relationship between income, inequalities and growth. In most developing countries, some groups are marginalized because of certain identities such as gender, race, ethnicity, religion, and language. These excluded groups are denied opportunities consistently. Economic inequalities are often found in conjunction with these social inequalities which interact with and mutually reinforce inequalities (The World Bank, 2013). Greater inequalities might be good for growth as greater income inequalities redistribute income to the rich who save and invest more in productive activities. However, this shows that growth in an economy is at the cost of high inequalities. There are different ways in which inequalities effect economic growth (Stiglitz, 2012).

First, inequalities lead to weak aggregate demand because the poor spend a larger proportion of their incomes than the rich. Second, inequalities of outcomes are associated with inequalities of opportunity. When the poor or those at the bottom of the income distribution are at risk of not living up to their potential, the economy experiences weaker demand today and lower growth in the future. Third, it is not surprising that public investments are lower in countries with higher inequalities. Societies with greater inequalities are less likely to make public investments which enhance productivity such as investments in infrastructure, technology, and education.

Economic growth can modify the distribution of income and welfare through many channels. It modifies the distribution of resources, relative prices, and factor endowments of agents and these changes are likely to impact the distribution of income directly regardless of whether factors and goods' markets are perfect or not (Bourguignon, 2004). Distribution matters for poverty reduction and distributional changes may also be responsible for sizable changes in poverty due to growth (Bourguignon, 2004; Rohwerder, 2016). Some empirical research indicates that there is no clear relationship between growth and inequality (the incomes of the poor tend to rise with an improvement in growth). However, other studies have found a strong relationship between growth and inequality. There is consensus that during economic growth high inequalities reduce the rate at which the incomes of the poor increase in relation to that of the rich. So, growth cannot benefit the poor and the rich equally when there are high inequalities (Alexander, 2015). As compared to the poor, the rich save a bigger share of their incomes and consume smaller shares of their incomes implying that the rich people's marginal propensity to save is higher than that of the poor, suggesting that a higher degree of initial inequalities exacerbate inequalities in society.

Since the 1980s the poverty rate has been decreasing worldwide except in sub-Saharan Africa (SSA). Hence, SSA countries require special attention (Fosu, 2008). There are wide differences in the responsiveness of poverty to growth in SSA and the emphasis placed on growth relative to income distribution differs across SSA countries (Fosu, 2008). A cross-country analysis of growth, poverty, and inequality by Ali et al., (2000) found that poverty responded more to income distribution than to growth and that poverty reduction due to improved income distribution was more than it was when there was an increase in growth.

For effective poverty reduction, inequalities should also be given due attention along with growth to increase the welfare effect of growth.

In Ethiopia, poverty reduced by 31 percent between 1981-95 due to economic growth but it increased by 37 percent because of changes in the distribution of income and the net increase in the level of poverty during this time was about 6 percent (Bourguignon, 2004). Bourguignon adds that this is not so in all countries, for example, the opposite is true in Indonesia where reduction in poverty due to the growth effect was greater than the increase in poverty due to the distribution effect. Regional inequalities are large and the heterogeneity of regions suggests a differentiated approach across countries. Prospects for reducing poverty and vulnerability are crucially dependent on countries' abilities to accelerate economic growth and improve the quality of their education, healthcare, redistribution of income, and public infrastructure (The World Bank, 2005). Achieving these will require stepping up efforts to complete institutional and policy reforms. Absolute poverty reduction requires strong, country-specific growth and distribution policies.

Poverty and inequality have a negative impact on growth. As Stiglitz (2013) argues, inequalities undermine the institutions that distribute well-being in society. There is new focus on the relationship between inequalities and economic growth (Cingano, 2014; Ostry et al., 2014). Ostry et al., (2014) found that lower inequalities were correlated with faster economic growth. They also found that more unequal societies redistributed more, but this redistribution did not have a significant effect on economic growth. Cingano (2014) also showed that an increase in inequalities had a negative impact on economic growth and inequalities interacted with human capital to impede growth. The relationship between inequalities and economic growth has been studied over the years but the results are ambiguous. Empirical literature on economic growth and inequalities (Cingano, 2014; Halter et al., 2014) partly reflects on the fact that inequalities have a negative impact on economic growth and inequalities are irrelevant for economic growth while some studies find a positive relationship between the two.

There is a general assumption that growth will increase incomes across different income groups and reduce poverty (McCulloch, 2003; Partridge and Rickman, 2008). This view is also supported by empirical evidence. Dollar et al., (2013) point out that economic growth significantly reduced poverty. But there is increasing concern that the benefits of economic growth are not shared equally (OECD, 2014). The poverty reduction impact of economic growth depends on the initial level of income inequalities (Ravallion, 2005). If income inequalities are low, a 1 percent economic growth can reduce poverty up to 4.3 percent but in countries with high income inequalities the same 1 percent growth will reduce poverty only by 0.6 percent.

1.1.4 The Poverty, Vulnerability to Poverty, Risks, and Inequality Nexus

Poverty, vulnerability to poverty, and inequality are complex (Ravallion, 2001) and controversial subjects in developing economies. Poverty measures depend on the poverty line or on the average level of income or consumption and focus on individuals or households at the bottom of the distribution. Inequality is a broader concept than poverty and is concerned with the distribution of income, resources, and wealth in society and is defined for the entire population. Empirical research increasingly indicates that in many countries, low income inequalities appear to enhance the impact of economic growth on poverty reduction but when income inequalities increase, economic growth is less likely to help reduce poverty. Vulnerability and insecurity continue to affect millions of people worldwide. Since vulnerability is the state of the households at some point of time in the future it is more difficult to measure and monitor than income poverty and inequalities.

There are links between poverty and inequalities which help determine the incidence and depth of poverty; poverty measures can assess the size of the income distribution among the poor. Some measures incorporate special concerns for the poorest of the poor and are sensitive to inequalities among the poor. This sensitivity takes the form of including a measure of inequality for the poor (poverty depth) within the measure of poverty. Thus, to measure and understand the many dimensions of poverty, one must have a clear understanding of the inequality measures (Foster et al., 2013). Poverty focuses on deprived agents and there is concern only for those who are deprived, with incomes below the poverty line. Vulnerability is about households' likelihood of falling into poverty and is future focused. Sources of vulnerability to poverty are high exposure to risks and low or lack of abilities to cope with risks and shocks.

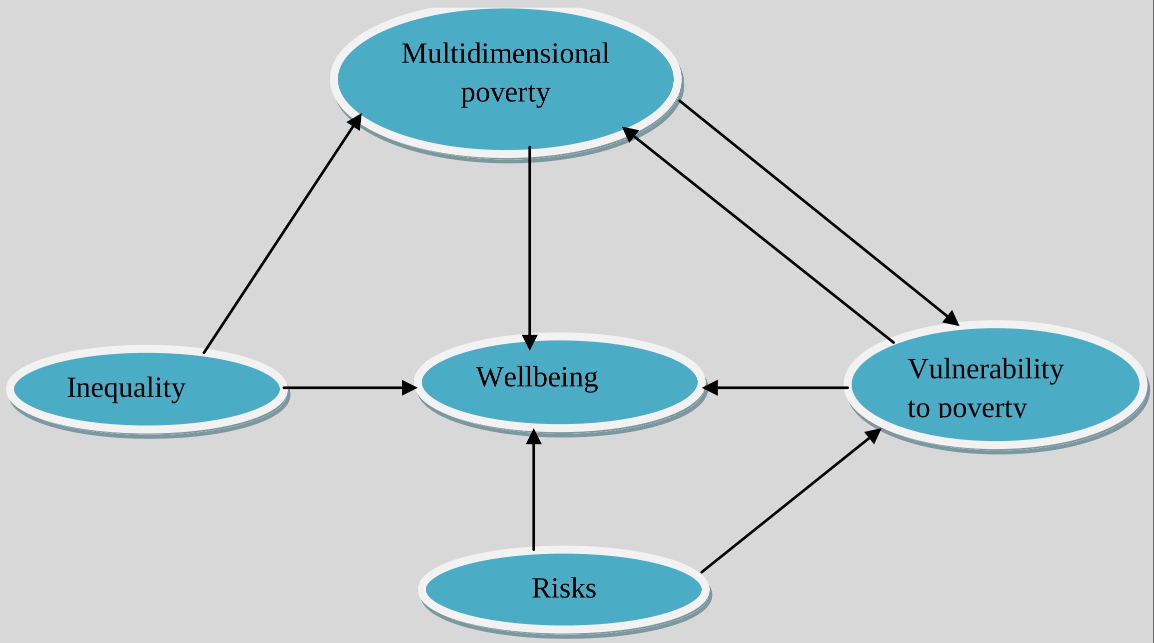
Since, poverty, vulnerability to poverty, and inequality affect the well-being of society their relationship is best explained using well-being (Figure 1.2). The capability approach is about a normative framework for the evaluation and assessment of individual well-being (Ingrid, 2005). It can be used for evaluating several aspects of people's well-being such as poverty and inequality, implying that inequality and poverty are aspects of well-being. The well-being of an individual or the average well-being of members of a group can also be explained or assessed using the capability approach. According to this approach, well-being should be conceptualized in terms of peoples' capabilities to function. These beings and doings, which Sen (1976) calls functioning, together constitute what makes a life valuable. Functioning includes working, being literate, being healthy, not being poor, not being vulnerable to poverty, being respected, and so forth. What is ultimately important is that people have freedom or valuable opportunities (capabilities) to lead the kind of lives that they want to lead (functioning). Being out of poverty or vulnerability is conditional on having capabilities for functioning or well-being. Having equitable distribution of incomes or capabilities in an economy, in general, is a means for achieving well-being. Well-being is a multidimensional concept focusing on three important dimensions of life: standard of living, health, and education (Decancq et al., 2006) and therefore, inequalities in these three dimensions show the extent of inequality in well-being. Multidimensional poverty and vulnerability to poverty are complex and multifaceted concepts that are interlinked in such a way that each causes the other, that is, while poverty makes people vulnerable to various shocks such as droughts, diseases, and other natural disasters, vulnerability to such shocks exacerbates poverty and hence vulnerability to future shocks.

One of the greatest challenges to development facing the world today is the elimination of poverty and vulnerability to poverty through raising income levels and reducing income inequalities (Gerald, 2012) because societies that are characterized by high levels of inequalities, poverty, and vulnerability are perceived as lacking the potential needed to get out of under-development. Recent heightened interest in studying poverty, inequalities, and vulnerability calls for a more robust and expanded empirical investigation of the interaction mechanism that drives them. However, a review of empirical literature provides insufficient evidence of the existence of the interaction and effect of one variable on the other. Inequalities matter for poverty. For a given average income, education, health, and land ownership any increase in inequalities in these characteristics implies higher levels of relative deprivation in these dimensions of multidimensional poverty. Poverty is not only about poor people but also about the social and economic inequalities that compound and reproduces poverty.

Mussa (2010) explored the direct relationship between poverty and inequality which ran from inequality to poverty. Using data from the second integrated household survey (HIS2) he investigated the poverty impact of changes within and between inequalities in Malawi. His results showed that the elasticity of poverty with respect to within region consumption inequalities was positive and higher than that of between region inequalities, suggesting that a reduction in inequalities in household consumption had a higher poverty reducing impact. He also found that between-region inequalities in health had a larger and positive effect on the health poverty headcount; on the other hand, within-region inequalities in health had a larger and positive relationship with the health poverty gap and severity. An increase in both within and between region educational inequalities reduced the education poverty headcount but increased the education poverty gap and severity.

The World Bank's (2005) World Development Report encapsulated one aspect of this link in the phrase 'inequality traps,' meaning that inequalities are self-reinforcing and hampering poverty reduction. Absolute poverty focuses on those whose incomes are below the poverty line but relative poverty is related to income distribution or inequalities and hence poverty and inequality are usually studied simultaneously (Fentaw et al., 2016). The research also added that an increase in inequalities increased poverty but income growth reduced the level of poverty in Ethiopia.

Figure 1. 2 Poverty, vulnerability to poverty, risks, and inequality relationships



Source: Author's interpretation.

1.1.5 Statement of the Problem

Poverty is pervasive and deep-rooted in Ethiopia. Poverty and vulnerability to poverty reduction are one of the top priorities of the country and are also one of the SDGs. Most research done on poverty, vulnerability to poverty, and inequality is unidimensional (consumption or income based) and overlooks other dimensions of well-being. There are few aggregate multidimensional indices but they are aggregate at the country level and hide the diversities within the country. Hence, a multidimensional poverty, vulnerability to poverty, and inequality analysis considering all these diversities is very essential. A rigorous multidimensional poverty analysis considering current regional conditions and using current data highlights the nature and depth of poverty and vulnerability to poverty and helps design appropriate poverty reduction policies.

Most multidimensional poverty, vulnerability to poverty, and inequality indices applied to Ethiopian data are aggregates except some regional multidimensional studies in Tigray, Oromia, and Amhara. Ethiopia is a country of great diversity (Fekadu, 2013). For example, South Nations and Nationalities (SNNP) is the most diversified region in many dimensions such as culture, ethnicity, the farming system, and land conservation practices. A multidimensional poverty analysis taking into account the diversities highlights poverty reduction intervention areas and policy directions. Other countries' experience also shows this. Tran et al.'s (2015) study in Vietnam showed that ethnic minorities suffered particularly from income shortfalls, presumably related to their remote locations and the disadvantages that they suffered while non-income dimensions appeared to partly make up for these shortfalls. Poverty and vulnerability to poverty are inter-related concepts and poverty measures the current poverty level in the country but vulnerability to poverty assesses the likelihood of a household being in poverty in the future making it forward looking. Risks are inherent in agricultural production and people in developing countries are vulnerable to poverty because of such risks. Farm households are exposed to many risks while risks in developing countries include natural, price, and production related ones. Most households in Ethiopia are engaged in subsistence traditional agricultural production and face low risk coping capacities because of low income levels in the sector. However, producers have better capabilities for reducing production risks than reducing natural and price risks in their farm production processes. This research examines smallholder farmers' input risks and identifies the types of risks that farmers face and the risk reducing strategies that they use to face these risks.

Income inequality is highly observed in most part of the developing economies and income and wealth seem to be un-evenly distributed (Bakare, 2012). Some people are rich whose living standards are relatively high and have access to the basic needs of life such as balanced diet and convenient shelter while others are very poor who are struggling to survive with less than a dollar a day. Income inequality can be considered in relation to other interrelated factors such as education, health and other living standards (Bekare, 2012). Poverty, vulnerability to poverty and inequality are multidimensional and can be examined using households' wellbeing. Multidimensional wellbeing is not a new idea, capability and functioning by Sen (1976) is among the pioneers to conceptualize multidimensionality of wellbeing (Sial et al., 2015). This thesis also shows how poverty, vulnerability to poverty, agricultural input risks and inequalities are interrelated and forwards possible solutions to reduce the existing poverty, vulnerability to poverty and inequality in the country.

Research Questions

Based on an analysis of the nexus between poverty, vulnerability to poverty, production risks, and inequalities and available data and conditions in Ethiopia the following research questions are formulated and analyzed:

i. What is the status of poverty incidence, intensity, and the multidimensional poverty index in the country and its various regions?

ii. Is there a difference between income poverty and the multidimensional poverty index in Ethiopia and its regions? What are the determinants of multidimensional poverty and deprivation?

iii. Are households in Ethiopia vulnerable to poverty? Does vulnerability to poverty vary across regions and different income groups?

iv. How is the extent of inequality in the country related to income, education, health, assets, land, and other indicators of living standards?

v. Which agricultural inputs used by smallholder farmers in Ethiopia are risk increasing and which ones have a risk decreasing impact on crop yields?

1.1.6 Objectives

The main objective of this thesis is examining poverty, vulnerability to poverty, and inequality in Ethiopia and the resulting inequalities in the different regions and identifying areas of intervention for reducing poverty, vulnerability to poverty, and inequality in Ethiopia both from unidimensional and multidimensional perspectives. As most households in the country are engaged in agriculture which faces risks related to agricultural inputs, this research examines agricultural input risks of smallholder farmers. The specific objectives of the study are:

- Assessing the extent of poverty in Ethiopia and identifying poor people using the one-dimensional and multidimensional approaches to be able to formulate appropriate interventions.
- Identifying the dimensions or factors that contribute more to households' poverty and identifying the interventions required for reducing poverty levels.
- Assessing the incidence and depth of multidimensional poverty in different regions using the multidimensional poverty index, considering the cultural and ethnic diversity of the regions.
- Examining rural people's vulnerability to poverty in different regions using different measures of poverty indicators such as income and consumption.
- Identifying the extent of multidimensional inequalities in Ethiopia and highlighting inequality reducing intervention strategies.
- Assessing production input risks associated with smallholder farmers and identifying which inputs are risk increasing and suggesting risk reducing inputs.

1.2 Data and Methodology

1.2.1 Data

This thesis uses the Ethiopian Demographic and Health Survey (EDHS) and data from the Household Consumption and Expenditure Survey (HCES) for a unidimensional and multidimensional poverty analysis respectively. DHS is cross-sectional data collected in Ethiopia almost every five years. This thesis uses four rounds of DHS data collected over years. The first round was in 2000; the second in 2005; the third in 2011; and the most recent in 2016. HCES has been conducted since 1995-96 at four or five-year intervals. The 2015-16 HCES is the fifth and the most recent survey in the series. DHS and HCES are comprehensive datasets that consist of samples from all regions in the country which represent the national population. DHS data contains information on household characteristics, households' dwelling units such as sources of water, types of sanitation facilities, access to electricity, and type of cooking fuel. The data also contains household members' level of education, children's school attendance, child health, child mortality, maternal mortality, and the nutritional status of household members.

This thesis uses HCES data in an analysis of unidimensional vulnerability to poverty. The survey provides income, expenditure, and other socioeconomic data at the household level which is useful in an analysis of vulnerability to poverty. HCES is a complex survey which uses a nationally representative sample to characterize important aspects of households' socioeconomic conditions. The primary purpose of the survey is providing information for monitoring poverty and measuring national accounts and consumer price indices. The household based questionnaire provides information on basic characteristics such as sex, age, household size, marital status, education, and employment. It also includes households' food and non-food consumption as well as quantities consumed and their values. Non-food consumption items include cigarettes, alcohol, clothes, household durable goods, transport, health, and education. For the vulnerability to multidimensional poverty analysis, this thesis uses EDHS data for 2011 and 2016. The sample was selected using a stratified; two-stage cluster design while enumeration areas (EAs) were the sampling unit for the first stage and households comprised the second stage of the sampling.

Since the DHS data has no income variable, we used HCES data for an analysis of unidimensional income inequalities. This survey uses a nationally representative sample to characterize important aspects of households' socioeconomic conditions. In Ethiopia, like in many other poor countries, where the main concern is fulfillment of basic needs it is more important to measure inequalities in the consumption expenditure as income data is not easily available and if available it is not reliable. So, in the multidimensional inequality analysis this thesis uses DHS data for an analysis of multidimensional inequalities and HCES data for an analysis of unidimensional inequalities.

The data used for the last chapter is obtained from the Ethiopian Rural Household Survey (ERHS). The data includes household characteristics and information about agriculture and livestock. For this research, we took four rounds of ERHS data collected in 1995, 1999, 2004, and 2009 as a repeated cross-section. Cereal crops constitute a major portion of the total agricultural production in the country. For this study, out of the total annual crops produced in the country, 12 crops were selected based on their share in the country. The last ERHS data was collected in 2009. Hence, for more recent information we used the Ethiopian Living Standard data for 2015. The data has enough information about farm inputs and outputs which enable us to do mean and variance estimations to get a picture of farm input risks.

1.2.2 Methodology and Applications

1.2.2.1. Multidimensional Poverty

We use the Alkire-Foster method of multidimensional poverty analysis for an analysis of multidimensional poverty. The first step in this approach is identifying the dimensions and indicators of the multidimensional poverty index (MPI). There is no fixed list of what should be included in MPI (Ravallion, 2011) but the most important thing is the process through which the components are selected (Alkire et al., 2011). The indicators were selected after consultations with experts on all the three dimensions (Alkire et al., 2011). The choice of the indicators had to be reconciled with data availability. We used three dimensions and ten indicators suggested by Alkire and Foster (2011). The three dimensions are - health, education, and living standards. The health indicators were selected based on internationally agreed measures of health and the data available. Child mortality and nutrition status of household members were the health indicators. A household is considered to have child mortality if there has been at least one child death in the household. Child malnutrition can have a lifelong effect in terms of cognitive and physical development (Sawaya, 2006). Children are considered malnourished if their standard score is less than -2 for their age and a household is considered health deprived if there is at least one adult person in the household whose body mass index (BMI) is less than 18.5.

Two indicators (year of education and child school attendance) are used for representing the education component of MPI. If we observe at least one member in the family with six or more years of education, then we classify the household as non-deprived. The second indicator is child school attendance. If any school attending child has dropped out of school for at least one or more years, the household is considered deprived. Living standards is the third dimension in the analysis of multidimensional poverty. The indicators of living standards that are used include access to electricity, sanitation facilities, cooking fuel, drinking water, floor material, and asset ownership. Households with access to electricity, sanitation facilities, and cooking fuel are considered non-deprived. Households with access to water from an unprotected well, unprotected spring, water provided by carts with small tanks/drums, and water provided by tanker trucks or surface water taken directly from rivers, ponds, streams, lakes, dams or irrigation channels are considered as deprived. A household is also deprived of drinking water if the source of water is more than 30 minutes walking distance (round trip). Households using soil, sand, dung, wood planks, and reed/bamboo are deprived of floor material, whereas households using floor material such as cement, tiles, ceramic, bricks, and carpet are classified as non-deprived. The other living standard indicator is related to asset ownership; in the analysis of multidimensional poverty assets related to living standard indicators are divided into three asset categories: information, mobility, and livelihood. A household is not deprived in assets if it owns at least one of the assets in two or more asset categories.

In the multidimensional poverty analysis, the deprivation and poverty cut-offs are specified. A deprivation cut-off vector $z = (z_1, \dots, z_d)$ is used to determine whether a household is deprived in that indicator. If the household's achievement level in a given dimension j falls short of the respective deprivation cut-off zj, the household is said to be deprived in that indicator and will have a value of 1. If the household's level of achievement is at least as large as the deprivation cut-off, the household is not deprived in that indicator and will have a value of 0 in that indicator. Finally, we have a deprivation score matrix of $(n \times d)$ dimensions with a value of 0 and 1. After identifying the indicators, a weight has to be assigned to each indicator (Berenger and Verdire_Chouchane, 2007). Weights play a crucial role in aggregation (Decancq and Lugo, 2008). For this, the equal weights approach can be used (Alkire and Foster, 2011; Atkinson, 2003; Dhongda et al., 2015; Salazar et al.,

2013) but most multidimensional poverty indicators are assumed to be correlated and we need to have weights which consider these correlation relations. Since a factor analysis (FA) model considers the correlation between indicators and reduces redundancy or duplication from a set of correlated variables, we used the factor analysis weighting system to find the weights of the indicators in MPI. Following Nawal and Iqbal (2016) the deprivation score of each household (C_i) is calculated by taking a weighted sum of the deprivations experienced. A household is considered poor if its deprivation score is equal to or greater than the poverty cut-off, $C_i \geq k$. This is represented by the binary variable (y_i) that takes a value of 1 or 0 as:

(1.1) $$y_i = \begin{cases} 1 \; if \; and \; only \; if \; c_i \geq k \\ 0 \; otherwise \end{cases}$$

In MPI, a household is identified as poor if it has a deprivation score greater than or equal to one-third (33 percent) (Alkire and Santos, 2011; OPHI, 2013). MPI is the product of both incidence (H) and severity or depth (A) of multidimensional poverty. There are different household characteristics that determine or affect a household's poverty status (Adetola, 2014; Berenger et al., 2007). To identify the determinants of multidimensional poverty we used the deprivation score as the dependent variable and different household characteristics as independent variables. Since the outcome variable has only two values (binary), we used a logistic regression model which is a limited-dependent variable model to determine the determinants of poverty.

1.2.2.2. Vulnerability to Poverty

Since vulnerability to poverty can be defined as expected poverty, we use vulnerability as expected poverty in this study. Measuring vulnerability to poverty needs to obtain an estimate of a household's expected consumption per capita in the next period and the household's variance in consumption expenditure per capita (Suryahadi and Sumarto, 2003). A vulnerability estimation method using cross-section data was developed by Chaudhuri (2000) and has been used by different authors' (Azam and Imai, 2009; Iqbal, 2013; Novignon et al., 2012). Some information and assumptions are needed to measure households' vulnerability to poverty including a household's expected consumption per capita in the next period $E(C_{t+1})$, variance in the household's expected level of consumption per capita in the next period δ_{t+1}^2, and the poverty line Z. It is possible to arrive at reasonable estimates by building a model of the determinants of consumption. A household's probability of being poor in the future depends both on the mean and variations in consumption expenditure. As done by Chaudhuri et al., (2002) the stochastic process generating household h's consumption is given by:

(1.2) $$\ln C_h = X_h \beta + e_h$$

where $\ln C_h$ is log per capita consumption expenditure and X_h represents a bundle of observable household characteristics. Characteristics' variables include household size, location and the educational attainment level of the household head. β is a vector of unknown parameters to be estimated and e_h is a disturbance term that captures shocks. To have a consistent estimator of the parameter, it is necessary to allow for heteroskedastic variances. Heteroscedasticity allows the variance of e_h to depend on observable household characteristics in some parametric way:

$$\delta^2_{e,h} = X_h\theta \tag{1.3}$$

We estimate β of Equation (1.2) and θ of Equation (1.3) using a three-step feasible generalized least squares (FGLS) procedure suggested by Amemiya (1977); this procedure has also been used by others (Chaudhuri et al., 2002; Novignon et al., 2012; Sricharoen, 2011). Equation (1.2) is first estimated using an ordinary least square (OLS) method and then the estimated residuals from Equation (1.2) are used for estimating the following equation again by using OLS:

$$\hat{e}^2_{ols,h} = X_h\theta + \eta_h \tag{1.4}$$

The estimation from Equation (1.4) is then used to transform the equation and then we can use these estimates to form an estimate of the probability that a household with characteristics X_h, will be poor. Letting Φ (.) denote the cumulative density of the standard normal, the estimated probability will be given by:

$$\hat{V}_h = \hat{P}_r\left(\ln C_h < \ln Z \mid X_h\right) = \Phi\left(\frac{\ln Z - X_h\hat{\beta}}{\sqrt{X_h\hat{\theta}}}\right) \tag{1.5}$$

Equation (1.5) gives the estimation of vulnerability to poverty $\hat{V}_h$ or the probability that the per capita consumption level (C_h) will be less than the poverty line (Z), conditioned on household characteristics (X_h).

Vulnerability to poverty should also be multidimensional. According to Hoddinott and Quisimbung (2003) there is no reason why vulnerability cannot be measured without consumption expenditure that is often used for measuring vulnerability. Feeny and McDonald (2015) also acknowledge that vulnerability can, and should, be expressed with other well-being indicators including health, education, and housing. In estimating vulnerability to multidimensional poverty, the multidimensional deprivation score can be used as a welfare indicator and can be a solution for the inherent limitations of relying on only consumption expenditure in measuring vulnerability to poverty (Feeny et al., 2015). In a country like Ethiopia where a large proportion of the population lives in rural areas and has limited engagement in the formal market, consumption expenditure does not fully reflect these people's welfare to measure households' vulnerability to poverty. Therefore, vulnerability to multidimensional poverty should include other well-being indicators in the analysis to address the inherent limitation of relying on consumption-based measures of vulnerability to poverty. This thesis addresses vulnerability as a multidimensional concept. Equation (1.6) provides a reduced form equation for the household deprivation score (dC_h

), which is used as a well-being indicator in this analysis of vulnerability to multidimensional poverty:

$$dC_h = X_h\beta + e_h \quad (1.6)$$

The deprivation score can be used as a well-being indicator in a multidimensional poverty analysis. Increase in dC_h represents increasing level of destitution in one or more of the three dimensions of deprivation: health, education, and living standards. According to Chaudhuri (2003) and Sricharoen (2011) the errors term in this equation is inter-temporal variance. The usual OLS assumption of constant variance across households is somewhat restrictive. However, this also presumes that the model is fully specified, given that households' experiences of shocks and their responses to these shocks are not excluded which is a somewhat strong assumption.

1.2.2.3. Multidimensional Inequality

An analysis of inequalities has a long history and a plethora of inequality measures and combinations of these are used in different studies. In this study, both unidimensional and multidimensional measures of inequality are used. One-dimensional measures of inequality are the Gini coefficient, Atkinson's measure of inequality, the Theil index, and the Generalized entropy index. There is no consensus on using a single inequality measure in all cases because each inequality measure has its own advantages and limitations. The Gini coefficient is the most widely used measure of inequality in empirical literature which measures the extent to which the distribution deviates from equal distribution. This index also facilitates a direct comparison with any quantitative variables which describe two or more populations regardless of their size. It can, therefore, be used easily for comparing inequalities between groups, regions or countries. The Gini coefficient satisfies the important principles of anonymity, scale independence, population independence, and transfer. One limitation of the Gini coefficient is that it is not additive across groups and most sensitive to inequalities in the middle part of the income spectrum. Because of this and other limitations, the Atkinson and Theil indices are also frequently used as inequality measures in empirical literature.

Atkinson's inequality measure is a welfare-based measure of inequality. It is useful in measuring inequality and it determines which end of the distribution contributes most to the observed inequality. It shows the percentage of total income the society should forego in order to have more equal distribution of income. This depends on the degree of aversion to inequality, the inequality aversion parameter ε measures the social utility gained from complete redistribution of resources. The choice of Atkinson inequality measure relative to the Gini coefficient is guided by subgroup consistency and sensitivity to the inequality of lower tail of the distribution. If inequality increase in one subgroup and remain unchanged in all other groups, then the overall inequality increases but the Gini coefficient does not have this property. Atkinson inequality measure puts more weight to the lower tail of the distribution, but the Gini coefficient put equal weights to the entire distribution. Atkinson coefficient is more appropriate when we are more interested in the lower tail of the distribution such as poverty, child mortality and illiteracy.

The generalized entropy (GE) index is one of the most widely used measures of inequality. The parameter α (α ≥ 0) in this index represents the weight given to distances between income or other values at different parts of the distribution. The most common values of α are 0, 1, and 2. When α = 0 more weight is given to distances at the lower tail of the distribution, that is, GE is more sensitive to changes at this end of the distribution. If α = 1, equal weights are given across the distribution, while α = 2 gives more weight to distances between incomes at the upper tail of the distribution. The GE measure with GE(0) and GE(1) become two of Theil's measures of inequality. In the unidimensional inequality analysis, we use the Gini coefficient, the Atkinson index, and the GE methods to measure inequalities.

Individual well-being is inherently a multidimensional concept. Hence, the inequality measure also needs to be multidimensional. The multidimensional measure of inequality is the Gini pair wise (two indicators at a time) measure of inequality and the Araar (2009) multidimensional inequality index. Any inequality measure of well-being should take this multidimensionality explicitly into account. In this research, we use the most recent multidimensional inequality index – the Araar (2009) multidimensional inequality index -- which satisfies a fundamental set of desired properties. The Araar multidimensional inequality index for the k-dimension of well-being can be formulated as:

(1.7) $$I = \sum_{i=1}^{K} \phi_k \left[\lambda_k I_k + (1-\lambda_k) C_k \right]$$

where I is the Araar multidimensional inequality index, k is the dimensions considered in the multidimensional inequality analysis, and ϕ_k is the weight attributed to each dimension (which can take the same value across the dimension or can take the average value of the well-being dimensions). The parameter λ_k shows the sensitivity to the inter-correlation between different dimensions of well-being. I_k is the relative inequality index of component k and C_k is the absolute concentration index of component k. The index has a more flexible functional form in multi-aspects of social preferences. It satisfies the main desirable properties and allows establishing a complete order for social welfare. The index has understandable components and can be easily interpreted considering its functional form. Moreover, this index is multi-level decomposable by components or dimensions, and by the uni- and multidimensional forms of inequality. MDI is quite sensitive to the choice of parameter λ. Araar (2009) states that the nature of the components used in the analysis determines the size of this parameter. If the components are perfect substitutes for the other set of components, it is appropriate to set λ at zero. But if the components are a perfect complement then λ will converge to one. Setting λ = 0.5 probably leads to reasonable values in the multidimensional inequality measure. In computing this multidimensional inequality we use a two-stage approach. In the first stage, we consider inequalities in living standards (electricity, sanitation, water, floor, cooking fuel, and asset ownership). We follow this approach because we observed that there are large variations or inequalities in the households with respect to these facilities. In the second stage, multidimensional inequality index is estimated using living standard, health and education.

1.2.2.4. Input Risks

Different methodologies have been developed to analyze production related risks. The Just and Pope (1979) production function is a widely used framework in agricultural risk modeling (Guan et al., 2017) and has been used by different authors (Shankar, 2012; Waduge et al., 2014). The Just and Pope stochastic production function is specified as:

$$y = f(x;\alpha)\exp(g(x;\beta)\varepsilon) \tag{1.8}$$

where y is the mean output level, $f(x;\alpha)$ and $g(x;\beta)$ are the mean (deterministic), and the stochastic variance or risk components of the production function respectively. x represents the level of inputs used in the production process, α and β are parameters to be estimated, and ε is the error term whereas $E(\varepsilon)=0$ and $\mathrm{var}(\varepsilon)=\delta_{\varepsilon}^{2}$. A positive feature of the Just and Pope production function is that it separates the mean production function and the variance function of the input level used. The mean output level is represented by $E(y)=f(x;\alpha)+u$, the variance function is represented by $\mathrm{var}(y)=[g(x;\beta)]^{2}\delta_{\varepsilon}^{2}$, and the input level x is assumed to affect both the mean and variance functions.

Since input levels affect both the mean and variance functions, heteroscedasticity is assumed in this production function. The assumption in this model is that the variance of production function (error term) is related to the explanatory variables. The model is heteroscedastic with a known determinate form. Inputs in the production process can be risk increasing, risk neutral, or risk decreasing. The log linear production function allows input elasticity to vary in input levels in both mean and variance functions. The return to scale (RTS) can be estimated (Heshmati et al., 2014) from these log functions since the coefficients are elasticity in the log function form. Variance or standard deviations are used for measuring risks, however, the main problems with using these measures of risk is that they treat fluctuations above and below the mean in the same way. In an agricultural production risk analysis, it is important to distinguish between downside risks and upside risks. Barnwal et al., (2013) point out that the skewness captures the exposure to downside risks; in pig production expenditure for feed and the time length of production reduced both the variation in productivity and downside risks. Since considering downside risks is very important, it is possible to break the variance so that it accounts only for fluctuations below the mean (Elizabeth et al., 2013; Estrada, 2006; Huyen et al., 2016; Mukasa, 2018).

1.3 Summary of the Chapters and Conclusion

1.3.1 Multidimensional Poverty

The first chapter of this thesis covers multidimensional poverty and its dynamics in Ethiopia. It uses DHS data and the Alkire-Foster method of multidimensional poverty analysis for the estimation. It also uses a factor analysis weighting system and the results show that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular. Poverty in rural Ethiopia has been decreasing moderately but in urban Ethiopia multidimensional poverty has been increasing over time. Even though the country is committed to attaining rapid and broad–based growth to end poverty, poverty in Ethiopia has remained high. The multidimensional poverty level was high in almost all regions of the country, in particular in Amhara, Afar, Somali, and Tigray regions in 2000; in Afar, Tigray, Amhara, and Somali regions in 2005; in Somali, Benishangul, and SNNP regions in 2011; and in SNNP, Amhara, Somali, and Afar regions in 2016.

In Addis Ababa, Dire Dawa, and Harari regions the multidimensional poverty was relatively lower. The different regions contributed different shares to multidimensional poverty. For example, Oromia, Amhara, and SNNP regions contributed more to multidimensional poverty whereas the Harari, Addis Ababa, and Dire Dawa regions contributed less to multidimensional poverty compared to their population share. Therefore, regional heterogeneity needs to be considered when designing region-specific poverty reduction policies to speed up regional equalities. Of the dimensions that we use in this multidimensional poverty analysis, living standards contributed the most (46 percent) to multidimensional poverty followed by education and health.

Among the indicators used there was high deprivation in sanitation, cooking fuel, floor material and electricity. Further, deprivations in sanitation and cooking fuel increased over time but educational and school attendance deprivations decreased over time. MPI's comparisons using equal weight and a factor analysis weight system showed that in both the weighting approaches, the contribution of living standards was higher than that of education and health. The results of our logistic model's estimation for identifying the determinants of multidimensional poverty show that as the family size increased its likelihood of falling into multidimensional poverty decreased. As the number of children under-5 and the number of dependent family members increased, a household's probability of being poor also increased. This is mainly because children under-5 and old age family members or dependent family members do not engage in income generating activities. Education makes people more productive and increases their earning capacity which makes them less likely to be poor; this is consistent with other findings (Adetola, 2014; Berenger et al., 2007).

Earnings increase during young ages or economically active ages. Households' probability of multidimensional poverty decreases as age increases. Increase in the age of the household head reduces the household's likelihood of being multidimensionally poor initially, but as age increases beyond a threshold then it increases (Adetota, 2014). Those households which have bank accounts are less poor as compared to those who did not have bank accounts. Households in the countryside, towns, and small cities were poorer compared to households in large cities (the reference area) as their coefficients were positive and significant. Regions in Ethiopia are different with respect to social, cultural, and resource endowments. Hence, poverty reduction policies and implementation strategies need to consider these differences. Regional heterogeneity should be considered when designing region specific poverty reduction policies. Poverty is multidimensional and thus a response to poverty should involve many sectors and stakeholders; collective efforts are the right approach and should be scaled up and practiced more extensively.

This chapter's contribution to literature is that in earlier research having any asset made the household non-deprived. However, in this thesis assets are divided into three categories: information assets, mobility assets, and livelihood assets. A household is not deprived of assets if it owns at least one asset from two or more asset categories. This is a new approach in the empirical use of a multidimensional poverty analysis. This thesis also did a sensitivity analysis by allowing for changes in the weights of indicators and poverty cut-offs and highlights how the choice of the weighting system used in a multidimensional poverty analysis resulted in a different multidimensional poverty index. It examines the correlation coefficient of the deprivation scores of households' in the two weighting systems and the correlation in Ethiopia in general and in rural/urban Ethiopia in particular was large enough to conclude that there was strong rank correlation of deprivation scores of households in the two weighting systems. Thus, the multidimensional poverty analysis is sensitive to the weights attached to the indicators. A change in multidimensional poverty for poverty cut-offs indicates that a decrease in multidimensional poverty was relatively higher for an increase in poverty cut-offs compared to an increase in multidimensional poverty when there was a decrease in poverty cut-offs. We found that the proportion of the multidimensionally poor was less sensitive to downward as opposed to upward revisions in the poverty cut-off.

1.3.2 Vulnerability to Poverty

The second chapter of this thesis covers vulnerability to poverty in Ethiopia. It uses the Households Income and Consumption Expenditure data for a unidimensional vulnerability analysis. This analysis using one common poverty line indicated that in 2016, 31 percent of the population in Ethiopia was under the poverty line. Of these, 50 percent was rural population and 18 percent was urban population. Using a relative poverty line, around 28 percent of the population in Ethiopia was under the poverty line which is less than poverty estimates (31 percent) using a common poverty line. The relative poverty line is different across regions and places of residence. In almost all regions in the country the urban poverty line is more than it is in the rural areas as living costs in urban areas are more than those in rural areas. However, even though the poverty headcount is less, the poverty gap is higher in urban areas as compared to rural areas in the country. In Ethiopia, 31 percent of the population is below the poverty line while 35 percent is vulnerable to poverty. These estimates support the claim that the observed incidence of poverty under-estimates the fraction of the population that is vulnerable to poverty (Azam and Imai, 2009; Dercon and Krishnan, 2000; Raghbendra et al., 2009).

Certain factors or household characteristics affect households' vulnerability to poverty. Households with an older household head tend to have lower consumption per capita with a non-linear effect. A large family size and a high dependency ratio tend to reduce a household's future consumption thereby increasing its vulnerability; this is almost similar to other findings (Edoumiekumo et al., 2013; Novignon et al., 2012; Tu Dang, 2009).

Households with many children and other non-productive family members are on average poorer than households with fewer children and fewer dependent family members. Education has a significant positive impact on the per capita consumption expenditure in this analysis. This basically confirms conclusions reached by other studies that literacy and educational attainments decrease poverty and vulnerability to poverty (for example, Fekadu, 2013; Novignon et al., 2012; The World Bank, 2002).

Female headed households have significantly higher mean future consumption expenditure compared to their male counterparts. Households in big cities and towns tend to have higher expectations of future consumption per capita compared to rural households. There is significant evidence that households in urban areas have lower variance or volatility in their consumption expenditure. Marital status, religion, and profession matter in households' vulnerability to poverty. Married, divorced, separated, and widowed households have lower consumption per capita than never married household heads (the reference group) in Ethiopia and are less vulnerable to poverty. Per capita log consumption expenditure of households who are followers of Catholic, Protestant, Waq feta, and traditional religions is significantly less than that of Orthodox (the reference group) followers. This implies that if we keep all other factors affecting vulnerability constant, followers of Catholic, Protestant, and Waq feta religions are more vulnerable to poverty than Orthodox households. Households differ in their professions and skills, so the less skilled and less professional the household heads, the lower their consumption per capital; these differences are more pronounced in urban than in rural areas in the country.

Multidimensional poverty and vulnerability to multidimensional poverty are very high in Ethiopia. Multidimensional poverty (90 percent) is by far greater than unidimensional poverty (31 percent). In 2016, multidimensional vulnerability to poverty was 86 percent which was almost similar to multidimensional vulnerability to poverty estimates for 2011 (87 percent); however, there was a marked difference in vulnerability to multidimensional poverty between rural and urban areas. In 2011, rural and urban vulnerability to multidimensional poverty was 98 and 58 percent respectively. Similarly, in 2016 rural and urban vulnerability to multidimensional poverty was 98 and 41 percent respectively. There was significant reduction in vulnerability to multidimensional poverty in urban areas from 58 percent in 2011 to 41 percent in 2016 but the overall reduction in vulnerability to multidimensional poverty was very small.

Multidimensional vulnerability increases with family size in Ethiopia in general and in rural Ethiopia in particular. Increase in household head's level of education and household head's age decreases multidimensional poverty because as people get older they accumulate more life and work experiences and have a better capacity to escape multidimensional poverty. The dummy variable wealth index shows that when a household head gets richer, multidimensional poverty decreases; however, vulnerability to multidimensional poverty increases especially in rural areas. Marital status also matters in vulnerability to multidimensional poverty. Hence, as compared to never married households, the deprivation score is higher for other marital status household heads. If we keep other factors affecting vulnerability to multidimensional poverty constant, vulnerability is higher for other marital status household heads as compared to never married household heads.

Earlier research on vulnerability to poverty has focused only on one-dimensional vulnerability to poverty but they do understand the limitation of this approach as poverty reflects deprivation in multiple dimensions. Using rigorous modeling techniques and stochastic dominance, this chapter estimates households' vulnerability to both unidimensional and multidimensional poverty and contributes to literature on vulnerability to poverty. Its focus on vulnerability estimates based on deprivation scores of the multidimensional poverty index where no similar research has been done is another contribution of this chapter as it puts forth an approach or perspective for addressing or measuring multidimensional vulnerability to poverty. Accounting for heterogeneity, this chapter suggests that vulnerability in religion, marital status, and profession plays an important role in a poverty analysis. This research also did a stochastic dominance test for unidimensional vulnerability to poverty which has not been done earlier. Our results show that poverty second order stochastic dominated expected poverty implying that vulnerability to poverty is greater than the current poverty.

1.3.3 Multidimensional Inequalities

The third chapter discusses multidimensional inequalities. Its results show that per capita consumption inequality is quite high in Ethiopia (Gini=0.385 and Atkinson index=0.221, with epsilon=1) and inequalities are higher in urban than in rural areas using both indices. Similarly, there are also differences in regional consumption per capita inequalities. Inequalities in the multidimensional indicators are quite high in Ethiopia (except for child mortality and nutrition) and the inequalities of these indicators decrease over the wealth quintiles in general. However, inequalities in asset ownership increase over the last wealth quintiles. Educational inequalities are high in Ethiopia in general and in Afar, Somali, and Amhara regions in particular but they are less in Addis Ababa and Dire Dawa regions. These regions are urban areas and their lower inequalities may be a reflection of differing access to education across regions because of poor infrastructure development in rural areas as compared to urban areas. Educational inequalities are also different across wealth quintiles. High educational inequalities are observed in the poorest households compared to the richest households.

A large share of the Ethiopian population is engaged in agriculture and farmers use traditional farming systems. Production and accumulation of wealth are highly associated with agricultural activities which in turn are related to landholdings (Charles, 2011) but there are significant agricultural landholding inequalities in the country. Higher landholding inequalities are observed in SNNP followed by Tigray and Somali regions. There are less landholding inequalities in Gambela and Benshiangul regions and these regions are known to be less densely populated with large arable land. Currently, these regions are attracting more domestic and foreign investors in the agricultural sector as compared to the other regions. Landholding inequalities are the highest among poor rural households compared to middle and rich rural households.

Multidimensional poverty is quite high in Ethiopia, but multidimensional inequalities are low. Living standards contribute the most to multidimensional inequalities except for some regions. Inequalities in living standards were very high in Ethiopia and these are higher in rural areas (0.747) as compared to urban areas (0.342). Of the living standard indicators considered in the analysis, cooking fuel and sanitation contributed the most to LSMII (living standard multidimensional inequality index) and access to electricity and water contributed less to LSMII in urban areas. But assets' contribution to LSMII was less (9.75 percent) in rural areas. Policies aimed at reducing inequalities in living standards should therefore focus on cooking fuel and access to electricity, floor material, and sanitation.

Within-group consumption inequalities as calculated by the Gini coefficient, dominated the between-groups inequalities. If the government or policymakers were to target consumption differences within groups, this could help in reducing overall consumption inequalities. Urban households will benefit more because the marginal impact of inequalities is higher for urban households than for their rural counterparts. Reducing inequalities between groups (rural-urban) will have more of an impact in reducing poverty than reducing inequalities within groups (households) as between group elasticity is greater than within group elasticity. The incidence of consumption poverty is high for male-headed households as compared to female-headed households and inequalities among male-headed households are greater than those for female-headed households. Reducing the average number of deprived households among male-headed and female-headed households will reduce overall deprivation more than reducing deprivation between these two groups. Region based decomposition results show that between regions inequalities are greater than within region inequalities. The differences in inequalities between regions in Ethiopia need to be considered.

Educational inequalities are high in Ethiopia in general and in some regions in particular. Therefore, this dimension requires further analysis for identifying areas for interventions for reducing education and multidimensional inequalities. There are different factors that contribute to educational inequalities. One of the factors that is assumed to affect children's level of education is parents' level of education. Educated parents like to educate their children more than uneducated parents. Within educated parents, father's education and mother's education may have a different impact on children in general and on sons' and daughters' education in particular. We disaggregated parents' education into father's education and mother's education and our analysis showed that a mother's education impacted both sons and daughters' education as compared to a father's education, other factors being controlled for. Educating daughters (tomorrow's mothers) has a more positive intergenerational inequality reducing effect than educating sons. Girls, especially in rural Ethiopia, frequently confront heavy workloads, early marriages, abductions, and stigmas associated with gender. Because of social and cultural reasons, girls are marginalized and have less access to education than boys. Providing better access to education to girls increases their level of education which has strong educational and multidimensional inequality reducing effects.

The contribution of this chapter is that since multidimensional poverty indicators make different contributions to multidimensional poverty, this research introduces a multistage inequality analysis to compute the multidimensional inequality index based on the indicators of multidimensional poverty. We used this approach because the contribution of living standards to multidimensional inequalities is more significant than the other indicators in Ethiopia. First, it does an aggregation of indicators in one dimension and then it aggregates the different dimensions to find the multidimensional composite inequality index. Parental intergenerational inequality estimations and decompositions highlight how parental education affects intergenerational inequalities.

1.3.4 Input Risks in Agriculture

The fourth chapter estimates input risks involved in agricultural production by smallholder farmers. It uses the Ethiopia Rural Household Survey (ERHS), data from the Ethiopian Living Standard Survey, and the average stochastic production function to analyze the mean production and risks of common inputs used in the agricultural sector. The estimation results of mean crop production show that almost all variables in the analysis have the expected signs and are statically significant. This study's results show that most inputs used in crop production increased smallholder farmers' revenues. Some inputs are risk increasing while others are risk decreasing. As the results of the variance analysis clearly show, fertilizer was a risk decreasing input. Land was a risk increasing input in 1995 and 2015, but there is no statistical evidence that it was a risk increasing input in the other years. Family labor was a variance decreasing input in 2009 but the risk decreasing effect of family labor was not significant in the other years (1995, 1999, 2004 and 2015).

The returns from labor power in general decreased from 1995 to 2004, which may be because of population growth in rural areas. As the population growth rate increased, farm land size per household decreased which resulted in disguised unemployment in rural areas which is very common in most developing countries like Ethiopia. The coefficients of the crop diversification index are negative and statically significant. Smallholder farmers' increase in crop diversification increased their revenues.

Most farmers in developing nations are risk averse (Kristin et al., 2006) and risk averse farmers consider both the mean and the variance of output to determine the optimal level of inputs. Considering risks or variances are very important along with mean agricultural production in smallholder farming production processes. The results of the variance or risk estimation show that some farm inputs used by smallholder farmers in rural Ethiopia were risk increasing while others were risk decreasing. Land was a risk increasing input in 1995 and 2015; the more land farmers used, the higher was the yield variability or risk. Fertilizers and seeds were risk decreasing inputs for smallholder farmers in rural Ethiopia.

Crop diversification is quite common in smallholder farmers in rural Ethiopia and there is less specialization. Crop diversification has a risk decreasing effect for smallholder farmers in rural Ethiopia. All regions are not similar and there are regional differences with respect to agricultural input risks. The results of the regional input risk analysis show that there were regional differences in input risks in agricultural production for smallholder farmers.

In a risk analysis, it is important to distinguish between downside risks (unexpected bad events) and upside risks (unexpected good events). Land is a downside risk increasing input and fertilizers are a downside risk decreasing input in each case. Some variables which were not significant in the risk analysis were significant in an estimation of downside risks. Most farmers in developing nations are risk averse (Brauw et al., 2014; Di Fako, 2006; Kristin et al., 2006). Agricultural input risks can easily be managed by the farmers themselves as most inputs are under their control unlike other risk factors like droughts, pests, and crop affecting diseases which are not under their direct control. The Ministry of Agriculture, regional governments, and extension workers who are interested in reducing agricultural production risks should consider these agricultural risks. Further, differences in regional input risks have to be considered for smallholder farmers' crop production in rural Ethiopia.

This chapter does an input risk analysis of Ethiopian smallholder farmers and their risk attitude and how they manage such risks using their own risk management strategies. Its contribution to existing literature is that farmers in different cultures with different living conditions have different risk attitudes and risk management strategies. It analyzes the role of crop diversification in reducing input risks and traditional views of diversification are supported by empirical evidence. This chapter integrates farmers risk aversion behavior and input risks considering the existing condition of Ethiopian farmers and identifies which inputs are risk increasing and which are risk decreasing in Ethiopia. Considering downside risks and their estimation are new perspectives in agricultural risk estimation. Farmers' risk consideration helps farmers and policymakers develop appropriate policies and strategies to reduce input risks in the agricultural sector to achieve a better food security condition.

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Chapter 2: Multidimensional Poverty and its Dynamics in Ethiopia

Abstract

Poverty is pervasive and deep-rooted in Ethiopia. Traditional unidimensional income or consumption expenditure based poverty measures provide incomplete guide for addressing poverty. Recent research trends are shifting from a unidimensional to a multidimensional poverty analysis. This study uses the Alkire-Foster multidimensional poverty analysis on data from four rounds of the Ethiopian Demographic and Health Survey. The study concludes that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular. In Ethiopia, multidimensional poverty has been decreasing moderately over time but still large proportions of the population live under multidimensional poverty. Living standards contribute the most (more than 46 percent) to multidimensional poverty while education contributes about 29 percent and health dimensions contribute approximately 25 percent to multidimensional poverty. Among the indicators used in this multidimensional poverty analysis there are high deprivations in sanitation, cooking fuel, floor material, and electricity. Further, sanitation and cooking fuel deprivations are increasing but education and school attendance deprivations have been decreasing over time. Level of education, having a bank account, and the number of working family members is associated with multidimensional poverty but the number of children under-5 years and dependent family members (dependency ratio) increase Ethiopian households' multidimensional poverty.

Keywords: Poverty, Ethiopia, multidimensional poverty, deprivation

JEL Classification Codes: C250; C430; I320;

2.1 Introduction

Ethiopia is the second most populous country in Africa with a diverse population mix of ethnic and religious groups. Large proportions of its population live in rural areas and are engaged in agriculture which accounts for 43 percent of the country's gross domestic product (CSA, 2009). Coffee and other agricultural products are the main export commodities. Ethiopia is one of the least urbanized countries in the world (CSA, 2009).

Poverty is a development challenge for most developing countries (Dercon et al., 2009) and poverty reduction is an important priority for their governments. Ethiopia adopted the Plan for Accelerated and Sustainable Development to end Poverty (PASDEP) to attain the Millennium Development Goals (MDGs) by 2015. The first Growth and Transformation Plan (GTP-I) was also developed to bring about rapid and broad-based growth to eventually end poverty (MoFED, 2010b). Despite all these steps, according to NPC (2016), around 23.5 percent of the population was still living under the poverty line.

Measuring poverty levels is the first step for coming up with poverty reduction strategies. Earlier approaches for measuring poverty were unidimensional. They were based on a single indicator, usually income or consumption expenditure, showing the level of deprivation. These monetary measures separated the population between poor and non-poor by identifying thresholds or poverty lines. Although income measures of poverty have been used frequently, they also have some limitations because human life is affected not only by income but also by other dimensions of life like education and health. In a social welfare measure based on a monetary variable it has been recognized that poverty is a multidimensional phenomenon, which cannot be adequately represented only by the monetary variable (Arndt and Tarp, 2017). Therefore, an analysis of poverty should consider all other dimensions of life. Literature on multidimensional poverty is growing fast (for example, Adetola, 2014; Alemayehu et al., 2015; Alkire and Foster, 2011; Alkire and Santos, 2010; Alkire et al., 2015; Bourguignon and Chakravarty, 2003; Dhongda et al., 2015; Hishe Gebreslassie, 2013; Maasoumi and Xu, 2015; Steff et al., 2016).

In a country like Ethiopia where poverty is deep-rooted, a rigorous multidimensional poverty measure, trend development, and a dynamic adjustment analysis of poverty are important for understanding the history of poverty in the country. In addition, this will also help shed light on whether poverty reduction strategies implemented by federal and regional governments so far have been effective in reducing multidimensional poverty so that appropriate poverty reduction policies can be designed and implemented in the future.

This study uses the Demographic and Health Survey (DHS) data over the years 2000-16 and examines the extent, trends, and dynamics of multidimensional poverty in the country, across regions, and over years in the components most relevant and locally feasible. It uses the Alkire-Foster (2011) method of the multidimensional poverty index (MPI) measure, adapting the method on which MPI is based to better address local realities, needs, and the available data.

This study's contribution to literature is in its application of MPI's indicators' weights using a factor weighting system, a sensitivity analysis of the weights used, and poverty cut-offs. The study concluded that MPI is sensitive to the weighting system used in the multidimensional poverty index. The research did a sensitivity analysis of changes in poverty cut-offs and poverty rankings of regions and sub-regions when different poverty cut-off rates were used in MPI. A proportion of the multidimensionally poor were less sensitive to downward as opposed to upward revision of the poverty cut-off. This can be seen as one of the limitations of multidimensional poverty index.

The rest of this chapter is structured as follows. Section 2 discusses the motivations for conducting this research while section 3 reviews related literature. Section 4 discusses the data and methods of data analysis and section 5 presents the results and discusses the findings of the study. Section 6 gives the conclusion and makes some recommendations based on its results.

2.2. Research Motivation

Earlier approaches to measuring poverty have some limitations which are mainly related to the way in which they measure income, market failures, and how household incomes are used for household members' (women and children) well-being. While using income or consumption expenditure as a measure of poverty, a part of a household's income including home production and consumption of goods and services may not be reported correctly. This lack of accuracy is attributed to the absence of records and because of tax reasons leading to unreliable statistics. Even if measured and reported, households' income as a measure of poverty relate only to the resources required to achieve well-being and not necessarily to the outcomes, that is, the final conditions of the individuals.

The logic behind the income approach is that a household above the income poverty line possesses the potential purchasing power to acquire a bundle of goods and services yielding a level of well-being that is sufficient for its members to function (Thorbecke, 2008). The income or consumption expenditure measure indicates the means and not the end. It is not the amount of tuition fee that determines the level of education, rather the level of education or knowledge acquired that determines the productive capacity of an individual, a household or society. It is not the amount of money that one spends on medical services, but the number of days of illness, maternal deaths, and child mortality rates that need to be reduced to determine the level of healthcare. Therefore, emphasis has to be shifted from the means to the end.

Poverty exists because poor people's lives can be affected by multiple deprivations that are all important (Sen, 1992). Hence, arguing against a single monetary dimension (income or consumption) as a sufficient proxy of human welfare and shifting to other non-monetary values such as health, education, contribution of the public sector, and political participation will result in shifting focus from the means to the end.

A poverty measure at one point of time or year does not indicate whether poverty reduction policies implemented by federal and regional governments have been effective in reducing multidimensional poverty. Repeated cross-sections with time invariant common characteristics or panel data are required to investigate the dynamics of poverty. Poverty trends and an analysis of their dynamics are essential. Thus, it is important to know the history and the dynamics of poverty based on which appropriate national and regional policies can be designed.

In Ethiopia, most existing research is unidimensional (Berisso, 2016; Stifel and Woldehanna, 2017; Woldehanna and Hagos, 2013) that shows the poverty history of the country and forwards possible recommendations for alleviating poverty. There is also some research on multidimensional poverty which shows the extent of multidimensional poverty in the country. However, this research is very general and overlooks the differences within the country, regions, and ethnic groups. Ambel et al., (2015) considered health, education, and standard of living and examined poverty dimension by dimension thus ignoring interdependence and the correlation between the dimensions and did not come up with a multidimensional poverty index.

Bruck and Workneh (2013) computed the multidimensional poverty index for Ethiopia but did not include some living standards' indicators like electricity, sanitation, and cooking fuel variables in the analysis. Using Ethiopia Demographic and Health Survey data, Alemayehu et al., (2014) found the multidimensional poverty index; however, their research did not consider variations within the regions and the poverty trends and their dynamics over time. Others have focused on some deprivation while underestimating deprivation in some other dimension. Bersisa and Heshmati (2016) focused on energy poverty but did not show poverty changes over time. The most recent study on multidimensional poverty using the equal weights approach is by OPHI (2017) which discusses the multidimensional poverty status of the country and the differences between the regions.

This study examines multidimensional poverty levels in Ethiopia and changes across regions and over time in the components most relevant and locally feasible. It uses the multidimensional poverty measure (Alkire-Foster, 2011). This study is different from other studies in three aspects. First, it uses the most recent data and the four rounds EDHS cross-section data for 2000-16 for measuring MPI. Second, it estimates MPI in these four rounds and does a trend and dynamic analysis and makes decompositions along time, regions, and dimensions. Third, in earlier multidimensional poverty research, having any two or more assets, regardless of the type of assets, made the households non-deprived in assets. In my study, the living standards indicator assets are divided into three categories: information assets, mobility assets, and livelihood assets. A household is non-deprived in assets if it owns at least one of the assets from two or more of these asset categories.

2.3. Literature Review

2.3.1. Poverty

Poverty has to be clearly defined or at least be understood conceptually before it can be analyzed in a meaningful way (Thorbecke, 2008). Existing literature defines poverty in different ways and there is no consensus on one definition of poverty. According to the basic needs approach, poverty is insufficiency of resources and opportunities to satisfy basic human needs. The main approach used for measuring absolute poverty in most developing countries is the basic needs approach. Cost in this approach is defined as the absolute minimum resources usually in terms of consumption goods, necessary for long term physical well-being (Ravallion, 2016). Poverty line in the basic needs approach is then defined as the amount of income required to satisfy those needs.

The World Bank (2014) says, "Poverty is pronounced deprivation in well-being." Well-being in this sense means an individual or household's command over commodities in general. It focuses on whether households or individuals have enough resources to meet their needs. Poverty in this case is measured mainly in monetary terms. This is the starting point for most analysis of poverty. The second view is whether people are able to obtain basic consumption goods such as food, shelter, clothes, healthcare and education. In this approach, the emphasis shifts from resources (money) to outcomes.

Other authors define poverty in different ways. Foster et al., (2013) define poverty as the absence of acceptable choices across a broad range of important life decisions, as well as lack of freedom to be or to do what one wants. The inevitable outcome of poverty is insufficiency and deprivations across many facets of a fulfilling life.

The most comprehensive and logical attempt to capture the concept of poverty has been Sen's (1992) capability and functioning approach. According to Sen, well-being comes from one's capability to function in society, and poverty is a lack of pre-requisites for a self-determined life and the "lack of capabilities" to function or manage one's life. People are considered poor when they lack key capabilities and so face inadequate incomes, education, poor heath, low self-confidence, and powerlessness. The human rights-based approach emphasizes that respect for human rights is a necessary condition for various social and economic outcomes. To some extent it challenges the approach that poverty can be measured by a unidimensional criterion based on income and/or consumption expenditure and therefore it addresses the multidimensional nature of poverty going beyond lack of income (UNDP, 2013).

Poverty is a challenge for developing countries and requires worldwide efforts and collaborations for reducing it. Extreme poverty is observed in many parts of the world and this is a global challenge including in developed countries. In 2013, 767 million people were estimated to be living below the international poverty line of US$1.90 per person per day (The World Bank, 2016). Almost 10.7 percent of the global population was poor by this standard of which sub-Saharan Africa's share was about 41 percent showing that poverty is still widespread in Africa (Chen and Ravallion, 2008). In 2013, the World Bank adopted two ambitious goals: ending extreme global poverty by reducing the poverty headcount ratio from 10.7 percent globally in 2013 to 3.0 percent by 2030 and promoting shared prosperity in every country in a sustainable way (The World Bank, 2016). These two goals are part of a wider international development agenda and are closely related to United Nations' Sustainable Development Goals (SDGs). According to the World Bank (2016) extreme poverty decreased over time; between 1990 and 2015 the percentage of the world's population living in extreme poverty fell from 37.1 percent to 9.6 percent. However, according to estimates it will take 100 years to bring the world's poorest up to the previous poverty line of $1.25 a day (The World Bank, 2016).

2.3.2. Multidimensional Poverty

There has been a shift of focus from one dimension to multiple dimensions of poverty. The multidimensional nature of poverty has become increasingly important in recent years and different contributions to this have been (Alkire et al., 2011). In addition to money income or consumption expenditure, human lives and well-being are affected by different dimensions such as health and education. A unidimensional measure of poverty using income or consumption expenditure presupposes that a market exists for all goods and services; however, often markets do not exist for many goods and services or they function imperfectly (Bourguignon and Chakravarty, 2003; Thorbecke, 2008; Tsui, 2002) and therefore, monetary values cannot be assigned to particular aspects of well-being (Hulme and McKay, 2008; Thorbecke, 2008). Also, having a sufficient income for purchasing a basic basket of goods does not imply that it is spent on that basket of goods (Thorbecke, 2008). Individual well-being is a multidimensional notion (Stiglitz et al., 2009), individuals care about many different aspects of their lives, including their material standard of living, health, and schooling. As stated by Alkire and Santos (2011) low income, poor health, inadequate education, job insecurity, disempowerment, and precarious housing are clear manifestations of multidimensional poverty. The components of poverty change across people, time, and context but multiple domains are involved. Empirical literature has documented a mismatch between monetary and non-monetary deprivations (Berenger and Verdire_Chouchane, 2007; Hishe Gebreslassie, 2013; Tran et al., 2015). This difference is attributed to a possible bias in the single dimensional measure of poverty. For example, a study in India by Stewait et al., (2007) found that 53 percent Indian children living in income-poor households were not malnourished and 53 percent of malnourished children were not living in income poor households.

MPI was developed by the Oxford Poverty and Human Development Initiative (OPHI) at the University of Oxford (Alkire and Santos, 2011; Alkire et al., 2011). It is a comparable multidimensional measure of acute poverty in over 100 developing countries. MPI acknowledges that income or consumption is a necessary but not a sufficient measure of gauging social well-being. In addition to poverty headcount, the depth, persistence, and complexities of poverty must also be understood. It considers many deprivations faced by severely disadvantaged groups and it is closely linked to the MDGs' or SDGs' targets. MPI incorporates alternative indicators; poverty cut-offs, and weights and is composed of three dimensions made up of ten indicators. Each indicator is based on international consensus (such as the MDGs) and the minimum level of satisfaction is called a deprivation cut-off. MPI combines the percentage of people who are poor (headcount ratio) and the average percentage of dimensions in which poor people are deprived (intensity).

2.3.3. Measurements of Poverty

It is important to identify who the poor are and where they live for measuring the level of poverty so that resources can be directed at them more effectively for addressing poverty. The measurements paint a picture of the magnitude of the problem and can help identify programs that will work well in addressing poverty (Foster et al., 2013). Governments can be accountable for their policies and researchers can explore the relationships between poverty and other economic and social variables (Foster et al., 2013).

Poverty has often been measured using income or consumption expenditure and can thus be measured in relative, absolute, and subjective terms. Relative poverty measures a household or individual's income relative to a certain average income (for example, mean or median), while absolute poverty measures individuals or households' incomes relative to a certain income threshold (poverty line). The subjective approach defines poverty as the subjective judgment of an individual of what constitutes a socially acceptable minimum standard of living in society. People value their poverty status within their society using different dimensions and indicators. Thus, this approach provides more information than relative and absolute measures of poverty and is therefore multidimensional in nature and perspective.

The Human Development Reports introduced poverty as a multidimensional phenomenon, and the Millennium Declaration and MDGs have been highlighting multiple dimensions of poverty since 2000. The first well-being measure on a worldwide scale was the Human Development Index (HDI). The Human Development Report ranks countries by HDI, which consists of their achievements in economic and social spheres such as life expectancy, educational attainments, and income. The Human Poverty Index (HPI) was developed by the UN for complementing HDI; however, in 2010 HPI was substituted by the UN's multidimensional poverty index (UNDP, 2013).

The multidimensional poverty index measures a range of deprivations such as inadequate living standards, lack of income, poor health, lack of education, disempowerment, and threat of violence (Alkire and Santos, 2010) and is currently used in more than 100 countries. In academic literature, interest in multidimensional poverty measurements is growing (Alkire and Foster, 2011). Effective multidimensional poverty measures have practical applications such as they can replace or supplement the income or consumption poverty measure. Dimensional decomposability of the multidimensional poverty measure can help monitor the level and composition of poverty and also help evaluate the impact of programs (for example, health and education programs). The multidimensional poverty measure gives more policy relevant information as it can single out the effect of each dimension on poverty and therefore policies for reducing poverty should rely on a multidimensional analysis of poverty (Adetola, 2014).

The dashboard approach is a starting point for measuring the multidimensionality of poverty to assess the level of deprivation in dimensions separately; it applies a standard unidimensional measure to each dimension (Alkire et al., 2011; Ravallion, 2011). The dashboard approach tries to find deprivation indices for all indicators considered in a multidimensional poverty analysis. The dashboard approach has the advantage of increasing the set of dimensions considered, offering a rich amount of information and potentially allowing the use of the best data source for each particular indicator and for assessing the impact of specific policies (such as nutritional or educational interventions). However, this approach has some significant disadvantages. First, dashboards do not reflect joint distribution of deprivations across the population precisely and because of this they are marginal methods (Alkire et al., 2015).

In literature, the distinction between being poor in all dimensions and in only one dimension has been referred to as the intersection and union definitions of poverty. This can be illustrated using an example from Duclos and Younger (2006) who state that if well-being is measured in terms of all dimensions then a person can be considered poor if his achievements in each dimension are less than the poverty threshold set for that particular dimension. This is defined as an intersection definition of poverty and will generally produce untenably low estimates of poverty. In contrast, a union definition considers an individual to be poor only if her achievements in one of the dimensions fall below its respective threshold. This is very commonly used and may lead to exaggerated estimates of poverty. In between these two extremes, the most widely used measure of multidimensional poverty currently is the multidimensional poverty index (MPI).

MPI uses different dimensions and indicators. A poverty cut-off is set for each indicator and finally the multidimensional poverty cut-off is set by combining all the indicators based on the weight assigned to each indicator. MPI has several main features that can be used as important tools for a poverty analysis. First, MPI can be expressed as a product of the incidence of poverty (headcount ratio H) and the intensity of poverty or the average deprivation score (A) among the poor. Second, the MPI measure can be decomposed across population sub-groups which can be geographic regions or ethnic or religious groups. We use this feature to create poverty measures for regions within a country. Third, MPI can be broken down into the indicators in which the poor people are deprived (Alkire and Foster, 2011). In other words, it is possible to compute the contribution of each indicator to overall poverty.

2.3.4. Poverty in Ethiopia

Ethiopia continues to be one of the poorest countries in the world by different standards and measures of unidimensional and multidimensional poverty (Apablaza and Yalonetzky, 2013). Even though there have been improvements in living standards, subjective poverty measures indicate that poverty still remains high in Ethiopia. The United Nations' HDI ranked Ethiopia 174 out of 187 countries where average per capita income was less than half of the sub-Saharan average (The World Bank, 2014).

Similarly, a young lives multidimensional poverty analysis also indicated that Ethiopia's multidimensional poverty index was very high (Alemayehu et al., 2015). Ethiopia is one of the poorest countries according to multidimensional poverty measures. Despite some progress, significant multidimensional poverty reduction has not been observed in Ethiopia. The OPHI (2013) showed that 87 percent of the population was multidimensionally poor in 2011 which made Ethiopia the second poorest country in the world.

However, some studies have indicated that since 2000, Ethiopia has shown a reduction (around 33 percent) in the share of its population living in poverty (Apablaza and Yalonetzky, 2013; Stifel and Woldehanna, 2017; The World Bank, 2014) and there have been improvements in overlapping deprivations. Further, life expectancy has increased, infant and child mortality rates, and the share of population without education, electricity, and clean water have also dropped considerably (Table 2.1).

Table 2.1. Ethiopia's progress (2000-11)

	2000	2011
Percentage of the population		
Living below the national poverty line	44	30
Living on less than US$1.25PPP a day	56	31
Without education	70	50
With electricity	12	23
With piped water	17	34

Percentage of children under-5 years who are stunted	58	44
Life expectancy (years)	52	64
Fertility rate	6	4

Source: The World Bank Group (2014).

In Ethiopia, the proportion of the population living below the poverty line deceased from 48 percent in 1990-91 to around 38.7 percent in 2004-05. A notable reduction in the poverty gap and the depth of poverty was observed in the country in general and in rural Ethiopia in particular (Woldehanna and Hagos, 2013). Stifel and Woldehanna (2016) state that despite a nominal increase in income in Ethiopia over 2000 and 2011, the poorest urban population experienced no real change in their consumption levels.

2.3.5. Empirical Evidence

There is some empirical evidence on unidimensional and multidimensional poverty. Using panel household survey data from Vietnam focusing on multidimensional poverty and its link to income poverty measurement, Tran et al., (2015) indicated that the monetary poor (or non-poor) were not always multidimensionally poor (or non-poor) and the overlap between the two measures was much less than 50 percent. Thus, income poverty does not indicate multidimensional poverty. Bersisa and Heshmati's (2015) income and multidimensional poverty study's results also show that intensity and depth of poverty varied considerably across the unidimensional and multidimensional poverty measures.

Alkire and Santos (2010) assessed if there were poverty differences between social and regional groups in Bolivia, Kenya, and India by decomposing MPI by state and by ethnic groups and found large differences between social and ethnic groups. So, state and ethnic groups are clearly a key variable to consider in analyzing the causes of and responses to multidimensional poverty. MPI allows these group differences to be measured and studied in detail and is important for designing effective policies.

Alkire and Foster (2011) provide an example which first decomposes a population by ethnic sub-groups and then by dimensions. They found that one ethnic group's contribution to total poverty was much higher for multidimensional poverty than for income poverty. There were also gaps between the risks of being poor in each measure of poverty across regions and ethnic groups (Tran et al., 2015). Alkire et al., (2011) also provide information on two regions in India. The regions have roughly the same population sizes and share a MPI of 0.39. A decomposition by dimensions showed how the underlying structure of deprivations differed across the regions in the ten indicators. A comparison of the two regions showed that in Madhya Pradesh, nutritional deprivations contributed the most to multidimensional poverty, whereas in the Congo in India the relative contribution of nutritional deprivations was much less. Therefore, even if the overall poverty levels are very similar, decompositions by regions show different underlying structures of poverty, which could suggest different policy responses.

Hishe Gebreslassie (2013) points out that the headcount poverty measure using the unidimensional measure of poverty is by far less than the multidimensional measure of poverty. His research in urban areas of the Afar regional state indicated that only 33.9 percent of the households were poor in the unidimensional measures, whereas the multidimensional poverty approach showed that over 63 percent of the households were multidimensional poor.

2.4. Data and Methodology

2.4.1. Data

This research used data from the Ethiopian Demographic and Health Survey (EDHS). EDHS is conducted by the Ethiopia Central Statistical Agency (CSA) with support from the worldwide Demographic and Health Survey (DHS) project. DHS is a comprehensive dataset that consists of samples from all regions in the country (nine regional states and two city administrations) which represent the national population of Ethiopia. Regions in Ethiopia are divided into zones, and zones into smaller administrative units called woredas. Each woreda is further sub-divided into the smallest administrative units - kebeles (CSA, 2012). DHS used this administrative structure and further divided kebeles into census enumeration areas (EAs), which were convenient for implementing the census. The sample was selected using a stratified, two-stage cluster design and EAs were the sampling unit for the first stage. Households comprised the second stage of the sampling.

DHS is cross-section data collected in Ethiopia almost every five years. The first round was in 2000; the second in 2005; the third in 2011; and the most recent in 2016. The data collected contains information on household characteristics, households' dwelling units such as the source of water, types of sanitation facilities, access to electricity, types of cooking fuel and materials used for floor of the house, and ownership of various assets like TV, radio, telephone, land, car, bicycle, cattle, sheep, goats and others. The data also contains household members' level of education, children's school attendance, child health, child mortality, maternal mortality, and the nutrition status of the members. However, according to a CSA report, in 2011 ten of the 65 selected EAs were not listed in EDHS due to security reasons (CSA, 2012) and 18 of the 55 selected EA-listed households were not interviewed. However, national-level estimates were not affected as the percentage of population in the EAs not covered in the Somali region was proportionally very small (Central Statistical Agency of Ethiopia and ICF International, 2012). In this research, the unit of analysis is a household; a household has common resources and takes decisions that affect almost all its members.

2.4.1.1 Components of Multidimensional Poverty

There is no fixed list of what should be included in a MPI (Ravallion, 2011). The list is open and the most important thing is the process through which the components are selected (Alkire et al., 2011). This must be agreed upon with a certain degree of consensus.

Such a consensus may derive from participatory experiments, a legal basis, international agreements such as the MDGs or those on human rights, and empirical evidence regarding people's values. Statistical relationships or the correlation between the variables must also be explored and understood.

MPI's indicators were selected after a thorough consultation process involving experts in all the three dimensions (Alkire et al., 2011). The ideal choice of indicators had to be reconciled with what was possible in terms of data availability. This study uses three dimensions and ten indicators suggested by Alkire and Foster (2011) -- health, education, and living standards. These three dimensions are now described.

Healthcare is very important for daily life and professional work. A nation's development depends on productive human resources which partly depend on good healthcare. Provision of medical care services has become a top priority of all governments (Mekonnen et al., 2012). This study used a household's health indicators which were selected based on the internationally agreed measures of health and the availability of data. Child mortality and the nutritional status of household members were indicators used in this analysis. These indicators are also part of the MDGs and the first Growth and Transformation Plan (GTP-I) of Ethiopia. Most of the time, child mortality is related to infectious diseases or diarrhea which are easily preventable. In Ethiopia, infant mortality declined from 97 deaths per 1,000 in 2000 to 59 deaths per 1,000 in 2010, and under-5 mortality decreased from 166 deaths to 88 deaths per 1,000 in the same period (Alemayehu et al., 2015). In this MPI, a household is considered to be deprived if child mortality has been observed in terms of at least one child death in the household.

The second indicator is nutrition. For example, child malnutrition can have a lifelong effect in terms of cognitive and physical development (Sawaya, 2006). Adults or children who are malnourished are also susceptible to other health disorders; they learn and concentrate less and may not perform well at work. Nutritional deficiencies are highly related to not having energy to walk and doing very small tasks (Riordan, 2012). Children are considered malnourished if their standard score is less than -2 for which they have the same age. A widely used index for adult nutritional status is the body mass index (BMI) (Ravallion, 2016). DHS data includes BMI for an adult household member which is weight in kilograms divided by height in meters squared. A household is considered to be deprived if there has been at least one adult person in the household whose BMI was less than 18.5.

Human resources are the most important resource in an economy and education is the key for human capital development. It is a well-established fact that education is a key instrument for socioeconomic development and hence it is considered to be one of the basic human rights and achieving universal primary education is also one of the MDGs. Ethiopia's Growth and Transformation Plan (GTP) was framed to foster educational achievements for all up to primary school (MoFED, 2012). This study uses two indicators (year of education and child school attendance) for representing the education component of MPI. For the indicator on years of education, for household members whose age is more than or equal to 13, (child school enrolment age is 6 to 7 years in most rural areas of the country, if one is enrolled at age 7 she/he is expected to complete grade six at age 13). If there is at least one member with six or more years of education then we classify the household as non-deprived. If more than one-third of the household members have missing information on years of education, and the people for whom we observe the years of education as less than six years, the household is given a missing value in this indicator. Households with no school-aged children are considered non-deprived.

The second indicator is children's school attendance. Educating children is a pillar in the development of a country. For example, in 2005 the primary school net attendance rate for 7-12 year old children was 42.3 percent. In 2011, this increased by about 20 percentage points to 62.2 percent (CSA, 2013). Some children are forced to quit studies because of various reasons like no access to a nearby school and refusal of the household head to send his/her child to school at the expense of domestic work or personal interests. Hence, if any school attending children have dropped out of school for at least one or more than a year, all members of the household are considered deprived.

The next dimension in this multidimensional poverty analysis is living standards. The most widely agreed living standard indicators are electric access, sanitation facilities, cooking fuel, drinking water, floor material, and asset ownership. A household is deprived in electric access if it does not have electricity. Improved sanitation facilities are defined using the MDGs' definition and include flush or pour-flush to piped sewer system or septic tank, ventilated improved pit latrines, and pit latrines with slabs and composting toilets. A household with such sanitation facilities is considered non-deprived. Households are considered deprived when sanitation facilities are shared with other households or are open to the public.

Clean drinking water is the most essential thing for a person's healthy existence. Clean water is defined using the MDGs' definition and includes piped water in a dwelling, plot or yard; public tap/standpipe; borehole/tube well; a protected dug well; protected spring; rainwater collection; and bottled water. Households having access to such water sources are considered non-deprived in water whereas household with access to water from unprotected wells, unprotected springs, water provided by carts with small tanks/drums, and tanker truck-provided or surface water taken directly from rivers, ponds, streams, lakes, dams or irrigation channels are considered deprived. A household is also deprived of drinking water if the source of water is more than 30 minutes walking (round trip).

The other living standard indicator is the type of cooking fuel used by a household. A household is not deprived in cooking fuel if it uses electricity, natural gas, biogas, or kerosene for its daily cooking. Households using charcoal, wood, animal dung, and grass are considered deprived of cooking fuel.

Material used for the floor is also considered an indicator of living standards in this research. Households using soil, sand, dung, wood planks, and reed/bamboo are deprived of floor materials, whereas households using floor materials such as cement, tiles, ceramic, bricks, and carpets are classified as non-deprived.

The other living standard indicator is asset ownership. In this research, assets related living standard indicators are divided into three asset categories: information, mobility, and livelihood. Assets for access to information are phone (mobile or fixed), radio, and TV. Assets for easy mobility include bicycle, motorbike, motorboat, car, truck, or an animal wheel cart. Assets for livelihood include refrigerator, agricultural land, livestock (at least one cattle or at least one horse or at least two goats or at least two sheep, or at least 10 chickens); these are considered separately and combined to show the asset deprivation level of a household. A household is not deprived in assets if it owns at least one of the assets from two or more of these asset categories. The deprivation dimensions and indicators used in this multidimensional poverty analysis are listed in Table 2.2.

Table 2.2. MPI's dimensions and indicators used in the analysis

Dimensions	Indicators	A household is deprived in the indicator if:
Health	Child mortality	One or more children have died in the household after the last survey.
	Nutrition	There is child malnutrition in the household and/or adult malnutrition in the household after the last survey.
Education	Highest grade completed	No household member whose age is 13 years or older has completed six years of schooling.
	School attendance	Any school age child in the household not attending school in that academic year.
Standard of living	Electricity	The household has no access to electricity.
	Sanitation	There is no facility / bush / field, or sanitation facilities are open to the public or shared with other households.
	Sources of water	A household's source of water is an unprotected spring, well or river/dam/lake/pond/stream.
	Floor materials	The floor material is earth, sand, dung or something similar.
	Cooking fuel	The cooking fuel used by the household is charcoal, firewood, straw or dung.
	Assets ownership	The household has at most one asset in one of the three asset categories: access to information (phone (mobile or fixed), radio, TV); asset for easy mobility (bicycle, motorbike, motorboat, car, truck or animal wheel cart); asset for livelihood (refrigerator, agricultural land or livestock (at least one cattle or at least one horse or at least two goats or at least two sheep or at least 10 chicken).

The weights of the Indicators

After identifying the dimensions and indicators of multidimensional poverty, the crucial problem is assigning suitable weights to the indicators (Berenger and Verdire_Chouchane, 2007). Weights play a crucial role in aggregation and determining the trade-off between the dimensions (Decancq and Lugo, 2008). The equal weights approach has been used by different authors (Alkire and Foster, 2011; Atiknson, 2003; Dhongda et al., 2015; Salazar et al., 2013). However, this approach is controversial and it has its share of critics (Decancq and Lugo, 2008). Most multidimensional poverty indicators are assumed to be correlated and the equal weights approach fails to consider these correlations and therefore multidimensional poverty dimensions cannot have similar importance or weights (Ravallion, 2011). One of the options as an alternative method is using individual preferences as a weighting scheme (Decancq et al., 2013; Takeuchi, 2014). In this weighting scheme, the relative importance and trade-off among the dimensions are left to the individual. The problem with this approach is that individuals may not reveal their real preferences (Takeuchi, 2014). Following this criticism other weighting approaches such as a parametric or a statistical approach have been used. Statistical techniques are widely used in designing poverty measures and in giving a weight to each indicator (Maggino and Zumbo, 2012). Key techniques include descriptive and model-based methods. Descriptive methods are principle component analysis (PCA), multiple correspondence analysis (MCA), and a cluster analysis (CA). Model based methods are latent class analysis (LCA), structural equation model (SEM), and factor analysis (FA).

The main difference between PCA and MCA is the scale of the variables used. PCA is used when the variables are of a cardinal scale, while MCA is appropriate when variables are categorical or binary. The model-based methods are latent variable models and cover latent class analysis (LCA), factor analysis (FA), and more generally, structural equation models (SEM). When the indicators are ordinal, binary, or categorical, a more suitable multivariate technique for a lower-dimensional description of the data is a correspondence analysis (CA).

Like PCA, FA is also used as a data reduction method; however, there is a fundamental difference between the two methods. PCA is a descriptive method that interprets the underlying (latent) structure of a set of indicators on the basis of their total variations (common variation and unique variation), while FA is a model-based method that focuses on explaining the underlying common variance across indicators instead of total variance. The observed dimensions are a manifestation of the factors and have been used by different authors (Decancq and Lugo, 2008; Noble et al., 2007). Since a factor analysis (FA) makes no prior assumptions regarding the pattern of relationships among the observed indicators (Alkire et al., 2015), it can be used for cardinal and categorical data. Further, it considers the correlation between indicators and removes or reduces redundancy or duplication from a set of correlated variables. A factor analysis is used to model the relationship between the indicators in a multidimensional poverty analysis with a fewer number of factors while the factor loading expresses the relationship of each variable or indicator with the underlying factor. In other words, factor loading can be interpreted as a regression coefficient in a standard regression analysis. Our research uses the factor analysis model to determine the weights of the indicators. In finding the weights of the indicators using a factor analysis, if the observed variables are $X_1, X_2,..., X_n$, the common factors are $F_1, F_2,..., F_m$ and the unique factors are $e_1, e_2,..., e_n$, the variables may be expressed as a linear function of the factors:

$$
\begin{aligned}
X_1 &= a_{11}F_1 + a_{12}F_2 + a_{13}F_3 + \ldots + a_{1m}F_m + a_1e_1 \\
X_2 &= a_{21}F_1 + a_{22}F_2 + a_{23}F_3 + \ldots + a_{2m}F_m + a_2e_2 \\
&. \\
&. \\
X_n &= a_{n1}F_1 + a_{n2}F_2 + a_{n3}F_3 + \ldots + a_{nm}F_m + a_ne_n
\end{aligned} \tag{2.1}
$$

Factors capture a certain amount of the overall variance or variability in the variables. The model assumes that each observed variable is a line function of these factors with residual variables. The model produces the maximum correlation and seeks to find the coefficients $a_{11}, a_{12}, \ldots, a_{nm}$. The coefficients are weights or factor loadings in the same way as regression coefficients (as the variables are standardized, the constant is zero and is not shown). The factor loading gives us the strength of the correlation between the variables and the factors.

It is possible to solve Equation (2.1) for the factor score so as to obtain a score for each subject. The equation is of the form:

$$
\begin{aligned}
F_1 &= \lambda_{11}X_1 + \lambda_{12}X_2 + \lambda_{13}X_3 + \ldots + \lambda_{1m}X_m \\
F_2 &= \lambda_{21}X_1 + \lambda_{22}X_2 + \lambda_{23}X_3 + \ldots + \lambda_{2m}X_m \\
&. \\
&. \\
F_n &= \lambda_{n1}X_1 + \lambda_{n2}X_2 + \lambda_{n3}X_3 + \ldots + \lambda_{nm}X_m
\end{aligned} \tag{2.2}
$$

In this model, each factor is a weighted combination of the input variables. The main idea behind this model is that the factor analysis seeks to find factors such that when these factors are extracted, there remain no correlations between the variables as the factors account for the correlations.

2.4.2. Aggregation of MPI

We have n-households in each round representing the population of interest and d-indicators for the selected dimensions for which $\mathrm{d} \geq 2$. Once the data is available and the range of dimensions and indicators have been selected, we get the achievement level matrix of dimension $(\mathrm{n} \times \mathrm{d})$ of n-households and d-indicators of the selected dimensions. Let $\sum \mathrm{Y} = [\mathrm{Y_{ij}}]$ denote the $\mathrm{n} \times \mathrm{d}$ matrix of achievement for i household across j dimension. The typical entry is the achievement $\mathrm{Y_{ij}} \geq 0$, which represents individual i′s achievement in indicator j. Each row vector $\mathrm{Y_i} = (\mathrm{Y_{i1}}, \mathrm{Y_{i2}}, \ldots, \mathrm{Y_{id}})$ gives household i′s achievement in different dimensions j across individuals and the column vector $\mathrm{Y_j} = (\mathrm{Y_{1j}}, \mathrm{Y_{2j}}, \ldots, \mathrm{Y_{nj}})$ gives the achievements of all households in the sample for j indicators.

In MPI we have the deprivation cut-off and the poverty cut-off. A deprivation cut-off vector $\mathrm{z} = (\mathrm{z_1}, \ldots, \mathrm{z_d})$ (deprivation cut-offs for each dimension) is used for determining whether a household is deprived in that indicator. If the household’s achievement level in a given dimension j falls short of the respective deprivation cut-off zj, the household is said to be deprived in that indicator and will have a value of 1. If the household's level of achievement is at least as great as the deprivation cut-off, the household is not deprived in that indicator and will have a value of 0 in that indicator. Finally, we have a deprivation score matrix of $(n \times d)$ dimension with values of 0 and 1.

Following Nawal and Iqbal (2016) each household is assigned a deprivation score according to its deprivations in the component indicators. The deprivation score of each household (C_i) is calculated by taking a weighted sum of the deprivations experienced. A household not deprived in any indicator receives a deprivation score equal to 0 and the score increases as the number of deprivations of the household increase.

The deprivation score of each household (C_i) is calculated by:

$$C_i = W_1 I_1 + W_2 I_2 + \cdots + W_d I_d \tag{2.3}$$

where $I_i = 1$ if the household is deprived in indicator i and 0 otherwise, and W_i is the weight attached to indicator i with $\sum_{i=1}^{d} W_i = 1$. A column vector $C = (C_1, \dots, C_n)$ of the deprivation score reflects the breadth of each household's deprivation.

A second cut-off, which in the Alkire-Foster methodology is called the poverty cut-off, is the share of (weighted) deprivations that a household must have to be considered multidimensional poor and is denoted by k. A household is considered poor if its deprivation score is equal to or greater than the poverty cut-off, $C_i \geq K$.. In MPI, a household is identified as poor if it has a deprivation score greater than or equal to one-third (33 percent) (Alkire and Santos, 2011; OPHI, 2013).

In the AF methodology, the poverty cut-off denoted by k, is a normative decision. It reflects a normative judgment regarding the maximally acceptable deprivations that a person experiences not to be considered poor (Alkire et al., 2015). Though it is a normative decision, it needs to be reasonable. The reasonability of the selection of this threshold depends on the purpose of the measure, the number and type of the indicators considered, and their relative weights. The normative notion could come from participatory processes, subjective poverty assessments, and qualitative studies (Alkire et al., 2015).

MPI is an index designed to measure poverty. Following the Alkire and Foster (2011) method, the structure of the adjusted headcount measure of MPI combines two key pieces of information: the proportion or incidence of households whose share of weighted deprivations is k or more and the intensity of their deprivations is the average deprivation that poor households' experience. Formally, the first component is called the multidimensional headcount ratio (H):

$$H = \frac{q}{n} \tag{2.4}$$

here q is the number of households that are multidimensional poor and n is the total population. However, the headcount ratio (H) violates dimensional monotonicity (Bruck and Workneh, 2013). To solve the dimensional monotonicity of the headcount ratio, Alkire and Foster (2011) developed the second component of MPI called the intensity (breadth) of poverty (A). This is the average deprivation score of multidimensionally poor households and can be expressed as:

(2.5) $$A = \frac{\sum_{i=1}^{n} c_i(k)}{q}$$

where $C_i(k)$ is the censored deprivation score of household i and q is the number of households that are multidimensional poor. MPI is the product of both incidence (H) and severity or depth (A) components:

(2.6) $$MPI = H \times A$$

In MPI, due to the sensitivity of the outcome to the weights applied to the indicators, several other methods of measuring multidimensional poverty have been proposed. Weight determination is not an easy task in the multidimensional poverty measure. In response to this limitation, others have developed the first-order (stochastic) dominance (FOD) approach (Arndt et al., 2012; Arndt and Tarp, 2017) which can be applied to ordinal multidimensional data. It requires that the outcomes in each dimension be ranked from worse to better and is thus robust across all possible weighting schemes.

2.4.2.1 Decomposition by Sub-Groups

It is important to decompose multidimensional poverty by regions, sub-regions, or ethnic groups to design appropriate region-specific intervention policies or strategies. One good feature of MPI is that it can be decomposed by population sub-groups such as regions, zones or rural/urban areas, depending on the sample design. For example, if there are n sub-groups by which the survey is represented, the decomposition is:

(2.7) $$MPI_{country} = \frac{n_1}{N} MPI_{n_1} + \frac{n_2}{N} MPI_{n_2} + \cdots + \frac{n_n}{N} MPI_{n_n}$$

where $\mathrm{n_i}$ denotes the population sub-group (regions, zones or rural/urban) and N denotes the total population ($\mathrm{n_1 + n_2 + \cdots + n_n = N}$). This relationship can be extended for any number of groups as long as their respective populations add up to the total population. Therefore, MPI can be analyzed by sub-national regions, ethnic groups, and rural/urban areas.

Given Equation (2.7), we can easily compute the contribution of each sub-group to overall poverty by using:

(2.8) $$Controubtion\ of\ sub-group\ (n_i)\ to\ MPI = \frac{\frac{n_i}{N} MPI_{n_i}}{MPI_{country}} \times\ 100$$

When a sub-group's contribution to poverty exceeds its population share, it suggests that there is a seriously unequal distribution of poverty in the country or the region with some regions/sub-regions/ethnic groups bearing a disproportionately high share of poverty.

The average annual absolute change of each indicator X can be computed by using the formula:

(2.9) $$\Delta X_{t-s} = (X_t - X_s)/(t - s)$$

where X_t, denotes the performance or MPI of a country or a region in period t and X_s is the performance or MPI of a country or region in period s. The average annual change of each indicator X is:

(2.10) $\Delta\%X_{t-s} = ((X_t - X_s)/X_s)/(t - s)$

The estimated percentage of absolute or relative changes for different sub-groups provides information about the effects of various policies aimed at reducing poverty. A change in MPI over time can provide information about changes in the incidence or intensity of poverty levels or their combined changes. Following Apablaza and Yalonetzky (2011) we decompose the change in MPI as:

(2.11) $\Delta\%MPI_{t-s} = \Delta\%H_{t-s} + \Delta\%A_{t-s} + (H_{t-s} * \Delta\%A_{t-s} * (t - s))$

2.4.2.2. Decomposition by Indicators

MPI can also be decomposed by indicators. An easy way of doing this is by computing the censored headcount ratio in each indicator. We can get the censored headcount ratio by adding up the number of people who are poor and deprived in that indicator and dividing this by the total population. Once all the censored headcount ratios have been computed, we can find the multidimensional poverty index of a country as:

(2.12) $MPI_{country} = W_1CH_1 + W_2CH_2 + \cdots + W_{10}CH_{10}$

here $W_1$is the weight of indicator 1 and $CH_1$is the censored headcount ratio of indicator 1, and so on for the other nine indicators, with $\sum_{i=1}^{d} W_i = 1$. From Equation (2.12), one can compute the contribution of each indicator to overall poverty by:

(2.13) $Contribution\ of\ indicator\ i\ to\ MPI = \frac{W_iCH_i}{MPI_{country}} \times 100$

If a certain indicator's contribution to poverty widely exceeds its weight, this suggests that there is relatively high deprivation in this indicator as compared to the other indicators and this requires appropriate policy interventions.

2.4.3 Determinants of Multidimensional Poverty

Besides the extent of multidimensional poverty and its dynamics, we are also interested in identifying the determinants of multidimensional poverty. These are essential for reducing multidimensional poverty. There are different household characteristics that determine or affect a household's poverty status (Adetol, 2014; Berenger and Verdire-Chouchane, 2007; Berisso, 2016). We consider the variable family size of the household, number of children under-5 years, age of the household head, and the education level of the household head.

Because of differences in job opportunities and uneven distribution of infrastructure across the country, people living in different places such as cities, large towns, small towns, and the countryside or rural areas are exposed to different levels of multidimensional poverty. Therefore, place of residence needs to be controlled for. Livestock are important assets for rural people as they are used as food, drought animals, and sources of cash. We used tropical livestock units to represent livestock assets of the households.

In the AF method of measuring multidimensional poverty, a household's deprivation score (c_i) is compared with the multidimensional poverty cut-offs (k). If the deprivation score is greater than or equal to the poverty cut-off ($c_i \geq k$), a household is considered to be multidimensional poor. This is represented by the binary variable (y_i) that takes the value 1 or 0, as:

$$y_i = \begin{cases} 1 \textit{ if and only if } c_i \geq k \\ 0 \textit{ otherwise} \end{cases} \tag{2.14}$$

The binary variable (y_i) occurs with probability p_i, which is conditional on the explanatory variables (x_i), and is represented as:

$$p_i = pr(y_i = 1) = pr(y_i = 1 | x_i) \tag{2.15}$$

The outcome variable has only two values (binary). Therefore, we use the logistic regression model which is a limited-dependent variable model. The logit of p_i is the natural logarithm of odds that the binary variable (y_i) takes a value 1 rather than 0 which is the relative probability of being multidimensionally poor. The logit model is a linear model for the natural logarithm of the odds:

$$\ln \frac{p_i}{1 - p_i} = \eta_i = \beta_0 + \beta_1 x_{i1} + ... + \beta_k x_{ik} \tag{2.16}$$

In our logistic model, y_i is the dependent variable, $y = 1$ indicates that a household is multidimensionally poor, which is our variable of interest and p is the probability of success of being boor. In this case the p-value indicates the probability that a household is multidimensionally poor, x is the independent variable, and β is the coefficient to be estimated.

Coefficient β_j is the change in the logit model due to a one-unit increase in x_j, while holding all other explanatory variables in the model constant. e^{β_j} gives the odds ratio associated with a one-unit increase in x_j.

The logit model is also a multiplicative model for the odds as:

$$\frac{p_i}{1 - p_i} = e^{\eta_i} = e^{\beta_0}(e^{\beta_1})^{x_{i1}} ... (e^{\beta_k})^{x_{ik}} \tag{2.17}$$

The conditional probability p_i is then given as:

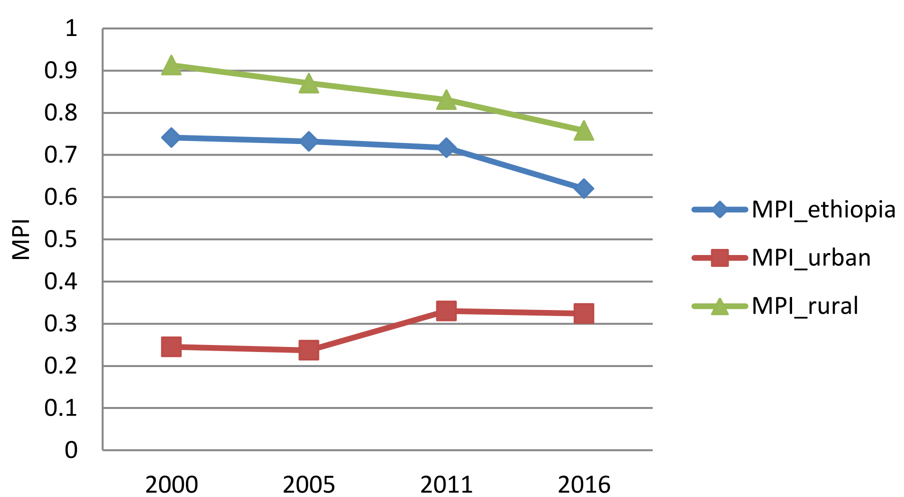
$$p_i = \frac{1}{1+e^{-\eta_i}} = \frac{1}{1+e^{-\sum_{j=0}^{k}\beta_j x_{ij}}} \tag{2.18}$$

The logistic regression estimation results of determinants of multidimensional poverty are presented in Table 2.3. We performed the model specifications, goodness of fit, and multicollinearity tests.

2.5. Results and Discussion

The results of the multidimensional poverty analysis' results show that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular (Tables 2.7 and 2.8). Because of the traditional farming system followed in rural Ethiopia and given that most of the rural population is dependent on agriculture for its livelihood; poverty is by and large a rural phenomenon (Alemayehu et al., 2014; GTP-II, 2016). In 2000, MPI in rural Ethiopia was very high (0.913) relative to urban Ethiopia (0.245). Over time, poverty in rural Ethiopia decreased moderately (Figure 2.1). But in urban Ethiopia multidimensional poverty increased over time. This may be because of difference in infrastructure and public service. Access to electricity, water and health services are better in urban than in rural areas and these are components of multidimensional poverty and less access to these services increase MPI in rural areas compared with urban areas. However, MPI in rural area is decreasing moderately but that is not the case in urban areas. This is mainly because our government was focusing on rural areas and the urban area did not get equal attention as that of rural areas. Ethiopia was committed to attaining the MDGs by 2015. It developed the first Growth and Transformation Plan (GTP-I) which was designed to maintain rapid and broad–based growth and eventually end poverty. Despite all these steps, multidimensional poverty in Ethiopia has remained high. Our MPI estimation results are fairly similar to those of other MPI measures (Alemayehu et al., 2014).

Figure 2.1. MPI trends in rural and urban Ethiopia (2000-16)



A comparison of regional multidimensional poverty shows that even though there were some differences over years (regions are different in terms of social, cultural, types of agriculture (agrarian and nomadic) and resource endowment and differences are expected), the multidimensional poverty levels were high in almost all the regions of the country (Table 2.7). In particular, multidimensional poverty was the highest in Amhara, Afar, Somali, and Tigray regions in 2000; in Afar, Tigray, Amhara, and Smalli regions in 2005; in Somali, Benishangul, and SNNP regions in 2011; and in SNNP, Amhara, Somali, and Afar regions in 2016. Whereas Addis Ababa, Dire Dawa, and Harari regions were among the regions where multidimensional poverty was relatively lower (Tables 2.7 and 2.8).

Out of the nine regions in Ethiopia (excluding the two-city administrations), Tigray, Amhara, Oromia, and SNNP regions constituted about 90 percent of the total population of the country (CSA, 2010). Hence, a poverty analysis of these regions can give us a good picture of regional multidimensional poverty in Ethiopia. Multidimensional poverty was very high in these regions; however, a moderate reduction was observed in Amhara, Oromia, and Tigray regions, but in SNNP there was no such reduction in multidimensional poverty over the study period (Figures 2.2 and 2.3).

Figure 2.2. Development of regional MPI in Ethiopia (2000-16)

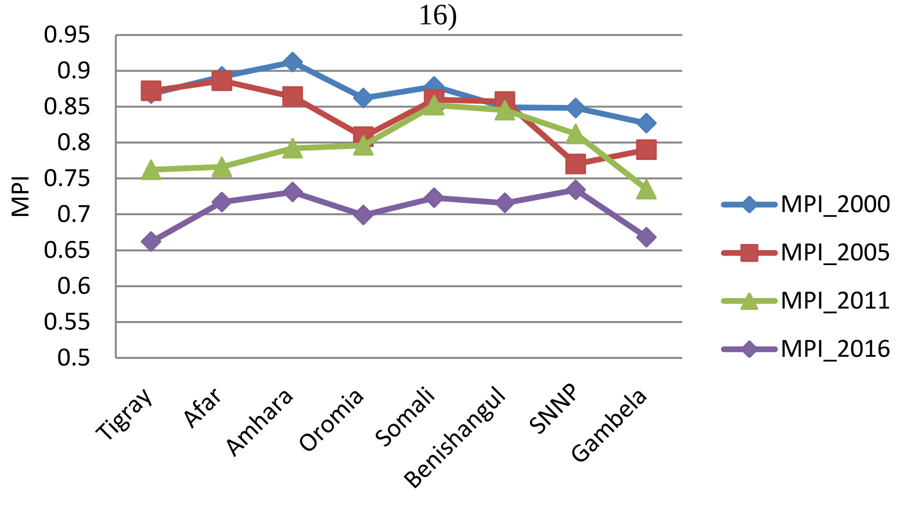
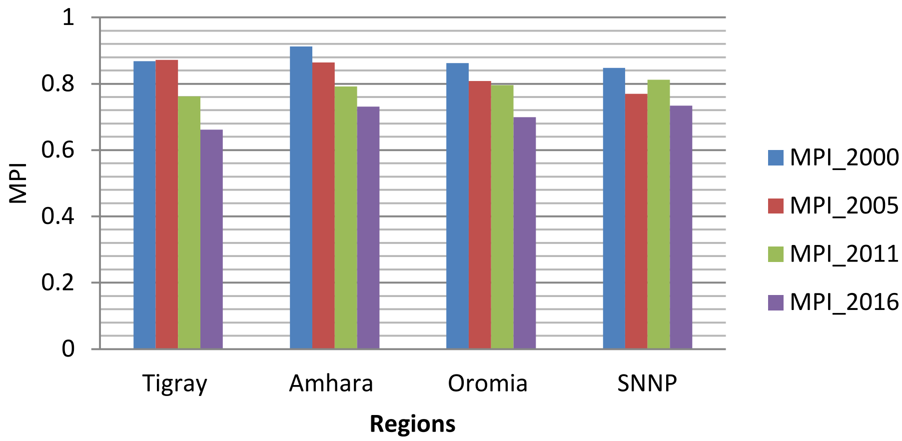
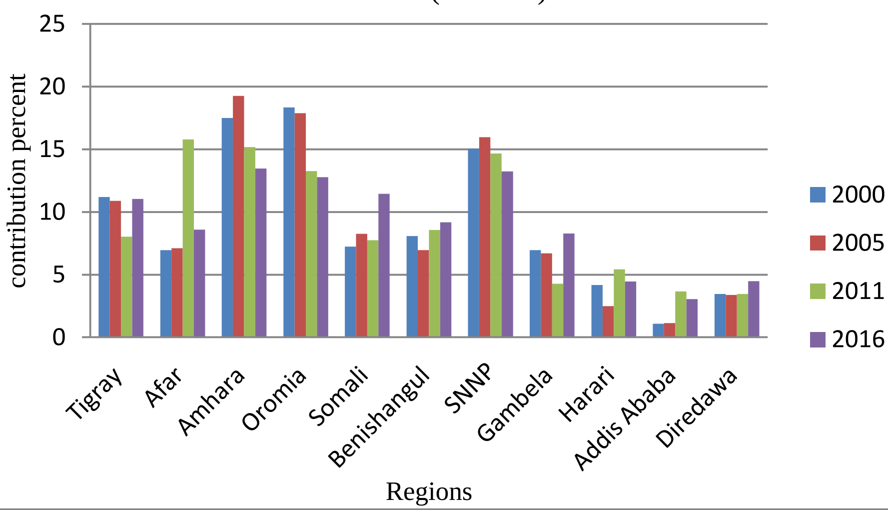


Figure 2.3. Multidimensional poverty of selected regions (2000-16)



One advantage of MPI is that it makes it possible to see the contribution of each region or sub-group to multidimensional poverty. The contribution of regions to the overall (country) multidimensional poverty indicated that different regions contributed different shares to multidimensional poverty. Harari, Addis Ababa, and Dire Dawa regions contributed less to multidimensional poverty compared to their population shares, whereas Oromia, Amhara, and SNNP regions contributed more to multidimensional poverty (Table 2.13 and Figure 2.4). These regions are urban areas compared with other regions of the country and they have better access to public services than the other regions of the country. Less MPI in these regions might be because of these. Whenever a sub-group or region's contribution to poverty exceeds its population share, this suggests that poverty in some regions is more serious than in other regions. Heterogeneity in regions' ability to escape poverty can be used for designing region specific poverty reduction policies to speed up regional equalities.

Figure 2.4. Regions' contribution to MPI and its development over time (2000-16)



When we consider the contributions of different dimensions to multidimensional poverty, in 2016 living standards contributed the most (46 percent) to multidimensional poverty followed by education and health which were at about 29 percent and 24.7 percent respectively (Table 2.11).

Among the indicators used in our multidimensional poverty analysis, we found high deprivations in sanitation, cooking fuel, floor material, and electricity. Further, sanitation and cooking fuel deprivations increased over time, but education deprivation and school attendance deprivation decreased over time (Figure 2.6). These results are in line with other recent studies, for example, Alemayehu et al., (2015), showed that the proportion of population deprived in multiple indicators declined but deprivations in some indicators of multidimensional poverty were quite high in Ethiopia. To improve access to public facilities government need to have plan and should allocate enough budget to improve these. On top of that following how the budget is being used for its intended purpose and how effective and efficient are government offices in implementing what the government has planned. In most corrupted country like Ethiopia budget are not being used for their intended purpose. Most government activities are not efficient and cost effective and there is no proper and continuous follow up in the implementation of the programs.

Our multidimensional poverty dynamic results show that in 2005, the highest annual MPI change was in Harari region at about a 3.7 percent reduction relative to 2000, whereas in 2016 the highest annual MPI change was in Harari and Addis Ababa regions at about 11.5 percent reduction. Significant reduction was observed in other regions such as Oromia, Somali, Benishangul, SNNP, and Dire Dawa (Table 2.12).

This research compared MPI using equal weights and different weights (factor analysis). In both weighting approaches, the contribution of living standards was higher than that of education and health (Tables 2.10 and 2.11). However, the factor analysis weighting method gives more weight to living standards compared to equal weights. Therefore, multidimensional poverty index using the factor analysis is greater than following the equal weights approach (Tables 2.7 and 2.9).

2.5.1 Results of the Econometric Model

In addition to estimating MPI and its decomposition by regions and indicators, it is very important to identify the determinants of multidimensional poverty to identify areas for interventions in multidimensional poverty reduction efforts. Our logistic model's estimation results show that the family size coefficient was negative and significant (Table 2.3) which shows that as the family size increased the likelihood of the household falling into multidimensional poverty decreased. This finding is different from other studies, for example Bruck and Workneh, (2013) who showed that family size mattered in consumption poverty (the larger the family size the higher the probability that the household will fall into consumption poverty) but family size had no significant impact on multidimensional poverty. However, on the contrary, some studies indicate a direct relationship between consumption poverty and family size (Adetola, 2014; Berisso, 2016). One possible reason for this is that most people in Ethiopia live in rural areas and are engaged in traditional agriculture. Traditional agriculture, by its nature, is labor intensive. Hence, all working age (even underage) rural household family members are engaged in family farm activities in one way or another. Therefore, households with more family members who are actively involved in family farm activities can manage their family farm easily and the more economically active household members in a family, the less likely the family is to fall into poverty.

The number of children under-5 and the dependency ratio were positive and significant, implying that as the number of children under-5 and the number of dependent family members increased, a household's probability of being poor also increased. This is mainly because children under-5 and old aged family members or dependent family members do not engage in productive or income generating activities. As expected, education of the household head (education) was negative and significant because as people get more educated, they become more productive and earn more income which makes them less likely to be poor. This is also consistent with other findings (Adetola, 2014; Berenger and Verdire_Chouchane, 2007)

Table 2.3. Logistic regression model estimation results of the determinants of multidimensional poverty-coefficients

Multidimensional poverty	Round1_2000	Round2_2005	Round3_2011
Family size	-0.4993***	-0.3706***	-0.3079***
Children under-5	0.9074***	0.6536***	0.2082
Age of household head	-0.0040	-0.0159***	-0.0233***
Education	-1.1776***	-0.2134***	-0.0833*
TLU (tropical livestock unit)	0.9682***		-0.0151
Land for agriculture_1(0=No, 1= yes)	0.6416***	0.8611***	0.5448
Sex_2 dummy (1=Male, 2=female)	-0.1744	0.1169	-0.0451
Place of residence-dummy (capital or large city is the reference)			
Small city	1.9615***	0.2296*	
Town	4.7096***	2.4594***	
Countryside	8.9348***	6.6189**	
Regions dummy (Tigray_1 is the reference)			
Afar_2	-0.1526	-0.1543	0.9875***
Amhara_3	0.8522**	1.8270**	3.5669***
Oromia_4	0.9508***	0.6753	0.7255
Somali_5	0.4325	1.4830	2.0259***

Benishangul_6	2.1498***		
SNNP_7	-0.1742	1.0721*	0.1592
Gambela_12	2.2209***	0.6639	0.5866
Harari_13	-0.6238	0.4407	0.3575
Addis_14	(omitted)	(omitted)	0.4153
Dire Dawa_15	-1.2098***	0.2333	-0.1379
Dependency ratio		0.2590**	0.6722***
Bank account_1 dummy (0=No, 1= yes)		-2.0827***	-1.3829***
Hectare of land			-0.0016**
Residence_2 dummy (1=urban, 2= rural)			4.9809***
Cons	0.8011***	-0.3451	2.4084***
N	13811	5367	2335
Chi2	9653.8885	3131.1694	798.95555
Bic	2296.9858	1275.7274	803.5593
Note: * P < 0.1, ** P < 0.05, and *** P < 0.01.			

People usually like to invest in human capital at a young age as they have enough time to get the returns. Earning readily increases with age as new skills and knowledge are acquired through life and work experience and also by investing in human capital (education). So, during the young age or in an economically active age, households' probability of multidimensional poverty decreases as age increases. According to Adetota (2014) an increase in the age of the household head reduces the household's likelihood of being multidimensionally poor initially till a threshold and then increases.

The dummy variable bank account is negative; those households which had bank accounts were less poor as compared to those who did not have a bank account. We also considered place of residence as a variable in our analysis. In 2000 and 2005 households in the countryside, towns, and small cities were poorer compared to households in large cities (the reference area) as their coefficients were positive and significant. Data on place of residence was not available for 2011, so as an alternative we used residence (rural/urban). Households in rural areas were poorer than those in urban areas.

Region is a dummy variable and region 1 --Tigray is the base or reference region. In 2000, Afar, SNNP, Harari, and Dire Dawa regions had intense multidimensional poverty compared to the Tigray region, whereas in other regions multidimensional poverty was relatively greater than that in Tigray region. In 2005 and 2011 (except Afar in 2005), no region was significantly better than the Tigray region as far as intensity and depth of multidimensional poverty is concerned and some regions like Afar, Amhara, and Somali had significantly intense multidimensional poverty.

2.5.2 MPI's Robustness to Change in the Weights of the Indicators

We estimated MPI using the factor analysis weight which considers the correlation among the indicators. We also used the equal weights approach as an alternative. In this approach, each dimension is equally weighted at one-third; each indicator within a dimension is also equally weighted. Then we verified if the rankings were stable using both approaches. We calculated the correlation coefficients using different ranking methods- Pearson's correlation coefficient, Spearman's rank correlation coefficient, and Kendall's rank correlation coefficient (Tau-b). As a starting point, we estimated the correlation coefficient of the deprivation scores of households' in the two weighting systems and found that the correlation in Ethiopia in general and in rural/urban Ethiopia in particular was large enough to conclude that there was strong rank correlation of deprivation scores of households in the two weighting systems (Table 2.4)

Table 2.4. Correlation of households' deprivation scores (ci) using equal weight and factor analysis weight

Regions	Correlation coefficient measures used	Deprivation score correlation coefficients for years, 2000-16			
		2000	2005	2011	2016
Ethiopia	Pearson	0.823	0.825	0.778	0.716
	Spearman	0.865	0.837	0.809	0.792
	Tau-b	0.744	0.695	0.553	0.613
Rural	Pearson	0.583	0.626	0.600	0.562
	Spearman	0.758	0.718	0.692	0.624
	Tau-b	0.646	0.580	0.553	0.542
Urban	Pearson	0.802	0.802	0.778	0.687
	Spearman	0.818	0.784	0.692	0.578
	Tau-b	0.661	0.644	0.659	0.611

Changing the indicators' weights affected MPI. We compared the correlation coefficient of MPI of regions in Ethiopia for a change in the weights of the indicators for 2000-16. Interestingly, the correlation coefficient obtained between the two alternative weighting systems was high and the regions' rankings remained quite stable, thus one region had higher poverty than the other regions regardless of the weighting system used (Table 2.5).

Table 2.5. Regions' correlation coefficient of MPI using equal weight and factor analysis weight

Correlation coefficient measures used	MPI correlation coefficients for years, 2000-16			
	2000	2005	2011	2016

Pearson	0.992	0.988	0.986	0.812
Spearman	0.930	0.868	0.930	0.796
Tau-b	0.824	0789	0.824	0.682

2.5.3. Sensitivity Analysis of MPI and Different Choices

A multidimensional poverty analysis is based on certain selected dimensions and indicators. Once we had identified the dimensions and indicators, we aggregated them using weights and finally we categorized people or households into multidimensional poor or non-poor based on the agreed poverty cut-off. Hence, it was important to test the sensitivity of the poverty measures to different weights and poverty cut-offs.

2.5.3.1 Sensitivity to Change in the Weights of the Indicators

We used a factor analysis weighting system to determine the weights of the indicators. We used the factor analysis and equal weights for the comparison and sensitivity analysis. The multidimensional headcount ratio and MPI were different when equal weight and factor analysis weights were used (Tables 2.6, 2.7, 2.8, and 2.9). The headcount ratio (H) using a factor analysis weight was greater than that of equal weight (except in 2005). Similarly, MPI using a factor analysis weight was greater than that of equal weight in each year. The differences were mainly because of the differences in the weights given to the indicators. Thus, the multidimensional poverty analysis was sensitive to the weights attached to the indicators (Decancq and Lugo, 2008).

Table 2.6. Multidimensional poverty with equal weight and factor analysis weight

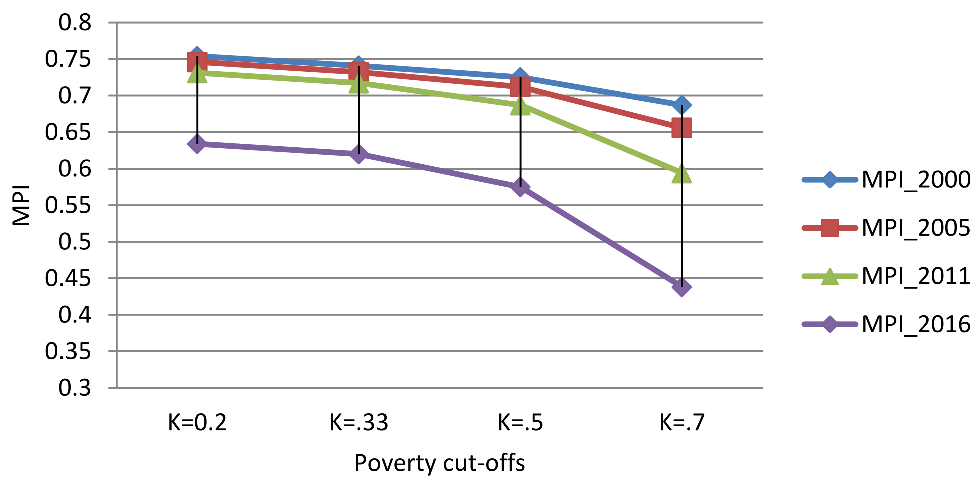
	Aggregation with equal weight		
Years	H	A	MPI
2000	0.832	0.645	0.531
2005	0.877	0.667	0.585
2011	0.809	0.632	0.511
2016	0.697	0.473	0.330
	Aggregation with factor analysis weight		
Years	H	A	MPI
2000	0.843	0.879	0.741
2005	0.872	0.839	0.732
2011	0.908	0.789	0.717
2016	0.882	0.703	0.620

2.5.3.2. Sensitivity to Changes in Poverty Cut-offs (K)

Alkire and Foster's MPI method has two cut-offs: the deprivation cut-off (z_i) and the poverty cut-off (k). The poverty cut-off is used for identifying those households as multidimensional poor if their weighted deprivation score (c_i) is greater than or equal to the poverty cut-off k ($c_i \geq k$). In this sub-section, we see MPI's sensitivity to changes in the poverty cut-offs. A sensitivity analysis is required to know how the poverty rankings of regions or sub-regions changes when different poverty cut-offs are used in MPI (Alkire et al., 2015)

In the Alkire and Foster method, a household is multidimensionally poor if its deprivation score is greater than or equal to 33 percent. The changes in multidimensional poverty for some selected poverty cut-offs ($k = 0.2, k = 0.5, k = 0.7$), relative to the benchmark poverty cut-off ($k = 0.33(33\%)$), indicated that a decrease in multidimensional poverty was relatively higher for an increase in the poverty cut-off compared to an increase in poverty when there was a decrease in the poverty cut-off. We found that the proportion of the multidimensionally poor was less sensitive to downward as opposed to an upward revision of the poverty cut-off (Figure 2.5).

Figure 2.5. Sensitivity of MPI to the change in poverty cut-offs (K)



2.6. Conclusions and Recommendations

Despite various efforts, multidimensional poverty is still high in Ethiopia. The dynamics of a multidimensional poverty analysis show that poverty in rural Ethiopia is decreasing, but this is not observed in urban Ethiopia. Even though Ethiopia is an agrarian country and a majority of its population lives in rural areas, the country's poverty reduction policies should also consider urban poverty.

The intensity and depth of poverty is different in different regions and the level of multidimensional poverty reduction is not the same in all the regions in the country. There are differences in poverty levels across the country with some regions having a disproportionately high share of poverty. Regions in Ethiopia are different in many contexts, for example, in social, culture, and resource endowments. Poverty-reduction policies and implementation strategies need to consider these differences. Regional heterogeneity should also be considered when designing region-specific poverty reduction policies to accelerate the speed of reducing regional inequalities. In some regions (for example, Afar, Somali, and Bensihangul) multidimensional poverty is very high relative to the other regions. Poverty reduction policies in these regions do not seem to be as effective as they are in the other regions of the country. This results in regional differences in the prevalence and intensity of poverty within the country which raises a question of equity.

Poverty reduction interventions require identifying the determinants of multidimensional poverty. Level of education, having a bank account, and more working family members in a household help reduce multidimensional poverty. On the other hand, number of children under-5, number of dependent family members, and households' engagement in agriculture increase multidimensional poverty. Multidimensional poverty is sensitive to the weight of the indicator and the poverty cut-offs used in the analysis.

Poverty reduction policies should focus on living standard indicators as these indicators contribute the most to multidimensional poverty in almost all regions in the country. There are high deprivations in sanitation, cooking fuel, floor material, and electricity in Ethiopia; thus, these indicators require careful interventions by federal and regional governments to reduce multidimensional poverty in Ethiopia. Government has to plan and allocate enough budgets to improve these things. Following how the budget is being used for its intended purpose and how effective and efficient are government offices in implementing what the government has planned. Poverty is multidimensional and thus a response to poverty should involve many sectors and stakeholders. Collective efforts are the right approach to take and should be scaled up and practiced more extensively.

Our analysis used a household as the unit of analysis. However, in Ethiopia where there is high ethnic and cultural diversity, intra-household inequalities (between men and women, adults and children) may be severe. Our household multidimensional poverty analysis did not consider intra-household inequalities because of unavailability of data at an individual level. A multidimensional poverty analysis at the individual level has the potential for future research if individual level data is available. DHS data provides individual level data but some data such as asset ownership is not available at an individual level. Multidimensional issues such as child poverty and a nutrition-based poverty analysis are also potential research areas.

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Table 2.7. Headcount(H), Intensity (A) and Multidimensional Poverty Index (MPI) in Ethiopia by Regions for the 2000,2005, 2011, and 2016 (factor weight)

Regions or Residence	2000			2005			2011			2016		
	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI
Ethiopia	0.843	0.879	0.741	0.872	0.839	0.732	0.908	0.789	0.717	0.823	0.753	0.620
Urban	0.401	0.612	0.245	0.423	0.559	0.237	0.634	0.522	0.330	0.512	0.631	0.323
Rural	0.997	0.916	0.913	0.997	0.872	0.870	0.993	0.836	0.831	0.914	0.829	0.758
Regions:												
Tigray	0.959	0.905	0.868	0.987	0.883	0.872	0.941	0.810	0.762	0.782	0.847	0.662
Afar	0.975	0.914	0.892	0.972	0.912	0.886	0.932	0.822	0.766	0.812	0.883	0.717
Amhara	0.978	0.933	0.912	0.985	0.877	0.864	0.984	0.805	0.792	0.793	0.922	0.731
Oromia	0.969	0.889	0.862	0.965	0.837	0.808	0.969	0.821	0.796	0.803	0.870	0.699
Somali	0.961	0.915	0.878	0.955	0.901	0.860	0.994	0.857	0.852	0.925	0.782	0.723
Benishangul	0.986	0.861	0.849	1.00	0.857	0.857	1.000	0.845	0.845	0.953	0.751	0.716
SNNP	0.967	0.877	0.848	0.953	0.808	0.770	0.991	0.819	0.812	0.886	0.828	0.734
Gambela	0.984	0.841	0.827	0.963	0.820	0.790	0.929	0.791	0.735	0.786	0.850	0.668
Harari	0.637	0.782	0.498	0.600	0.674	0.405	0.873	0.692	0.604	0.705	0.294	0.207
Addis Ababa	0.162	0.510	0.083	0.213	0.456	0.097	0.546	0.461	0.251	0.492	0.839	0.413
Dire Dawa	0.516	0.776	0.401	0.567	0.766	0.434	0.730	0.795	0.580	0.653	0.605	0.395

Table 2.8. MPI and the 95 percent confidence interval for 2000-16(factor weight)

	2000		2005		2011		2016	
	MPI	95% confidence interval	MPI	95% confidence interval	MPI	95% confidence interval	MPI	95% confidence interval
Ethiopia	0.741(0.003)	(0.736, 0.746)	0.732(0.004)	(0.725, 0.739)	0.717(0.005)	(0.708, 0.726)	0.620(0.015)	(0.590, 0.650)
Urban	0.245(0.005)	(0.236, 0.254)	0.237(0.007)	(0.224, 0.250)	0.330(0.008)	(0.314, 0.346)	0.323(0.030)	(0.264, 0.382)
Rural	0.913(0.001)	(0.911, 0.915)	0.870(0.018)	(0.866, 0.874)	0.831(0.003)	(0.825, 0.837)	0.758(0.035)	(0.689, 0.827)
Regions:								
Tigray	0.868(0.005)	(0.858, 0.878)	0.872(0.006)	(0.860, 0.884)	0.762(0.015)	(0.733, 0.791)	0.662(0.061)	(0.542, 0.782)
Afar	0.892(0.006)	(0.881, 0.903)	0.886(0.008)	(0.870, 0.902)	0.766(0.012)	(0.743, 0.789)	0.717(0.046)	(0.634, 0.800)
Amhara	0.912(0.003)	(0.905, 0.919)	0.864(0.006)	(0.855, 0.873)	0.792(0.009)	(0.774, 0.810)	0.731(0.054)	(0.624, 0.838)
Oromia	0.862(0.004)	(0.855, 0.869)	0.808(0.006)	(0.797, 0.819)	0.796(0.010)	(0.777, 0.815)	0.699(0.033)	(0.634, 0.764)
Somali	0.878(0.006)	(0.866, 0.890)	0.860(0.010)	(0.841, 0.879)	0.852(0.010)	(0.832, 0.872)	0.723(0.044)	(0.636, 0.810)
Benishangul	0.849(0.005)	(0.839, 0.859)	0.857(0.006)	(0.845, 0.869)	0.845(0.008)	(0.829, 0.861)	0.716(0.062)	(0.594, 0.838)
SNNP	0.848(0.004)	(0.840, 0.856)	0.770(0.006)	(0.757, 0.783)	0.812(0.008)	(0.797, 0.827)	0.734(0.038)	(0.662, 0.806)
Gambela	0.827(0.006)	(0.816, 0.838)	0.790(0.010)	(0.770, 0.810)	0.735(0.020)	(0.695, 0.775)	0.668(0.048)	(0.575, 0.761)
Harari	0.498(0.012)	(0.474, 0.522)	0.405(0.019)	(0.368, 0.442)	0.604(0.018)	(0.570, 0.638)	0.207(0.060)	(0.089, 0.325)
Addis Ababa	0.083(0.005)	(0.073, 0.093)	0.097(0.007)	(0.083, 0.111)	0.251(0.010)	(0.231, 0.271)	0.413(0.065)	(0.286, 0.540)
Dire Dawa	0.401(0.012)	(0.377, 0.425)	0.434(0.019)	(0.397, 0.471)	0.580(0.032)	(0.517, 0.643)	0.395(0.036)	(0.325, 0.465)

Source: Author’s computations using DHS data.

Table 2.9. Headcount(H), Intensity (A) and Multidimensional Poverty Index (MPI) in Ethiopia by Regions for the 2000,2005, 2011, and 2016(equal weight)

Regions or Residence	2000			2005			2011			2016		
	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI
Ethiopia	0.823	0.645	0.531	0.877	0.667	0.585	0.809	0.632	0.511	0.697	0.473	0.330
Urban	0.386	0.476	0.184	0.494	0.472	0.233	0.374	0.499	0.187	0.438	0.411	0.180
Rural	0.974	0.668	0.651	0.877	0.666	0.585	0.944	0.645	0.612	0.818	0.489	0.400
Regions:												
Tigray	0.943	0.655	0.618	0.978	0.692	0.677	0.847	0.614	0.520	0.740	0.490	0.363
Afar	0.945	0.699	0.661	0.974	0.733	0.714	0.874	0.693	0.606	0.797	0.492	0.392
Amhara	0.967	0.645	0.624	0.979	0.692	0.677	0.905	0.617	0.558	0.762	0.476	0.363
Oromia	0.929	0.645	0.599	0.942	0.667	0.628	0.894	0.660	0.590	0.789	0.490	0.386
Somali	0.949	0.681	0.639	0.943	0.719	0.678	0.977	0.684	0.668	0.809	0.486	0.393
Benishangul	0.938	0.639	0.600	0.972	0.681	0.662	0.954	0.632	0.603	0.748	0.474	0.355
SNNP	0.918	0.651	0.597	0.930	0.665	0.618	0.902	0.609	0.549	0.802	0.473	0.380
Gambela	0.911	0.602	0.549	0.957	0.630	0.603	0.830	0.596	0.494	0.711	0.488	0.347
Harari	0.599	0.599	0.359	0.596	0.577	0.344	0.740	0.556	0.412	0.464	0.428	0.199
Addis Ababa	0.229	0.422	0.097	0.363	0.426	0.155	0.264	0.476	0.126	0.359	0.390	0.140
Dire Dawa	0.535	0.589	0.315	0.654	0.613	0.401	0.600	0.673	0.404	0.546	0.435	0.237

Table 2.10. Percentage contribution of multidimensional poverty's dimensions to MPI , by years and regions(unequal weight)

	2000				2005				2011				2016			
Regions or Residence	Living stand.	Educ.	Health	Total	Living stand	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total
Ethiopia	85.74	13.72	0.54	100	86.22	13.13	0.64	100	87.87	11.52	0.61	100	85.76	13.60	0.64	100
Urban	85.81	13.61	0.58	100	87.33	11.98	0.69	100	90.47	8.95	0.58	100	93.87	5.75	0.37	100
Rural	85.73	13.74	0.54	100	86.14	13.22	0.64	100	87.56	11.83	0.61	100	83.46	15.83	0.56	100
Regions																
Tigray	85.58	13.91	0.51	100	86.55	12.86	0.59	100	89.05	10.46	0.48	100	82.00	17.45	0.56	100
Afar	85.29	14.09	0.63	100	84.58	14.85	0.56	100	85.68	13.64	0.68	100	84.54	14.91	0.55	100
Amhara	85.71	13.79	0.50	100	86.21	13.13	0.66	100	88.66	10.72	0.63	100	82.08	17.03	0.89	100
Oromia	85.92	13.51	0.57	100	86.52	12.84	0.65	100	87.23	12.14	0.64	100	85.91	13.64	0.45	100
Somali	84.61	14.96	0.44	100	84.95	14.58	0.46	100	86.22	13.13	0.66	100	91.13	8.33	0.54	100
Benishangul	85.89	13.58	0.53	100	86.26	13.02	0.72	100	87.37	11.96	0.67	100	82.12	17.26	0.62	100
SNNP	86.32	13.12	0.56	100	86.39	12.87	0.72	100	89.88	9.55	0.57	100	86.42	12.91	0.67	100
Gambela	88.06	11.38	0.56	100	88.89	10.47	0.64	100	91.18	8.24	0.59	100	89.65	9.81	0.54	100
Harari	84.78	14.66	0.57	100	85.01	14.32	0.68	100	86.34	13.20	0.46	100	88.81	10.35	0.84	100
Addis Ababa	80.08	19.27	0.64	100	84.49	14.72	0.79	100	89.90	9.55	0.55	100	92.84	7.07	0.08	100
Dire Dawa	83.92	15.15	0.57	100	85.32	13.96	0.72	100	86.87	12.55	0.59	100	83.65	15.05	1.29	100

Table 2.11. Percentage contribution of multidimensional poverty dimensions to multidimensional poverty index, by years and regions(equal weight)

	2000				2005				2011				2016			
Regions or Residence	Living stand.	Educ.	Health	Total	Living stand	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total
Ethiopia	46.68	34.79	18.53	100	43.00	30.00	27.00	100	45.99	26.33	27.68	100	46.21	29.11	24.68	100
Urban	39.02	33.14	27.83	100	35.84	24.90	39.30	100	44.50	18.57	36.93	100	64.15	16.56	19.29	100
Rural	47.43	34.45	17.62	100	43.47	30.00	26.00	100	46.17	27.29	26.53	100	43.45	34.56	21.99	100
Regions																
Tigray	47.58	35.47	16.95	100	44.3	29.6	26.10	100	48.87	24.64	26.49	100	47.50	30.71	21.79	100
Afar	45.24	34.18	20.58	100	42.0	34.56	23.41	100	42.09	28.75	29.16	100	47.82	30.48	21.17	100
Amhara	48.48	35.29	16.23	100	43.8	29.44	26.76	100	47.91	24.95	27.14	100	41.25	34.24	24.51	100
Oromia	47.13	34.76	18.12	100	43.52	29.80	26.67	100	44.43	29.17	26.40	100	42.65	32.15	25.20	100
Somali	45.66	38.26	16.08	100	42.91	34.43	22.66	100	43.63	29.75	26.63	100	21.87	39.06	39.06	100
Benishangul	47.52	34.22	18.26	100	43.76	28.01	28.23	100	47.26	25.46	27.29	100	43.44	33.94	22.62	100
SNNP	47.23	34.50	18.26	100	42.15	30.18	27.67	100	49.37	23.52	27.11	100	44.10	32.61	23.29	100
Gambela	50.25	28.30	21.44	100	46.57	23.94	29.50	100	50.91	18.37	30.72	100	57.83	23.10	19.07	100
Harari	44.84	34.83	20.32	100	39.21	29.41	31.38	100	45.49	29.91	24.59	100	50.12	25.39	24.49	100
Addis Ababa	24.37	38.71	36.93	100	26.55	26.48	46.97	100	42.55	19.88	37.58	100	74.75	15.15	10.10	100
Diredawa	40.85	36.48	22.67	100	37.9	30.73	31.34	100	44.89	28.70	26.41	100	38.75	31.13	30.12	100

Source: Own computation from DHS data

Table 2.12. MPI, Absolute Annual Change, and Relative Annual Change in MPI Relative to the Previous survey years (by Rural/urban and Regions)

Regions or Residence	MPI_2000	MPI_2005	Annual Change		MPI_2011	Annual Change		MPI_2016	Annual Change	
			Absolute	Relative		Absolute	Relative		Absolute	Relative
Ethiopia	0.741(0.003)	0.732(0.004)	-0.002**	-0.24%	0.717(0.005)	-0.003**	-0.34%	0.620(0.017)	-0.032**	-4.51%
Urban	0.245(0.005)	0.237(0.007)	-0.002	-0.65%	0.33(0.008)	0.016***	6.54%	0.324(0.020)	-0.002**	-0.61%
Rural	0.913(0.001)	0.87(0.002)	-0.009***	-0.94%	0.831(0.003)	-0.007***	-0.75%	0.758(0.035)	-0.024***	-2.93%
Tigray	0.868(0.005)	0.872(0.006)	0.001	0.09%	0.762(0.015)	-0.018***	-2.10%	0.662(0.053)	-0.033	-4.37%
Afar	0.892(0.006)	0.886(0.008)	-0.001	-0.13%	0.766(0.012)	-0.020***	-2.26%	0.717(0.061)	-0.016	-2.13%
Amhara	0.912(0.003)	0.864(0.005)	-0.010**	-1.05%	0.792(0.009)	-0.012***	-1.39%	0.731(0.054)	-0.020	-2.57%
Oromia	0.862(0.004)	0.808(0.006)	-0.011***	-1.25%	0.796(0.01)	-0.002	-0.25%	0.699(0.041)	-0.032**	-4.06%
Somali	0.878(0.006)	0.86(0.01)	-0.004	-0.41%	0.852(0.01)	-0.001	-0.16%	0.723(0.065)	-0.043**	-5.05%
Benishangul	0.849(0.005)	0.857(0.006)	0.002	0.19%	0.845(0.008)	-0.002	-0.23%	0.716(0.062)	-0.043*	-5.09%
SNNP	0.848(0.004)	0.77(0.006)	-0.016***	-1.84%	0.812(0.008)	0.007***	0.91%	0.734(0.047)	-0.026*	-3.20%
Gambela	0.827(0.006)	0.79(0.01)	-0.007***	-0.89%	0.735(0.02)	-0.009**	-1.16%	0.668(0.068)	-0.022	-3.04%
Harari	0.498(0.012)	0.405(0.02)	-0.019***	-3.73%	0.604(0.018)	0.033***	8.19%	0.395(0.055)	-0.070***	-11.53%
Addis Ababa	0.083(0.005)	0.097(0.007)	0.003	3.37%	0.251(0.01)	0.026***	26.46%	0.207(0.056)	-0.015	-11.53%
Dire Dawa	0.401(0.012)	0.434(0.019)	0.007	1.65%	0.58(0.032)	0.024***	5.61%	0.413(0.060)	-0.056**	-9.60%

Note: *** P < 0.01, ** P < 0.05, and * P<0.1. Standard errors in parentheses.

Source: Author's computations using DHS data.

Table 2.13. Population Share and Multidimensional Poverty Contribution of Regions

	2000			2005			2011			2016		
Regions	percent	cont	diff	percent	cont	diff	percent	cont	diff	percent	cont	diff
Tigray	9.55	11.18	1.63	9.15	10.89	1.74	7.55	8.03	0.48	7.79	8.28	1.51
Afar	5.79	6.96	1.17	5.87	7.10	1.23	14.77	15.78	1.01	8.23	9.35	2.37
Amhara	14.19	17.49	3.3	16.34	19.25	2.91	13.73	15.16	1.43	13.85	13.42	0.53
Oromia	15.78	18.35	2.57	16.22	17.88	1.66	11.94	13.26	1.32	15.15	16.37	1.22
Somali	6.10	7.23	1.13	7.04	8.26	1.22	6.51	7.74	1.23	3.51	4.23	2.11
Benishangul	6.96	8.08	1.12	5.96	6.96	1.00	7.25	8.55	1.30	8.23	9.65	1.42
SNNP	13.14	15.04	1.63	15.21	15.97	0.76	12.96	14.67	1.71	14.29	15.33	1.12
Gambela	6.24	6.96	1.90	6.22	6.70	0.48	4.17	4.27	0.10	7.36	9.85	2.49
Harari	6.19	4.16	-2.03	4.50	2.49	-2.01	6.44	5.42	-1.02	6.98	7.21	-1.13
Addis Abeba	9.66	1.08	-8.58	7.80	1.13	-6.49	10.42	3.66	-6.76	9.09	6.55	-2.54
Dire Dawa	6.41	3.46	-2.95	5.69	3.38	-2.31	4.28	3.47	-0.81	6.49	5.92	-0.57

Note: percent- population percentage share of the regions; cont.- region’s multidimensional poverty contribution; diff- difference between multidimensional poverty contribution and population percentage share.

Table 2.14. Weight of MPI's indicators using equal weight and the factor weighing system

Dimensions	Indicators	Equal weight	Factor weight
Living Standard	Electricity	0.056	0.159
	Sanitation	0.056	0.122
	Water	0.056	0.136
	Cooking	0.056	0.139
	Floor	0.056	0.149
	Asset	0.056	0.122
Health	Child mortality	0.167	0.010
	Nutrition	0.167	0.003
Education	HGC	0.167	0.119
	School attendance	0.167	0.041

Table 2.15. Key References				
Authors	Year	Approach	Contribution	Main findings
Maasoumi, E. and T. Xu	2015	Maasoumi's two-step measures of aggregation based on an entropy distance measures for aggregate well-being.	An aggregation formula for the aggregate well-being function and distribution of the self-reported indicators.	Incorporating substitution among attributes and considering group heterogeneity are very important in a multidimensional analysis of well-being or poverty.
Ravallion, M.	2011	Two approaches for the aggregate poverty index: to use price to form the composite index or to measure poverty in each dimension separately and then aggregate dimension specific deprivations into a composite index.	Rather than having one index like MPI, there should be a credible set of multiple indices, spanning the dimensions of poverty, most relevant to a specific setting.	A single index can never be sufficient statistics for poverty assessment. When weights are needed for aggregation, they should be consistent with well-informed choices made by poor persons.
Dhongda et al.	2015	Grouping multiple dimensions as basic and non-basic attributes.	Proposed multidimensional poverty indices suitable for data which are binary, ordinally measurable.	Developed a class of deprivation measures when the available data is whether an individual is deprived in an indicator or not.

Atkinson, A.B.	2003	Accounting approach based on social welfare.	Bringing out key features of different approaches and setting them in a common framework.	Place in a common framework of two approaches apparently at variance with identifying the key differences underlying the judgment.
Berenger,V and Verdier_chouchane, A.	2007	Two well-being measurement approaches are used to measure well-being: the totally fuzzy analysis and the factorial analysis of correspondences approach.	The two methods of well-being measurement, TFA and FAC, take into account several dimensions of well-being and enable two indices to be constructed according to Sen's capability approach.	Measuring two well-being measures: standard of living and quality of life using Sen's capability approach.
Decancq and Lugo	2008	Data driven weighting schemes and normative weighting of the indicators.	A unifying framework that allows us to compare the different approaches and analyze the specific role of the dimension's weight.	For interaction and choices about the transformation and aggregation of the different attributes. The weights play a crucial role in determining the trade-offs between the dimensions.
Duclos and Younger	2006	Dominance approach in poverty comparisons.	It is possible to make very general poverty comparisons for multiple dimensions of well-being.	Multidimensional poverty orderings are robust to the poverty line and valid for the choice of any poverty frontier over broad ranges.

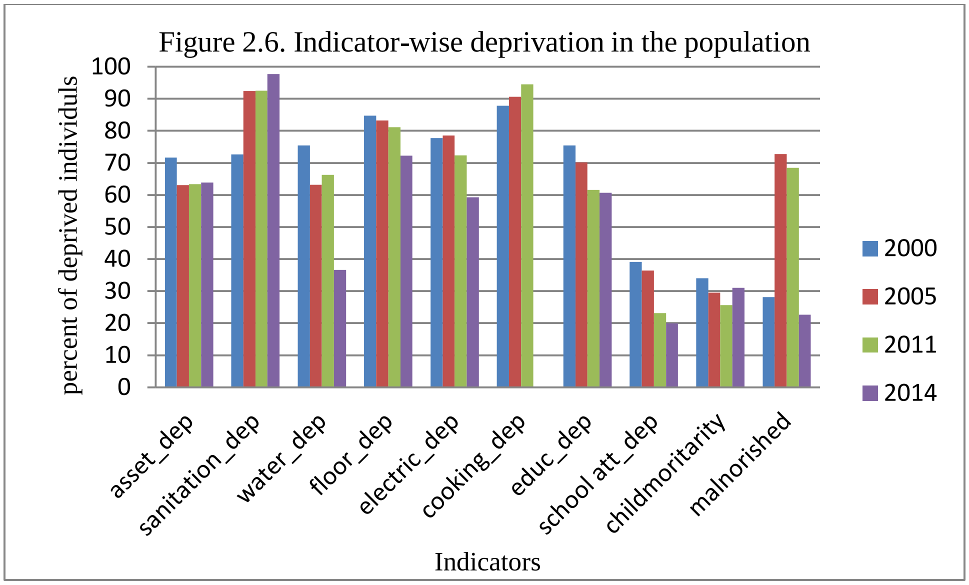
Figure 2.6. Indicator-wise deprivation in the population
percent of deprived individuls
100
90
80
70
60
50
40
30
20
10
0
asset_dep
sanitation_dep
water_dep
floor_dep
electric_dep
cooking_dep
educ_dep
school att_dep
childmoritarity
malnorished
Indicators
2000
2005
2011
2014

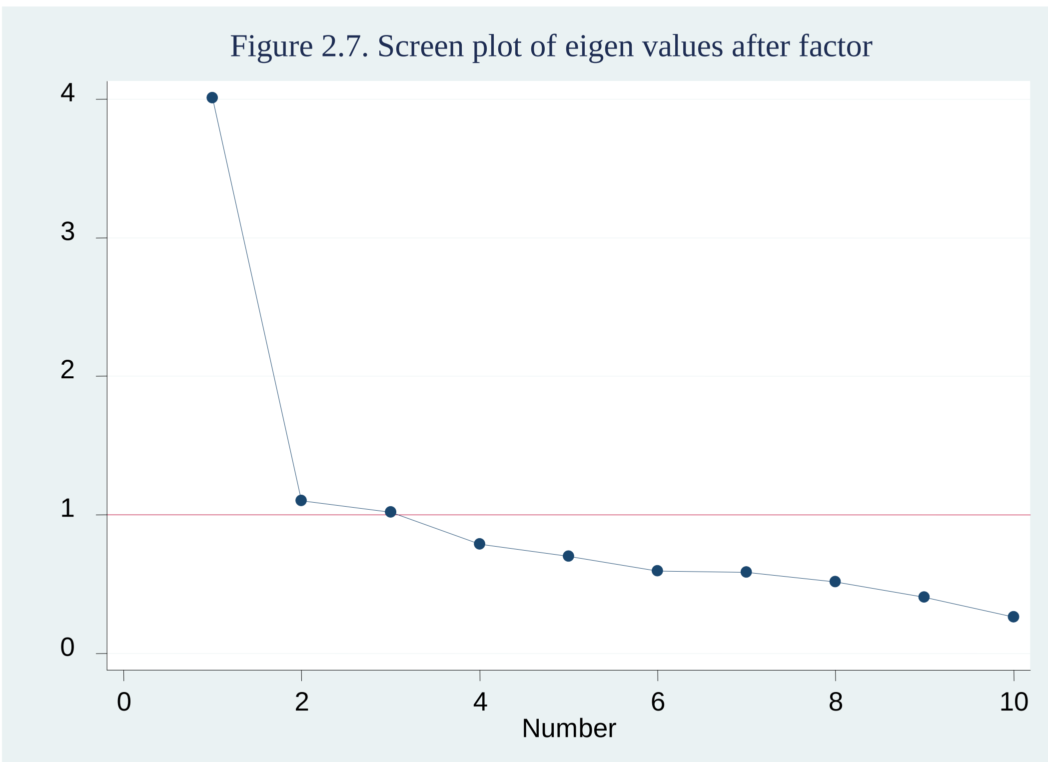
Figure 2.7. Screen plot of eigen values after factor
4
3
2
1
0
0
2
4
6
8
10
Number

Chapter 3: Vulnerability to Poverty in Ethiopia

Abstract

Income or consumption expenditure has been regarded as a proxy for households' material well-being. However, economists have long recognized that households' well-being depends not just on their average income or consumption expenditure but also on the risks or vulnerabilities that they face and their ability to deal with them. Therefore, vulnerability is a more satisfactory measure of welfare. This study examines households' vulnerability to poverty and estimates the extent of vulnerability using vulnerability as an expected poverty approach. The unidimensional vulnerability measure using consumption expenditure shows that 35 percent of the population is vulnerable to poverty in 2016. Rural households' vulnerability is relatively high as compared to urban areas. A multidimensional vulnerability estimate (86 percent) is markedly different from a unidimensional vulnerability estimate (35 percent). The distribution of vulnerability across different segments of the population differs from the distribution of poverty. This study argues that there is a need for a distinction between poverty prevention (vulnerability) and poverty alleviation programs. Households that are poor at any given point in time may differ from those who are vulnerable to poverty; therefore, interventions and programs meant for reducing the level of vulnerability in the population need to be targeted differently from those aimed at poverty alleviation.

Keywords: vulnerability; poverty; consumption expenditure.

JEL Classification Codes: I32; C31; D3

3.1 Introduction

Like many other developing countries, poverty reduction is a top policy priority in Ethiopia. Poverty reduction policies in most developing countries, including in Ethiopia, focus on people or households that are currently poor and ignore those who are likely to be poor in the future. For more than two decades now, poverty assessments or analyses have been done to inform policymakers on how to alleviate poverty in developing economies. These poverty assessments have shown detailed profiles of the poor to understand the incidence or depth of poverty in various socioeconomic groups. But poverty is a stochastic phenomenon; poor households today may or may not be poor tomorrow. Currently non-poor households may become poor in the near future because of some adverse shock. Among the currently poor households there may be some who will continue to be poor. In general, a poverty analysis (households' current poverty level) is an ex-post measure of households' well-being and may not be a good guide to the households' vulnerability to poverty. Inadequate data and research in vulnerability to poverty contributed to the focus on current poverty (Novignon et al., 2012). For policy purposes, what really matters is the likelihood of households or individuals remaining or falling into poverty in the near future - vulnerability to poverty. The most effective way of ensuring households' economic well-being is by getting them out of poverty or preventing them from falling into poverty rather than attending to poverty after households have become poor.

Although Ethiopia has achieved economic growth it is not clear whether vulnerability to poverty has also declined in the country. Considering households' vulnerability to poverty is essential for any poverty reduction efforts and for bringing about sustainable growth and development. Risk is inherent in human life and households in Ethiopia are exposed to different kinds of risks (for example, droughts, crop and animal diseases, floods, population growth, low productivity, and unstable political conditions). Households' exposure to different risks, whether idiosyncratic or covariate is the main reason for examining vulnerability to poverty. According to Hoddinott and Quisumbing (2008) vulnerability is uninsured exposure to different risks and can be defined as the risk of non-poor individuals or households falling below the poverty line or those already below the poverty line remaining in poverty.

Unavailability of data in developing nations which can help in predicting risks makes vulnerability estimations very difficult. Financial markets are not well-developed and are less efficient so households in developing nations have limited market based instruments like insurance. Social insurance programs related to unemployment, sickness, and injuries are hardly there. In developing nations, policies designed to reduce poverty should consider current non-poor but vulnerable to poverty households with the poor households. As pointed out by Raghbendra et al., (2009) the part of the population that faces vulnerability to poverty is considerably different from the part that is observed to be poor. In Ethiopia, around 48 percent households are highly vulnerable to poverty and about 18 percent of the non-poor are highly vulnerable to poverty **(**Fekadu, 2013). Moreover, the distribution of vulnerability to poverty across different regions of the country differs significantly from the distribution of poverty. Hence, poverty reduction strategies need to consider both poverty alleviation and poverty prevention (vulnerability to poverty) programs.

Poverty and vulnerability to poverty are closely related concepts. The poor are typically the most exposed to different types of risks and the poor have the fewest instruments to deal with these risks and hence, poverty and vulnerability to poverty are two sides of the same coin (Chaudhuri et al., 2002; Tu Dang, 2009). It is now widely recognized that policy designs aimed at combating poverty ought to focus not only on those who are currently poor but also on those facing the risk of moving into poverty and those already trapped in it. That is why, currently, an analysis of households' vulnerability to poverty is becoming the main focus of development economics literature.

There is widespread poverty in Ethiopia and many households suffer spells of chronic and transient poverty. Researches show that the expected poverty (vulnerability) is much higher in Ethiopia than the point in time estimates of poverty (Demissie and Kasie, 2017; Fekadu, 2013; Negassa and Fekadu, 2014). Various interventions have been made to reduce the incidence of poverty. However, it is difficult to solve these problems due to the depth and complexity of poverty and vulnerability to poverty. Hence, vulnerability to poverty has to be a point of concern in Ethiopia which needs a rigorous analysis. The few available studies on vulnerability to poverty focus on one dimensional vulnerability to poverty, using income or consumption expenditure (Demissie and Kasie, 2017; Dercon and Krishnan, 2000; Megersa, 2015; Negassa and Fekadu, 2014) and overlook vulnerability to multidimensional poverty. Some unidimensional vulnerability to poverty studies are also region specific. For example, Fekadu (2013) studied vulnerability to poverty in the Oromia regional state which does not show vulnerability to poverty in the country. Others are gender based, for example Negassa and

Fekadu (2014) studied vulnerability of female-headed households and does not give a clear picture of households' vulnerability to poverty in the country. OPHI (2017) used the weighted deprivation score as an indicator of vulnerability to multidimensional poverty using a different approach. Households with deprivation scores of 20 to 33.3 percent were considered vulnerable to multidimensional poverty.

This research on vulnerability to poverty studies both the aspects from the one dimensional and multidimensional perspective and provides a detailed account of vulnerability in Ethiopia. By identifying the indicators that contribute more to multidimensional poverty the research estimates vulnerability based on deprivation scores of the multidimensional poverty index using factor analysis weights where no similar research has been done so far. It also highlights an approach or perspective of addressing or measuring multidimensional vulnerability to poverty. Using rigorous modeling techniques and stochastic dominance, this study estimates households' vulnerability to both unidimensional and multidimensional poverty and contributes to literature on vulnerability.

The rest of the chapter is structured as follows. Section 2 discusses the conceptual frameworks of the research while Section 3 reviews related literature. Section 4 discusses the data and methodology used and Section 5 presents the results and discusses its findings. Section 6 gives a conclusion based on the findings of the study and Section 7 forward some recommendations.

3.2 Conceptual Frameworks

Vulnerability to poverty can be conceptualized as having two components: households' exposure to a shock and their ability to manage it. Shocks include natural shocks such as a drought, flood, and crop failure or economic shocks such as a financial crisis. There are different mechanisms that households can use to protect themselves from such risks or vulnerabilities. People can protect themselves by drawing on their savings, diversifying their livelihoods or by building social networks that provide informal social assistance. People become vulnerable when all these risk coping mechanisms fail. An assessment of vulnerability includes households' welfare incorporating both average expenditure (expected expenditure) and the risks (volatility) that they face.

One of the greatest challenges to development facing the world today is the elimination of poverty through reducing vulnerability to poverty (Gerald, 2012). This is because a society that is characterized by high levels of poverty and vulnerability to poverty is seen as lacking the potential needed to get out of underdevelopment. Poverty and vulnerability to poverty are complex and multifaceted concepts that are interlinked in such a way that each causes the other. While poverty makes people vulnerable to various shocks such as droughts, diseases, and other natural disasters, vulnerability to such shocks exacerbates their poverty and hence their vulnerability to future shocks.

A poverty assessment that includes an analysis of vulnerability to poverty is both desirable and necessary (Chaudhuri, 2003). First, for thinking about appropriate forward-looking anti-poverty interventions, it is clearly necessary to go beyond a cataloging of who is currently poor and how poor they are to an assessment of households' vulnerability to poverty–who is likely to be poor? How likely are they to be poor? And why are they likely to be poor? Second, focusing on vulnerability to poverty highlights the distinction between poverty prevention interventions and poverty alleviation interventions. Third, vulnerability is an inherent aspect of human well-being and exposure to risks and uncertainties about the future certainly affect current well-being (Tu Dang, 2009).

Households' current multidimensional poverty indicators such as assets and entitlements cannot guarantee their future vulnerability to poverty status. For instance, if there are two households (A and B) on the same iso-poverty surface and if household A is relatively healthy and well-educated but deprived income-wise, it may be less vulnerable and better able to withstand a shock than household B that has a higher income but is more deprived in terms of health and education. In other words, when present measures of multidimensional poverty compare individuals they ignore the differential risks and vulnerability conditions of alternative portfolios of attributes yielding the same level of poverty today (Thorbecke, 2008). However, there is dependence between the form that poverty takes today and possible poverty outcomes in the future.

3.3 Literature Review

3.3.1 Vulnerability to Poverty

Poverty affects the lives of millions of people worldwide. Poverty measures are widely used for designing poverty alleviation policies by governments and international organizations. Poverty alleviation policies are future focused; however, the most commonly used poverty measures indicate the current poverty or poverty history of a country and do not say anything about future poverty or vulnerability to poverty of the households and hence do not provide forward looking information. If policymakers design poverty alleviation policies on the basis of the poverty status in the current year, the poor may escape from poverty and the non-poor may slip into poverty in the future due to various reasons. The question is who is likely to suffer the most poverty in the future and an important way of measuring this is by considering vulnerability to poverty (Iqbal, 2013). Therefore, a poverty analysis should consider households' vulnerability to poverty for designing appropriate poverty reducing policies. It is also suggested that ex-ante measures to prevent households from becoming poor as well as ex- post measures to alleviate those already in poverty should be combined in evaluating poverty (Azam and Imai, 2009).

There is no consensus on a definition of vulnerability to poverty. However, research increasingly defines vulnerability to poverty as the probability of falling into poverty or remaining in poverty (Chaudhuri, 2003; Chaudhuri et al., 2002). Vulnerability to poverty can also be defined as the probability that an individual or a household may be poor in the near future regardless of whether it is currently poor or not (Demissie and Kasie, 2017). Duflo (2005) defined vulnerability as the probability or the risk of a household falling into or remaining in poverty at least once in the near future. Unlike poverty, vulnerability to poverty is a more future oriented concept that considers households' possible welfare changes in the future. Therefore, vulnerability has the nature of a probability forecast and is seen as expected poverty (Gowon et al., 2013; Novignon et al., 2012; Tu Dang, 2009). Poverty is the ex-post realization of a variable such as well-being or income with respect to a socially determined minimum threshold (poverty line), while vulnerability is the ex-ante expectation of that variable relative to this threshold (Dercon, 2005). The World

Development Report (2000-01) defines vulnerability as the risk that a household or an individual will experience an episode of income or health poverty over time.

There are three widely used approaches for measuring vulnerability to poverty (Hoddinott and Quisumbing, 2003, 2008): vulnerability as expected poverty (VEP), vulnerability as a low expected utility (VEU), and vulnerability as an uninsured exposure to risk (VER). These approaches construct a model that predicts a measure of welfare. VEP and VEU share two further commonalities: they refer to a benchmark for this welfare indicator, z, and enumerate a probability of falling below this benchmark. Vulnerability is the likelihood that realized consumption will fall below the poverty line. The VEP and VEU approaches measure vulnerability at the individual level; however, when aggregation of all individuals or households is considered it gives a measure of aggregate vulnerability. Expected poverty is more easily measurable than utility-based measures (Ligon and Schechter, 2003) and conceptualizing vulnerability in terms of expected poverty seems reasonable in assessing ex-ante household welfare.

VER assesses whether observed shocks generate welfare losses but does not measure vulnerability as it does not construct probabilities. These are ex-post assessments of the degree to which a negative shock causes a household to deviate from expected welfare. In terms of policy implications, the VEP approach can help distinguish between those who are currently poor and those who are permanently poor and so could help design preventive measures before adverse events actually happen (Kamanou and Morduch, 2004). Vulnerability as expected poverty has been widely used in literature (Gunther and Harttgen, 2009; Imai et al., 2010; Jha et al., 2010; McCullach and Calandrno, 2003; Novignon et al., 2012; Sricharoen, 2011). Approaches have been also used to estimate vulnerability to poverty in different developing countries' contexts like Vietnam (Imai et al., 2011a), Bangladesh (Azam and Imai, 2009), rural China (Zhang and Wan, 2006), and Guatemala (Tesliuc and Lindert, 2004).

There are different ideas about the poverty line and the vulnerability to poverty line. Chakravarty et al., (2016) argue that in the presence of vulnerability to poverty, the poverty line is adjusted in such a way that the utility of a person at the current poverty line and that at the adjusted poverty line become equal. The adjusted poverty line is a simple relative augmentation of the current poverty line under a multiplicative model of vulnerability with a constant Arrow-Pratt relative risk aversion. Therefore, a household or a person who is non-poor (poor) currently may not be treated as non-poor (poor) in a vulnerable to poverty situation. The authors also studied the implications of vulnerability for the poverty line and the issue of adjusting the poverty threshold under vulnerability so that the corrected poverty line also represented the standard of living in an environment of vulnerability. According to Dang and Lanjouaw (2014), two thresholds are important for identifying poor and vulnerable groups. These are poverty line and vulnerability to poverty line, below which non-poor households can face a higher risk of falling back into poverty. The first approach is identifying a population that is not vulnerable and the lower bound income level for this population group is the vulnerability line. The second approach is considering the population that is clearly not poor but faces a real risk of falling into poverty and the upper bound income level for this population can be set as the vulnerability line. This approach avoids the arbitrariness and indirectness of scaling up the poverty line by a certain factor to get the vulnerability line.

Vulnerability as an area of economic research has been widely explored by scholars using panel data. However, due to the limitations imposed by lack of reliable and up to date panel data in developing countries, a vulnerability analysis using cross-sectional data in such a way that utilizes the variance of consumption to estimate the expected poverty of households is now widely used (Azam and Imai, 2009; Chaudhuri, 2003; Chaudhuri et al., 2002; Fekadu, 2013; Gowon et al., 2013; Jha and Dang, 2010; Iqbal, 2013; Imai et al., 2010; McCullach and Calandrno, 2003; Megersa, 2015; Raghbendra et al., 2009; Novignon et al., 2012; Sricharoen, 2011). Besides the lack of long panel data for an analysis of vulnerability to poverty, most current surveys often do not contain sufficient information about the shocks that households face to estimate the impact that these shocks have on vulnerability. Important shocks that households' face, which make them likely to be vulnerable to poverty are illnesses, floods, and droughts. There may be other shocks as well such as asset losses, labor market disturbances, harvest failure, and civil unrest. Economists have also recognized that households' well-being depends not just on their average income or expenditure, but also on the risks that they face (Dercon and Krishnan, 2000; Raghbendra et al., 2009; Tu Dang, 2009). Hence, collecting data on some of these and other relevant indicators may prove valuable for an analysis of vulnerability to poverty.

3. 3.2 Determinants of Vulnerability to Poverty and Empirical Evidence

Literature shows that there are demographic, socioeconomic, and community characteristics that affect vulnerability to poverty. Vulnerability to poverty varies across regions and seasons (Iqbal, 2013). A household head's education level and ownership of agricultural land have a positive effect on consumption and reduce vulnerability to poverty. Fujii (2016) showed that location was an important determinant of vulnerability to poverty in many of the studies that he did. This is not surprising because infrastructure is not evenly distributed across the regions in most developing countries as a result of which economic conditions are different across different locations. Location matters for access to markets, credit, and other public services, hence understanding the underlying cause of vulnerability to poverty at each location is a first step in determining appropriate location-specific policies to cope with vulnerability. Fujii, however, underscores that currently there is little knowledge about what location-specific characteristics affect vulnerability.

Using cross-sectional data from Indonesia and a three-stage feasible generalized least squares procedure, Chaudhuri et al., (2002) estimated the variance of the log of consumption on household characteristics. Their results showed that at the national level 23 percent of the Indonesians were poor and 45 percent were vulnerable to poverty. A study in Bangladesh showed that poverty was not the same as vulnerability to poverty as a substantial share of those currently above the poverty line was highly vulnerable to poverty (Azam and Imai, 2009). Their study stated that those without education were likely to be the most vulnerable. In investigating factors that affect vulnerability, McCulloch and Calandrino (2003) also found that demographic characteristics, education, household's location, and assets were important factors in vulnerability to poverty.

Using a large repeated cross-sectional survey dataset collected under the Chinese Household Income Project, Imai et al., (2010) found that poverty and vulnerability to poverty significantly decreased in China during the study period (1988 to 2002). They also showed that household head's education and access to electric power were negatively associated with both poverty and vulnerability to poverty. On the other hand, agricultural land size and irrigated land area were associated with vulnerability but not poverty. Their study also stated that education and location were among the factors that consistently emerged as significant covariates of vulnerability to poverty.

Using the expected poverty measures approach, Imai et al., (2011b) estimated the vulnerability of various ethnic groups in Vietnam. They found that households in ethnic minority groups were poor and more vulnerable than those in ethnic majority groups and the study highlighted the importance of ethnic considerations in vulnerability to poverty studies. An analysis of poverty and vulnerability in Tajikistan, using a panel dataset and an expected poverty approach showed that rural households were poorer and more vulnerable than urban households (Jha et al., 2010).

Using a panel dataset for villages in rural Ethiopia, Dercon and Krishnan (2000) showed that on average year-to-year poverty in Ethiopia was very similar; however, they found high vulnerability in consumption and poverty over the seasons and year-by-year. They computed poverty under different scenarios: whether there was a safety net program, whether the rainfall in the area where the household resided was normal or bad, and whether there were seasonal price fluctuations. A comparison of these scenarios showed that poverty could change substantially within a relatively short period of time and a large number of households were vulnerable to shocks than implied by the standard poverty statistics. The number of households in rural Ethiopia that fall below the poverty line when serious shocks hit the households and the community is about 50 to 75 percent greater than the poverty estimates obtained using the current cross-sectional estimates in each period (Dercon and Krishnan, 2000). Based on the Ethiopian Rural Household Surveys for 1999-2000, Negassa and Fekadu (2014) showed that on average 38 percent of the sampled households were highly vulnerable to poverty and 16.38 percent of the non-poor were highly vulnerable to poverty. However, based on recent data used for this study, only 35.26 percent of the households in rural Ethiopia were poor. This shows that expected poverty or vulnerability to poverty was greater than the point in time estimates of poverty which shows the importance of a forward looking poverty analysis (vulnerability to poverty).

Studies on vulnerability to poverty in Ethiopia using the same Ethiopian Rural Household Survey data as this study do show some differences in their results. For example, using Ethiopian Rural Household Survey data, Megersa (2015) found that vulnerability to poverty in Ethiopia was 51 percent. Villages in the northern (Tigray) and the southern regions (SNNP) had the highest average vulnerability of approximately 52 percent which is a bit higher than the national average (51 percent). Vulnerability to poverty in Amhara and Oromia regions was 50 percent and 49 percent respectively which is less than that in SNNP (52 percent) and even the national level (51 percent). This implies that vulnerability to poverty of rural households in Ethiopia is not the same; farmers in different regions have different levels of vulnerability to poverty.

Vulnerability to multidimensional poverty is the threat of facing multidimensional poverty in the future related to both predicted shortfalls in any well-being dimensions and also to the effects of uncertainty and well-being risks. A vulnerability analysis involves identifying threats and responses to exploiting opportunities and resisting or recovering from the negative effects of a changing environment. Therefore, the assets and entitlements available to individuals and households are critically related to vulnerability. Fujii (2016) underscores the importance of building productive assets to increase income and decrease the variances in income to escape from the threat of poverty. Literature also redefines poverty and draws attention away from income or consumption expenditure shortfalls to other forms of deprivation (Calvo, 2008). Calvo's research showed vulnerability to multidimensional poverty using data from Peru (1998-2002) and discussed bidimenional vulnerability to poverty and shed some light on the importance of vulnerability to multidimensional poverty. However, the research was limited to only two dimensions (consumption and leisure). Therefore, multidimensional vulnerability to poverty studies using health, education, and other important indicators of well-being are important to bridge this gap in literature.

3.4 Data and Methodology

3.4.1 Data

This research used data from the Household Consumption and Expenditure Surveys (HCES) for a unidimensional vulnerability to poverty analysis. Household Consumption and Expenditure Surveys (HCES) are complex surveys conducted on a nationally representative sample to characterize important aspects of households' socioeconomic conditions. The Consumption Expenditure Surveys have been conducted by the Central Statistical Agency (CSA) of Ethiopia since 1995-96 at four or five-year intervals. The 2015-16 HCES is the fifth survey in the series. The primary purpose of the surveys is providing information for monitoring poverty, measuring national accounts, and consumer price indices. The food data collected in HCES can be used for producing a variety of food security and nutrition indicators.

The surveys provide income, expenditure, and other socioeconomic data at the household level, which is useful in an analysis of poverty and vulnerability to poverty. It also includes households' food and non-food consumption as well as the quantities consumed and their values. Non-food consumption includes cigarettes, alcohol, clothes, household goods, transport, health, and education. We consider land ownership as a proxy for physical capital ownership and household head's education level as a proxy for human capital ownership of a household as shown in most poverty research.

For a vulnerability to multidimensional poverty analysis, we used Ethiopian Demographic and Health Survey (EDHS) data for 2011 and 2016. This is a comprehensive dataset that consists of samples from all regions in the country which represent the national population of Ethiopia. The data also contains household members' level of education, children's school attendance, child health, child mortality, maternal mortality, and the nutritional status of the household's members (CSA, 2012).

3.4.2. Unidimensional Poverty

Income or consumption expenditure measures of poverty have been used widely in poverty analyses. Despite its limitations, the unidimensional measure of poverty provides good information for assessing public policies and evaluating the impact of the interventions. However, this chapter's focus is not on absolute poverty and relative poverty measures but on vulnerability to poverty. Hence, it is important to highlight the extent of poverty in the country. Relative poverty is more important than absolute poverty as the cost of living is different based on regions or places of residence. Therefore, it is essential to examine unidimensional poverty using consumption expenditure before we analyze vulnerability to poverty.

In this research, we used the family of Foster, Greer, and Thorbecke (FGT) poverty measures (P_α), that are widely used because they are consistent and additive decomposable (Foster et al., 1984). The FGT index is given by:

(3.1) $$P_\alpha = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{Z - CE_i}{Z}\right)^\alpha$$

where Z is the poverty line, CE_i is the per capita consumption expenditure in increasing order of $CE_1 \le CE_2 \le ...... \le CE_q \le Z \le CE_{q+1} \le ..... \le CE_N$ for all households N, q is the number of poor people in a population of size N, and α measures policymakers' degree of aversion to inequality among the poor that takes on the values zero, one, and two. The higher the value of α , the higher is the weight attached to the poorest of the poor. Three indices of poverty can be measured using different values of α $(\alpha = 0, \alpha = 1, \alpha = 2)$. For $\alpha = 0$, the poverty index is the headcount poverty index, (P_0) which measures the proportion of population whose per capita consumption expenditure is less than the poverty line or it measures the incidence of poverty. Poverty rate is simple to compute and easy to understand. But the index ignores difference in well-being between poor households, it does not take the intensity of poverty into account, and it is not sensitive to changes in consumption or income as long as they remain below the poverty line. For $\alpha = 1$, the poverty measure is the poverty gap index (P_1), which measures how far the poor households are from the poverty line. It gives a better understanding of the depth of poverty and shows how much would have to be transferred to the poor to bring their expenditure up to the poverty line. Finally, for $\alpha = 2$ we get the squared poverty gap index (P_2) which measures the severity of poverty. It measures the inequalities among the poor besides measuring the distance from the poverty line.

3.4.3. Vulnerability to Unidimensional Poverty

It is important to get an estimate of households' variance in consumption expenditures to estimate a household's vulnerability to poverty (Suryahadi and Sumarto, 2003). A reliable estimate of variance in consumption expenditure can be obtained from panel data with a sufficiently long period of observations (Holzmann et al., 2003; Ligon and Schechter, 2003). But most household survey data available to date in most developing nations is cross-sectional. Hence, there is clearly a need for developing a method for estimating variance in households' consumption expenditure from cross-sectional data. Such a method was developed by Chaudhuri (2000) and has been used by different authors (Azam and Imai, 2009; Iqbal, 2013; Novignon et al., 2012; Suryahadi and Sumarto, 2003).

In principle, the task of measuring vulnerability to poverty requires information about the resources that the households' can draw on in the next period, including assets such as land as well as education and the risks that they face. However, it is impossible to collect all the information needed for such an analysis and also hard to model all the possible behavioral responses by households. The solution, as in all models, is simplifying the problem enough to make it tractable. In the simplest case three pieces of information and one additional assumption are enough to measure households' vulnerability to poverty. The required information is the household's expected consumption per capita in the next period $E(C_{t+1})$, variance of the household's expected level of consumption per capita in the next period δ^2_{t+1} and the poverty line Z. The assumption is that the expected level of consumption follows a known distribution like a normal distribution.

Although we do not know what a household's exact level of consumption will be next year, it is possible to arrive at reasonable estimates by building a model of determinants of consumption and using the model we can predict next year's consumption. A household's probability of being poor in the future depends both on its mean consumption expenditure and the variation in consumption expenditure. Therefore, estimating vulnerability to poverty requires estimating future mean consumption as well as its variability or volatility. As done by Chaudhuri et al., (2002) we begin by assuming that the stochastic process generating household h's consumption is given by:

(3.2) $$\ln C_h = X_h\beta + e_h$$

where C_h is per capita consumption expenditure and X_h represents a bundle of observable household characteristics. Characteristics include household size, location, and educational attainments of the household head, β is a vector of parameters to be estimated, and e_h is a disturbance term that captures idiosyncratic factors (shocks) that contribute to different consumption levels for households.

Household future consumption is further assumed to be dependent on uncertainty about some idiosyncratic and community characteristics. To have a consistent estimator of the parameter, it is necessary to allow heteroskedasticity. We do, however, allow the variance of e_h (and hence of $\ln C_h$) to depend on observable household characteristics in some parametric way. The estimates are generated assuming the following simple functional form:

(3.3) $$\delta^2_{e,h} = X_h\theta$$

We estimate β of Equation (3.2) and θ of Equation (3.3) using a three-step feasible generalized least squares (FGLS) procedure suggested by Amemiya (1977) which has also been used by others (Chaudhuri et al., 2002; Novignon et al., 2012; Sricharoen, 2011). Equation (3.2) is first estimated using an ordinary least squares (OLS) procedure and the estimated residuals from Equation (3.2) are used for estimating the following equation, again by using OLS:

(3.4) $$\hat{e}^2_{ols,h} = X_h\theta + \eta_h$$

This is then used to transform Equation (3.4) into:

(3.5) $$\frac{\hat{e}^2_{ols,h}}{X_h\theta_{ols}} = \left(\frac{X_h}{X_h\theta_{ols}}\right)\theta + \frac{\eta_h}{X_h\theta_{ols}}$$

This transformed equation is estimated using OLS to obtain an asymptotically efficient FGLS estimator $\hat{\theta}_{FGLS}$. $X_h\hat{\theta}_{FGLS}$ is a consistent estimate of $\delta^2_{e,h}$, which is the variance of the idiosyncratic component of household consumption expenditure. This is then used to transform Equation (3.2) into:

$$\text{(3.6)} \qquad \frac{\ln C_h}{\sqrt{X_h\hat{\theta}_{FGLS}}} = \left(\frac{X_h}{\sqrt{X_h\hat{\theta}_{FGLS}}}\right)\beta + \frac{e_h}{\sqrt{X_h\hat{\theta}_{FGLS}}}$$

Using the estimates $\hat{\beta}$ and $\hat{\theta}$ we can directly estimate the expected log consumption:

$$\text{(3.7)} \qquad E[\ln C_h \mid X_h] = X_h\hat{\beta}$$

And the variance of log consumption given the characteristics of the household X_h is:

$$\text{(3.8)} \qquad V[\ln C_h \mid X_h] = \delta^2_{e,h} = X_h\hat{\theta}$$

For each household h, by assuming that consumption is log-normally distributed (that is, $\ln C_h$ is normally distributed), we are able to use these estimates to form an estimate of the probability that a household with characteristics, X_h, will be poor, that is, the household's vulnerability level. Letting Φ (.) denote the cumulative density of the standard normal, the estimated probability is given by:

$$\text{(3.9)} \qquad \hat{V}_h = \hat{P}_r(\ln C_h < \ln Z \mid X_h) = \Phi\left(\frac{\ln Z - X_h\hat{\beta}}{\sqrt{X_h\hat{\theta}}}\right)$$

This equation gives us vulnerability to poverty $\hat{V}_h$ or the probability that the per capita consumption level (C_h) will be less than the poverty line (Z), conditional on the household characteristics (X_h) and $\Phi(.)$ denotes the cumulative density of the standard normal distribution. Our measure of vulnerability as the probability of poverty captures the likelihood that incomes will fall below the poverty line at some point in the future. The advantage of this vulnerability measure is that it can be measured with cross-sectional data, but this measure requires a large sample in which some households' experience a good time and others suffer from negative shocks and it is also likely to reflect unexpected large negative shocks.

Identifying household characteristics that are associated with vulnerability necessitates making strong assumptions about the stochastic process that generates consumption as the available data for the estimation of vulnerability consists of a single cross-section (Chaudhuri, 2000). The most important identifying assumption is that cross-sectional variance can be used for estimating inter-temporal variance (Sricharoen, 2011). Due to the idiosyncratic components in the model, cross-sectional variance is most likely to explain a part of the inter-temporal variance. Errors in measuring consumption may result in a significant overestimation of the variance of consumption, and thus of vulnerability. An advantage of a FGLS approach for estimating the variance of the idiosyncratic component of household consumption is that it yields a consistent estimate of the true variance of consumption even when consumption is measured with an error (Tesliuc and Lindert, 2002). In these types of models, due to the measurement error (from unobserved and omitted variables) associated with the use of cross-sectional data in consumption studies, a low R square value is very common (Sricharoen, 2011)

Identifying whether a given household is vulnerable or not is an important exercise that has important implications for targeting development assistance. Generally speaking, we require a threshold probability level of poverty above which a household is considered vulnerable. There are two vulnerability thresholds (Chaudhuri et al., 2002): the observed current poverty rate in the population and the alternative threshold which is 0.5. The most commonly used threshold in existing literature is a poverty probability of 0.5. This threshold indicates that a household whose poverty probability level is greater than 50 percent is more likely to be poor and thus can be considered vulnerable (Chaudhuri et al., 2002; Sricharoen, 2011). This vulnerability threshold has been used extensively in literature (for example, Christiaensen and Subbarao, 2004; Imai et al., 2010; Zhang and Wan, 2006). The use of this line has been justified based on several features. First, this threshold defines the point in Equation (3.9) where expected income exactly equals the poverty line. Second, a 50 percent or more chance of a household falling into poverty makes intuitive sense and seems a reasonable threshold to demarcate the vulnerable from those who are not vulnerable. In this study, we use this vulnerability threshold. According NPC (2017), in Ethiopia, the poverty line per adult person per year for 2017 was determined to be birr 7,184.

The covariates used in this analysis are: a linear and quadratic term in the age of household head, household characteristics' variables including number of children and the dependency ratio, characteristics of the household head such as sex, marital status, educational attainment (can read and write, has formal education, and the highest grade completed), occupational characteristics and religion. The descriptions of the variables used in unidimensional vulnerability analysis are given in Table 3.1 and the summary statistics of the variables are given in Table 3.2. The FGLS estimation results for expected consumption and variance for the whole sample, rural and urban is given in Table 3.7.

3.4.4. Multidimensional Poverty Measures

Vulnerability is complex and is a multidimensional concept that must be understood in relation to outcomes of interest (poverty). Community, households, and individuals are responsive to or have coping strategies for vulnerability while policy interventions can help address vulnerability in many different ways. The assessment of vulnerability to multidimensional poverty is based on the multidimensional poverty index (MPI). MPI is the most prominent household poverty assessment measure which goes beyond using the monetary (income or consumption expenditure) measure and accounts for the multidimensionality of poverty. The multidimensional poverty index measures a range of deprivations such as living standards, health, education, empowerment, and threat of violence and is currently used in more than 100 countries (Alkire and Foster, 2011; Alkire and Santos, 2010) and interest in multidimensional poverty measurement is growing (for example, Adetola, 2014; Alkire and Foster, 2011; Alkire and Santos, 2010; Bourguignon and Chakravarty, 2003; Dhongda et al., 2015; Hishe Gebreslassie, 2013; Maasoumi and Xu, 2015).

In MPI we have the deprivation cut-off. A deprivation cut-off vector is used for determining whether a household is deprived in that indicator. If the household's achievement level is less than the respective deprivation cut-off, the household is said to be deprived in that indicator and will have a value of 1. Households will have a value of 0 if they are not deprived in that indicator. So, we have a deprivation score matrix with values 0 and 1.

After identifying the dimensions and indicators, the crucial problem is assigning suitable weights to the indicators (Berenger and Verdire_Chouchane, 2007). In a multidimensional poverty analysis, there is no general consensus on the relative weights of the indicators (Decancq and Lugo, 2013; Maasoumi and Xu, 2015; Ravallion, 2011). An equal weight approach has been used by different authors (Atkinson, 2003; Alkire and Foster, 2011; Dhongda et al., 2015; Salazar et al., 2013). However, an equal weight approach has been criticized because most multidimensional poverty indicators are assumed to be correlated and the equal weight approach fails to consider these correlations (Ravallion, 2011). Following this criticism, other weighting approaches have been used. One of the weighting systems proposed and used is a factor analysis. The factor analysis (FA) model makes no prior assumptions regarding the pattern of relationships among the observed indicators (Alkire et al., 2015) and can be used for cardinal and categorical data. It also places variables in meaningful categories and reduces the number of variables.

Once the deprivation score is obtained for each household, the households are categorized into poor or non-poor based on the poverty cut-off. In the Alkire-Foster (2011) method of the MPI measure, a household is categorized as multidimensionally poor if its deprivation score is greater than or equal to one-third (33 percent) and non-poor otherwise (Alkire and Santos, 2011; OPHI, 2013).

3.4.5. Vulnerability to Multidimensional Poverty

Vulnerability to poverty can be defined in terms of a single measure (Chaudhuri et al., 2002; Hoddinott and Quisumbing, 2008; Imai et al., 2011a). However, researchers do understand the limitation of this approach as poverty reflects deprivation in multiple dimensions and hence vulnerability to poverty should also be multidimensional. Hoddinott and Quisimbung (2003) stated that there is no reason why vulnerability cannot be measured without consumption expenditure that is often used for measuring vulnerability. Feeny and McDonald (2015) also acknowledge that vulnerability can and should be expressed with other well-being indicators including health and education. Others also underscore the importance of other dimensions such as the body mass index (Decron and Krishnan, 2000) or access to social services (Coudouel and Hertschel, 2000) in studies on multidimensional vulnerability. In vulnerability to multidimensional poverty, the multidimensional deprivation score can be used as a welfare indicator and can be a solution for the inherent limitation of relying on only consumption expenditure in measuring vulnerability to poverty (Feeny and McDonald, 2015). Moreover, in a country like Ethiopia where more than 85 percent of the population lives in rural areas and has limited access to formal markets, consumption expenditure does not fully reflect households' welfare for measuring vulnerability. Therefore, vulnerability to multidimensional poverty should include other well-being indicators in the analysis to address the inherent limitation of relying on consumption based measures of vulnerability to poverty.

Besides its analysis of vulnerability to unidimensional poverty, this study also addresses vulnerability as a multidimensional concept. Equation (3.10) provides a reduced form equation for the household deprivation score (dC_h) which is used as a well-being indicator in this vulnerability to multidimensional poverty analysis:

$$dC_h = X_h\beta + e_h \qquad (3.10)$$

A household deprivation score dC_h in this case is the weighted deprivation score of households according to the Alkire and Foster (2011) method for calculating MPI. The deprivation score can be used as a well-being indicator in a multidimensional poverty analysis. Increase in dC_h represents an increasing level of destitution in one or more of the three dimensions: health, education, and living standards. X_h is household characteristics. Household characteristics include family size, number of children under-5 years, household head's age, land for agriculture, wealth index, bank account, and marital status of the household head. A dummy variable is used for assessing vulnerability to multidimensional poverty differences between regions. β is the parameter to be estimated and e_h is the disturbance term. According to Chaudhuri (2003) and Sricharoen (2011) the error term in this equation is inter-temporal variance. The usual OLS assumption of constant variance across households is somewhat restrictive. However, this also presumes that the model is fully specified, given that, households' experiences of shocks and their responses to those shocks are not excluded, which is a somewhat strong assumption.

Therefore, multidimensional vulnerability to poverty of household h at time t ($V_{h,t}$) is given as the probability that the weighted deprivation score one period ahead ($dC_{h,t+1}$) will be greater than the multidimensional poverty cut-off (k):

$$V_{h,t} = P_r\left(dC_{h,t+1} > k\right) \qquad (3.11)$$

Households face different risks and have different risk management strategies so the variance of the disturbance term is interpreted as the inter-temporal variance of well-being (Chaudhuri et al., 2002). This allows for heteroskedasticity in the model by regressing the variance of the disturbance term on the observed characteristics of households X_h given by:

$$\delta^2_{e,h} = X_h\theta + u_h \qquad (3.12)$$

The level of variance of a household's deprivation ($\delta^2_{e,h}$) is a function of its demographic and local characteristics (X) as well as the stochastic nature of the shock. Presence of heteroskedasticity makes OLS estimates inefficient. Therefore, an estimation of β and θ requires a three-stage feasible generalized least squares (FGLS) procedure as indicated by Amemiya (1977). FGLS' main advantage is that the mean and the variance of household well-being are unbiased predictors of future well-being, even when there is a measurement error (unless there is a systematic variation in the measurement error).

To overcome a systematic measurement error in well-being, given the difference in employment sources and domestic food production, a number of authors stratify the sample of households in developing countries according to rural and urban regions (Chaudhuri et al. 2002; Tesliuc and Lindert, 2004). Accordingly, our study uses the estimation of vulnerability to poverty by separating the sample into rural and urban areas.

First, we estimate Equation (3.10) using OLS, and then from this estimation we get the residual. Squared residual is used as a dependent variable in Equation (3.12) and X as an independent variable in the estimation. Equation (3.12) is transformed to produce asymptotically efficient FGLS estimates of the variance of future well-being as:

(3.13) $$\frac{\hat{\delta}^2_{e,h}}{X_h\theta} = \left(\frac{X_h}{X_h\theta}\right)\theta + \frac{u_h}{X_h\theta}$$

The estimated variance is used to transform Equation (3.10) to produce an asymptotically efficient estimator of $\hat{\beta}_{FGLS}$:

(3.14) $$\frac{dC_h}{\sqrt{X_h\hat{\theta}_{FGLS}}} = \left(\frac{X_h}{\sqrt{X_h\hat{\theta}_{FGLS}}}\right)\beta + \frac{u_h}{\sqrt{X_h\hat{\theta}_{FGLS}}}$$

Given this, households' vulnerability to multidimensional poverty ($V_{h,t}$) is estimated as:

(3.15) $$\hat{V}_{h,t} = \hat{P}_r\left(dC_{h,t+1} > K \mid X_h\right) = \Phi\left(\frac{X_h\hat{\beta}_{FGLS} - k}{\sqrt{X_h\hat{\theta}_{FGLS}}}\right)$$

where $dC_{h,t+1}$ is the estimated household weighted multidimensional poverty deprivation score in the next period, K is the conventional multidimensional poverty cut-off in Alkire and Foster's (2011) method and is equal to 33 percent (Alkire and Santos, 2011; OPHI, 2013). The probability density function which is denoted by (Φ) is the cumulative density function of the standard normal distribution as indicated in many studies (Azam and Imai, 2009; Chaudhuri et al., 2002; Jha et al., 2010; Zhang and Wan, 2006).

3.4.6. Stochastic Dominance

A stochastic dominance analysis is a statistical method of determining the superiority of one distribution over another. Two distributions can be compared using the stochastic dominance test. We can test the dominance of one distribution using the degree of stochastic dominance. There are usually persuasive reasons to select one option or distribution over another or compare one distribution with another distribution. We can test poverty distribution with vulnerability to poverty distribution and conclude that the incidence of poverty is greater than household vulnerability to poverty or the other way around. Given two distributions (A and B) if the cumulative distributions function of A is $F_A(x)$ and the cumulative distribution function of B is $F_B(x)$ if:

(3.16) $$F_A(x) \leq F_B(x) \quad for\ all\ x$$

Then distribution A has first order stochastic dominance over distribution B (the cumulative distribution of A is to the right of cumulative distribution of B) if:

(3.17) $$D(z) = \int_{\min}^{z} \left(F_B(x) - F_A(x)\right) dx \geq 0 \quad for\ all\ z$$

Then distribution A has second order stochastic dominance over distribution B. In terms of the cumulative distribution function, F_A is second order stochastically dominated F_B if and only if the area under F_A from min to z is less than or equal to the area under F_B from min to z for all real numbers z.

3.5. Results and Discussion

3.5.1. Unidimensional Vulnerability to Poverty

The unidimensional vulnerability to poverty analysis is done using the feasible generalized least squares (FGLS) method. It is well-understood that one of the basic assumptions of ordinary least squares (OLS) is that the error term has a mean zero and constant variance. If this assumption is violated, there is heteroscedasticity and hence it requires using FGLS. The results of the model for the log consumption expenditure and variance of log consumption expenditure are shown (Table 3.7). Vulnerability as expected poverty is used in this research. Log per capita household consumption expenditure is used as a dependent variable and different demographic and socioeconomics variables are used as independent variables. The description of variables and summary statistics of explanatory variables used in the regression are given in Tables 3.1 and 3.2. The variables' family size, highest grade completed, number of children under-5, dependency ratio, and age of the household head and its square are included in the model.

A unidimensional poverty analysis using household income and consumption expenditure data from 2016 and using the common poverty line showed that in Ethiopia 31 percent of the population was under poverty in 2016; 50 percent of the rural population and 18 percent of the urban population was under the poverty line (Table 3.3). However, there are arguments that a relative poverty line should be used as living costs are different across regions and place of residence (rural/urban). Living conditions and cost of living are not the same in different regions or socioeconomic groups in a country. For example, living costs are relatively high in urban than in rural areas. Housing rent in particular is very expensive in urban areas as compared to rural areas and in cities as compared to other urban areas. Poverty is a relative term and suggests using a different poverty line based on the existing differences in living costs. The reasoning for using relative poverty lines is that poverty has to be measured using the standard of living of a specific group or society; using one poverty line across the board underestimates the differences in living costs across the country

Using a grouped relative poverty line, in 2016 around 28 percent of the population in Ethiopia was under the poverty line which is less than the poverty estimates (31 percent) using the common poverty line (Table 3.4). Estimates of the relative poverty line show that the relative poverty line was different across regions and places of residence. In almost all the regions of the country the urban poverty line was higher than the rural poverty line (Table 3.4). This is in fact what we would expect as living costs in urban areas are higher than those in rural areas of the country. Our analysis also highlighted a poverty gap in the sample used. The sample size used in the analysis is 24,323 (Table 3.5). It requires transfer of about 20 million birr to the poor to bring their consumption expenditure up to the poverty line (Table 3.4). The sample size in Addis was 2,630 which is less than that in Oromia, Amhara, and SNNP (Table 3.5) but the poverty gap was the highest. This shows that even though the poverty headcount was less, the poverty gap was higher in urban than in rural areas of the country (Table 3.4).

The research also showed that 35 percent of the households in Ethiopia were vulnerable to poverty (Table 3.6), while the poverty rate was 31 percent. Even though vulnerability and poverty rate's figures are different, there may not be a significant statistical difference between the two. But there are claims that the observed incidence of poverty underestimates the fraction of the population that is vulnerable to poverty (Azam and Imai, 2009; Dercon and Krishnan, 2000; Raghbendra et al., 2009). Among the rural people, 76 percent were vulnerable to poverty; but only 21 percent of the urban people were vulnerable to poverty (Table 3.6). This result is similar to what other studies have also found (Azam and Imai, 2009).

Controlling for other determinants of unidimensional vulnerability to poverty, households with an older household head tend to have lower consumption per capita with a non-linear effect as the household head's age coefficient is negative and significant (and its square is positive and significant) (Table 3.7). A large family size and a high dependency ratio tend to reduce future consumption of the household thereby increasing household vulnerability; this is almost similar to other findings (Edoumiekumo et al., 2013; Novignon et al., 2012; Tu Dang, 2009). It is well-known that households with many children and other non-productive family members are on average poorer than households with fewer children and fewer dependent family members. An increase in schooling has an impact on productivity and hence on earnings of the household and could also influence the productivity of other members of the family. Therefore, educational attainment is a variable that needs to be considered. Increase in the household head's years spent in school has a significant positive impact on the per capita consumption expenditure in this analysis; this basically conforms with other studies that literacy and educational attainments decrease poverty and vulnerability to poverty (for example, Fekadu, 2013; Novignon et al., 2012; The World Bank, 2002). There is also statistical evidence that the ability of a household head to read and write, and a household head's formal education level increases per capita consumption expenditure and affects vulnerability to poverty (Table 3.7).

Female headed households have significantly higher mean future consumption expenditure as compared to their male counterparts (Table 3.7) this is because women have better consumption management skill than men. This research also compared people living in rural areas, towns, and big cities[1] and the results showed that households in big cities and other towns tend to have

[1] Big city includes all regional capitals and Addis Ababa. Town are urban centers in the country other than big cities. Rural-rural areas of all regional states as well as rural parts of Dire Dawa

higher expectations of future consumption per capita compared to rural households. This is assumed to be associated with differences in access to infrastructure and public services. Infrastructure will provide access to markets, health, and education; however, transportation facilities, production support services, and social infrastructure are less developed in rural areas leading to a reduction in opportunities of earning a living. There is significant evidence that households in urban areas have lower variance or volatility of consumption expenditure. Marital status is a variable considered in this analysis. Married, divorced, separated, and widowed household heads have lower consumption per capita than never married household heads (the reference group) in Ethiopia and are more vulnerable to poverty; this finding is similar to other findings (Novignon et al., 2012). This difference is also significant in both rural and urban areas. Our analysis also showed that religion matters in consumption expenditure. Per capita log consumption expenditure of Catholic, Protestant, Waq Feta, and traditional religion following households was significantly less than that of Orthodox (the reference) households implying that if we keep all other factors affecting vulnerability constant Catholic, Protestant, and Waq Feta followers are more vulnerable to poverty than Orthodox religion's follower households.

It is assumed that skills and profession abilities of the household head increase productivity thereby increasing earning capacity. This result also shows that the less skilled and professional the household head, the lower the consumption per capital and the differences are more pronounced in urban than in rural areas (Table 3.7); keeping all other things affecting vulnerability constant, as the skills and profession capabilities of the household head decrease vulnerability to poverty increases. A dummy variable is used if there are regional variations in consumption expenditure. Taking Tigray as the reference region, the analysis showed that there were regional variations in consumption per capita. Consumption per capita in all other regions (except Somali region) was significantly less than that in Tigray.

The stochastic dominance graph of the incidence and expected poverty incidence are shown in Figure 3.3. The stochastic dominance tests of the unidimensional poverty and unidimensional vulnerability to poverty show that poverty second order stochastic dominated expected poverty implying that vulnerability to poverty is greater than the current poverty.

3.5.2. Multidimensional Vulnerability to Poverty

The multidimensional vulnerability to poverty analysis' results show that in 2011, 90 percent of the population was multidimensional poor (Table 3.8) and 87 percent of the population was vulnerable to multidimensional poverty (Table 3.6), which shows that multidimensional poverty and vulnerability to multidimensional poverty were very high in Ethiopia. Multidimensional poverty (90 percent) was far greater than unidimensional poverty (31 percent) (Table 3.3) in Ethiopia. This difference is attributed to the use of health and education indicators in a multidimensional poverty analysis in addition to income or living standard indicators used in a unidimensional poverty analysis. In 2016 multidimensional vulnerability to poverty was 86 percent which is almost similar to multidimensional vulnerability to poverty estimates of 2011 (87 percent) (Table 3.6). However, there was a marked difference in the vulnerability to multidimensional poverty between rural and urban areas. In 2011 rural and urban vulnerability to multidimensional poverty was 98 percent and 58 percent respectively. Similarly, in 2016 rural and urban vulnerability to multidimensional poverty was 98 percent and 41 percent respectively. There was a significant reduction in vulnerability to multidimensional poverty in urban areas from 58 percent in 2011 to 41 percent in 2016 but the overall vulnerability to multidimensional poverty reduced very less (Table 3.6).

In this multidimensional vulnerability to poverty study different variables of household characteristics were used (Table 3.9) for identifying the determinants of vulnerability to multidimensional poverty. Family size had a vulnerability increasing impact in Ethiopia in general and in rural Ethiopia in particular (Table 3.10), as its variance coefficient was positive and statistically significant, which is consistent with other studies (for example, Fekadu, 2013). Increase in household head's level of education and household head's age decreased multidimensional vulnerability to poverty, because as people get older they get more life and work experience and have a better capacity to get out of multidimensional poverty. Similarly, as a household head's education level increases multidimensional poverty decreases. The dummy variable wealth index showed that when a household head got richer multidimensional poverty decreased.

Marital status also matters in vulnerability to multidimensional poverty as compared to the never married households (the reference) as the deprivation score was higher for other marital status households (married, divorced, separated, and widowed household heads). If we keep other factors affecting vulnerability to multidimensional poverty constant, vulnerability was higher for other marital status households as compared to the never married household heads (Table 3.10). A regional comparison is important in poverty and vulnerability studies because regional differences in poverty and vulnerability to poverty are common in many developing economies (Chaudhuri et al., 2002). The deprivation scores of Amhara, Oromia, Somali, and SNNP regions were significantly higher than those of Tigray but deprivation scores of Harari, Addis Ababa, and Dire Dawa were less than that of Tigray. Vulnerability to poverty in the Dire Dawa region was greater than that in Tigray but vulnerability to poverty was less in Afar and Harari regions as compared to Tigray (the reference group).

3.6. Conclusion

We used the expected poverty approach to assess vulnerability to poverty. Vulnerability to poverty studies require panel data at best; however, in developing countries panel data is rarely available. Estimating vulnerability with cross-sectional data is the second-best alternative, but this requires a strong assumption that the environment is stationary so that cross-sectional variances can be used for estimating inter-temporal variances. In this case, the model is likely to produce good estimates of vulnerability for situations where the distribution of risks and risk-management instruments are similar from one period to another.

We used the methods proposed using data from the Household Income and Consumption Expenditure Surveys and the Demographic and Health Survey. The variables included in the analysis had some influence on household's vulnerability to poverty. For instance, the number of children, family size, and dependency ratio had a negative influence on a household's consumption expenditure. Three main conclusions can be arrived at from this analysis. First, the fraction of the population that faces risk of poverty is greater than the fraction that is observed to be poor. While 31 percent of the population was observed to be poor, over 35 percent of the population was vulnerable to poverty in 2016. In a multidimensional poverty analysis, the difference between the proportion of the population under multidimensional poverty (90 percent) and the proportion of the population vulnerable to multidimensional poverty (86 percent) is quite high in 2011. Second, the distribution of vulnerability across different segments of the population can differ markedly from the distribution of poverty. We argue that this indicates the need for a distinction between poverty prevention programs that is programs aimed at reducing vulnerability and poverty alleviation programs.

Third, we found differences in the sources of vulnerability to poverty for different segments of the population. For rural households, the main source of vulnerability was low mean consumption prospects and high consumption volatility. This has important implications for the types of poverty prevention programs that are needed to address the vulnerabilities of different groups within the population. In general, poverty reduction strategies in Ethiopia need to incorporate not just alleviation efforts but also preventive ones. The distribution of vulnerability to poverty across different regions can differ significantly from the distribution of poverty. Programs that aim to reduce vulnerability to poverty need to be targeted differently from programs aimed at poverty reduction even at the regional level. Otherwise, poverty and vulnerability to poverty reduction programs should be implemented together to alleviate poverty.

3.7. Recommendations

Based on vulnerability estimation results and the conclusions drawn from the analysis, the following recommendations are made:

- Priority should be given to vulnerability to poverty. In both unidimensional and multidimensional poverty analyses vulnerability to poverty is very high in Ethiopia and therefore, priority should be given to vulnerability to poverty. Reducing the incidence of poverty (vulnerability) is better than supporting households' after they have fallen into poverty - prevention is better than cure.
- Region specific vulnerability to poverty policies are needed. Vulnerability to poverty is different across regions and between rural and urban areas. One policy cannot fit all the regions as regions have different social, cultural, and economic conditions.
- An effective family planning policy is needed. The vulnerability analysis showed that a large family size and high dependency ratio increased a household's vulnerability to poverty. One way of reducing family size and thereby the dependency ratio is by having an effective family planning policy.
- Combined policies. Poverty policies focus on the currently poor households and overlook those who are likely to be poor (the vulnerable). Policies designed to reduce poverty should consider vulnerable to poverty households with poor households.

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Tables and Figures

Table 3.1. Description of variables used in the determinants of vulnerability to unidimensional poverty

Variables	Description
Age	Age of the household head
Age2	Age square of the household head
Family size	Number of household members in the household
Number of children	Number of children in the household
Dependency ratio	Dependency ratio of the household
Years in school	Years the household head was in school.
Sex	Sex of the household head
RAW	The household head can read and write (1=yes, 2=no)
AFE	The household head attended formal education (1=yes, 2 =no)
Residence	Residence of the household
Marital status	Marital status of the household head
Religion	Religion of the household head
Occupation	Occupation of the household head

Table 3.2. Summary statistics of variables used in the unidimensional vulnerability analysis (N=24,323)

Variables	Description	Mean	Std Dev	Minimum	Maximum
Age	Age of the household head	41.3	15.48	11	97
Age2	Age square of the household head	1945.37	1488.56	121	9409
Family size	Number of family members	4.12	2.31	1	20
Number of children	number of children in the household	1.85	1.79	0	15
Dependency ratio	Dependency ratio of the household	0.303	0.266	0	1
Years in School	years the household head was in School	7.92	10.27	0	30
Sex	Sex of the household head (1=Male, 2=Female)	1.34	0.474	1	2
RAW	The household head can read and write (1= yes, 2= no)	1.37	0.48	1	2
AFE	The household head attended formal education (1= yes, 2= no)	1.32	0.466	1	2

Table 3.3. Poverty head count (Po), poverty gap index(P1), and squared poverty gap index(P2) (2016)

	Po	P1	P2
Ethiopia	0.31	0.096	0.042
Rural	0.50	0.165	0.075
Urban	0.18	0.047	0.019

Table 3.4. Grouped poverty estimates (headcount) and poverty gap using relative poverty line based on regions and place of residence

No	Group	Residence	Estimates	STE	LB	UB	Poverty line	Poverty gap
1	Tigray	Urban	0.2639	0.0129	0.2386	0.2892	12303.02	1,201,518
		Rural	0.2161	0.0117	0.1932	0.2390	5813.21	353,162.2
2	Afar	Urban	0.2318	0.0154	0.2016	0.2619	10749.35	461,918.6
		Rural	0.1563	0.0254	0.1065	0.2060	5784.14	79,060.63
3	Amhara	Urban	0.2655	0.0074	0.2510	0.2799	11420.12	2,912,415
		Rural	0.1438	0.0079	0.1283	0.1594	4521.92	261,711.7
4	Oromia	Urban	0.2374	0.0067	0.2243	0.2505	11069.58	3,280,724
		Rural	0.1224	0.0067	0.1092	0.1356	6156.02	546,741
5	Somali	Urban	0.1979	0.0133	0.1719	0.2239	9936.90	591,416.3
		Rural	0.1597	0.0137	0.1329	0.1865	6617.26	156,535.1
6	Benshangul	Urban	0.2617	0.0146	0.2331	0.2903	10249.43	612,243.2
		Rural	0.1257	0.0185	0.1895	0.2619	5565.01	145,683.4
7	SNNP	Urban	0.2651	0.0076	0.2501	0.2801	11156.49	2,839,861
		Rural	0.1751	0.0078	0.1598	0.1904	5584.21	592,450.4
8	Gambella	Urban	0.2673	0.0147	0.2385	0.2961	12328.94	843,301
		Rural	0.1823	0.0159	0.1511	0.2135	6224.59	132,403.3
9	Harari	Urban	0.2344	0.0209	0.1934	0.2753	13868.21	314,408.9
		Rural	0.1215	0.0179	0.0864	0.1566	8273.66	149,310.4
10	Addis	Urban	0.2409	0.0071	0.2269	0.2548	13790.99	3,565,504
11	Dire Dawa	Urban	0.2786	0.0221	0.2354	0.3219	14980.91	468,749.1
		Rural	0.111	0.0193	0.0733	0.1490	5928.48	34,515.72
	Total		0.2781	0.0027	0.2729	0.2833	9718.92	19,543,633

Table 3.5. Sample size used in the analysis of poverty and vulnerability to poverty

No	Regions	Place of Residence		Total
		Urban	Rural	
1	Tigray	860	847	1707
2	Afar	663	497	1160
3	Amhara	2560	1642	4202
4	Oromia	3325	2062	5390
5	Somali	691	445	1136
6	Benshangul	678	523	1201
7	SNNP	2694	1872	4566
8	Gambella	647	544	1191
9	Harari	321	257	578

10	Addis Ababa	2630	0	2630
11	Dire Dawa	304	258	562
	Total	15,373	8950	24,323

Table 3.6. Unidimensional and multidimensional vulnerability to poverty (headcount)

	Unidimensional vulnerability to poverty (2016)	Multidimensional vulnerability to poverty (2011)	Multidimensional vulnerability to poverty (2016)
Ethiopia	0.353	0.865	0.859
Rural	0.761	0.984	0.982
Urban	0.212	0.577	0.411

Table 3.7. Determinants of vulnerability to unidimensional poverty estimation results

Variables	Total sample		Rural		Urban	
	Consumption	Variance	Consumption	Variance	Consumption	Variance
Age	-0.0068***	-0.0009	-0.0119***	-0.0024	-0.0046**	0.0017
Age2	0.0001***	0.0000	0.0001***	0.0000	.0001**	-0.0000
Family size	-0.1144***	0.0248***	-0.1110***	0.0024	-0.1189***	0.0305***
Number of children	0.0052	-0.0157***	0.0130	0.0052	.0.0074	-0.0174**
Dependency ratio	-1.0878***	-0.0080	-0.0530***	-0.0168**	-0.1393***	-0.0105
Years in school	0.0152***	-0.0003	0.0186**	-0.0009	0.0133***	-0.0004
Sex (F)	0.0556***	-0.0013	0.0905***	-0.0025	0.0260**	-0.0046
RAW(no)	-0.0678***	-0.0222*	0.0019	-0.0133	-0.0994***	-0.0242
AFE (no)	-0.0548***	0.0175	-0.0475**	0.0085	-0.0485**	-0.0590***
Residence (rural is base)						
Big city	0.4198***	-0.0032	-0.0368	0.0342	0.0091	-0.2869***
Town	0.2985***	-0.0014	0.1699	-0.1093	-0.1252	-0.2868***
Marital status (never married is the reference)						
Married	-0.1066***	-0.0508**	-0.0677*	-0.0442	-0.0791***	-0.0590***
Divorced	-0.1519**	0.0219	-0.1515***	0.0165	-0.1145***	0.0121
Separated	-0.1524***	-0.0429**	-0.1468***	-0.0378	-0.1320***	-0.0547**
Widowed	-0.1986***	0.0396**	-0.1468***	-0.0351	-0.1841***	-0.0596***
Living together	-0.2370	0.1419	0.0322	-0.2496	-0.2732	0.1532

Religion (Orthodox is base)						
Catholic	-0.0724*	-0.0253	-0.0233	0.0191	-0.0882	-0.0529
Protestant	-0.0960***	-0.0070	-0.0653***	0.0117	-0.1035***	-0.0095
Muslim	0.0373***	-0.0121	0.0673***	0.0141	0.0070	-0.0232**
Waq feta	-0.1182*	0.0961*	-0.3074***	0.1784***	0.1587	-0.1443
Tradition	-0.4128***	0.0761	-0.4449***	0.0858*	-0.2177	-0.2162
No religion	-0.2257***	0.0068	-0.2482***	-0.0166	-0.1902	0.5715***
Others	0.1445	0.0762	0.3717	-0.2414	0.1517	0.0871
Occupation (senior officials is the reference)						
Professional	-0.0916***	-0.0034	-0.1095	0.0329	-0.1592***	-0.003
Associate professional	-0.1572***	-0.0189	0.0803	0.0332	-0.1590***	-0.0150
Clerks	-0.1299***	-0.0379	-0.1712	-0.0733	-0.2031***	-0.0286
Service worker	-0.1746***	0.0350	-0.0491	0.0439	-0.1630***	0.0425
Skilled Agri.	-0.1404***	-00543*	-0.2121**	-0.0063	-0.1507***	-0.0182
Craft workers	-0.3019***	-0.0328	-0.1814*	-0.0077	-0.2303***	-0.0262
Machine operator	-0.0642*	-0.0053	-0.0124	-0.0888	-0.1091***	0.0016
Elementary occup.	-0.4432***	-0.0195	-0.2471***	-0.0120	-0.4686***	-0.0061
Defense force	-0.2326***	-0.0586	-0.0715	-0.1562	-0.2660***	-0.0439
Regions (Tigray is the base)						
Afar	-0.0352*	-0.0842***	0.0095	-0.0680***	-0.0966***	-0.0843***
Amhara	-0.1299***	-0.0098	-0.2300***	-0.0697***	-0.1128***	-0.0044
Oromia	0.0450***	-0.0424***	0.1701***	-0.0637***	-0.0930***	-0.0326*
Somali	0.2376***	-0.0753***	0.2680***	-0.0680***	0.1891***	-0.0850***
Benishan	-0.1155***	-0.0528***	-0.0622**	-0.0651***	-0.2096***	-0.0416*
SNNP	0.0145	-0.0414***	0.0655***	-0.0397**	-0.0728***	-0.0419**
Gambela	0.1129***	-0.0834***	0.1219***	-0.0924**	0.0775***	-0.0838***
Harari	0.2343***	0.0570***	0.3537***	0.2122***	0.0864**	-0.0789**
Addis	0.2060***	-0.0674***	-	-	0.1082***	-0.0673***
Dire Dawa	0.2087***	-0.0720***	0.1298***	-0.1297***	0.2339***	-0.0492
_Cons	10.5631**	0.3234***	10.1878***	0.3310***	10.6886**	0.2608***

	*				*	
N	24323	24323	8950	8950	15373	15373
R2	0.5943	0.0156	0.4012	0.0313	0.5321	0.0183
R2_a	0.5931	0.0127	0.3937	0.0193	0.5304	0.0146
Note: * P < 0.1, ** P <0.5, and *** P < 0.01.						

Table 3.8. Multidimensional poverty index (MPI) estimation (2011 and 2016)

	2011				2016			
	H	A	MPI	95% CI of MPI	H	A	MPI	95% CI of MPI
Ethiopia	0.904	0.789	0.717	(0.708, 0.726)	0.882	0.703	0.620	(0.590, 0.650)
Rural	0.920	0.903	0.831	(0.825, 0.837)	0.647	0.500	0.323	(0.264, 0.382)
Urban	0.647	0.510	0.330	(0.314, 0.346)	0.910	0.832	0.758	(0.689,0.827)

Table 3.9. Summary Statistics of variables used for multidimensional vulnerability analysis (N=2,683)

Variables	Description	Mean	Std Dev	Minimum	Maximum
Family size	Household family size	4.7	2.501	1	22
Children under 5	Number of children under five years	0.86	0.980	0	10
Hheadage	Household head age	43.6	16.431	15	95
Education	Household head education	3.4	2.762	0	8
Dependency ratio	Dependency ratio	1.408	1.254	0	10
TLU	Tropical livestock unit	3.125	7.619	0	166.7
Land for agri.	Land for agriculture	0.642	0.297	0	1
Bank account	Bank account	0.098	0.297	0	1
HHhead sex	Household head sex	1.293	7.619	1	2
Marital status	Marital status	1.496	1.243	0	9
Wealth index	Wealth index	2.987	1.566	1	5

Table 3.10. Determinants of vulnerability to Multidimensional Poverty estimation

Variables	Total sample		Rural		Urban	
	Deprivation score	Variance	Deprivation score	Variance	Deprivation score	Variance
Family size	0.0001	0.0008***	0.0014	0.0004**	-0.0167***	0.0002
Children underm5	-0.0028	-0.0006	-0.0091***	-0.0005	-0.0231**	0.0033
Hhead age	-0.0006***	-0.0000	-0.0001	-0.0000	-0.0009*	0.0001
Education	-0.0161***	-0.0002	-0.0169***	0.0001	-0.0059**	-0.0004
Dependency ratio	0.0146***	-0.0005	0.0120**	-0.0001	.0275***	0.0004
TLU	-0.0000	-0.0000	-0.0003	0.0000	-0.0095**	-0.0008
Land for Agri.	-0.0047	0.0027**	-0.0320***	0.0031**	-0.0185	-0.0008
Bank account	-0.0764***	0.0025	0.0100	0.0009	-0.0912***	-0.0016
HHhead sex	0.0005	-0.0008	0.0056	-0.0007	-0.0005	0.0015
Marital status (never married is the base)						
Married	0.0243**	0.0023	0.0226*	0.0024	0.0244	-0.0010
Divorced	0.0516***	0.0033	0.0282	0.0044	0.0745***	-0.0008
Separated	0.0233*	0.0032	0.0258*	0.0033	0.0157	-0.0078
Widowed	.0413***	0.0064**	0.0109	0.0074***	0.0812***	-0.0005
Living together	0.0444	-0.0010	0.0185	-0.0003	0.0257	-0.0237
Wealth index (the poorest)						
Poorer	-0.0375***	0.0044***	-0.0409***	0.0037***	-0.1088	0.0042
Middle	-0.0432***	0.0043***	-0.0463***	0.0037***	-0.1091	-0.0035
Richer	-0.1263***	0.0096***	-0.1240***	0.0070***	-0.1235**	-0.0012
Richest	-0.3813***	0.0242***	-0.2889***	0.0182***	-0.2975***	0.0072
Regions (Tigray is the base)						
Afar	-0.0156	0.0008	-0.0284**	0.0018	0.0988***	0.0102
Amhara	0.0362***	-0.0010	0.0050	0.0003	0.1723***	0.0006
Oromia	0.0255**	-0.0026	0.0074	-0.0019	0.1304***	0.0174**
Somali	0.0314**	0.0046*	-0.0174	0.0037**	0.3362***	-0.0004
Benishang	0.0117	-0.0008	-0.0083	0.0001	-	-
SNNP	0.0351***	-0.0008	0.0093	-0.0002	-	-
Gambela	-0.0054	0.0008	-0.0218	0.0030	0.1121***	0.0057
Harari	-0.0551***	0.0002	-0.0849***	0.0040**	0.0390	0.0064
Addis	-0.0979***	-0.0027	-	-	0.0366	0.0094
Dire Dawa	-0.0265*	0.0055**	0.0641***	-0.0045**	-0.0009	0.0083
_Cons	0.9161***	-0.0010	0.9447***	-0.0012	0.7057**	0.0031

N	2585	2585	1963	1963	622	622
R2	0.7646	0.1513	0.5332	0.1300	0.5133	0.0401
R2_a	0.7620	0.1420	0.5267	0.1178	0.4926	0.0018
Note: * P < 0.1, ** P < 0.5, and *** P < 0.01.						

Table 3.11. Headcount ratio (H), intensity(A) and Multidimensional poverty index(MPI) in Ethiopia and its regions (2011)

Regions or Residence	H	A	MPI
Ethiopia	0.908	0.789	0.717
Urban	0.634	0.522	0.330
Rural	0.993	0.836	0.831
Regions:			
Tigray	0.941	0.810	0.762
Afar	0.932	0.822	0.766
Amhara	0.984	0.805	0.792
Oromia	0.969	0.821	0.796
	0.994	0.857	0.852
Benishangul	1.00	0.845	0.845
SNNP	0.991	0.819	0.812
Gambela	0.929	0.791	0.735
Harari	0.873	0.692	0.604
Addis Ababa	0.546	0.461	0.251
Dire Dawa	0.730	0.795	0.580

Table 3.12. Multidimensional poverty and vulnerability to poverty headcount (2011 and 2016)				
	2011		2016	
	Poverty	Vulnerability to Poverty	Poverty	Vulnerability to Poverty
National	0.908	0.865	0.823	0.859
Rural	0.993	0.984	0.914	0.982
Urban	0.634	0.577	0.312	0.411

Figure 3.1 Joint distribution surface of log consumption and log expected consumption

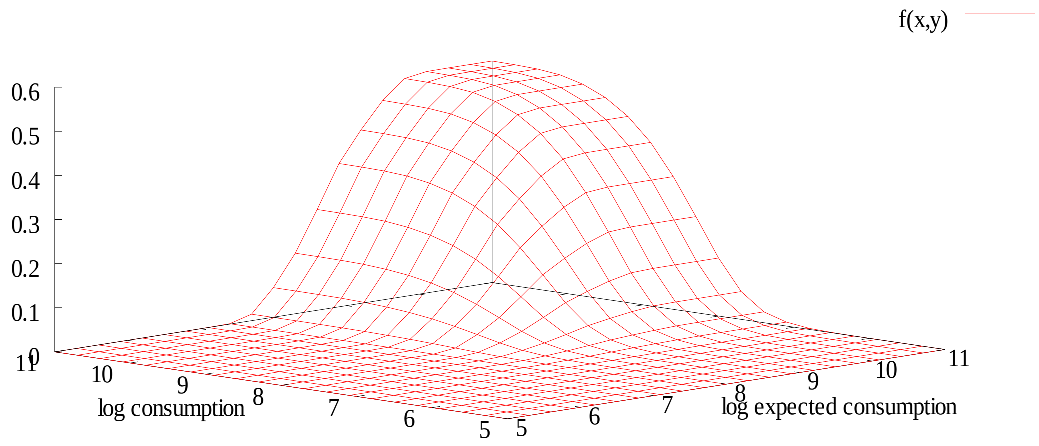
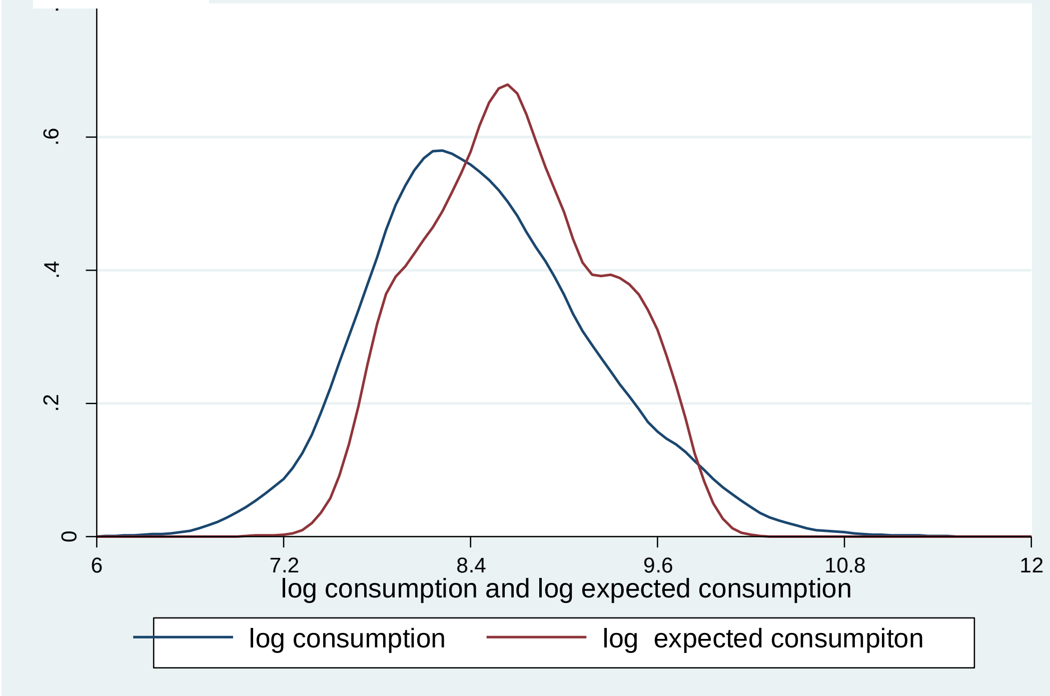


Figure 3.2 Density of log consumption and log expected consumption



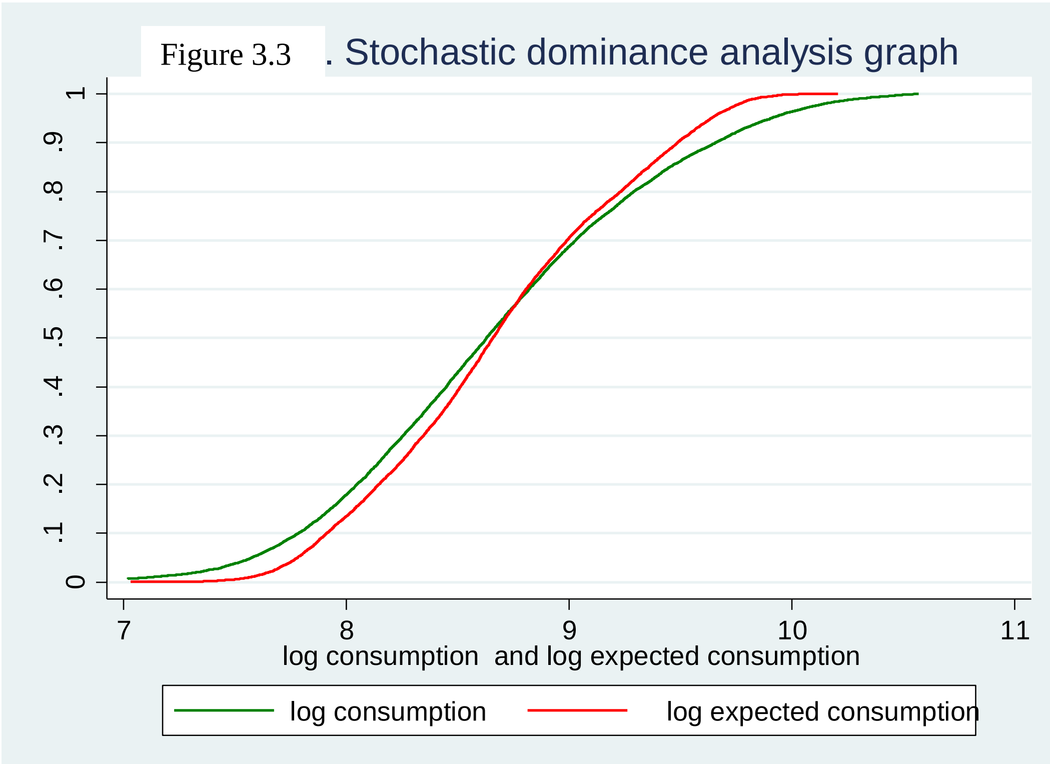


Figure 3.3 . Stochastic dominance analysis graph
0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1
7
8
9
10
11
log consumption and log expected consumption
log consumption
log expected consumption

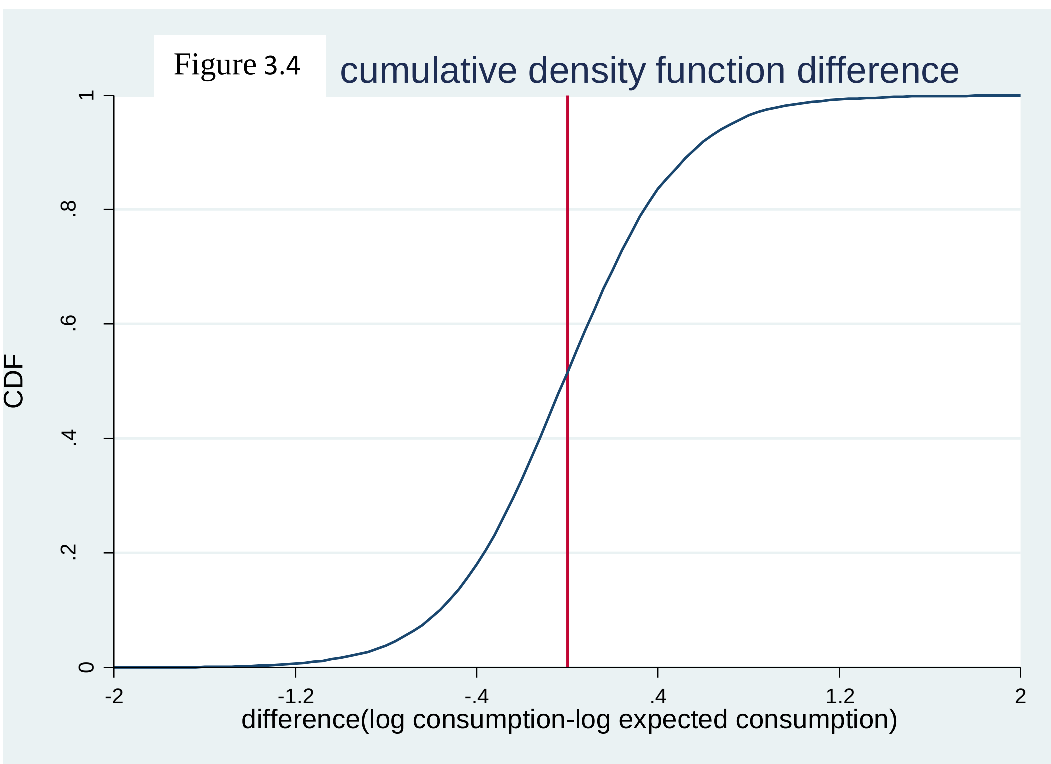
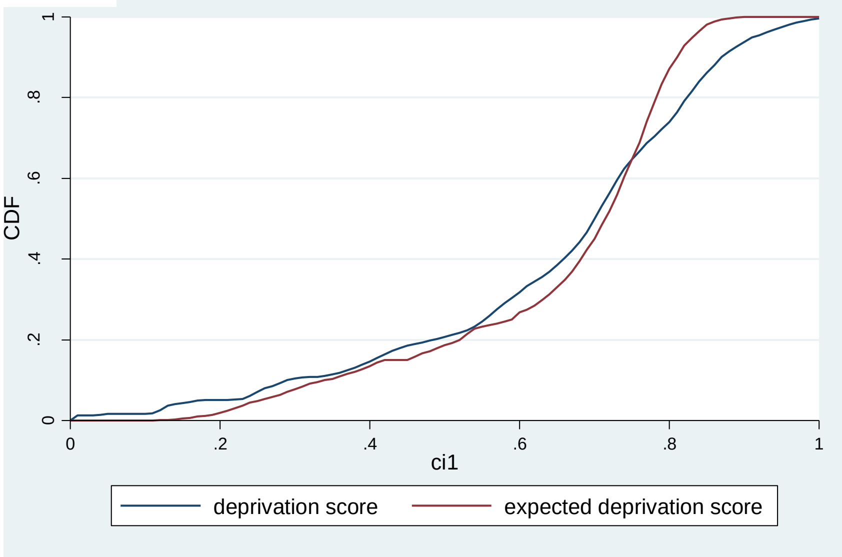


Figure 3.4 cumulative density function difference
CDF
0
.2
.4
.6
.8
1
-2
-1.2
-.4
.4
1.2
2
difference(log consumption-log expected consumption)

Figure 3.5 cumulative density function of deprivation score and expected deprivation score



Chapter 4: Multidimensional Inequality in Ethiopia

Abstract

This study investigates multidimensional inequality in Ethiopia using data from the Ethiopian Demographic and Health Survey (EDHS) and the Household Consumption and Expenditure Survey (HCES). There are consumption inequalities in Ethiopia and these are higher in urban as compared to rural areas in the country. There are also considerable differences in consumption inequalities across regions. A multistage multidimensional inequality analysis shows that multidimensional inequalities are quite low in Ethiopia. Inequalities in the multidimensional indicators decrease over the wealth quintiles and living standards contribute the most to multidimensional inequalities. In rural Ethiopia production and generation of wealth is highly associated with agricultural activities which are related to the size of the landholdings. There are inequalities in landholdings in Ethiopia and these differ across regions and wealth quintiles. Reducing inequalities between socioeconomic groups will have more of an impact on reducing poverty than reducing inequalities within groups as between-group elasticity is greater than within-group elasticity. Gender based decomposition of inequality shows that within-group inequalities, the marginal impact of inequality, and the marginal impact of poverty are greater than the between-group components. Between- regions inequalities are more than within-region inequalities, so there are significant differences in inequalities between the regions which need to be considered. Parents' education has a positive impact on children's education, while mothers' education has more weight than fathers' education both for sons and daughters' education. In countries like Ethiopia where girls are marginalized, educating daughters (tomorrow's mothers) has positive intergenerational inequality reducing effects.

Keywords: inequality; education; Ethiopia; multidimensional; elasticity.

JEL Classification Codes: I31; C21; C43; D63

4.1 Introduction

The recent increase in income inequalities in a number of developed and developing countries and their potential impact on an economy have made inequality a central issue in economics. Many African nations are growing but the growth is not equally distributed across socioeconomic groups and regions. While poverty reduction is of wide interest and a top policy priority in Ethiopia, inequality is less frequently addressed. Inequalities need to be considered because high levels of inequalities present a serious threat to progress and social stability. There is consensus that high levels of inequalities are socially unjust. Traditionally, economists developed a number of indices to measure inequality in one dimension, most often income. Conventional inequality indices are based on the assumption that individuals and groups of individuals can be ranked according to specific characteristics such as income and this is a straightforward exercise. For measuring income correctly, a precise record of income is essential which is very unlikely in developing nations like Ethiopia (Vida et al., 2008). Consumption is generally considered a more appropriate measure of well-being than income, especially in poor countries where the main concern is fulfilling basic needs (Idrees and Ahmad, 2010). Gross and net incomes are different in progressive tax systems and in this case consumption is better than gross income. Hence, it is important to measure inequalities in consumption expenditure including food, housing, education, and health expenditures. The superiority of consumption is attributed to its close correspondence with individuals' basic needs and its low dispersion.

Besides income or consumption expenditure, people care about other aspects of inequalities such as their health, housing, and schooling. Human well-being is multidimensional and any analysis of inequality should also take the dimensions of well-being into account (Bourguignon and Morrisson, 2002). Academic research such as that by Stiglitz et al., (2009) and Bosman et al., (2015) also points out the importance of going beyond income inequality by adding material and non-material dimensions of inequality. Hence, measuring inequality inevitably becomes a multidimensional exercise. In a multidimensional inequality analysis there may be compensating effects of one form of inequality by another which can change the evaluation of overall inequality. Interest in multidimensional inequality is mainly because of: first, the commonly used average income or per capita income level in a country does not necessarily tell us much about the well-being of the entire population. When income inequalities are extreme, a high average level of income can be associated with a large population share of absolutely poor households. Similarly, the extent to which economic growth reduces poverty depends on the equitable nature of income distribution. Growth is more pro-poor with less income inequalities. Second, many people regard societies with a more equal distribution of income and equal access to health and education as better places to live in. Third, unequal distribution of income, education, and health can also hinder growth (Cingano, 2014; Ostry et al., 2014). Unequal societies tend to lose part of their talent pool if individuals with a poor background do not have access to proper productivity enhancing schooling and jobs. Situations like this can be more prevalent in developing countries.

However, measuring inequality along several dimensions is not an easy task. Ranking individuals along educational, health, and other non-monetary attributes is a complex exercise. This complexity is associated not only with differences between the various distributions but also because of possible correlations between the various attributes of welfare. This study examines inequality in different dimensions of well-being focusing on three important dimensions of life: standard of living, health, and education. This research uses two approaches: inequality in each dimension and inequalities in the combined indicators of well-being. Inequality in each dimension indicates the extent of inequalities in each indicator and can help the government and other actors to take some corrective measures to reduce inequalities in that dimension. It also helps identify areas of interventions to reduce existing multidimensional inequality. A combined inequality considers the correlation between indicators and gives us the combined effect of inequalities on well-being which helps compare households and regions in the country.

Inequality has been analyzed in Ethiopia (Gelow, 2009; Kedir et al., 2014; MoFED, 2014; Tesfaye and Mulberge, 2014; Woldehanna et al., 2008). These studies use inequality indices to discuss inequalities in income and consumption expenditures in Ethiopia and show the existing levels of inequalities and highlight areas of interventions to reduce existing income inequalities in the country. However, these studies focus on inequality in households' income and consumption expenditure and overlook other dimensions of inequality such as health and education. This is the observed gap in this area. In this research, we used a multistage multidimensional inequality analysis. First, we found a living standard index from the living standard indicators and then computed the multidimensional inequality index with education and health components. An exhaustive measure of inequality is when different indices are combined and applied (Vida and Jonas, 2008). Living standard multidimensional inequality is also computed because living standards contribute the most to multidimensional inequality as compared to the education and health dimensions which are functions of the income level.

The rest of the chapter is organized as follows. Section 2 presents a review of theoretical and empirical literature while Section 3 discusses the data used for the analysis and the unidimensional and multidimensional inequality measures used in the analysis. Section 4 discusses the research's results. Section 5 gives the findings of the research and Section 6 provides some recommendation based on the reviewed theoretical literature and our results of the empirical analysis.

Objectives of the Study

The general objective of this study is assessing the extent of inequalities in the country, regions, and income groups and highlighting areas of interventions to reduce existing multidimensional inequality in the country, regions, and within income groups.

The specific objectives of the study are:

i. Examining the extent of unidimensional and multidimensional inequality in the country, between regions, and income groups.
ii. Identifying the determinants of intergenerational multidimensional inequality.
iii. Identifying areas of interventions to reduce the existing multidimensional inequality and the inequalities in the components of multidimensional inequality.

4.2. Literature Review

4.2.1. Unidimensional Measures

Inequality is a developmental challenge both in rich and poor countries and is clearly an important issue which requires more attention. The Oxford Dictionary of Economics defines inequality as differences in the distribution of economic stock or flows among economic agents. Scott and Marshall (2009) define inequality as unequal rewards or opportunities for different individuals or households within a group or groups within a society. In this definition, unequal rewards refer to outcomes or achievements while unequal opportunities are concerned with freedom to obtain alternative outcomes. Inequality weakens the poverty reducing capability of economic growth and there is an increasing pressure on governments to address inequality. Increased inequalities can also lead to dissatisfaction, social unrest and violence, and hinder the growth process in a country and worsen insecurity (Ostry et al., 2014).

Measuring inequality has received much attention both in theoretical and empirical research. The most commonly used inequality dimension examined in most literature is income or consumption expenditure, which is the traditional variable used when studying the magnitude and change in economic inequalities. Literature on inequality measures has expanded since the publications of the Lorenz curve and the Gini index in the early 1900s.

On top of these well-known methods, an interesting measurement of inequality theory was proposed by Theil (1967, 1979). The extension of Theil's inequality decomposition technique provides a useful tool for examining the contributions of different sub-groups to total inequality.

Another measurement of inequality is the Atkinson's (1970) index which generates multiple inequality calculations. The argument in favor of using a monetary attribute in an analysis of inequality is clearly that there are reasons to believe that economic conditions drive other aspects of living standards and that a monetary indicator does tell us what we need to know about wider aspects of well-being. On the other hand, although the permanent income hypothesis suggests that current consumption is related to lifetime welfare, capital market imperfections and other market failures that are common in developing countries, imply that it is important to include other indicators of welfare in measuring inequality. Moreover, a monetary metric of measuring inequality is satisfactory if it is able to catch relevant heterogeneity between households or individuals and their different situations (Ruggeri et al., 2003). But monetary inequality is ambiguous when households have different characteristics (Maasoumi, 1999). It should also be noted that a change in consumption inequalities might be a result of bad outcomes in other dimensions of welfare. In addition, the well-being of a household might have dimensions that cannot be purchased (Duclos et al., 2001).

4.2.2. Multidimensional Measures of Inequality

Conventional techniques for measuring inequality are useful and also important to broaden the concept of inequality. Stiglitz et al., (2009) argue that individual well-being is multidimensional. Individuals care about the non-monetary aspects of their lives, including their material standard of living, health, and schooling. If we want to take the multidimensionality of individual well-being seriously, it follows that we need to incorporate these various dimensions explicitly into an analysis of inequality and consider their correlations. The simplest or straightforward approach of taking the multidimensionality of well-being into account is by considering each dimension separately, that is, the evaluation of inequality dimension by dimension (The World Bank, 2005). The advantage of this strategy rests on its simplicity; however, as the indications of inequality's of different dimensions diverge, it is not possible to draw any general conclusion on overall inequality and ignore the inter-relationships and possible correlations between the dimensions of well-being. In doing so, one should account for the inter-relationship and correlation between the different dimensions in measuring and analyzing inequality (Heshmati, 2014).

The most popular multidimensional inequality index of well-being is the Human Development Index (HDI) which summarizes the performance of countries on three dimensions of well-being: standard of living, health, and education. Two alternative approaches for multidimensional inequality can be distinguished: the normative approach and the two-stage approach (Bosmans et al., 2015). The normative approach was developed in a unidimensional setting by Atkinson (1970) and was extended to the multidimensional setting by Kolm (1977). In the normative approach, measures of inequality are derived from social welfare functions and therefore inequality is defined as a social welfare gain that can be obtained by optimally redistributing the available goods. The two-stage approach was pioneered by Maasoumi (1986), in which the first stage associates a well-being level to a bundle of goods for each individual. Once we get the well-being level of each household the second stage simply applies a unidimensional inequality measure. The Lorenz zonoid was introduced as m-dimensional generalization of the standard Lorenz curve by Koshevoy and Mosler (1996). A multidimensional Gini coefficient can be derived from Lorenz zonoid (Decancq and Lugo, 2012). An alternative strategy by Anderson (2004) proposed a multidimensional distance measure to measure the pair wise distances between the vectors of the outcomes. Both approaches represent a mathematical or geometrical extension of the unidimensional Gini coefficient. However, they lack normative content in the sense that inequality cannot be readily interpreted in terms of welfare losses. Hence, we find them as less attractive for measuring inequalities in well-being (Decancq and Lugo, 2012).

In the two-stage approach, two indices for measuring multidimensional inequality are derived by an aggregation both across dimensions and across individuals. The sequencing of aggregations turns out to be essential in terms of the underlying principles. In the first approach, aggregation is first done across individuals and then across dimensions which is not sensitive to the correlation between dimensions. In the second approach the first aggregate is across dimensions and then across individuals which can be sensitive to the correlations between the dimensions. To obtain a correlation sensitive rank dependent inequality index one must be willing to give a large weight to the bottom of the distribution (Decancq and Lugo, 2012). Nilsson (2007) studied inequality in Zimbabwe and pointed out that comparisons of inequalities taking the inter-relations between the attributes into account repeatedly were at odds with comparisons of independent distributions. Literature emphasizes the relationship between dimensions and indicators; it is also suggested that an item-by-item approach should be applied and at minimum, one should check the correlations between welfare distributions.

There is no single best measure of inequality; each measure has its own advantages and limitations. An exhaustive measure of inequality is possible only when different methods and indices are combined and applied (Vida and Jonas, 2008). Following Weymark (2006), there are a number of basic properties that a multidimensional inequality index should satisfy. These can be grouped into two sets of axioms. The first one focuses on those properties that are not concerned with the distributional sensitivity of the inequality measures. These non-distributional axioms which are straightforward generalizations of their unidimensional counterparts include continuity, anonymity, normalization, replication invariance, scale invariance, decomposability, and additive reparability (by population sub-groups and by dimensions).

While inequality can be considered or measured in many different dimensions, the two main measures are inequality of outcomes and inequality of opportunities. Inequality of outcomes shows inequalities in wealth, education, and health status among others. While inequality of opportunities refers to the choice offered to an individual or a household. The notion of equal opportunities is that success in life reflects a person’s choices, efforts, and talent and not a person’s background defined by circumstances such as race, place of birth, and family origin. According to Roemer (2014) opportunities have to be equitable and equality in opportunities is an attractive notion of justice. In an equal opportunity society, there is no significant association between circumstances which do not affect individuals’ and their life outcomes. An individual’s outcomes or achievements are a mix of opportunities afforded to the individual, the choices she/he makes and luck. While inequality in outcomes can be directly observed and measured inequality of opportunities cannot be directly measured using standard indicators. Currently there is an argument that inequality of opportunities has to be given due attention and therefore equality of opportunities is getting the attention of policymakers. Equality of opportunities aims to level the playing field so that circumstances such as gender, birthplace, and ethnicity which are beyond the control of an individual do not influence one’s life chances. An equal-opportunity policy should aim at providing everyone with the same opportunities to achieve or enjoy an excellent outcome. Though more difficult to measure, inequality of opportunities and ensuring individuals have equal opportunities (equality of opportunities) is a policy goal for achieving equal outcomes.

4.2.3. Empirical Evidence

There is considerable income inequality in Ethiopia across regional and ethno-linguistic groups (Kedir et al., 2014; Tesfaye and Mulberge, 2014). Inequality requires careful consideration because it increases criminal acts and violence. Sachsida et al., (2010) examined the relationship between inequality and crime in Brazil and concluded that high inequalities increased criminal behavior but they could not find significant evidence that inequalities increased violence. Gelow's (2009) study of rural poverty in Ethiopia using a fixed effect model showed that changes in inequalities significantly affected the poverty gap. Inequality emphasizes dispersion across agents or households and how the welfare cake (for example, GDP) is shared among the population. Some recent income inequality analyses have pointed out that there are higher inequalities in urban than in rural areas of Ethiopia (Table 4.1).

Table.4.1. Consumption inequality trends in Ethiopia as measured by the Gini coefficient

Residence	1995/96	1999/2000	2004/5
Rural	0.27	0.26	0.26
Urban	0.34	0.38	0.44
National	0.29	0.28	0.30

Source: Woldehanna et al., (2008).

According to Woldehanna et al., (2008) in Ethiopia the Gini coefficient for consumption inequality which was 0.29 in 1995-96 increased to 0.30 in 2004-05. Their research also found that there was a substantial increase in inequalities in urban areas as compared to rural areas in the country. Therefore, the increase in inequalities at the national level was mainly due to an increase in inequalities in the urban areas as the Gini coefficient remained almost unchanged in rural areas over the years that they considered. According to Fentaw (2016), in Ethiopia the consumption inequality Gini coefficient was 0.38 in 2010-11 and the decile dispersion ratio indicated that the richest 10 percent households consumed 9.18 times the income of the poorest 10 percent households. This shows that there was a huge gap in consumption inequalities among the population in Ethiopia. Fentaw's study added that in South Wollo zone, inequality estimates of all indices showed that the highest inequalities were in major towns, followed by emerging towns in the region and smaller inequalities were observed in small towns. Similarly, the Gini coefficient measure of inequality showed that urban inequalities (0.37) were greater than those in rural areas (0.27) (MoFED, 2014). Cain et al., (2012) showed that urban biased policies used in developing countries exacerbated inequalities between urban and rural areas. Lack of public investments in infrastructure too hindered private investments in the rural agricultural sector and reduced rural economic growth. Growth is mainly associated with geographic concentration of economic resources and economic activities which is related to the development of infrastructure. Adverse agro-climatic conditions, employment opportunities, and poor infrastructure are major causes of spatial inequalities. This brings spatial inequalities across different geographical areas of a given country to the center of attention. Therefore, analyses of inequality differences across different regions of the country are essential for highlighting inequality reducing interventions in regions and across the country.

According to Gakidou et al., (2000) and Ribero and Nunez (1999) sustainable development cannot be achieved without significant investments in human capital of which education and health are key elements. Access to education and health services is, however, not equally distributed across countries or even across regions. Given the impact of human capital on economic development, inequalities in education and health status represent a loss in aggregate welfare (Thomas et al., 2000). The recognition of this fact has resulted in a recent increased interest in inequality analyses of the distribution of education and health (Checchi, 2000; Thomas et al., 2000). Tranvag et al., (2013) examined health inequalities in Ethiopia using EDHS data and found that there had been general improvements in the health status in Ethiopia and health inequalities had declined over time. However, more effort is needed to reduce inequalities among poor and rural residents. Gallardo et al., (2017) offer evidence that inequalities exist in health status depending on the education level of the mother, household income, gender, and place of residence. Hence, there needs to be a joint effort to reduce health inequalities and identifying factors beyond wealth which might be responsible for health inequalities in the country.

4.2.4. Components of Multidimensional Inequality

Multidimensional inequality encompasses many development dimensions and indicators. Education and health are two key elements in human capital development. Sustainable development cannot be achieved without significant investments in human capital (Gakidou et al., 2000). Given the impact of human capital on economic development, inequalities in education and health status represent a loss in aggregate welfare (Thomas et al., 2000). Considering health and education inequalities together with the commonly used inequality variable (income) has resulted in the recent increased interest in including additional indicators to a multidimensional inequality analysis (Checchi, 2000).

Education

On average, Ethiopia has high illiteracy rates especially in rural areas because of less access to education and the nature of traditional smallholder farming activities in the country requiring a lot of labor power, including child labor (CSA, 2016). Education is one of the determinants of overall inequality. Inequality in education can be examined using levels of education (Bigotta et al., 2014), for example, by the percentage of individuals who have attained a particular level of education, or the number of years of education that they have attained (Meschi and Scervini, 2014; Morrisson and Murtin, 2013). Education is a key to attaining sustainable development goals by 2030. For education to have a positive impact on growth and development, it is necessary to ensure equality of learning. Education inequality can be the outcome of different factors. For instance, students from economically poor families, compared to those in more affluent areas are more likely to attend schools characterized by poor facilities, fewer qualified teachers, and outmoded pedagogical practices and hence are more likely to end up with lower learning outcomes. Different measures can be used for summarizing the degree of inequality of education in a given period of time and can also be examined across generations to measure progress over time. Households' inequality levels can be analyzed according to the educational level of the household head (Table 4.5). Fentaw's (2016) study in South Wollo region in Ethiopia estimated that the highest inequality levels were observed in a group of households, whose heads had lower educational levels, followed by those with high school and university degrees.

The World Inequality Database on Education (WIDE) highlighted that since 2010 fewer than 25 percent children in rural areas in 24 out of 52 countries had had an opportunity to attend a pre-primary program. Fewer than 50 percent of the poorest children in 40 out of 93 countries had completed primary school and less than 50 percent of the young people in 57 of the 127 countries had completed upper secondary school. Ethiopia is trying to increase level and access to education. There are some observed results in access to education. The percentage of women with no education decreased from 66 percent in 2005 to 48 percent in 2016 while the percentage of men with no education declined from 43 percent in 2005 to 28 percent in 2016 (CSA, 2016). Education is an important factor that influences an individual's attitudes and opportunities. Children who have more educated family members have better chances of getting educated. We expect educated household members to benefit their families. All household members benefit from having an educated person in the household as education is assumed to have positive externalities for other family members and for society. Children's education is influenced by parents' education because families are the building block of a society and are the primary institution for growing children. Parents' education and experiences play an important role in shaping children's future life (McLanahan et al., 2008). Children with educated families are better educated than those with uneducated families. In particular, children who have educated mothers get support and follow up than those who have least-educated mothers. Econometrically this can be estimated using:

$$y_{ij} = \alpha + \beta e_j + \gamma x_{ij} + \upsilon_{ij} \tag{4.1}$$

where y_{ij} is the educational attainment of child i in household j; e_j is the parental education attainment of the household head j; β is the intergenerational education coefficient; x_{ij} is the vector of household characteristics including gender and religion; and υ_{ij} is the error term.

Measuring inequality helps evaluate the impact of policies used and highlights areas of interventions for reducing inequalities. There is a need for developing infrastructure and supplying learning resources to all the schools. These factors have a positive impact on students' access to quality and equality in education (Woldehanna et al., 2008).

Health

Like wealth, health is not equally distributed among individuals or households. There exist significant differences in health between individuals, groups, and regions. Health inequalities have been a big challenge for public health policies. The World Health Organization (WHO) targeted the reduction of health inequalities and these inequalities should be a major concern in government policies in all countries, particularly among the most disadvantaged populations. Inequalities in health often reinforce and reproduce inequalities in other dimensions of life such as income and education over time (The World Bank, 2005). Improving healthcare facilities and reducing inequalities in health have been of major interest in both developed and developing countries. In Ethiopia, 1 in 15 children dies before reaching age 5, and 7 in 10 of the deaths occur during infancy (CSA, 2016). The World Bank report also adds that child mortality varies across regions in Ethiopia. Under-5 mortality ranges from 39 deaths per 1,000 live births in Addis Ababa to 125 deaths per 1,000 live births in Afar. Information on infant and child mortality is relevant and is an important indicator of a country's socioeconomic development and quality of life. Malnutrition among children and adults is one of the widely used health indicators in studying multidimensional poverty and inequality measures. The nutritional status of children and adults provides indicators that can be used in planning and monitoring national efforts for improving the nutritional status of the people. Stunting (low height-for-age) is a sign of chronic under-nutrition that reflects failure to receive adequate nutrition over a long period and can also lead to recurrent and chronic illnesses. Adults' nutritional status can be measured using the body mass index (BMI) which is calculated by dividing the weight in kilograms by height in meters squared (kg/m2) to see the inequalities in health outcomes between households and regions in the country.

Related to health, the post-2015 Sustainable Development Goals (SDGs) are based on the central notion of addressing health inequalities in all countries by promoting universal health coverage for people of all ages. There is consensus that health inequalities are not self-correcting and require interventions (policies and programs) to change. In Africa, there is little evidence of success in improving equality of health outcomes (Stephen and David, 2007). In Ethiopia, different households' have different access to health services. Some rich families may have access to private health services which are costly and unaffordable for the rest of the population. The rest of the population relies on a system of public clinics and hospitals, characterized by long waiting times and poor-quality services. This effectively constitutes a mechanism of social exclusion of the poor, the elderly, and the rural population, whereas others have no access to any kind of health services.

Using Ethiopian DHS data, Tranvag et al., (2013) showed that the distribution of health in Ethiopia was more equal in 2011 than in 2000, with inequalities in the length of life reduced for all population groups but there was potential for further improvements. The research also pointed out that inequalities in length of life within wealth quintiles were considerably larger than between them.

Living Standards

The term living standards is used for expressing the conditions in which a person or a nation lives. Living standards are represented by access to electricity, clean drinking water, improved sanitation, floor material, cooking fuel, and asset ownership. Electricity can be used for light, cooking, and electronic devices and is an important living standards indicator. If a household has no access to electricity, the household is deprived in this indicator.

Life is impossible in the absence of water. Contaminated groundwater is a source of many diseases like diarrhea and other diseases leading to death. A household or an individual is deprived in water if it has no access to safe drinking water. Sanitation is directly related to hygiene and access to improved sanitation is vital for a healthy life. Cooking fuel is important and related to the use of biomass in rural areas and also in some urban areas. Biomass fuel leads to environmental degradation. Use of appropriate cooking fuel indirectly provides environmental sustainability. Asset ownership is related to access to information (TV, radio, and mobile phone), access to easy mobility (bicycle, car, and motorbike), and assets for livelihood (livestock and agricultural land). In poorer countries, the dimension standard of living contributes the most to multidimensional poverty. Empirical research shows that in Ethiopia the living standard indicators contribute more than 50 percent to multidimensional poverty (Alkire et al., 2011). There are also rural-urban variations in access to some of the living standard's indicators in Ethiopia (Table 4.2).

Table 4.2. Households' access to different living standard's indicators

Living standard's indicators	Rural	Urban	Total
Access to improved sources of water	57%	97%	-
Access to electricity	8%	93%	25%
Use of improved toilet facilities	4%	16%	6%

Source: CSA (2016).

4.2.5. Basic Axiom Satisfied by Inequality Indices

The easiest or simplest way of comparing income and other welfare indicators' distribution is by using an index. To produce an appropriate index these indices have to satisfy a certain number of axioms (Idrees and Ahmad, 2017). The debate in literature on the theory of inequality measurement is essentially about the properties that the inequality functions or indices should possess. The basic axioms that inequality indices should satisfy are:

- Normalization (NORM). Normalization is an important property in an inequality index and in multidimensional inequality indices if each person has the same achievement vector, then I(X) = 0. If $X_n = X$ for all n, then $I(X) = 0$.
- Anonymity (ANON) (also called symmetry). Personal identity does not matter or an inequality measure should be invariant to who has the achievement vector. It is an attractive property in aggregation across individuals since it assures an impartial treatment of all individuals.
- Scale Invariance (SINV). Changes in scale do not affect the inequality of the distribution; if all elements in X are changed by an equal proportional amount then inequality does not change. $I(\lambda X) = I(X)$ where $\lambda > 0$.
- Translation invariance (TINV). Addition or subtraction of the same value from all the distributions does not affect the level of inequality; if all elements in X are increased by an equal additional amount then inequality does not change, $I(X + \lambda) = I(X)$ where $\lambda > 0$.
- Population replication invariance (POPRI) or replication invariance. Replication of the same population several times does not change overall inequality or who has a specific income does not make a difference. If vector Y is obtained by replicating vector Y, then I(Y`) = I(Y). This property allows comparing inequality across societies with different population sizes.

4.2.6. Multidimensional Distributional Concerns

It is important to introduce any property that captures distributional concerns. Distributional sensitivity is obtained in standard one-dimensional analyses by imposing some form of the Pigou-Dalton transfer principle. The Pigou-Dalton transfer principle states that a transfer of income from a poorer to a richer individual leads to a decrease in social welfare. While keeping the order of the income rank unchanged a transfer of income from a rich person to a poor person should decrease or at least should not increase inequality. To generalize the unidimensional Pigou-Dalton principle in a multidimensional setting we focus on two generalizations within the multidimensional framework. If a uniform mean-preserving averaging is done, the resulting distribution matrix is socially preferred to the original one. This distribution is called uniform majorization (Kolm, 1977; Marshall and Olkin, 1979; Tsui, 1995; Weymark, 2006); the other distributional concern is that a social evaluation function must consider the correlation between dimensions. Tsui (1999) formalized this notion of correlation by defining a correlation increasing transfer, which is a rearrangement of the outcomes of two individuals such that one individual gets the highest outcomes in all dimensions and the other the lowest. Based on the notion of a correlation increasing transfer, the second distributional concern says that a distribution matrix Z that is obtained from X by a series of correlation increasing transfers is socially inferior. Correlation increasing majorization captures the idea of compensating inequalities among different dimensions, hence implicitly assuming that the dimensions are substitutes.

4.3. Data and Methodology

4.3.1. Data

This research used data from the Ethiopian Demographic and Health Survey (EDHS). DHS is cross-sectional data collected in Ethiopia almost every five years. The first round was in 2000; the second in 2005; the third in 2011; and the most recent in 2016. The data collected contains information on household characteristics, households' dwelling units such as sources of water, types of sanitation facilities, access to electricity, types of cooking fuel, and other demographic and health variables. DHS is a comprehensive dataset that consists of samples from all regions in the country which represent the national population of Ethiopia. This research mainly used the most recent DHS data from 2016.

Since the DHS data has no income variable, we used the Household Consumption and Expenditure Survey (HCES) data for an analysis of the unidimensional income inequalities. HCES have been conducted by the Central Statistical Agency (CSA) of Ethiopia since 1995-96 at four or five-year intervals. It is a survey which contains a nationally representative sample to characterize important aspects of households' socioeconomic conditions.

In Ethiopia, like in many other poor countries where the main concern is fulfilling basic needs it is more important to measure inequalities in consumption expenditure as income data is not easily available and if available it is not reliable. In this research, the unit of analysis is a household; a household has common resources and takes decisions that affect all members of the household.

4.3.2. Methodology

Analyzing inequality has a long history but there is no agreement on how best to measure inequality. Different inequality measures exist and combinations of these are used in different studies. In this analysis, we used two approaches for measuring inequality: the unidimensional measure of inequality and the multidimensional measure of inequality. Unidimensional measures of inequalities are the Gini coefficient, Atkinson's measure of inequality, Theil index, and the generalized entropy index. These standard families of unidimensional inequality measures are inter-related in some way. The multidimensional measures of inequality are the Gini per wise (two indicators at a time) measure of inequality and the Araar et al., (2009) multidimensional inequality index.

4.3.2.1. Unidimensional Measures of Inequality

There are different measures of unidimensional inequality. There is no consensus on using a single inequality measure in all cases. All unidimensional inequality measures have their own advantages and limitations. We discuss some of the most commonly used inequality measures to decide which measure is best suited for our purposes and fits our data.

4.3.2.1.1. Gini Coefficient

The Gini coefficient is the most widely used measure of inequality in empirical literature which measures the extent to which the distribution deviates from equal distribution. The Gini coefficient was developed by Italian statistician Corrado Gini. It measures the average difference between pairs of incomes in a distribution relative to the mean. Graphically, the Lorenz curve represents the increase in the cumulated proportion of income due to the cumulated proportion of the population over the i^{th} person (x,y). The Gini coefficient can be easily represented by the area between the Lorenz curve and the line of equality (x=y). It is twice the area between the Lorenz curve (x, y) and perfect equality $(x = y)$. There are different ways of calculating the Gini coefficient and one of these is calculating the Gini coefficient (g) as:

(4.2) $$g = 2\int_0^1 (x - y)dx$$

The Gini coefficient can be calculated from the Lorenz curve directly. If the Lorenz curve is represented by the function $y = f(r)$, then the Gini coefficient can be calculated from the following integration formula (Charles, 2011):

(4.3) $$g = 1 - 2\int_0^1 f(r)dr$$

where r is the variable of interest (for example, income). The Gini coefficient varies from 0 which indicates complete equality to 1 when all income in the country is owned by one individual or a household (complete inequality). The closer the Gini coefficient is to 1, the higher the inequality and the closer it is to zero the less the inequality. The Gini coefficient is simple to calculate and easy to interpret and has been widely used in many empirical studies on inequality.

The Gini coefficient also facilitates direct comparisons with any quantitative variables which describe two or more populations, regardless of their sizes. It can therefore be easily used for comparing inequalities between groups, regions, or countries. The disadvantages of the Gini coefficient are that it is not additive across groups; the total Gini coefficient of a country is not equal to the sum of the Gini coefficients for its regions or other sub-groups. Idrees and Ahmad (2017) state that all inequality measures used in literature do not possess desirable properties of the inequality measure, and only a few measures possess these properties. When income data is less accurate the meaning and interpretation of the Gini coefficient could be misleading and may not show the true picture of income distribution. Researchers working with the Gini coefficient need to be aware that it is most sensitive to inequalities in the middle part of the income spectrum, but in some cases researchers will have valid reasons to emphasize inequalities at the top or bottom of the spectrum. Because of these and other limitations, besides the Gini coefficient, entropy measures (for example, the Atkinson and Theil indices) are frequently used inequality measures in empirical literature.

4.3.2.1.2. Atkinson's Measure of Inequality

British economist Anthony Barnes Atkinson developed the Atkinson index (Atkinson inequality measure), which is useful for measuring inequality and helps determine which end of the distribution contributes the most to the observed inequality. Atkinson's inequality measure is a welfare-based measure of inequality. It shows the percentage of total income that society should forego to have more equal distribution of income. This depends on the degree of aversion to inequality, the inequality aversion parameter ε measures the social utility gained from a complete redistribution of resources. The choice of the Atkinson inequality measure relative to the Gini coefficient is guided by the sub-group's consistency and sensitivity to the inequality of the lower end of the distribution. If inequalities increase in one sub-group (region, religion, ethnic group) and remain unchanged in all other groups, then overall inequality increases. But the Gini coefficient does not have this property. The Atkinson inequality measure puts more weight on the lower end of distribution but the Gini coefficient put equal weight on the entire distribution. The Atkinson coefficient is more appropriate when we are more interested in the lower end of the distribution such as child mortality and illiteracy. The Atkinson (1970) measure of inequality (I_A) can be calculated as:

(4.4) $$I_A = 1 - \frac{y_e}{\bar{y}}$$

where y_e is defined as the equally distributed equivalent income; and $\bar{y}$ is the average income. Atkinson emphasizes the relationship between inequality and social welfare based on the aggregation of individual utilities. Equal distribution occurs when the equally distributed equivalent income y_e is equal to the average income $\bar{y}$. The difference between these two variables results in inequalities. The larger the difference between y_e and $\bar{y}$, the higher is the inequality level. This result indicates that social wealth loss is proportionate to the level of inequality. Alternatively, using the social welfare function (SWF) inequality can be measured as:

(4.5)

$$I_A = \left[\sum_{i=1} \left(\frac{y_i}{\bar{y}} \right)^{1-\varepsilon} f(y) \right]^{\frac{1}{1-\varepsilon}}$$

In Equation (4.5), the level of inequality is clearly subject to changes in the inequality aversion degree $-\varepsilon$. The greater the ε, the greater the weight given to the lower end of the distribution.

4.3.2.1.3. Theil Index

The Theil index is one of the members of generalized entropy class of inequality measures. It can use individual as well as group data and allows decomposing inequality into within-group and between-group components. The Theil index is a widely used inequality measure because it has the desirable properties of decomposability. If the population is divided into groups, overall inequality is the sum of within and between-group inequalities. The within groups inequality measures inequality due to variations within individuals, whereas the between-group inequality measures inequalities between groups. In contrast to the standard entropy indices, the Theil index can be calculated for continuous variables. The Theil index also has many desirable properties such as population replication invariance, translation invariance, and scale invariance. The Theil index (I) is written as:

(4.6)

$$I = \frac{1}{N} \sum_{i=1}^{N} \frac{y_i}{\bar{y}} \log \frac{y_i}{\bar{y}}$$

where y_i is the income of an individual or a household, $\bar{y}$ is the average income, and N is population size. The index measures the difference between the observed distribution and the mean. The Theil index has a wider range of scalar variations and is bound to 0 and infinity. The closer it is to zero, the lower the inequality. When all incomes are equal or when all individuals or households earn a mean income, there is no inequality and I (Theil index) is 0. This index cannot directly compare populations of different sizes or group structures. The Theil index gives equal weight to each group or sub-group regardless of the population size. In a situation where the population sizes of the groups being considered are different, the difference in the index among the regions or groups may be partially because of differences in population sizes.

4.3.2.1.4. The Generalized Entropy Index

The generalized entropy index is one of the most widely used measures of inequality and all generalized entropy (GE) class of inequality measures can be expressed in terms of the following general formula:

$$GE(\alpha) = \frac{1}{\alpha^2 - \alpha} \left[\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y}{\bar{y}} \right)^{\alpha} - 1 \right]$$

(4.7)

where GE(α) is the generalized entropy index, the value of GE ranges from 0 to ∞, zero represents perfect equality and the larger its value the higher the inequality. The parameter α (α ≥ 0) represents the weight given to distances between incomes or other values at different parts of the distribution. The most common values of α are 0, 1, and 2. When α = 0 more weight is given to distances at the lower end of the distribution, that is, GE is more sensitive to changes at this end of the distribution. If α = 1 equal weights are given across the distribution, while α = 2 gives more weight to distances between incomes at the higher end of the distribution. This decomposition is usually applied only to the generalized entropy index GE (0) because the arithmetic can be complex for some inequality measures; it can also be shown that the generalized entropy measure with GE(0) and GE(1) becomes two of Theil's measures of inequality:

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n}\log\frac{\bar{y}}{y_i} \qquad (4.8)$$

$$GE(1) = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\bar{y}}\log\frac{y_i}{\bar{y}} \qquad (4.9)$$

4.3.2.2. Multidimensional Measurements of Inequality

Individual well-being is inherently a multidimensional concept. The recent recognition of this fact has resulted in an increased interest in the distribution analysis of education and health dimensions (Bakare, 2012). Education status and access to education are not equally distributed across countries or population groups. Given the impact of education and health on economic development, inequalities in education and health status represent a loss in aggregate welfare. Any inequality measure of well-being should take this multidimensionality explicitly into account. Education, living standards, and health status are multivariate distributions that make the traditional univariate measures of inequality such as the Gini coefficient and the concentration index less attractive. Most inequality measures are unidimensional; however, there are also several multidimensional measures of inequality.

4.3.2.2.1. Multidimensional Inequality Measuring Frameworks

The first step in measuring multidimensional inequality is identifying the indicators of well-being and the second step is measuring these inequality indicators for each person or household based on the unit of analysis. Measuring households' achievements in each indicator requires the availability and reliability of data but an exhaustive measure of these indicators is not easy in developing countries. Let us assume that the domains of well-being have been identified and households' achievements in all the dimensions have been measured and are comparable. Suppose there are n individuals and there are j relevant dimensions of well-being. Each distribution matrix X in $R_{++}^{n\times j}$ represents a particular distribution of the outcomes for n individuals in the j dimension:

(4.10) $$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} & . & x_{1j} \\ x_{21} & x_{22} & . & . & x_{2j} \\ x_{31} & . & . & . & . \\ . & . & . & . & . \\ x_{n1} & x_{n2} & . & . & x_{nj} \end{bmatrix}$$

A row of matrix X refers to the outcomes of one individual and a column refers to the outcome of one dimension. The set of bundles is $B = R_{++}^{j}$ and the set of all distributions is $D = B^{n}$. Dimensions can be measured in an interpersonal comparable way; some standard dimensions considered include income, living standard, health, and education. Let x_j^i be the non-negative achievement of an individual or household i in dimension j and let the achievement vector $x = (x_1^i, x_2^i, ..., x_m^i)$ summarize these achievements across all m dimensions for individual i. The distribution matrix can be compared by making use of a social evaluation function that maps a positive $n \times j$ distribution matrix to the positive real line. The social welfare function is $W : D \to R$. The value W(x) is the social welfare level associated with distribution x in D. Of the two aggregation processes, the first is aggregating across dimensions and then across individuals and the second is aggregating first across individuals and then across dimensions. In this study, we use aggregation first across dimensions and then across individuals. We prefer this because it considers the correlation or interdependence between dimensions which is very important in a multidimensional inequality analysis.

This multidimensional inequality index is different from the others. For example, it is different from the Human Development Index (HDI). Health indicators in HDI are life expectancy at birth but health indicators in this inequality measure are child mortality rate and child and adult malnutrition. Similarly, the living standard indicator in HDI is gross national income per capita but living standard indicators in this multidimensional inequality index are access to electricity, water, sanitation, cooking fuel, floor material, and asset ownership of households (such as land, car, and refrigerator).

4.3.2.2.2. Smeth and Alkire Methods of Multidimensional Inequality Measure

Smeth and Alkire suggest measuring multidimensional inequality using deprivation scores used in the multidimensional poverty measure. In this multidimensional inequality measure let $c_i(k)$ be the deprivation score measure for household i and A the average deprivation score of poor households, which is depth of poverty in multidimensional poverty, n is the number of poor households and b is a constant. The Smeth and Alkire method of multidimensional inequality can be formulated as:

(4.11) $$I_{md} = \frac{b}{n}\sum_{i=1}^{n}\left(c_i(k) - A\right)^2$$

Multidimensional inequality measure (I_{md}) for deprivation score ci(k) and b>0, satisfy important properties of inequality measures such as anonymity, transfer principle, additive decomposability, within-group mean independence, and replication invariance. The minimum value of this multidimensional inequality measure is zero, when the deprivation score of each household is equal to the average deprivation score of poor households (A). The value of b can be chosen in such a way that the value of the inequality measure is bounded between zero and one. This measure of multidimensional inequality measures inequality between poor households' only; however, when the aim is measuring multidimensional inequality of all the households in an economy, this method is marginally used.

4.3.2.2.3. The Araar (2009) Multidimensional Inequality Index

We used the most recent multidimensional inequality index- The Araar et al., (2009) multidimensional inequality index -- which satisfies a fundamental set of desired properties. The Araar multidimensional inequality index for the k-dimension of well-being can be formulated as:

$$I = \sum_{i=1}^{K} \phi_k \left[\lambda_k I_k + (1-\lambda_k) C_k \right] \quad (4.12)$$

where I is the Araar multidimensional inequality index, k are the dimensions considered in the multidimensional inequality analysis, and ϕ_k is the weight attributed to each dimension (which can take the same value across the dimension or can take the average value of the well-being dimension). The parameter λ_k controls the sensitivity of the index to the inter-correlation between dimensions in well-being. I_k is the relative inequality index of component k and C_k is the absolute concentration index of component k. The index has a more flexible functional form in multiple aspects of social preferences. It satisfies the main desirable properties and allows establishing a complete order for social welfare. The index has understandable components and is easily interpretable considering its functional form. Moreover, this index is multi-level decomposable by components or dimensions, and by the uni- and multidimensional forms of inequality. MDI is quite sensitive to the choice of parameter λ. Araar et al., (2009) state that the nature of the components used in the analysis determines the size of this parameter. If the components are perfect substitutes of another set of components, it is appropriate to set λ to zero. But if the components are a perfect complement, then λ will converge to one. Setting λ = 0.5 probably leads to reasonable values in the multidimensional inequality measure. In this multidimensional inequality measure we used the two-stage approach. In the first stage, we considered inequality in living standards (electric, sanitation, water, floor, cooking fuel, and asset ownership). We considered these because we observed that there were large variations or inequalities in households with respect to these facilities. Considering these inequalities as inequalities in living standards, as is increasingly mentioned in multidimensional poverty literature, and health and education as the other indicators of well-being, we estimated the multidimensional inequality index. In this multidimensional inequality index, the living standard's indicators are access to electricity, sanitation, water, floor material, cooking fuel, and asset ownership. Health inequality indicators are child mortality and nutrition levels of a household's members (adult and child nutrition). Educational inequality indicators are highest grade completed by the household members and child school attendance in the household.

4.3.3. Inequality Decomposition

Inequality measures are often decomposed by population sub-groups such as regions, gender or rural-urban groups to assess the extent and contribution of each group to total inequality. Inequalities within and between groups can also be used to assess the major contributors to inequalities. The Theil index and the indices of the generalized entropy class can be decomposed across these in additive ways. Inequality measures can be decomposed according to income sources and they can also be decomposed for each category or region (rural-urban, male-female, and regions). In this inequality estimation, the overall observed inequality can be decomposed into within (W), between (B), and overlapping (L) components. The Gini decomposition can be formulated as (Heshmati, 2004):

$$Gini = W_i + B_i + L_i = \sum_{i=1}^{n} Gini_i P_i \pi_i + \frac{1}{\mu}\sum_{i=1}^{n}\sum_{j>i}^{n}(y_j - y_i)P_i P_j + L_i \tag{4.13}$$

where $Gini_i$ is the Gini coefficient of group i, P_i is the population share of the group (rural-urban, male-female or regions), π_i is the income share of the total income in the region or group, μ is the mean income, and y_i is the mean income of group i. We decomposed our analysis into rural-urban and gender based (male headed and female headed) households and estimated within and between region inequalities (Table 4.10). Studies point out that rural-urban inequalities are a main contributor to total inequalities and inequalities are attributed to education and household residency (Charles, 2011; Deaton et al., 2002).

4.3.4. Inequality Dominance

Stochastic dominance is a useful and simple probabilistic concept that can be used for assessing inequalities. The most familiar graphical tool for examining inequalities of income or consumption is the Lorenz curve, which is a plot of a cumulative fraction of the population starting from the poorest (on the X-axis) against the cumulative fraction of income or consumption (on the Y –axis). We are interested in the notion of Lorenz curve (L) which is given by:

$$L = \int_0^p F^{-1}(q)dq, \quad for\ p \in [0,1] \tag{4.14}$$

where F is the probability distribution function, a Lorenz curve that is closest to the 45- degree line is more equitable than a Lorenz curve which is far away from the 45-degree line. In inequality sense distribution F is preferred to distribution G if and only if:

$$L_F(p) > L_G(p) \quad for\ \ p \in [0,1] \tag{4.15}$$

In comparing inequalities between two countries or regions if the value of the Gini coefficient for country 1 is greater than that of country 2, then the income distribution in country 2 is more equally distributed than in country 1. Equivalently, the Lorenz curve for country 2 will (first order) stochastically dominate that of country 1 which implies that a Lorenz curve for country 2 is closer to the 45-degree line and everywhere above the curve for country 1. If the Lorenz curve for country 2 stochastically dominates that for country 1 then the Gini coefficient for country 2 is smaller than that for country 1 and there are less inequalities in country 2 as compared to country 1.

4.4. Results and Discussion

The per capita consumption inequality analysis in this research using HICE data and Gini and Atkinson indices showed that consumption per capita inequalities were quite high in Ethiopia (Gini=0.385 and Atkinson index=0.221, with epsilon=1) (Table 4.3). Per capita consumption inequalities were higher in urban than in rural areas in both indices. A regional comparison pointed out that there were regional consumption per capita inequality differences between regions (Table 4.3). The multidimensional inequality indicators over the wealth quintiles showed that inequalities of the multidimensional indicators were quite high in Ethiopia (except for child mortality and nutrition) (Table 4.4). Inequalities in these indicators decreased over the wealth quintiles in general; however, inequalities in asset ownership increased over the last wealth quintiles (Table 4.4 and Figure 4.8). Education develops human capital and increases labor's productive capacity. An education inequality analysis showed that education inequalities are high in Ethiopia in general and in Afar, Somali, and Amhara regions in particular (Table 4.5). Less education inequalities were observed in Addis Ababa and Dera Dawa regions of the country. These are urban areas as compared to the other regions in the country. This difference may be a reflection of the differences in access to education across regions because of poor infrastructure development in rural areas as compared to urban areas. In most developing countries including Ethiopia, education and health facilities are not equally distributed across rural and urban areas. Education inequalities also differ across wealth quintiles. DHS uses quintiles in the wealth index. Quintiles are used instead of percentiles to limit the number of categories into five. Each member is given a wealth index and then ordered by the scores. The distribution is divided into five 20-percent sections. Then the household score is recoded into the quintile variable so that each member of a household receives that household's quintile category. High educational inequalities were observed within poorest households and less educational inequalities were observed within the richest households (Figure 4.1). Health inequalities in Ethiopia are less than living standard and education inequalities (Table 4.6)

A large proportion of Ethiopian households lives in rural areas and is engaged in agriculture. Ethiopian farmers are smallholder farmers who use traditional farming systems. On top of this there are small landholdings and also unequal distribution of agricultural landholdings in the country. Production and accumulation of wealth are highly associated with agricultural activities which in turn are related to landholding inequalities (Charles, 2011). Hence, rural agricultural society's income inequalities are associated with landholding distribution. High landholding inequalities are observed in SNNP (Gini=0.603) followed by Tigray (0.578) and Somali (0.563) (Table 4.7). SNNP is known to be the most densely populated region in the country and so small landholdings are expected here. Less agricultural landholding inequalities are observed in Amhara, Gambela, and Benshiangul regions. Though there are less landholding inequalities in Amhara region, this region is known to be a small landholding region. But Gambela and Benshiangul regions are known to be less densely populated with less landholding inequalities (Gini=0.42) next to Amhara region (Table 4.7). Because of availability of large arable land in these regions, they are attracting more domestic and foreign investors in the agricultural sector as compared to the other regions. Inequalities in agricultural landholdings also differ across wealth quintiles, and landholding inequalities are the highest for poor rural households compared to middle and rich rural households, especially in the higher percentiles (Figure 4.2).

This research focused on multidimensional inequality in Ethiopia as most other researchers have focused on income or consumption inequality. The analysis in this research was on the distribution of multidimensional inequality's indicators. It is very important to see the distribution of multidimensional inequality indicators before we estimate the combined multidimensional inequality index for these indicators. The Araar (2009) multidimensional inequality index's (MII) estimation results show that multidimensional inequality is low (0.301) (Table 4.9) in Ethiopia even though multidimensional poverty is quite high.

Living standards (electricity, sanitation, water, cooking fuel, floor material, and assets) contributed the most to multidimensional inequality except for some regions (Afar, Somali, and Addis Ababa) (Table 4.9). High contribution of living standards to multidimensional inequality made us analyze the inequalities in living standards. The living standard multidimensional inequality index (LSMII) showed that living standard inequalities were very high in Ethiopia (0.642). The inequalities were higher in rural areas (0.747) as compared to urban areas (0.342) (Table 4.8). Amhara, Afar, Smalli, and SNNP regions had the highest LSMII. However, Addis Ababa, Harrari, and Dera Dawa had less inequality in living standards. Of the living standard's indicators considered in the analysis, cooking fuel and sanitation contributed the most to LSMII at the country level (Table 4.8). Access to electricity and water contributed less to LSMII in urban areas. But the contribution of assets to LSMII was less (9.75 percent) in rural areas. Policies aimed at reducing living standard inequalities should hence focus on cooking fuel, access to electricity, floor material, and sanitation. Multidimensional inequality indices are quite sensitive to the choice of parameter λ. By setting the parameter λ to different values (Table 4.10) the estimated results differ considerably for different values (λ = 0.1, 0.3, 0.5, 0.7, 0.9) but they follow the same pattern in each range. In other words, as the values of λ increase the multidimensional inequality index also increases for all regions considered in the multidimensional inequality index. This range represents the most applicable range for the multidimensional inequality index (Table 4.10).

The consumption decomposition results showed that the incidence of consumption poverty was higher in rural than in urban Ethiopia (Table 4.11). But inequalities among urban households were greater than in rural households. Within-group consumption inequalities as calculated by the Gini coefficient, dominated between-groups inequalities (rural-urban) (Table 4.11). This shows that if the government or policymakers were to target consumption differences within groups, this could help in reducing overall consumption inequalities more than targeting consumption differences between groups. Urban households will benefit more because the marginal impact on inequalities is higher for urban households than their rural counterparts. Reducing inequalities between groups (rural-urban) will have more impact on reducing poverty than reducing inequalities within groups (households) as between-group elasticity is greater than within-group elasticity (Table 4.11). Gender based decomposition's results (Table 4.11) also show that the incidence of consumption poverty is high for male-headed households than for female-headed households. In addition, inequalities among male-headed households are greater than those in female-headed households. If income was used, the results might have been different. Research indicates that men earn more than women as there is gender based discrimination in developing countries like Ethiopia. Men earn more than women but women manage consumption expenditure better than men. Within-group inequalities, the marginal impact of inequalities, and the marginal impact of poverty register larger values than between-group components (Table 4,11). Therefore, reducing the average number of deprived households among male-headed and female-headed households will reduce overall deprivation more than reducing deprivations between these two groups. Region based decomposition's results showed that between-group inequalities were greater than within-group inequalities. This means that inequalities between regions were greater than within region inequalities so there were differences in inequalities between regions in Ethiopia which need to be considered.

Educational inequalities are high in Ethiopia in general and in some regions in particular (Table 4.5) and these are the second largest contributor to multidimensional inequality next to living standards (Table 4.9). Therefore, this dimension requires further analysis to identify areas of interventions in reducing educational and multidimensional inequalities. Different factors contribute to educational inequalities. One of the factors that is assumed to affect children's level of education is parents' level of education. Educated parents have better knowledge and understand the benefits of education and would like to educate their children as compared to uneducated parents. Within educated parents, father's education and mother's education have different impact on children in general and on sons and daughters' education in particular. In this analysis, we disaggregated parents' education into father's education and mother's education and estimated their contributions to children's academic levels. Our analysis revealed that parents' education had a positive impact on children's education. Mothers' education contributed more both to sons and daughters' education than fathers' education, other factors being controlled for (Table 4.12). This result is consistent with the saying that educating a mother (woman) is like educating a family. Therefore, educating daughters (tomorrow's mothers) has more positive intergenerational inequality reducing effects than educating sons. In Ethiopia, because of social and cultural reasons, girls are marginalized and have less access to education than boys. This situation has to be changed and daughters should have equal access to education. Providing better access to daughters' education will have a strong effect on reducing multidimensional inequality.

4.5. Conclusions

Consumption inequalities are quite high in Ethiopia in general and these are higher in urban as compared to rural areas. The results of a regional comparison showed that there were differences in regional consumption per capita inequalities between regions which require careful consideration both by federal and regional governments. Inequality of multidimensional indicators over the wealth quintiles was quite high in Ethiopia but the inequality of these indicators decreased over the wealth quintiles. Education inequalities were high in Ethiopia; however, educational inequalities in rural areas were greater than those in urban areas. This difference may be because of poor infrastructure development in rural areas as compared to urban areas. Development of schools at different levels and other infrastructure is very important to improve access to education thereby reducing the existing educational inequalities. Rural areas and poor households require special attention for reducing educational inequalities in Ethiopia. Large proportions of the Ethiopian population live in rural areas and are engaged in agriculture. Ethiopian farmers are smallholder farmers who use traditional farming systems. There are high agricultural landholding inequalities and these differ across wealth quintiles. Landholding inequalities are the highest for poor rural households compared to middle and rich rural households. Agricultural transformation is very important for improving smallholder farmers' productivity and for developing manufacturing and other industries to create jobs for these large proportions of rural smallholder agricultural households. There are considerable living standard multidimensional inequalities in Ethiopia. Cooking fuel and sanitation contribute the most to multidimensional inequality. Improved access to electricity and sanitation facilities reduces environmental degradation (due to use of firewood) and environmental pollution. If we want to reduce the inequalities in living standards, cooking fuel and sanitation facilities have to be improved. Policies aimed at reducing living standard inequalities should focus on cooking fuel, electric access, and sanitation and floor material.

The incidence of consumption poverty is high among rural households but consumption inequalities among urban households are greater than those in rural households. Hence, federal and regional governments who aim to reduce consumption inequalities should focus on within-group inequalities. This could help in reducing overall consumption inequalities more than targeting consumption differences between the groups. Urban households will benefit more because the marginal impact is higher for urban households than their rural counterparts. Reducing inequalities between groups (rural-urban) will have more impact on reducing poverty than reducing inequalities within groups will (households) as between-group elasticity is greater than within-group elasticity. Consumption poverty and inequalities are high for male-headed households as compared to female-headed households. Within-group inequalities, the marginal impact of inequalities, and the marginal impact of poverty registered larger values than between-group components. Therefore, reducing the average number of deprived households among male-headed and female-headed households will reduce overall deprivation more than reducing deprivation between these two groups. Region based decomposition results show that between-group inequalities are greater than within-group inequalities. This means that between regions inequalities are greater than within region inequalities, so there are differences in inequalities between regions in Ethiopia which require careful consideration. Parental education has a positive impact on children's education and educated mothers have a stronger influence on their children's education. Giving girls more access to education and encouraging them to get educated would have more intergenerational education and multidimensional inequality reducing effects. Therefore, federal and regional governments should give due emphasis to educating girls.

4.6. Recommendations

Based on the theoretical review of literature on unidimensional and multidimensional inequality and an empirical inequality analysis, the following recommendations are made:

- Attention should be paid to improving Ethiopians' living standards in general and poor and rural people in particular to reduce the existing inequalities in living standards and the multidimensional inequality index by improving access to living standard's indicators as there are high living standard inequalities in Ethiopian and living standards contribute the most to the multidimensional inequality index.
- In a country like Ethiopia where girls are marginalized because of social and cultural reasons increasing girls' access to education will reduce intergeneration inequality differences.

- In Ethiopia, a large proportion of the population is engaged in traditional agriculture. There are considerable landholding inequalities in rural Ethiopia so increasing land productivity through professional support systems and modernizing farming systems will help in reducing the existing inequalities in the country. Parallel to this, increasing industrialization in urban areas to create job opportunities both for urban and a rural growing population could help absorb the excess labor force in the agricultural sector.
- There should be combined efforts at reducing poverty, vulnerability to poverty, and inequality. Reducing inequalities in the country will enhance poverty and vulnerability to poverty reduction efforts. Inequality reduction significantly affects the poverty gap.
- Poverty, vulnerability to poverty, and inequality research has become extremely important in Ethiopia. There are some difficulties in measuring these problems: (1) availability and reliability of up to date panel and cross-sectional data, and (2) consistency and comparability of such data over time. Despite these measurement difficulties and data problems, poverty, vulnerability to poverty, and inequality measures remain useful for gaining some understanding of the severity of the problems and forwarding possible recommendations.

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Tables and Figures

Table 4.3. Per capita consumption inequality of households in Ethiopia using the Gini coefficient and the Atkinson inequality indices

	Gini index	Atkinson index		
		$\varepsilon = 0.1$	$\varepsilon = 0.5$	$\varepsilon = 1$
Ethiopia	0.385	0.026	0.121	0.221
Urban	0.369	0.024	0.111	0.205
Rural	0.295	0.015	0.072	0.138
Regions of the country				
Tigray	0.402	0.028	0.131	0.237
Afar	0.360	0.023	0.104	0.188
Amhara	0.415	0.030	0.136	0.247
Oromia	0.358	0.023	0.105	0.195
Somali	0.310	0.019	0.084	0.154
Benishangul	0.375	0.024	0.112	0.206
SNNP	0.375	0.025	0.115	0.211
Gambela	0.370	0.024	0.111	0.202
Harari	0.337	0.020	0.098	0.197
Addis Ababa	0.366	0.023	0.108	0.199
Dire Dawa	0.382	0.026	0.119	0.212

Source: Author’s calculations

Table 4.4. The Gini index of multidimensional inequality indicators across different income groups

Indicators	Poorest Quintile 1	Poorer Quintile 2	Middle Quintile 3	Richer Quintile 4	Richest Quintile 5	Overall Quintiles
Electric access	0.988*** (0.002)	0.948*** (0.005)	0.904*** (0.007)	0.790*** (0.010)	0.070*** (0.004)	0.641*** (0.004)

Sanitation	0.983*** (0.002)	0.961*** (0.004)	0.947*** (0.005)	0.930*** (0.006)	0.781** (0.006)	0.902*** (0.002)
Water	0.837*** (0.006)	0.776*** (0.009)	0.748*** (0.010)	0.682*** (0.011)	0.146*** (0.005)	0.568*** (0.004)
Cooking fuel	0.999*** (0.000)	0.997*** (0.001)	0.997*** (0.001)	0.989*** (0.002)	0.678*** (0.006)	0.890*** (0.003)
Floor	0.990*** (0.001)	0.978*** (0.003)	0.936*** (0.006)	0.856*** (0.008)	0.202*** (0.006)	0.702*** (0.004)
Asset	0.648*** (0.007)	0.541*** (0.011)	0.405*** (0.011)	0.259*** (0.010)	0.450*** (0.007)	0.493*** (0.004)
Child mortality	0.002*** (0.000)	0.002** (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.000)	0.001 (0.000)
Nutrition	0.262*** (0.007)	0.212*** (0.009)	0.202*** (0.010)	0.199*** (0.009)	0.134*** (0.005)	0.197*** (0.003)
Education	0.581*** (0.009)	0.426*** (0.010)	0.356*** (0.013)	0.292*** (0.015)	0.180*** (0.007)	0.422*** (0.005)
Child school attendance	0.493*** (0.007)	0.421*** (0.011)	0.402*** (0.011)	0.359*** (0.011)	0.159*** (0.005)	0.344*** (0.004)
Note: * P < 0.1, ** P < 0.05, and *** P < 0.01.						

Source: Author's calculations using DHS data (2016).

Table 4.5. Education inequalities across regions

Region	Gini coefficient	Generalized entropy measure of inequality		
		GE(0)	GE(1)	GE(2)
Tigray	0.371	0.167	0.174	0.473
Afar	0.644	0.311	0.358	1.851
Amhara	0.469	0.225	0.253	0.867
Oromia	0.413	0.194	0.188	0.483
Somali	0.573	0.220	0.170	0.545
Bensihangul	0.392	0.173	0.185	0.541
SNNP	0.366	0.155	0.137	0.301
Gambela	0.303	0.110	0.104	0.245
Harari	0.329	0.143	0.108	0.167
Addis Ababa	0.146	0.042	0.035	0.036
Dire Dawa	0.299	0.153	0.139	0.264
Ethiopia	0.422	0.185	0.175	0.479

Source: Author's calculations using DHS data.

Table 4.6. Health inequalities across regions

Region	Gini coefficient	Generalized entropy measure of inequality		
		GE(0)	GE(1)	GE(2)
Tigray	0.197	0.118	0.096	0.086
Afar	0.213	0.126	0.107	0.095
Amhara	0.137	0.085	0.066	0.054

Oromia	0.139	0.086	0.067	0.055
Somali	0.147	0.091	0.071	0.058
Bensihangul	0.115	0.072	0.055	0.044
SNNP	0.093	0.058	0.044	0.034
Gambela	0.187	0.110	0.091	0.080
Harari	0.108	0.067	0.051	0.041
Addis Ababa	0.110	0.068	0.052	0.042
Dire Dawa	0.141	0.087	0.068	0.056
Ethiopia	0.145	0.089	0.070	0.058

Source: Author's calculations using DHS data.

Table 4.7. Agricultural landholding inequalities in rural households across regions

Region	Gini	Generalized entropy measure of inequality		
		GE(0)	GE(1)	GE(2)
Tigray	0.578	0.627	1.014	6.338
Afar	0.557	0.577	0.881	3.628
Amhara	0.393	0.273	0.290	0.468
Oromia	0.562	0.577	0.794	3.150
Somali	0.563	0.569	0.815	2.718
Bensihangul	0.417	0.307	0.318	0.458
SNNP	0.603	0.694	1.130	7.700
Gambela	0.424	0.337	0.349	0.563
Harari	0.556	0.556	0.773	2.732
Dire Dawa	0.434	0.348	0.354	0.528
Ethiopia	0.543	0.548	0.762	3.511

Source: Author's calculations using DHS data.

Table 4.**8.** Living standard mutlidimensional inequality index (LSMII) and contribution of each indicator to LSMII

	LSMII	Contribtuion of each indicator to the LSMII (percentage)						
		Electric	Sanitation	Water	Cooking fuel	Floor	Asset	Total
Ethiopia	0.642	16.15	20.79	13.62	22.29	17.60	9.56	100
Urban	0.342	3.20	33.22	5.49	28.82	9.38	19.89	100
Rural	0.747	18.63	18.60	14.71	19.46	18.87	9.73	100
Regions of the country								
Tigray	0.668	16.01	19.69	13.89	22.14	19.81	8.45	100
Afar	0.762	16.78	19.72	16.51	19.43	18.05	9.51	100
Amhara	0.765	17.03	19.80	14.17	19.77	19.03	10.20	100
Oromia	0.711	18.37	19.45	14.27	20.69	18.70	8.52	100
Somali	0.732	18.30	18.19	16.54	20.78	16.99	9.20	100
Benishangul	0.718	17.25	20.18	11.44	22.25	19.23	9.64	100
SNNP	0.732	18.35	17.17	15.63	21.73	18.30	8.81	100
Gambela	0.666	16.49	20.61	8.65	23.88	19.28	11.09	100
Harari	0.421	7.21	28.87	10.68	27.39	12.19	13.66	100
Addis Ababa	0.26	0.29	45.16	2.99	21.37	2.65	27.55	100

Dire Dawa	0.425	9.12	25.32	10.47	27.43	10.22	17.44	100

Table 4.9. Mutlidimensional inequality index (MII) and contribution of each dimension to MII

	MII	Contribution of dimensions to MII (percentage)			
		Living standared	Health	Education	Total
Ethiopia	0.301	51.61	6.09	42.30	100
Urban	0.168	51.01	11.08	37.91	100
Rural	0.303	50.61	6.11	43.12	100
Regions of the country					
Tigray	0.291	52.75	7.41	39.83	100
Afar	0.340	40.53	8.88	50.60	100
Amhara	0.343	53.38	4.70	41.92	100
Oromia	0.294	49.42	5.88	44.71	100
Somali	0.330	41.95	6.25	51.80	100
Benishangul	0.272	51.02	5.75	43.23	100
SNNP	0.286	56.06	3.77	40.17	100
Gambela	0.244	52.87	11.13	35.99	100
Harari	0.278	48.75	6.84	44.41	100
Addis Ababa	0.078	39.25	16.04	44.71	100
Dire Dawa	0.377	61.06	7.22	31.72	100

Table 4.10. Multidimensional Inequality Estimates - Robustness check

Multidimensional inequality index(MDII)	Selected regions of the country				
	Tigray	Amhara	Oromia	SNNP	Addis Ababa
MDII($\lambda = 0.1$)	0.250	0.306	0.258	0.256	0.030
MDII($\lambda = 0.3$)	0.259	0.316	0.268	0.265	0.034
MDII($\lambda = 0.5$)	0.268	0.325	0.278	0.274	0.037
MDII($\lambda = 0.7$)	0.277	0.335	0.287	0.282	0.041
MDII($\lambda = 0.9$)	0.286	0.344	0.297	0.291	0.044

Table 4.11. Poverty(FGT) and inequality(Gini) indices and marginal impacts and Elasticity by groups

Groups	Population share	Poverty (FGT)	Inequality (Gini)	Marginal impact on inequality	Marginal impact on poverty	Elasticity
Urban	0.764	0.175	0.361	0.282	0.412	1.966
Rural	0.236	0.666	0.316	0.033	-0.000	-0.019
Within	-	-	0.252	0.316	0.411	1.757
Between	-	-	0.118	0.082	0.115	1.905
Total	1.000	0.291	0.393	0.393	0.491	1.685
Gender based decompostion						
Male-headed hh	0.811	0.315	0.399	0.318	0.388	1.642

Femal-headed hh	0.189	0.186	0.355	0.068	0.096	1.871
Within	-	-	0.268	0.387	0.484	1.683
Between	-	-	0.028	0.003	0.005	2.448
Total	1.000	0.291	0.393	0.393	0.491	1.685
Region based decompostion						
Tigray	0.069	0.319	0.418	0.032	0.038	1.606
Afar	0.038	0.196	0.361	0.014	0.020	2.000
Amhara	0.163	0.276	0.382	0.061	0.075	1.652
Oromia	0.226	0.330	0.393	0.084	0.113	1.811
Somali	0.039	0.255	0.370	0.013	0.015	1.553
Benishangul	0.049	0.284	0.389	0.019	0.022	1.581
SNNP	0.155	0.412	0.420	0.061	0.060	1.340
Gambela	0.053	0.360	0.407	0.021	0.025	1.642
Harari	0.020	0.195	0.352	0.007	0.011	2.214
Addis Ababa	0.168	0.150	0.355	0.062	0.084	1.823
Dire Dawa	0.020	0.305	0.384	0.007	0.011	2.139
Within	-	-	0.055	0.380	0.476	1.685
Between	-	-	0.061	0.007	0.013	2.416
Total	1.000	0.291	0.393	0.393	0.491	1.685

Source: Author’s calculations using HICE data.

Table 4.12. Education regression results by gender

Variables	Sons education	Daughters education	Children (Total samples)
Father education	0.520**	0.539***	0.529***
Mother education	0.551***	0.572***	0.561***
Family size	0.044***	0.027	0.037***
Children under 5	-0.209***	-0.271***	-0.237***
Child age	0.217***	0.234***	0.223***
Have bank account	0.219***	0.143*	0.187***
Rural (urban is base)	-0.429***	-0.491***	-0.469***
Head’s age group			
30-39	0.518***	0.428***	0.477***
40-49	0.715***	0.698***	0.712***
50-59	0.864***	0.857***	0.868***
60-69	0.759***	0.750***	0.759***
70+	0.560***	0.484**	0.522***
Regions (Tigry-base)			
Afar	-0.523***	-0.813***	-0.667***
Amhara	-0.619***	-0.512***	-0.577***
Oromia	-0.542***	-0.770***	-0.663***
Somali	-0.175	-0.565***	-0.365***
Benishangul	-0.320***	-0.594***	-0.455***
SNNP	-0.308***	-0.762***	-0.518***

Gambela	0.207	-0.691***	-0.221**
Harari	-0.250	-0.864***	-0.537***
Addis Ababa	-0.213	-1.214***	-0.668***
Dire Dawa	-0.182	-0.641***	-0.399***
_cons	0.166	0.545***	0.373***
Note: * P < 0.1, ** P < 0.05, and *** P < 0.01.			

Figure 4.1 Lorenze curves based on years of schooling for different income quintiles

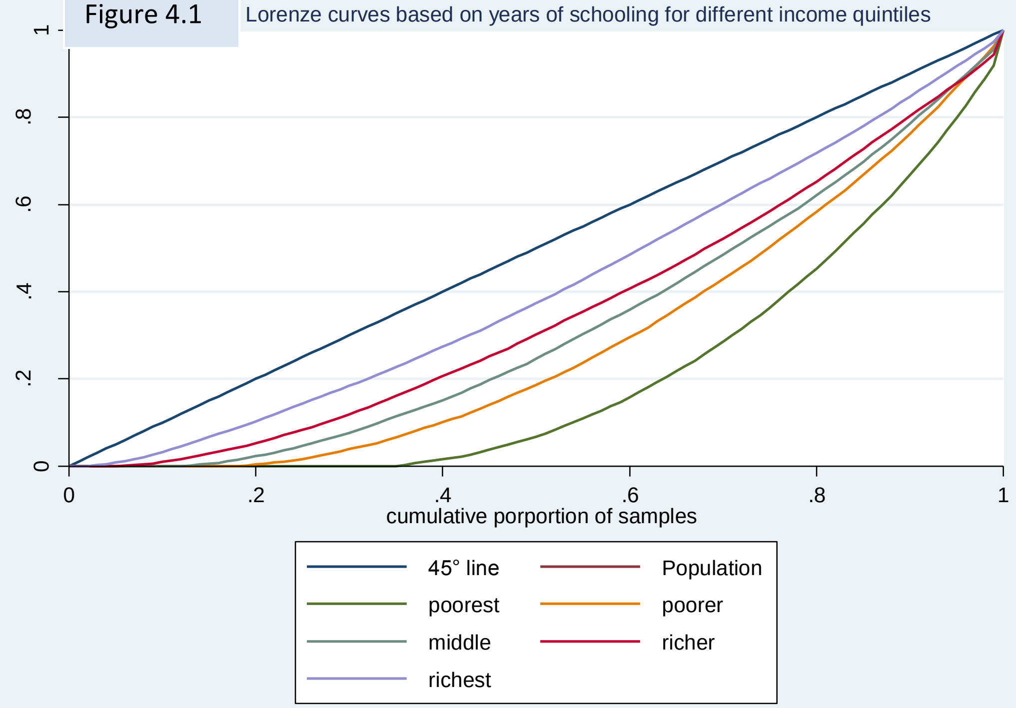


Figure 4.2 Lorenz Curves of agricultual land holding of rural households

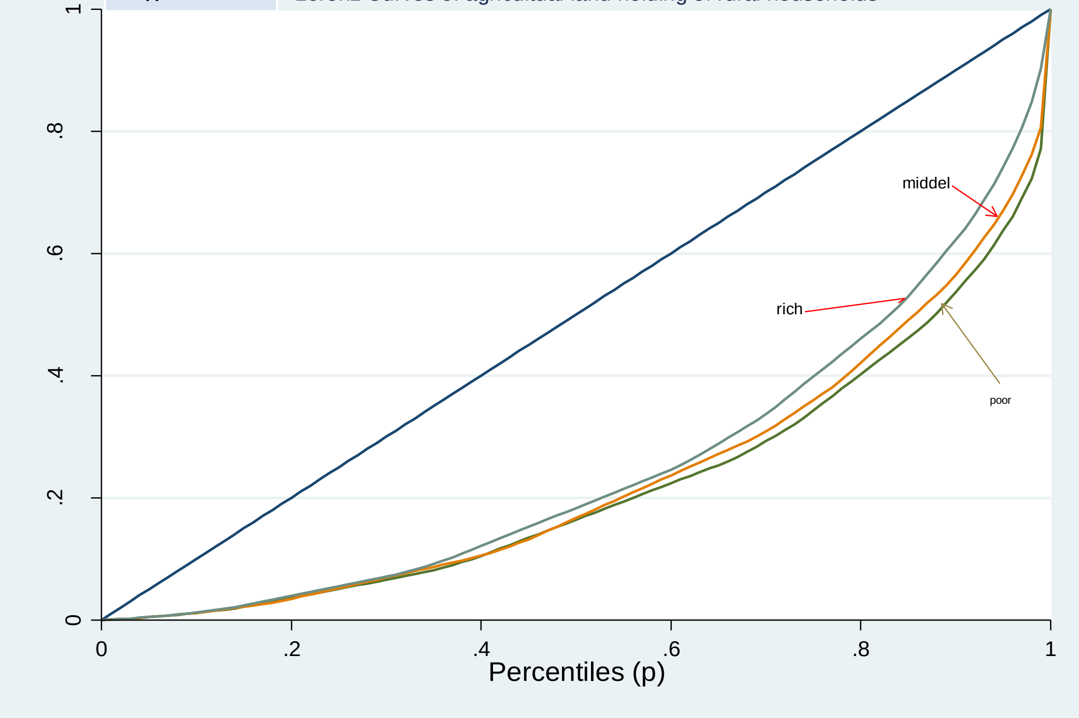


Figure 4.3 . Lorenz Curves of per capita consumption expenditure of rural and urband households

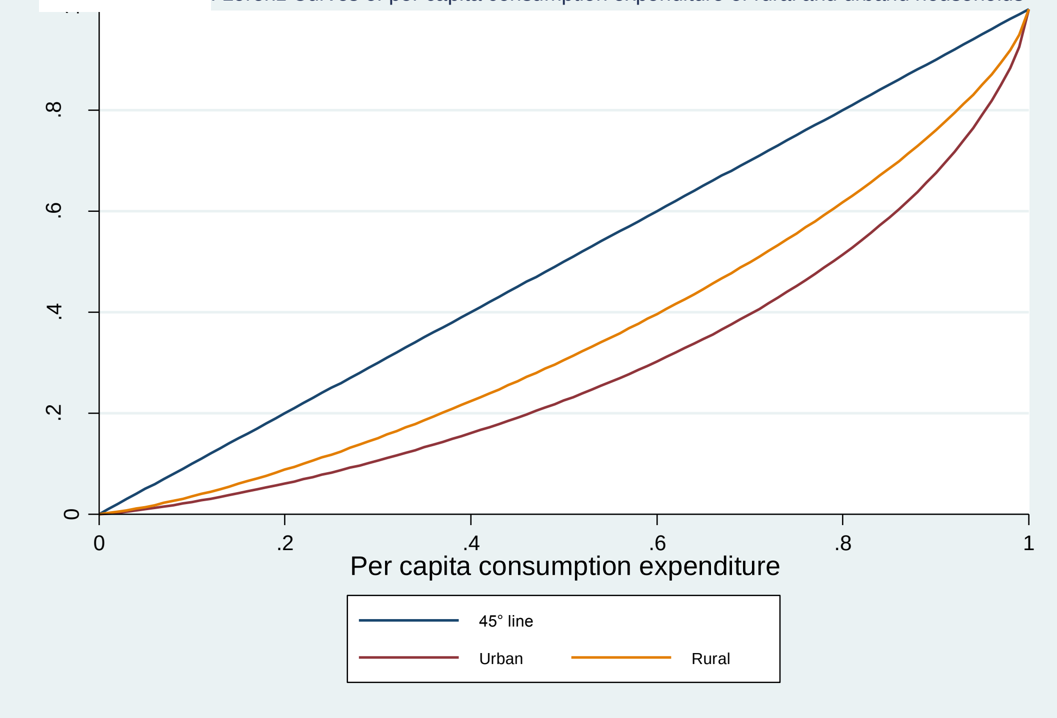


Figure 4.4 Cumulative density function curves of consumption per capita for rural and urban households

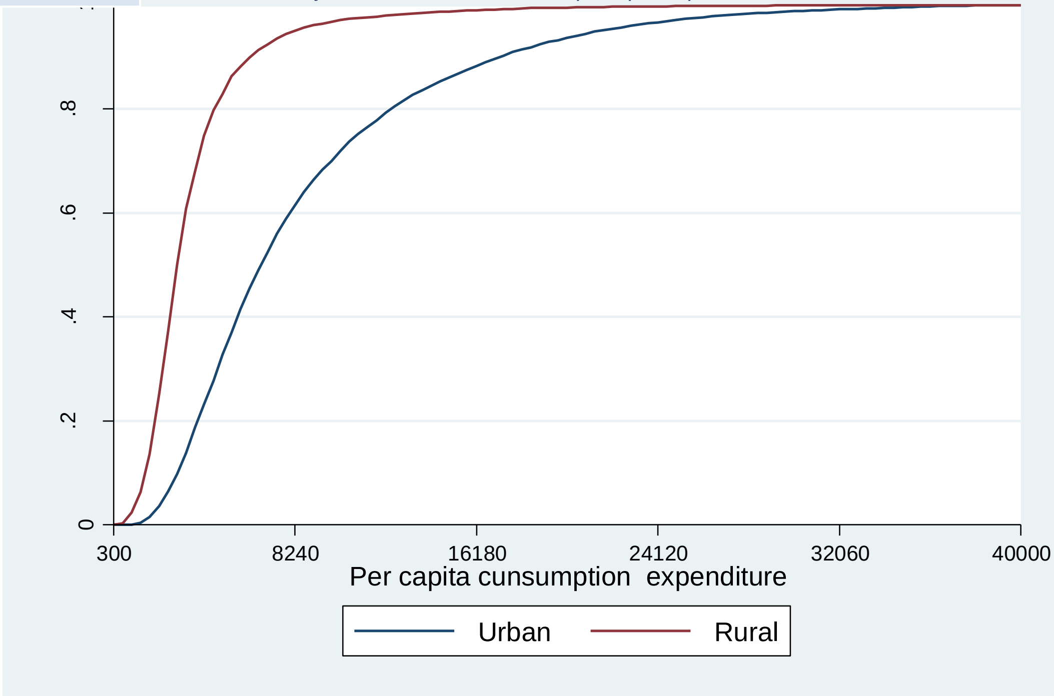


Figure 4.5 Joint distribution function of health and education

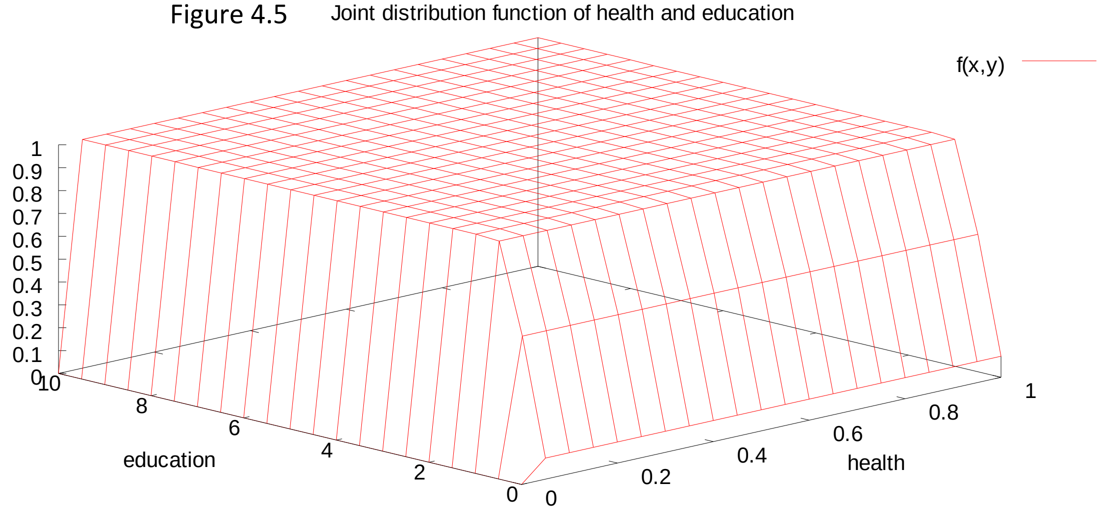


Figure 4.6 . Joint distribution function of living standard and education

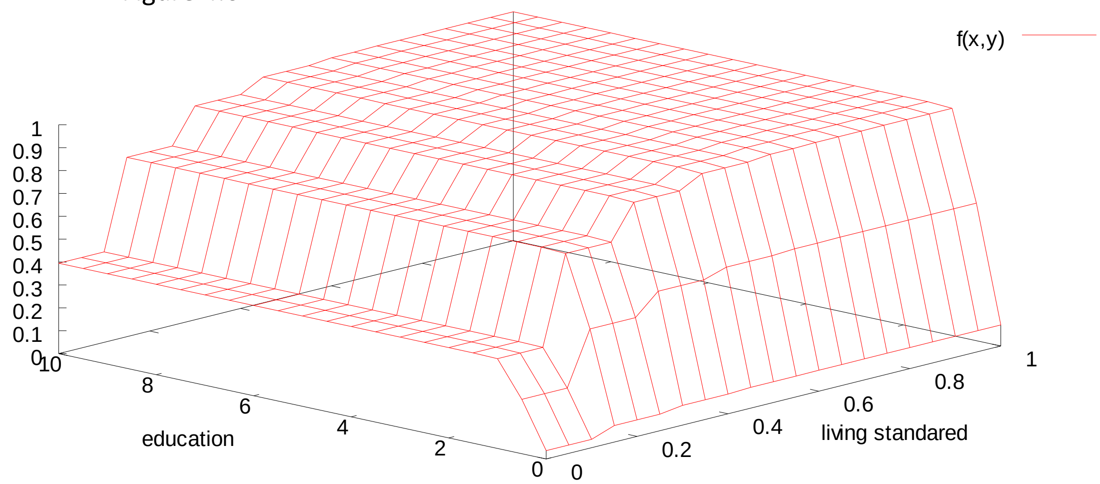
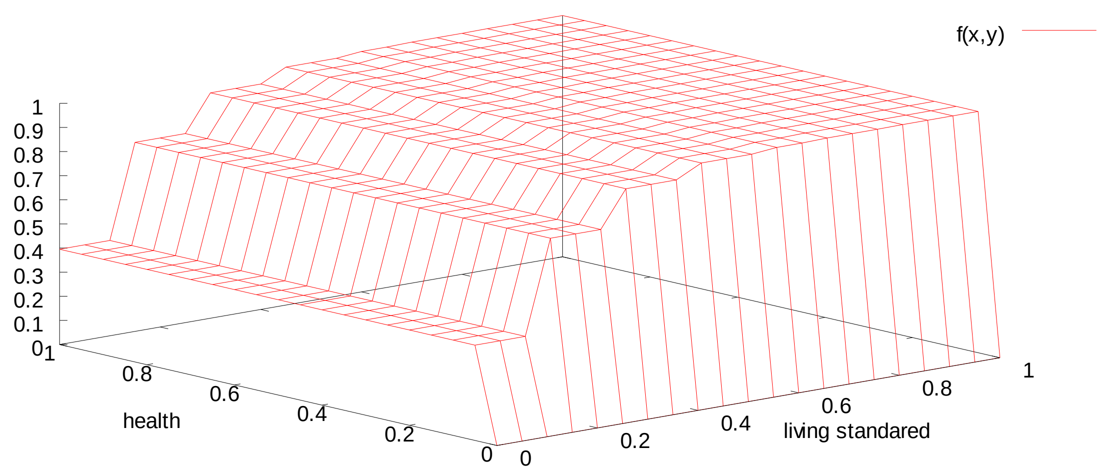


Figure 4.7 Joint distribution function of living standared and health



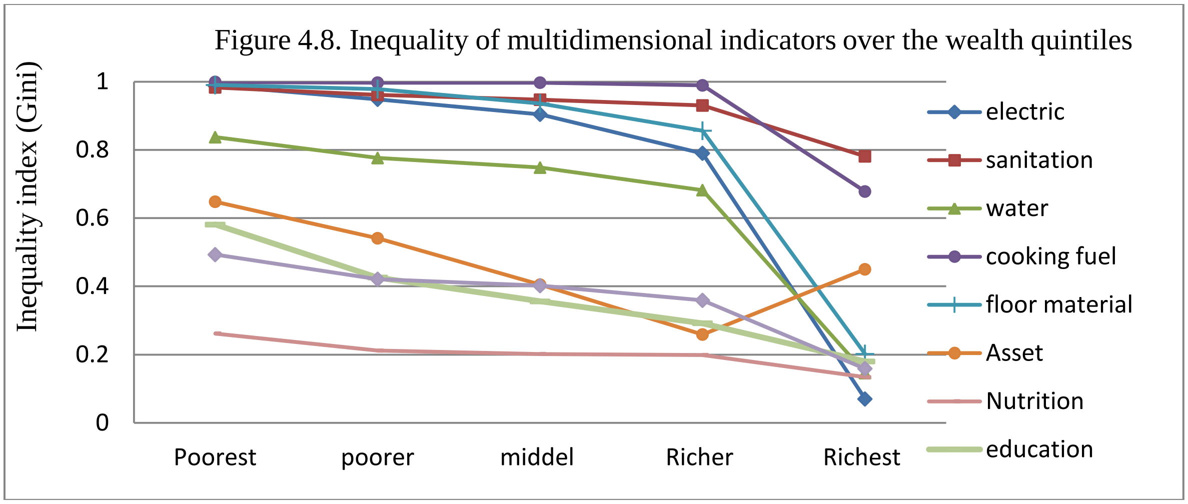


Figure 4.8. Inequality of multidimensional indicators over the wealth quintiles
Inequality index (Gini)
1
0.8
0.6
0.4
0.2
0
Poorest
poorer
middel
Richer
Richest
electric
sanitation
water
cooking fuel
floor material
Asset
Nutrition
education

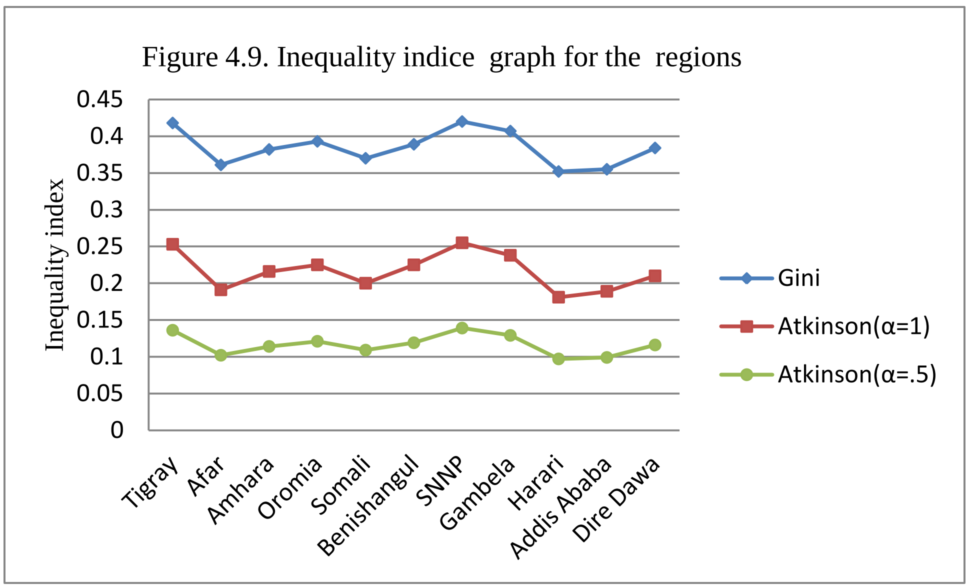


Figure 4.9. Inequality indice graph for the regions
Inequality index
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Tigray
Afar
Amhara
Oromia
Somali
Benishangul
SNNP
Gambela
Harari
Addis Ababa
Dire Dawa
Gini
Atkinson(α=1)
Atkinson(α=.5)

Chapter 5: Smallholder Farmers' Crop Production and Input Risk Analysis in Rural Ethiopia

Abstract

Different types of risks are inherent in agricultural production. This study examines agricultural input risks faced by smallholder farmers in rural Ethiopia. It uses data from farm household surveys covering the period 1995-2015. The study uses a stochastic production function approach for estimating the mean production and risks of agricultural inputs. The mean production estimation's results are consistent with econometric theory of conventional inputs. Land and labor power used by smallholder farmers have higher elasticities than the other inputs. The variance or risk estimation results show that inputs like fertilizers and labor are risk decreasing inputs while land is risk increasing inputs. In this research, crop diversification has a risk decreasing impact. The more farmers diversify their crops, the less is the yield variability. However, the risk decreasing/increasing effects of the farm inputs vary across regions in the country. For instance, risk decreasing effects of fertilizers are high in the Oromia region, moderate in the Southern Nations and Nationalities (SNNP), and low in the Amhara regional state. Variations in regional input risks need to be considered in national agriculture risk management and food security efforts. The risk increasing/decreasing effects of these inputs decreased over time in the study period.

Keywords: Input risks, production function, agriculture, Ethiopia

JEL Classification Codes: D24; C73; Q12;

5.1. Introduction

Ethiopia is fundamentally an agrarian country. Agriculture is the dominant sector of the economy and agricultural production is overwhelmingly subsistence. Many other economic activities including industrial processing, marketing, and exports of agricultural products depend on agriculture. A large part of export commodities is provided by small agricultural cash-crop producers and the agriculture sector is made up of smallholder farmers. In Ethiopia, agriculture is predominantly rain-fed and more than 95 percent of its output comes from subsistence smallholder farmers. The staple diet of a majority of Ethiopians consists of coarse grains such as maize, teff, and sorghum. In the agricultural sector, the average landholding per household is very small (less than one hectors). For instance, 29 percent of the grain farmers in Ethiopia cultivated less than 0.5 hector per household in 2006-07 (EEA, 2008) and households cultivated their plots mainly using family labor.

Risk is inherent in agricultural production (Guan et al., 2017; Sarker et al., 2016) and farmers take farming decisions under risky conditions: weather conditions change; prices at the time of the harvest could drop; hired labor may not be available at peak times; fertilizer application may not be optimal; animals might die due to a drought; and government policy can change overnight. All these are examples of the risks that farmers face in agricultural production (Kahan, 2008). Many of these risk factors that affect farmers' decisions cannot be predicted with complete certainty. Agricultural producers, unlike most other entrepreneurs, are not able to predict the amount of output that the process will yield with complete certainty due to external and internal risk factors. External risk factors include weather conditions, pests, and diseases and internal risk factors include quantities and qualities of inputs used and the efforts made by the producers. In addition to risks in preparing land and the cultivation processes, agricultural production can also be hindered by adverse events during harvesting or collection that may result in production losses. In countries where insurance and credit markets do not exist or are not well developed, production risks play a critical role in the choice and use of production inputs and adoption of new farm technologies (Dercon and Christiaensen, 2011).

Like many other developing nations, there is high yield variability or risks in smallholder farmers' crop production in rural Ethiopia. Since there are no insurance markets for most smallholder farmers in rural Ethiopia, farmers use their own strategies to combat agricultural production risks. There are tools available for managing production risks (Chuku and Okoye, 2009). For example, farmers may use crop diversification and/or use crop types with less risk (for example, drought tolerant crops). Farmers who produce multiple outputs use inputs to balance expected economic returns and the variance in the returns and try to mitigate risks or adverse outcomes through input choices (Tveteras et al., 2011). Which tools a farmer uses depends on his individual farm situation and risk bearing willingness and ability (Drollette, 2009). An understanding of the tools available for managing production risks can help agricultural producers develop better production and marketing plans that can reduce those risks and increase farm profitability.

Farmers' crop diversification strategies have been mentioned as strategies for reducing agricultural production risks. Crop diversification is an effective way of reducing income variability related to yield variability involved in the agricultural production processes because of production risks (Eneyew, 2012). Crop diversification is combining different production processes and is said to be effective if low income from one crop or farm is offset by high incomes from other crops or farms. Following literature, this study defines risk as a variation in yields or deviations from average production yields for given inputs.

Some of the risk factors are random and beyond the control of smallholder farmers like changes in weather conditions and pests and diseases. However, some of the risk factors can be controlled by the farmers if they are aware of the risk factors and are able to design appropriate risk reducing strategies. While farmers may adjust farm inputs to increase farm efficiency there are risks associated with farm resource adjustments (Ligeon et al., 2013). Production input risks are risks that can be managed by farmers as compared to other types of risks in the agricultural sector.

Farmers need to be concerned about the variables of on-farm decisions that affect risk and thus economic estimations of the relationship between input use and production risks are useful (Tveteras et al., 2011). Hence, farmers and policymaker should understand the structure of the risks. This research focuses on input risks that can be identified, controlled, and managed by the farmers themselves with some support from the government, NGOs, and extension services agents. Farmers need to have ways of dealing with input risks to protect themselves from high yield variabilities. Nevertheless, the risk effects of the major factors of production used by smallholder farmers have not been studied in detail except in some region-specific or crop-specific risk analyses. Therefore, the objective of this study is to analyze agricultural inputs risks of smallholder farmers in rural Ethiopia, whether the major inputs in the agricultural sector are risk increasing/decreasing and understanding and considering the effects of input risks at the farm level. These will benefit farmers and policymakers in developing appropriate strategies that can help farmers survive and confront input risks. It is also important to assess the impact of crop diversification strategies used by smallholder farmers for reducing agricultural production risks.

The estimation results show that almost all variables in the analysis have the expected signs and are statistically significant. The input land is a risk increasing input but fertilizers and labor are risk decreasing inputs for smallholder farmers in rural Ethiopia. Yield variability for a given crop differs geographically and depends on soil type, climate, and the inputs used. Crop diversification is the most significant risk decreasing variable in this analysis. The more farmers diversify their crop production the less is the risks they face. The production function had decreasing returns to scale except in 1995 and 2015. The production function also had negative input elasticity in 1999, 2004, and 2009, implying that the use of more inputs led to a decrease in input risks.

Marketing and price risks have been widely considered but production risks associated with the inputs used have attracted little attention in empirical literature. Production risks and uncertainties are the most important ingredients in formulating government policy and producers' decision making (Just and Pope, 1978). It is commonly accepted that production risks affect producers' decision making abilities about adopting and using new technologies. Given the importance of adoption of new technologies for improving farm productivity and the inevitable existence of production risks, considering the risks is very important for increasing technology adoption rates among our farmers. The Ministry of Agriculture, regional governments, and extension service workers who are interested in reducing agricultural production risks should consider the differences between agricultural input risks and regional input risks in Ethiopia.

The rest of the chapter is organized as follows. Section 2 reviews literature related to agricultural production risks, input risks for smallholder farmers and farmers' risk behavior in input use. Section 3 discusses the data, methods of analysis, and estimation procedures used in this research. Section 4 gives and interprets the results obtained from the analysis. Section 5 gives a conclusion and makes some recommendations based on the estimation results and existing agricultural farming conditions in the country.

5.2. Literature Review

5.2.1. Agriculture Production Risks

Low agricultural productivity is very common in Africa mainly due to nutrient depletion, inadequate rainfall, and lack of appropriate agricultural technologies and policies (Duflo et al., 2008). Enhancing agricultural productivity is the primary goal of governments, policymakers, and development partners in sub-Saharan African countries (Mukasa, 2018). Production or yield variability is one of the many risks that agricultural stakeholders face especially in sub-Saharan Africa (Chuku and Okoye, 2009). Agricultural production has its own unique nature. A unique and important characteristic of agricultural production is that there is a time gap between a production decision (plantation) and the cultivation of agricultural products (harvesting) and we commonly observe random production and price shocks after input decisions have been taken.

In the agricultural sector, there are also other types of risks besides production risks. Agricultural production exposes farmers to a variety of health risks (for example, exposure to chemicals), some agricultural products are perishable and lose their food value in a shorter period of time, and agricultural produce prices are often volatile (price risks). In addition to production shocks in the agricultural production process there are also input risks. Levels of inputs determine outputs and risks, we expect inputs to increase mean output (Roll et al., 2006). However, inputs either increase or decrease the level of output risks (Shankar et al., 2008). Literature exploring the causes of poverty in the developing world shows that a large portion of the world's poor relies on agriculture for their livelihood and agriculture is known to be inherently risky for many reasons (Ligeon et al., 2013; Shankar, 2012). Agricultural production depends on different factors that are not completely understood. Even when one understands the factors, little can be done to control them (for example, rainfall and droughts). Therefore, to understand the situation of many of the poor in Ethiopia, one must understand the causes and consequences of agricultural production risks.

In African countries, most rural households depend on agricultural activities for their livelihood (Mukasa, 2018). Governments in developing countries and their development partners have designed programs and allocated considerable resources for increasing agricultural productivity. Adopting agricultural technologies, agricultural extension services, soil and water conservation programs, agricultural marketing, and irrigation programs are some of the programs worth mentioning. In these programs, the emphasis is on the adoption of modern agricultural technologies such as the use of high-yielding varieties and using inorganic fertilizers and pesticides. These modern inputs are expected to increase agricultural productivity and transform the agricultural sector from subsistence farming to an agro-industry and subsequently enhancing farmers' well-being (Kassie et al., 2011; Kijima et al., 2008; Mendola, 2007). However, even though these inputs are assumed to increase productivity (Mukasa, 2018) they also affect output variability or risks.

A number of studies have documented the impact of production risks in agricultural production (Akhtaruzzaman et al., 2018; Guan et al., 2017; Groom et al., 2008; Kassie et al., 2011; Roll et al., 2006). Most framers in developing nations are risk averse and risk averse framers are reluctant to adopt new technologies because of insufficient knowledge about them (Dercon and Christiansen, 2011; Ligeon et al., 2013; Mukasa, 2018; Roll et al., 2006) and have insufficient savings and wealth to withstand difficult situations. Risks in production or production uncertainty is quite popular in applied work and is often explained by inputs (Kumbhakar and Tsionas, 2010; Ligeon et al., 2013; Shankar, 2012). Input quantity determines the volume of output produced and also the variability of output (production risks). Huyen and Hung (2016) point out that expanding the production scale increased both the variation in productivity and downside risks whereas expenditure on farm inputs and length of production time reduced production volatility and downside risks. Kim and Pang (2009) showed that temperature and precipitation were positively related to rice yield variability and were risk increasing inputs. Crop varieties, soil types, fertilizers, crop rotation, and intercropping had significant production risk reducing effects (Kansime et al., 2014). However, their effects consistently exhibited both yield-increasing and risk-decreasing effects across all the agro-ecologies. According to Chuku and Okoye (2009) production risks or yield variabilities are one of the most important risks that smallholder agricultural stakeholders face in sub-Saharan Africa (SSA). The results of their study indicated heterogeneous risk preferences. Farmers' socioeconomic characteristics were important for producers' risk preferences (Guan et al., 2017) and considering heterogeneity in risk preferences across individuals could result in consistent economic behavior.

The Just and Pope stochastic production function is one of the most widely used models in an agricultural production risk analysis (Akhtaruzzaman et al., 2018; Guan et al., 2017; Kansime et al., 2014; Kassie et al., 2011; Kato et al., 2009). The Just and Pope production function is mainly used to measure the production risks associated with the production process (Sarker, 2016). In this production function farm inputs are assumed to change the level of output variance in addition to the level of output produced. Hence, the Just and Pope stochastic production function addresses the heteroskedasticity of the error term in the production function. The model recognizes that input use such as fertilizers, land, and labor can change output levels and output variations or volatility. Therefore, producers can adjust the level of input use to manage production risks in agricultural production processes (Akhtaruzzaman et al., 2018; Guan et al., 2017; Sarker et al., 2016). The Just and Pope stochastic production function accommodates both risk increasing and risk decreasing inputs used in the production processes. This model was extended by Kumbhakar (2002) incorporating producer behavior towards risks in the model.

Like other economic agents, farmers with different demographic and socioeconomic characteristics generally have different risk attitudes and should have heterogeneous insurance demand for heterogeneous preferences (Guan et al., 2017; Howley and Dillon, 2012; Turvey et al., 2013). Producers reduce their farm output risks using institutional and managerial tools. For example, producers can reduce risk levels by changing the level of different inputs used in the production process (Heshmati et al., 2014). Empirical studies show that risk averse producers tend to use inputs optimally with less risky production conditions than they would under mere risky production conditions. For risk averse producers, optimal input levels increase if they increase the mean output level and reduce the yield variability or risk (Tvetera and Heshmati, 2002). Sarker et al.'s (2016) study on fish farms in Bangladesh showed that on average risk averse farmers used less inputs as compared to risk-neutral farmers. Nielsen et al., (2013) pointed out that among a sample of 300 rural households in Vietnam, 84 percent were risk averse and among these, 52 percent were very risk averse and substantial risk aversion was observed under different risk preference methods.

Grain production is inherently risky due to factors such as weather, soil, diseases, and the input levels used which result in significant variability in yields (Tveteras et al., 2011). The presence of risks in agricultural production affects farmers' behavior with regard to input use (Bokusheva and Hockmann, 2006). Since farmers are generally risk-averse they try to mitigate these risks through input level choices (Tveteras et al., 2011). Inputs' risk increasing or decreasing effects are environment, region, and situation specific. Hence, an analysis of the relationship between risk or output variance and level of input use is useful for an optimal level of input use (Bokusheva et al., 2006). Further, a farmer's technical efficiency may change significantly because of production risks and an analysis of this is also useful for policymakers involved in risk management in the agricultural sector.

In modern agricultural production processes, the use of modern inputs is very common for increasing agricultural productivity. However, these modern inputs are not always available and if available they are expensive and are unaffordable for most of the smallholder farmers in developing countries. Chavas et al., (2012) and Mukasa (2018) show that the application of modern inputs is associated with lower variance while their costs are variance increasing. Some other studies also point out that much of the production volatility associated with the use of modern inputs actually comes from variability in the costs of these inputs rather than from uncertainty regarding their potential impact on future yields (Moser et al., 2006).

Climate shocks are very common in developing countries and a significant variability in yields was observed because of climatic variables. The climate impact on yield variability depends on agro-climatic zones (Barnwal et al., 2013). Effects of climate change on rice yields are more sensitive to temperature and precipitation. These results call for location and season-specific adaptation policies for attaining food security and in reducing poverty. According to Barnwal et al., (2013) skewness captures the exposure to downside risks and expenditure for feed and time length of production reduces both the variation in productivity and downside risks in pig production.

In Sri Lanka, even when the price of rubber is high some smallholder rubber producers remain poor mainly because of the risks associated with rubber production. Waduge et al.'s (2014) risk estimation results in Sri Lanka showed that rainfall and labor usage were risk increasing while price was a risk decreasing factor in rubber production. They concluded that availability of farm labor which is the most required input in rubber production was a key issue in production risks.

Agricultural inputs used in agricultural production processes impact both the level of output and the level of risks and producers can adjust the level of input use to manage production risks (Guan et al., 2017). In agriculture, older farmers are usually more conservative in taking farm decisions and are reluctant to accept modern yield increasing technologies. Lower educational levels may increase their risk aversion; however, others also argue that better educated individuals are more aware of risks and their consequences and might be more risk averse.

5.2.2. Input Risks in Agriculture

A risk assessment of agricultural production is very essential and is now receiving the attention of agricultural economists more than ever before (Falco and Chavas, 2009; Huyen and Hung, 2016). Risks in agriculture are everywhere and dealing with them is difficult. One reason for these difficulties is because of different opinions about what a risk is and how it can be measured (Hardaker, 2000). Hardaker also adds that experts use the term risk in several different ways including the chance of a bad outcome, the variability of outcomes, and the uncertainty of outcomes. Risk is commonly understood as a chance of something negative happening and there are two common features in most risk characterizations. The first is that multiple outcomes are possible and the second is that the eventual outcome is a matter of chance or there is a certain probability that each possible outcome is realized. Although definitions of risk vary in literature, in agriculture, risks arise because of uncertainty over factors determining returns of agricultural production inputs (OECD, 2008). These are often characterized by high variability in agricultural production outcomes.

Input risks come from the uncertainties surrounding the inputs. The reasons for the variability in output yields can generally be traced back to changes in specified input factors (Dana, 2010). Dana also argues that production risks can be defined as input risks if the variability in the production process can be attributed to one of four cases: 1) uncertainty in the quality of one or more inputs, 2) uncertainty in the quantity of one or more inputs, 3) uncertainty in the timing of one or more inputs, and 4) uncertainty in the prices of one or more inputs. In my research, risk refers to the variability of yields or outcomes associated with the quantity of one or more inputs used in the production process. The quality of the inputs used is difficult to measure and hence, there is no enough data on the quality and timing of inputs used by the farmers. Since price risks are addressed by many researchers this research focuses on input quantity risks. Some inputs increase yield variability while others decrease yield variability.

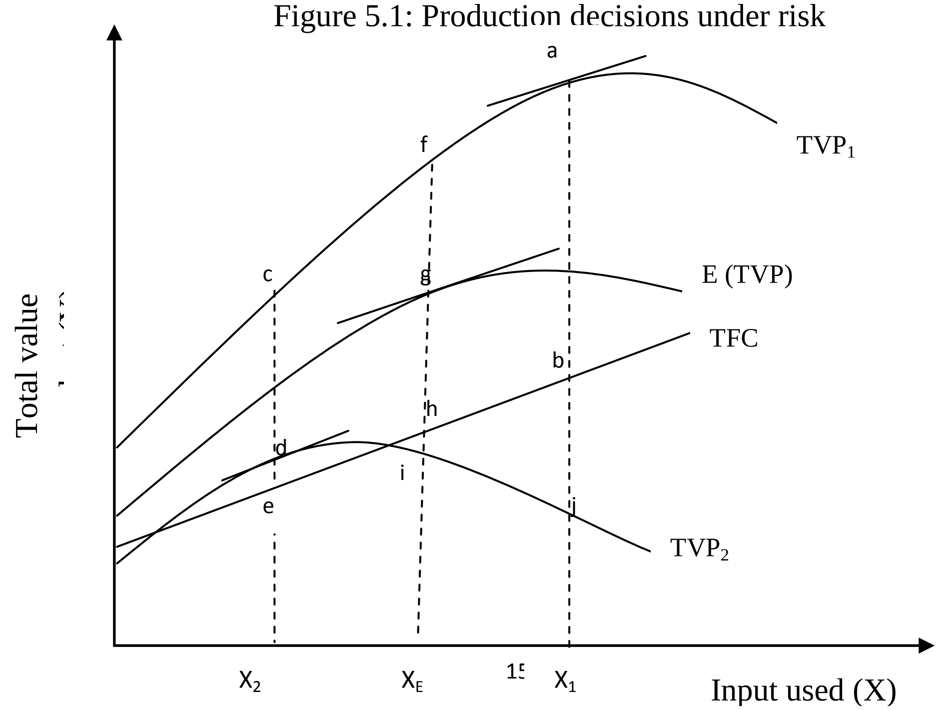
5.2.3 Farmers' Risk Behavior and Input Use

Agricultural production is a risky business and farm households have to tackle several risks. Production risks are of particular importance to farm households in developing countries. Risks are a major concern when famers have imperfect information about future input prices, output prices, and weather conditions. The severity of the risks differs from place to place (Nyikal et al., 2005; Pannell et al., 2000). Farm households' risk attitude and their decision making under such risky conditions affect their financial performance. Production risks influence the way a risk averse farmer chooses optimal input levels.

Although farmers in developing countries are generally thought to be risk averse (Isik and Khanna, 2003; Kristain et al., 2006; Kumbhakar and Tveteras, 2003) little is known about the actual form of their risk preferences (Brauw et al., 2014; Di Falco, 2006). Farmers differ in their risk behavior and risk averse farmers take into consideration the mean and the variance of output in their farm production and choose input levels which differ from the optimal input levels of risk taker and risk neutral farmers (Roll et al., 2006). Ellis (1992) explains the risk behavior of smallholder farmers considering two weather conditions: good weather conditions (with probability of occurrence of 0.6) and bad weather conditions (with probability of occurrence of 0.4).

The graph that Ellis' uses contains alternative output response curves to describe the outcome of these two events as well as farmers' subjective assessments of the balance between them according to flowing definitions: TVP_1 is total value product in good year, TVP_2 is total value product in a bad year, and $E(TVP) = 0.6TVP_1 + 0.4TVP_2$ is the expected total value of the product because the subjective probabilities attached by a farmer to the occurrences of good and bad years are 0.6 and 0.4 respectively (see Figure 5.1).

Figure 5.1: Production decisions under risk



Source: Ellis (1992).

A total factor cost (TFC) line represents the increase in total production costs as more input X is purchased and used. The impact of risks on efficiency can be examined using the line (TFC). According to Ellis (1992) the figure displays three alternative operating positions: X_1, X_E, and X_2, each of which is allocatively rational depending on a farmer's subjective preferences with respect to risks. According to the marginal approach, input use will increase until the marginal value product (MVP) of the input equals the marginal input costs.

A farmer who uses input level X_1 which is consistent with the allocative efficiency of TVP_1 is a risk-taker. If TVP_1 occurs, the largest possible profit, ab, is obtained. On the other hand, if TVP_2 occurs, a substantial loss, bj, is incurred. A farmer choosing to operate at this position is a risk-taker because he prefers to take a chance for the largest possible profit, even though it also has a substantial loss of probability (0.4).

A farmer, who chooses to use input level X_2 which is consistent with the allocative efficiency of $TVP_{2,}$ is risk-averse. This means that if TVP_1 occurs, a profit, ce, is obtained; and if TVP_2 occurs the farm still makes a small profit, de, as shown in the graph (Figure 5.1). A farmer choosing to operate at this position is risk-averse because he prefers the safety of acting as if the worst possible outcome will happen, even though in his own mind this only has a probability of 0.40.

A farmer who chooses to use input level X_E, which represents allocative efficiency consistent with a balanced assessment of the average outcome of good and bad seasons, is risk-neutral. The choice of his operating position is consistent with the average outcome of good and bad years taken together. This means that if TVP_1 occurs, a profit, fh, is obtained but this is not the largest profit possible on TVP_1. Similarly, if TVP_2 occurs a loss, hi, is incurred, and this is not the smallest loss possible on TVP_2. Each outcome is the weighted average outcome of good and bad weather conditions. Hence, an analysis of farmers' risk behavior shows that risk averse farmers use less inputs than risk-taking and risk-neutral farmers. One possible explanation why subsistence farmers in developing countries are reluctant to implement technologies that will apparently make them better-off can be the perceived risk profile associated with technology or input use (Roll et al., 2006).

5.3. Data and Methodology

5.3.1 Data

The data used in this analysis was obtained from the Ethiopian Rural Household Survey (ERHS). ERHS is a rich dataset containing several socioeconomic variables at individual and household levels. The data includes household characteristics, crop production, and information about livestock. The survey covers the country's major regions: Tigray, Amhara, Oromia, and South Nations and Nationalities (SNNP). This research uses data collected in 1995, 1999, 2004, and 2009 as a repeated cross-section. Cereal crops constitute a major portion of the total agricultural produce in the country. For this study, of the total annual crops produced in the country, 12 crops were selected (see Table 5.1) based on the percentage of total annual crops produced in the country. These crops constituted about 87 percent of the annual crops produced in the country. The last Ethiopian Rural Household Survey data comes from 2009 so to have more recent information we used data from the Ethiopian Living Standard Survey of 2015. This data has enough information about farm inputs and outputs which enables us to find mean and variance estimations to get a picture of farm input risks.

Table 5.1. Crops selected for revenue and crop diversification index's Estimation

No	Crop types	Percentage	Cumulative Percentage
1	White teff	14.27	14.27
2	Black & mixed teff	8.77	23.04
3	Barely	19.75	42.78
4	Wheat	17.94	60.73
5	Maize	11.29	72.01
6	Sorghum	5.05	77.07
7	Zengada	3.66	80.73
8	Horse beans	9.64	90.37
9	Linseed	2.89	93.26
10	Lentils	1.33	94.60
11	Chick peas	2.68	97.27
12	Cow peas	2.73	100.00

Source: Author's calculations using ERHS data

Since some inputs are not separable for smallholder farm households' especially family labor, we used the total revenue of the products obtained from crops produced in the cropping seasons. The dependent variable is not the physical output produced but is instead total revenue (Tvalue) obtained from crop production. Rural households in developing countries often use diversification. They pay a high price for such risk management by forgoing the gains of specialization. Traditional cropping in many places relies on crop and plot diversification. Most rural farmers in Ethiopia cultivate many crops and specialization is not common among smallholder farmers. Crop diversification is an effective way of reducing income variability in rural Ethiopia (Eneyew, 2012) as it involves combining different crop production processes and effective diversification occurs when low income from one crop is offset by satisfactory or high income from another crop's production.

Diversification in this research refers to crop diversification by smallholder farmers. We wanted to see whether this crop diversification was reducing risks in agricultural production. To address crop diversification, following Dimova and Sen (2010) we used the Herfindahl index constructed as the sum of squares of the shares of different incomes from different crops' yields for a household. The smaller the index value the higher the crop diversification. This crop diversification index is used in the regression to assess whether crop diversification increased or decreased agricultural production risks. The other variables used in the analysis are land, fertilizers, labor power used, enough rain during the beginning of crop production, enough rain during the growing season of annual crops, soil conservation practices, and water harvesting practices used by smallholder farmers in rural Ethiopia (Table 5.2).

5.3.2. Methodology and Estimation Procedure

5.3.2.1 The Stochastic Production Function

There is considerable evidence in literature that the distribution of output is a unique function of its moments. Thus, firms' behavior and stochastic production can be defined in terms of the relationship between inputs and these moments (Fufa and Hassen, 2003; Ligeon et al., 2013). The stochastic frontier production function model extends the classical production function estimation by allowing for the presence of technical inefficiency. Given the technology, fully efficient producers may realize the full potential of the technology and obtain the maximum possible output for given inputs. A production function which shows the maximum possible level of output is the stochastic frontier production function. The stochastic average production function shows the average production of a farm or producer when risks are considered. The actual outputs observed may fall below the frontier because of the presence of technical inefficiencies. The amount by which the actual production level of a farm falls from the stochastic frontier production gives the level of technical inefficiency.

Several methodologies have been developed to analyze production related risks. According to the traditional econometric specification of the stochastic production function, if any input has a positive effect on the mean of output then a positive effect on variability of output is also imposed (Just and Pope, 1979). Adequate production function specifications should include the effects of inputs on higher moments of the distribution of output such as variance. Following Just and Pope (1978, 1979) the Just and Pope stochastic production function is a widely used framework in agricultural risk modeling (Guan et al., 2017) and has been used by different authors (Shankar, 2012; Waduge et al., 2014). A stochastic production function[2] is specified as:

$$y = f(x;\alpha)\exp(g(x;\beta)\varepsilon) \tag{5.1}$$

where y is the mean output level, $f(x;\alpha)$ and $g(x;\beta)$ are the mean (deterministic) and the stochastic variance or risk components of the production function respectively. x represents the input level used in the production process, α and β are parameters to be estimated, and ε is the error term whereas $E(\varepsilon) = 0$ and $\mathrm{var}(\varepsilon) = \delta_\varepsilon^2$. In our analysis, the control variables are diversification, enough rain at the beginning and during the growing season, soil conservation practices, and water harvesting practices. A good feature of the Just and Pope production function is the separation of the mean production function and the variance function of the input level used. The mean output level is represented by $E(y) = f(x;\alpha) + u$, the variance function is represented by $\mathrm{var}(y) = [g(x;\beta)]^2 \delta_\varepsilon^2$, and input level x is assumed to affect both the mean and variance functions. Since the input level affects both the mean and variance functions, in this production function heteroskedasticity is assumed. Model (5.1) above can be written in logarithmic form as:

$$lny = lnf(x;\alpha) + g(x;\beta)\varepsilon \tag{5.2}$$

The premise of Model 5.2 is that the variance of production function (error term) may be related to the explanatory variable. If that is the case then inputs in the production process can be risk neutral, risk increasing, or risk decreasing. The log linear production function allows input elasticity to vary in input levels in both the mean production function and the variance or risk function. The returns to scale (RTS) can be estimated (Heshmati et al., 2014; Roll et al., 2006) from these log functions since the coefficients are elasticity in the log function form and therefore RTS can be calculated as the sum of input elasticities as:

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[2] The production function is stochastic by nature but it is specified as an average production function and is different from the stochastic production function used in estimating efficiency in production.

(5.3) $$RTS = \sum_{i=1}^{k} E_k = \sum_{i=1}^{k} \left[\frac{\partial y}{\partial x} \times \frac{x}{y} \right]$$

If the value of RTS is greater than one, the production function is increasing returns to scale and if it is less than one it is decreasing returns to scale. The production function is said to be constant returns to scale if returns to scale are equal to one. According to Roll et al., (2006) we can also estimate variance elasticity or risk elasticity from the variance function. Variance elasticity (VE) of inputs is defined as:

(5.4) $$VE = \sum_{i=1}^{k} VE_k = \sum_{i=1}^{k} \beta_k$$

VE is similar to the RTS elasticity obtained from the production function. If VE is a positive expansion of the output level using more inputs will lead to an increase in input risks and if VE is negative then the use of more inputs will lead to a decrease in input risks. Just and Pope (1979) presented eight postulates necessary for the function to be able to reflect all potential risk structures. They proposed that inputs can be risk increasing, risk decreasing, or neither risk increasing nor risk decreasing, that is:

(5.5) $$\frac{\partial \operatorname{var} y}{\partial x} = \frac{\partial g(x;\beta)\varepsilon}{\partial x} <=> 0$$

According to Fufa and Hassen (2003), the mean output and variance or variability estimation procedure is given as:

i. First, a non-linear least square estimation of α is obtained from the regression of lny on $lnf(x;\alpha)$ in logarithm under a broad range of considerations. The non-linear least squares of $\hat{\alpha}$ and $\hat{f}(x,\hat{\alpha})$ are shown to be consistent, the residual, $\hat{u}$ from the regression is then calculated as:

$$\hat{u} = lny - ln\hat{y}(x,\alpha) = \hat{g}(x;\beta)\varepsilon$$

ii. A non-linear least square estimation of β on $g(x;\beta)$ is obtained by regressing ln $(\hat{u}^2)$ on $lng(x,\beta)$ to produce a consistent estimator of $\hat{\beta}$ and $\hat{g}(x;\beta)$.

iii. Finally, the non-linear least square estimation of α is obtained by correcting for heteroskedasticity or by the weighted regression of lny on$lnf(x;\alpha)$. This would give consistent and efficient parameter values α of the function.

5.3.2.2. Downside Risks in Agricultural Production

A risk assessment of agricultural production is receiving the attention of agricultural economists (Falco and Chavas, 2009; Huyen and Hung, 2016). To determine the factors affecting agricultural risks, factors influencing the central moment of the production function need to be examined (Huyen and Hung, 2016). Determining the mean and variance of agricultural production does not distinguish between upside risks and downside risks. In an agricultural production risk analysis, it is important to distinguish between downside risks (unexpected bad events) and upside risks (unexpected good events) (Huyen and Hung, 2016). Huyen and Hung (2016) emphasize that expanding the production scale increases both the variations in productivity and downside risks whereas expenditure on farm inputs and length of production time reduces production volatility and downside risks. Variance or standard deviations are used for measuring risks; however, the main problem with using these measures of risk is that they treat fluctuations above and below the mean in the same way. Barnwal et al., (2013) point out that the skewness captured the exposure to downside risks; in pig production expenditure for feed and time length of production reduced both the variation in productivity and downside risks. Since downside risk consideration is very important, it is possible to break the variance so that it accounts only for fluctuations below the mean (Elizabeth et al., 2013; Estrada, 2006; Huyen et al., 2016; Mukasa, 2018). The downside risk (Vd) can be defined as:

$$V_d = \frac{1}{T}\sum_{i=1}^{n}\{min(Y - \hat{Y},\ 0)\}^2 \tag{5.6}$$

where Y is the actual output produced and $\hat{Y}$ is the estimated output. It takes the difference between the actual output and the estimated output if output is below the estimated output (downside differences) and zero if the output is above the estimated output. Conventionally risk is perceived by most as a chance of something bad happening. Risks are associated with outcomes that are worse than some specific target. This brings about a further class of risk measures often referred to as shortfall measures. Considering only the lower part of the distribution is called downside risks (Berg and Starp, 2006). Berg et al.'s (2006) results of a downside risk analysis showed that land had a downside risk increasing impact. Smallholder farmers' increasing the land size increased downside risks whereas fertilizers had a downside risk deceasing impact. The crop diversification index has a significant downside risk decreasing effect.

5.3.2.3. Estimation Procedure

This study estimates the mean production function and the risk function for smallholder farmers for the years 1995, 1999, 2004, 2009, and 2015. The dependent variable is the total value of crop production (Tvalue) and the independent variables are land, labor, fertilizers, the crop diversification index, enough rainfall at the beginning of the crop season, enough rain during the crop growing season, and soil conservation and water harvesting practices of smallholder farmers in rural Ethiopia.

Step1: We used the log transformed function of the stochastic production function (5.1). We transformed the dependent and all continuous independent variables into their log form except the dummy variables, which enter the function as a shift factor in the production function. The mean output function for the representative farm household is estimated as:

$$\begin{aligned}\mathrm{lnTvalue} = \alpha_0 + \alpha_1\mathrm{lnland} + \alpha_2\mathrm{lnfert.} + \alpha_3\mathrm{lnlabor} + \alpha_4\mathrm{lnindex} + \gamma_1\mathrm{enoughrainbeg} \\ + \gamma_2\mathrm{enoughraingrw} + \gamma_3\mathrm{soilcon} + \gamma_4\mathrm{waterhar} + \mathrm{u}\end{aligned}$$

where u is the residual of the estimated mean production function and $\alpha\ and\ \gamma$ are coefficients for the continuous and dummy variables respectively.

Step 2: Estimating the residuals (u)

The residuals can be estimated from the mean output estimation results of step 1 as:

$$\begin{aligned}\hat{\mathrm{u}} = \mathrm{lnTvalue} - (\hat{\alpha}_0 + \hat{\alpha}_1\mathrm{lnland} + \hat{\alpha}_2\mathrm{lnfert.} + \hat{\alpha}_3\mathrm{lnlabor} + \hat{\alpha}_4\mathrm{lnindex} + \hat{\gamma}_1\mathrm{enoughrainbeg} \\ + \hat{\gamma}_2\mathrm{enoughraingrw} + \hat{\gamma}_3\mathrm{soilcon} + \hat{\gamma}_4\mathrm{waterhar})\end{aligned}$$

which are then used to estimate the risk function which is written as in Just and Pope (1979).

Step 3: Estimating the variance or risk function

The variance or risk function can be estimated using the log of square of residuals of the estimated equation obtained in step 2:

$$\ln(\hat{u}^2) = \beta_0 + \beta_1 \mathrm{lnland} + \beta_2 \mathrm{lnfert.} + \beta_3 \mathrm{lnlabor} + \beta_4 \mathrm{lnindex} + \mu_1 \mathrm{enoughrainbeg} + \mu_2 \mathrm{enoughraingrw} + \mu_3 \mathrm{soilcon} + \mu_4 \mathrm{waterhar} + \varepsilon$$

Step 4: Using the third stage estimation of the variances and the square roots of these variances as weights, the mean output is re-estimated using the weighted least squares technique. The mean output for each year is also estimated.

5.4. Results and Discussions

This analysis used the Ethiopian Rural Household Survey (ERHS) data collected in 1995, 1999, 2004, and 2009. The 1995 data was the third round and the last survey was in 2009. This data contains information on agricultural output and inputs of smallholder farmers in rural Ethiopia like output, land, labor, fertilizers used, and types of crop grown by each sample household in each region of the country. Since 2009 was last round of the ERHS survey, as an alternative, we used data from the Ethiopian Living Standards survey done in 2015. This data contains smallholder farmers' agricultural yields and also the inputs used such as land, seeds, fertilizers, and labor. Since we have data for different years, before estimating the model, we had to test whether we needed to run the regression separately (year by year) or to pool it together. The null hypothesis (pooling together) was rejected because the F-value (40.47) was greater than the critical value (2.32).

5.4.1 Production Input Elasticity

The estimation results of mean crop production show that almost all the variables in the analysis had the expected signs and were statically significant in each year (Table 5.4) and all inputs increased mean output (Roll et al., 2006). Land used for the selected crops had high elasticity. A 10 percent increase in land use for these crops production in 1995, 1999, 2004, 2009, and 2015 increased smallholder farmers' revenues by about 3.7 percent, 4.6 percent, 3.2 percent, 3.2 percent, and 6.4 percent respectively. The responsiveness of total revenue to the change in land inputs was similar, except in 2015 when it was a bit higher (6.4 percent). A 10 percent increase in fertilizers increased smallholder farmers' revenues by 5 percent, 1.9 percent, 0.8 percent, 3.6 percent, and 1.8 percent in the respective years. We can see that fertilizers' returns in terms of revenue decreased from 1995 to 2004, but a significant increase is observed in 2009. Similarly, an increase in family labor by 10 percent, increased farmers' revenues by 3 percent, 2.3 percent, 1 percent, 1.7 percent, and 2.3 percent in 1995, 1999, 2004, 2009, and 2015 respectively, given all other factors are held constant. The returns from labor power in general seemed to decrease from 1995 to 2004, which may be because of population growth in rural areas. As the population growth rate increased, farm land size per household decreased which resulted in disguised unemployment in rural areas which is very common in most developing countries like Ethiopia.

The coefficients of the crop diversification index are negative and statically significant (Table 5.4). As the crop diversification index decreases (the smaller the crop diversification index value, the higher the crop diversification), crop yields or revenues increase. In other words, smallholder farmers' increase in crop diversification increases their yields or revenues. But this is contrary to the idea of specialization. However, we argue that in this case the gain because of diversification is greater than the loss due to lack of specialization. The variable enough rain during the beginning of the production season (dummy-yes/no) had an expected positive sign and was statistically significant in 1999. Those farmers who got enough rain during the beginning of the crop season had better yields or revenues than those who did not get enough rain at the beginning of the crop season. However, the variable enough rain during the growing season (dummy) had an unexpected sign and was statistically significant in 1995. Having enough rain during the crop growing season is expected to increase yields and revenue (sign expected to be positive) but that was not the case in this estimation result. This may be because of the price effect or farmers may have responded to this question considering enough rain during harvesting time which in most cases is expected to decrease yields.

Soil conservation practices had positive and statistically significant coefficients in 1999 and 2004, which implies that those farmers who practiced soil conservation had better yields or revenues than those who did not practice soil conservation (Table 5.4). One fact about soil conservation is that it is a long-term investment in which farmers invest their resources now in expectations of returns in the future. Soil conservation practices by the smallholder farmers require scarce resources such as labor, capital, and time, which compete with resources allocated to current crop production. The more resources allocated to soil conservation the less is resources available for crop production. Therefore, there is no reason not to expect the soil conservation coefficient to be negative if we are considering soil conservation practices in that crop season. When it is positive it is the effect of soil conservation practices in earlier years. Similarly, water harvesting practices by smallholder farmers have similar implications like soil conservation practices. In most cases, farmers harvest water to use it in the following crop season, especially when there is a drought, and hence the returns from water conservation are expected in the following crop season.

5.4.2 Factor Input Risks

Most farmers in developing nations are risk averse (Brauw et al., 2014; Di Faco, 2006; Kristin et al., 2006) which may be because of the subsistence nature of agriculture production and less savings for overcoming agricultural production risks. Kristin et al., (2006) argue that risk averse farmers take into account both the mean and the variance of output and are expected to choose input levels which differ from the optimal input level. Therefore, considering risk or variance is very important in addition to mean agricultural production in smallholder farmers' agricultural production processes.

The variance or risk estimation results show that some farm inputs used by smallholder farmers in rural Ethiopia were risk increasing while others were risk decreasing (Table 5.4). The input land had a positive coefficient in every year and was significant in 1995 and 2015 indicating that land was a risk increasing input in those years. The more land that the farmers used the higher the yield variability or risks. Fertilizers had a negative sign and were significant in 1995, 2004, and 2015. The analysis showed that fertilizers were a risk decreasing input for smallholder farmers in rural Ethiopia. However, this is different from some other findings in literature. As Dercon and Christiansen (2011) showed, fertilizer use while profitable was risky. They showed that lack of insurance against the risks faced led to low input use and inefficient production choices. The other input considered in 2015 was seeds used in agricultural production; seeds are a revenue increasing and risk decreasing input in smallholder farmers' agricultural production (Table 5.4).

The crop diversification index was positive and statistically significant (except in 2004) which can be interpreted as a decrease in the crop diversification index (increase in crop diversification -- the higher the index value, the less the crop diversification) leading to a decrease in the variance or risk. This is consistent with smallholder farmers' crop diversification practices which are common in most developing countries. Crop diversification is an effective way of reducing income variability or risks (Eneyew, 2012). Crop diversification is quite common among smallholder farmers in rural Ethiopia as there is less specialization. This might be because of the risk decreasing nature of crop diversification as is clearly shown in the variance estimation results. The analysis shows that crop diversification had a risk decreasing effect for smallholder farmers in rural Ethiopia (Table 5.4) as it is also commonly understood to be.

In this research, we were interested in finding out if there were regional differences in risks in the agricultural inputs used by smallholder farmers. The analysis showed that there were regional differences with respect to agricultural input risks. We took the three largest regions of the country for the analysis: Amhara, Oromia, and the South Nations and Nationalities (SNNP). The regional input risk analysis' results (Table 5.5) show that there were regional differences in the risk of inputs in agricultural production by smallholder farmers. For instance, land was a risk increasing input at the country level in 1995 (Table 5.4). However, in the regional risk analysis, the risk increasing effect of land was not uniform in the same year. It was a risk increasing input in Oromia and SNNP but land's risk increasing effect was not significant in the Amhara regional state. Fertilizers were a risk decreasing input nationally, especially in 1995, 2004, and 2015. But their risk decreasing effect was more significant in Oromia and SNNP.

The crop diversification index is the most significant risk decreasing variable in this analysis. The more farmers diversified their crop production the less the variance or risk. But there seem to be regional differences in the risk decreasing effects of crop diversification. Crop diversification had a high risk decreasing effect in the Oromia regional state and in SNNP. The risk decreasing effect of crop diversification was not significant in the Amhara region. The impacts of the variables - enough rain during the beginning of the crop season and enough rain during the crop growing season had more impact in the Oromia region than in the other regions of the country in 1995 and 1999 (Table 5.5).

An analysis of agriculture production risks is important for distinguishing downside and upside risks. Variance or risk estimations are given in Table 5.4. However, the main problem with using these measures of risk is that they treat fluctuations above and below the mean in the same way. It is possible to break the variance so that it accounts only for fluctuations below the mean. The results of the downside risk analysis (Table 5.6) showed that some variables which were not significant in the risk analysis were significant in the downside risk estimation. For example, land was not significant in increasing risks in 2004 but significantly increased the downside risks in 2004 (Table 5.6) thus highlighting the importance of considering downside risks.

5.4.3 Quantification of Risks and its Implication for the Agricultural and Food Security Policy

We estimated the returns to scale of the production function and the variance elasticity of the inputs. The analysis showed that the production function had decreasing returns to scale except in 1995 and 2015 (Table 5.7). The overall variance elasticity estimations showed that the production function had negative input elasticity in 1999, 2004, and 2009, implying that the use of more inputs led to a decrease in input risks (Table 5.8). Positive variance elasticity was observed in 1999 and 2015 indicating that expansion of the output level led to an increase in input risks.

Food self-insufficient countries like Ethiopia aim to increase agricultural productivity to ensure food security. But there are challenges in these efforts, one of which is the risks associated with input use. If inputs are risk increasing then farmers are reluctant to use these inputs even if they are yield increasing. Unless governments and policymakers reduce these risks farmers will not be willing to use more inputs and adopting high yielding inputs and technologies. Policymakers and the Ministry of Agriculture need to consider existing farm input risks and farmers behavior towards these risks to design appropriate agricultural policies to improve farm productivity and ensure food security for smallholder farmers in rural Ethiopia.

5.5. Conclusions and Recommendations

This study estimated input risks involved in agricultural production by smallholder farmers in rural Ethiopia. It used a stochastic production function to analyze the mean production and risk effects of the common inputs used in the agricultural. The estimated mean production and variance functions were consistent with econometric theory of conventional inputs. Our results showed that most inputs used in crop production increased smallholder farmers' revenues. Some inputs were risk increasing while others were risk decreasing. As the variance analysis' results clearly showed fertilizers were risks decreasing input in each year. Land was a risk increasing input in 1995 and 2015, but there is no statistical evidence that it was a risk increasing input in the other years. Family labor was a variance decreasing input in 2009 but its effect was not significant in the other years.

Crop diversification had a significant risk decreasing effect in the studied years, but the risk decreasing effect of crop diversification decreased from 1995 to 2009 (0.7659 to 0.3883). Water harvesting technologies had a risk decreasing effect in 2004, but they had no statistically significant risk decreasing impact in 2009. It is assumed that the more farmers engage in water harvesting the less are the risks associated with droughts or shortage of rain, which is very common in rural Ethiopia. Water harvesting technologies are very essential in drought prone areas of the country and are also useful for reducing risks in agricultural areas where there is shortage of water during the growing seasons of agricultural crops.

This research identified that land, fertilizers, labor, and crop diversification influenced the variance or risk in the sector nationally, but the risk increasing/decreasing effects of these inputs varied from one year to another. Further, there were regional variations in the impact of these inputs on yield variability or risks. Land was a risk increasing input in Oromia and SNNP but not in the Amhara regional state. Fertilizers was a risk decreasing input nationally, especially in 1995, but its risk decreasing effect was more significant in the Oromia regional state than in

SNNP. In places where famers had imperfect information about future input prices, output prices, and weather conditions, risks were a major concern and the severity of the risks differed by location (Nyikal et al., 2005; Pannell et al., 2000).

Most farmers in developing nations are risk averse (Brauw et al., 2014; Di Faco, 2006; Kristain et al., 2006). Agricultural input risks can easily be managed by the farmers themselves as most inputs are under their control unlike other risk factors like droughts, pests, and crop affecting diseases which are not under their control. Farmers who practice soil conservation have better yields or revenues than those do not practice soil conservation. Risk consideration and farmers' risk behavior are important for effective risk management and adoption of agricultural technologies. The Ministry of Agriculture, regional governments, and extension workers who are interested in reducing agricultural production risks should consider these agricultural input risks. Differences in regional input risks have to be considered in smallholder farmers' crop production in rural Ethiopia.

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Tables and Figures

Table 5.2. Variables used in the analysis and their descriptions

Variables	Description of the variables
Output:	
Tvalue	Total value of crops (in Birr) produced in the cropping season
Inputs:	
Land	Land used in the production (in hector)
Fertilizers	Fertilizers used in the production of crops
Labor	Labor power used (in days) for the production
Seeds	Seeds used in kg
Characteristics:	
index	Crop diversification index for each farm household
enoughrainbegin	There was enough rain during the beginning of the production season(dummy-yes/no)
enoughraingrow	There was enough rain during the crop growing season(dummy-yes/no)
Soil conservation	The farmer was engaged in soil conservation practices(dummy-yes/no)
Water harvesting	The farmer was engaged in water harvesting practices(dummy-yes/no)

Table 5.3. Summary Statistics of the Variables Used in the Analysis																
Variables	1995				1999				2004				2009			
	Mean	Std.Dev	Min	max	Mean	Std.Dev	Min	max	Mean	Std. Dev	Min	max	Mean	Std.Dev	Min	max
Tvalue	1135.6	1685.6	14.30	9481.5	1498.6	1594.1	11	12828	2056.1	2760.91	97	30102	1719.6	2177.1	8.5	12035.6
Land	1.395	3.696	0.0625	40	1.1463	0.9272	0.007	7	1.325	0.865	0.125	4	1.28	0.927	0.125	4.18
Fertilizer	64.3	84.18	0.5	443	40.086	75.9	0	500	55.63	97.77	0	1000	569.2	776.42	0	3750
Labor	20.2	23.73	0.25	124	59.37	174.1	2.5	5134.1	62.30	60.41	2	337	77.47	87.79	2	400
Index	8820.7	2085.5	2251.6	10000	4803.4	2576.9	723.7	10000	4736.0	2423.4	1042.3	10000	5090	2836.8	1469.5	10000
enoughrainbegin	0.47	0.45	0	1	0.6037	0.4893	0	1	-	-	-	-	-	-	-	-
enoughraingrow	0.39	0.46	0	1	0.5393	0.4987	0	1	-	-	-	-	-	-	-	-
Soil conservation	-	-	-	-	0.3724	0.4837	0	1	0.4312	0.50	0	1	0.747	0.437	0	1
Water harvesting	-	-	-	-					0.37	0.48	0	1	0.325	0.471	0	1
Observations	516				361				202				799			

Table 5.4. Aggregate Production and Variance(risk) Estimation Results

Variables	1995 Production	1995 Variance	1999 Production	1999 Variance	2004 Production	2004 Variance	2009 Production	2009 Variance	2015 Production	2015 Variance
Lnland	0.3720*** (0.0478)	0.2934*** (0.0630)	0.4581*** (0.0678)	0.0791 (0.1294)	0.3150*** (0.0575)	0.0902 (0.0854)	0.3182*** (0.0315)	0.0623 (0.0433)	0.6370*** (0.0646)	0.5228*** (0.1278)
Lnfertilizer	0.5037*** (0.0388)	-0.2777*** (0.0512)	0.1930*** (0.0553)	-0.1135 (0.1056)	0.0835** (0.0399)	-0.1009* (0.0592)	0.3594*** (0.0290)	-0.0625 (0.0400)	0.1829*** (0.0344)	-0.1386** (0.0683)
lnlabor	0.3031*** (0.0357)	0.0495 (0.0470)	0.2265*** (0.0509)	-0.1129 (0.0972)	0.1029* (0.0614)	-0.0060 (0.0913)	0.1707*** (0.0308)	-0.1070** (0.0424)	0.2262*** (0.0419)	-0.0111 (0.0829)
Lnindex	-0.7098*** (0.1373)	0.7659*** (0.1812)	-0.5724*** (0.0882)	0.4396*** (0.1685)	-0.8540*** (0.1220)	0.0378 (0.1813)	-0.5722** (0.0660)	0.3883*** (0.0910)	-	-
Enough rainbeig	0.0219 (0.1029)	0.2720** (0.1357)	0.2631*** (0.0780)	-0.1738 (0.1490)	-	-	-	-	-	-
Enogun raingrow	-0.2060** (0.0967)	0.1112 (0.1275)	-0.0788 (0.0741)	-0.0165 (0.1414)	-	-	-	-	-	-
Soil conservation	-	-	0.2690*** (0.0731)	0.2144 (0.1395)	0.2878*** (0.1074)	-0.2752* (0.1597)	-0.0808 (0.0565)	-0.1236 (0.0779)	-	-
Water harvesting	-	-	-	-	-0.1726 (0.1135)	-0.3299* (0.1687)	-0.0220 (0.1018)	0.0597 (0.1403)	-	-
Lnseed	-	-	-	-	-	-	-	-	0.2028*** (0.0433)	-0.3063*** (0.0857)
_const	8.7310*** (1.3195)	-9.8203*** (1.7404)	10.0873*** (0.7768)	-3.8131*** (1.4832)	10.5484*** (1.3321)	-1.5534 (1.9800)	6.0646*** (2.2916)	-3.9097*** (1.0179)	5.0034*** (0.2367)	0.1749** (0.4683)
N	516	516	361	361	202	202	799	799	174	174
R2_a	0.5653	0.0651	0.6715	0.0517	0.5164	0.0278	0.6569	0.0639	0.7996	0.1099

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0{:}01$. and Standard errors in parentheses.

Table 5.5. Disaggregated Variance (risk) Estimation by Regions (1995, 1999, 2004, and 2009)												
	1995			1999			2004			2009		
Variable	Amhara	Oromia	SNN	Amhara	Oromia	SNN	Amhara	Oromia	SNN	Amhara	Oromia	SNN
lnland	0.1618 (0.1369)	0.7946*** (0.1475)	0.3283*** (0.0778)	-0.0284 (0.3434)	0.0431 (0.2886)	-0.0130 (0.1806)	-0.1892 (0.5063)	0.1553 (0.0995)	-0.2729 (0.2659)	0.1688 (0.1848)	0.0755 (0.0571)	-0.0447 (0.0753)
lnfertilizer	-0.1806 (0.1329)	-0.2378* (0.1295)	-0.4662*** (0.1030)	-0.2726 (0.1837)	0.0021 (0.2094)	0.1012 (0.1636)	0.0429 (0.2054)	- 0.1718** (0.0699)	0.0692 (0.1770)	-0.1172 (0.0997)	-0.0924* (0.0550)	0.2485** * (0.0834)
lnlabor	0.4618*** (0.0918)	0.2544*** (0.0627)	-0.1136 (0.0942)	-0.2451 (0.1930)	-0.2693 (0.2207)	0.1143 (0.1439)	-0.1018 (0.1770)	0.0906 (0.1338)	0.0520 (0.1733)	-0.0772 (0.1021)	-0.0854 (0.0576)	-0.0911 (0.0893)
lnindex	0.3626 (0.2892)	1.4227*** (0.2151)	1.9338*** (0.3815)	0.2585 (0.4057)	0.4738 (0.3250)	-0.0743 (0.3165)	-0.4569 (0.5263)	0.4010 (0.2440)	-0.8589* (0.4673)	0.2414 (02075)	0.3897** * (0.1296)	0.3103* (0.1660)
enoughrainbeign	0.4455 (0.3512)	0.8565*** (0.2112)	0.1506 (0.1793)	0.3180 (0.5779)	-0.3082 (0.2826)	0.0149 (0.2246)	-	-	-	-	-	-
enough raingrow	-0.1592 (0.3047)	-0.5635*** (0.1560)	0.2646* (0.1587)	-0.3335 (0.2983)	0.4269 (0.2819)	-0.3526 (0.2157)	-	-	-	-	-	-
Soil conservation	-	-		0.2016 (0.2483)	0.4286 (0.3180)	0.1306 (0.2889)	-0.9559*** (0.3223)	-0.4071* (0.2138)	0.3385 (0.3410)	0.0753 (0.1743)	- 0.2392** (0.1095)	0.2068 (0.1791)
Water harvesting	-	-		-	-	-	0.8041* (0.4528)	-0.1051 (0.2364)	-0.7730** (0.3032)	-0.0140 (0.2524)	0.0070 (0.1984)	-0.1953 (0.3898)
_cons	-6.8181** (2.7563)	-20.4041*** (2.7298)	- 19.4541** * (3.7047)	-1.4077 (3.3016)	-4.3589 (2.7708)	-0.9119 (2.7575)	5.1541 (8.5537)	- 5.4316** (2.4455)	8.6178* (5.1306)	-3.8632 (2.9644)	- 3.8615** (1.4658)	- 3.9361** * (1.7480)
N	127	78	165	101	145	105	33	109	59	204	442	146
r2_a	0.1744	0.7072	0.3309	0.0084	0.0415	0.0045	0.1669	0.1101	0.0820	0.0279	0.0683	0.1017
Note: * p < 0.10, ** p < 0.05, and *** p < 0:01. and Standard errors in parentheses.												

Table 5.6. Aggregate Production and Downside Risk Estimation Results										
	1995		1999		2004		2009		2015	
Variables	Production	Downside risk	Production	Downside risk	Production	Downside risk	Production	Downside risk	Production	Downside risk
Lnland	0.3720*** (0.0478)	0.2521*** (0.0410)	0.4581*** (0.0678)	0.06552 (0.1174)	0.3150*** (0.0575)	0.1280* (0.0732)	0.3182*** (0.0315)	0.0526 (0.0388)	0.6370*** (0.0646)	0.1958*** (0.0572)
Lnfertilizer	0.5037*** (0.0388)	-0.1331*** (0.0333)	0.1930*** (0.0553)	-0.0037 (0.0958)	0.0835** (0.0399)	-0.0438 (0.0508)	0.3594*** (0.0290)	-0.0168 (0.0357)	0.1829*** (0.0344)	-0.0707** (0.0290)
lnlabor	0.3031*** (0.0357)	-0.0187 (0.0306)	0.2265*** (0.0509)	-0.0644 (0.0881)	0.1029* (0.0614)	0.0163 (0.0783)	0.1707*** (0.0308)	-0.0995*** (0.0379)	0.2262*** (0.0419)	0.0229 (0.0427)
Lnindex	-0.7098*** (0.1373)	0.7781*** (0.1179)	-0.5724*** (0.0882)	0.2808* (0.1528)	-0.8540*** (0.1220)	0.1265 (0.1554)	-0.5722** (0.0660)	0.2674*** (0.0814)	-	-
Enough rainbeig	0.0219 (0.1029)	0.1543 (0.0884)	0.2631*** (0.0780)	-0.2070 (0.1351)	-	-	-	-	-	-
Enogun raingrow	-0.2060** (0.0967)	-0.0503 (0.0831)	-0.0788 (0.0741)	-0.0247 (0.1283)	-	-	-	-	-	-
Soil conservation	-	-	0.2690*** (0.0731)	-0.0221 (0.1265)	0.2878*** (0.1074)	-0.2018 (0.1368)	-0.0808 (0.0565)	-0.0984 (0.0697)	-	-
Water harvesting	-	-	-	-	-0.1726 (0.1135)	-0.1587 (0.1446)	-0.0220 (0.1018)	-0.0255 (0.1255)	-	-
Lnseed	-	-	-	-	-	-	-	-	0.2028*** (0.0433)	-0.1345*** (0.0459)
_const	8.7310*** (1.3195)	-9.1190*** (1.1334)	10.0873*** (0.7768)	-2.4575* (1.3452)	10.5484*** (1.3321)	-2.5397 (1.6971)	6.0646*** (2.2916)	-2.6350*** (0.9103)	5.0034*** (0.2367)	1.0792*** (0.2202)
N	516	516	361	361	202	202	799	799	174	174
R2_a	0.5653	0.1318	0.6715	0.0690	0.5164	0.0115	0.6569	0.0402	0.7996	0.1703
Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0{:}01$. Standard errors in parentheses.										

Table 5.7. Returns to scale of agricultural production over years					
Inputs used	1995	1999	2004	2009	2015
Lnland	0.3720	0.4581	0.3150	0.3182	0.6370
lnfertilizer	0.5037	0.1930	0.0835	0.3594	0.1829
Lnlabor	0.3031	0.2265	0.1029	0.1707	0.2262
Lnseed	-	-	-	-	0.2028
Return to scale (RTS)	1.1788	0.8776	.5014	0.8483	1.2489

Table 5.8. Variance (risk) elasticity of inputs in agricultural production over years					
Inputs used	1995	1999	2004	2009	2015
Lnland	0.2934	0.0791	0.0902	0.0623	0.5228
lnfertilizer	0.2777	-0.1135	-0.1009	-0.0625	-0.1386
Lnlabor	0.0495	-0.1129	-0.0060	-0.1070	-0.0111
Lnseed	-	-	-	-	-0.3063
Variance elasticity(VE)	0.6206	-0.1473	-0.0167	-0.1072	0.0668