Dynamics of multidimensional child poverty and its triggers: Evidence from Ethiopia using Multilevel Mixed Effect Model

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Abstract

Empirical studies on the dynamics of multidimensional child poverty are very limited and still more research is required to understand its nature and triggering factors especially in the context of developing countries. In light of this, this paper tries to assess the dynamics of multidimensional child poverty and major factors associated with it using longitudinal data mainly collected to assess child poverty in Ethiopia. It uses multilevel mixed effect logit models that could possibly incorporates fixed and random effects to capture the effect of cluster level and time varying variables on multidimensional child poverty transition. Results of the multidimensional poverty analysis indicate that, although there were significant variations among regions, multidimensional child poverty has decreased during 2002-2009. The paper argues that multidimensional child poverty has dynamic nature that would possibly resulted from the interaction of multiple factors including household demographic, household capital (human, social and resources), household economic activities, geographic locations, and household shocks. Moreover, the study shows the relevance of considering cluster level differences during poverty analysis to generate information relevant for designing targeted policies and strategies that would help to distribute available development resources efficiently and achieve sustainable poverty reduction in developing countries.

Keywords: Multidimensional Child Poverty; Poverty dynamics, Mixed Effect; Multilevel Logit Model

1. Introduction

Child poverty has long-term outcomes including effects on the overall life of the child and social and economic costs on the community. Empirical findings show that child deprivation at early stage is often associated with undesirable life outcomes such as poor academic achievements, poor health, low economic status, behavioral problems, and other undesirable life skills and behaviors (Duncan et al., 2010; Engle and Black, 2008; Grantham-McGregor et al., 2007;Holzera et al., 2008; Johnson and Schoeni, 2011; Magnuson and Votruba-Drzal, 2009). Moreover, child poverty has perpetuate nature that could pass onto future generation with the possibility of trapping countries in a vicious cycle of poverty. This is because child poverty has repercussion on life-long cognitive and physical development of the child, with the possibility to lock future generation in poverty. Therefore, measuring child poverty and understanding its dynamic nature have paramount importance to predict its future trend and design sustainable policies and strategies that would contribute to break the vicious circle of poverty.

The extant child poverty literatures in developing countries have been dominated by unidimensional poverty measurements mainly based on household income and expenditure indicators at a point in time (Dieden and Gustafsson, 2003).This is warranted because income is highly correlated with non-monetary attributes. However, high income is not necessarily associated with increased individuals' wellbeing since individuals might not be able to access non-monetary goods and services due to market imperfection and transaction costs, which is particularly the case in developing countries including Ethiopia where market imperfections are rampant. In general, child poverty assessments based on unidimensional indicators at a point in time may have the following two major limitations. First, unlike to adult poverty, child poverty has different forms and child poverty measured by household income or expenditure may not fully reflect the real deprivation status of children in households, as income or consumption expenditures are not equally distributed among different household members (Bastos et al., 2004). This calls the need for destining child specific deprivation indicators to understand the true picture of child poverty. A good example for this is the recently developed multidimensional poverty approaches that has brought a new insight to measure the intensity of child poverty by using child specific and household level deprivation indicators that may include income or consumption indicators of households. Second, poverty measured at point in time has limited ability to show its dynamic nature and the effect of change in associated social, economic, institutional, and environmental factors that would play important roles in designing reduction policies and strategies. Nevertheless, poverty measures based on panel studies provide information on previous trends and future prospects of poverty that would help to design policies and intervention strategies that could help to address various deprivations.

There is paucity of empirical studies on the dynamics of multidimensional child poverty in the developing countries context. Against this backdrop, using three rounds of survey data from Ethiopia, this paper aims to shed insight on the dynamics of multidimensional child poverty and its drivers. To construct the poverty index, the paper uses multidimensional child specific indicators suggested by previous empirical findings and child specific theories of deprivation. Factors that could possibly be associated with entry or exit of poverty are selected based on previous empirical research results and major theories of poverty. Indicators that have policy implications for reducing the intensity of child poverty are identified using multilevel mixed effect logit model that could account possible sources of variations at different levels of the study population. Moreover, the paper tries to provide additional empirical evidences on the intricate nature of poverty by incorporating indicators from various theoretical perspectives.

The rest of this paper is organized as follows. Section two briefly describes summary of various theoretical and empirical evidences on poverty followed by the methods and description of the data on section three. Then in section four, empirical results and their implication are presented. Finally, conclusion and policy implications are forwarded in section five.

2. Theoretical and empirical evidences on poverty

2.1 Major theories of poverty and their relevance to empirical researches

Based on different schools of thought, theories of poverty can be broadly classified into Classical, Neo-classical, Keynesian/Liberal, Marxist/Radical, and Social Exclusion and Social Capital theories (Davis and Sanchez-Martinez, 2015). The underlining principle of each theory is mainly based on the economic thoughts of the respective schools. The classical economists' theory is based on their main assumption on market efficiency and the potential of wage fully reflecting individual productivity. Accordingly, poverty is consider as the consequence of individual choices. This theory may include behavioural decision and sub-culture theories. According to behavioural decision theory, poverty is highly associated with individual characteristics such as lack of work ethics and low level of education or skills (Yoon and Hirschl, 2003, Bradshaw, 2007). In additions to the concept of individual productivity, the sub-culture theory assumes that poverty resulted from behavioural problems passes from generation to generation as a culture because of genetic or upbringing factors (Blank, 2003, Townsend, 1979). Policy implications based on these theories mainly focuses on raising individuals' productivity and behaviours through training and education (Townsend, 1979). In general, according to the classical theories, the contribution of the government to combat poverty is minimal and suggested policy options mainly focus on shifting individual behaviours.

According to the neo-classical theory, poverty is assumed the result of unequal endowments in talents, skills and capital. This theory considers poverty as the result of lack of capital in different forms including human, physical, social, and institutional (Sachs, 2005). Moreover, market failure, shocks, lack of information and incentives, immigration, and other issues related with health and demographics are considered as possible causes of poverty (Banerjee and Duflo, 2011; Blume et al., 2007; Machin, 2011; Pemberton et al., 2013; Sachs, 2005). Like the classical theory, the expected role of government on the cause and alleviation of poverty is considered as minimal.

The Keynesian theory assumes that market inefficiency is a major obstacle to economic development, which in turn triggers individual into poverty. Therefore, unlike to the above theories, Keynesian/Neo-liberal theory stresses on the role of government by stimulating macro level variables such as aggregate investment, unemployment, inflation, debt, and asset market bubbles to enhance growth and address issues of poverty (Jung and Smith, 2007). Moreover, according to this theorist, poor capital (human and physical), poor infrastructures, lack of suitable institutions are considered as the main source of underdevelopment that leads to poverty (Sachs, 2005, Jung and Smith, 2007).

Marxian/Radical theorists believe that poverty is a structural problem created by capitalism and other related social structures because of unemployment (Blank, 2003). Therefore, they consider government as the key player in combating poverty using different interventions like market regulation and laws such as minimum wages and anti-discriminatory laws. Finally, the social exclusion and social capital theories underlie the important contribution of social and economic factors in the existence of poverty and its persistence nature (Morazes and Pintak, 2007, Johnson and Mason, 2012). Unlike to the previous theories, which are mainly depend on economic thoughts, the social exclusion theorists consider other broad aspects such as non-participation in production, consumption, political and social issues as the possible cause of poverty. Moreover, the social capital theorist also believe that low level of social capital either in the form of human capital or social networks have strong impact on poverty (Osterling, 2010; Pemberton et al., 2013).

Generally, the above theories show that poverty could be the result of deficiencies in individuals' character, market inefficiency, resource endowments, poor governance, and other social and economic factors, which implies the intricate nature of poverty that could not be easily addressed by using simple linear policies or strategies. Furthermore, since there is no single self-sufficient theory that can fully explain the nature and cause of poverty, having strong understanding on different competing theories may help to develop appropriate policies and intervention strategies that could shape the nature and extent of poverty especially in the context developing countries. This suggests the need for focusing on multiple indicators including capital (human, physical and social), market failures, social and economic discriminations, and other challenges related with community development to understand the causes and possible reduction strategies. Different empirical studies have also suggested the need for considering individuals, their culture, the social system, and the environment to develop sustainable reduction strategies (Bradshaw, 2007).

2.2 Empirical evidences on child poverty and measurements

2.2.1 The need for measuring child poverty and approaches used

Poverty experienced by children during their childhood is referred to as child poverty. The nature of child poverty is different from adult poverty because of differences on its causes, effects, and long-term impact on society. Naturally, children are more vulnerable than other parts of the community and focusing on child poverty as opposed to any other groups in the community may need little justification (Bradbury et al., 2001; Minujin et al., 2006). Child poverty has many consequences such as increasing the risk of adverse outcomes including educational failure, teenage pregnancy, truanting and anti-social behaviors (Engle and Black, 2008; Gupta et al., 2007; Holzera et al., 2008; Magnuson and Votruba-Drzal, 2009). Poverty during childhood can have a very wide range of adverse effects on those who experience it, ranging from immediate hardship to long-term damage of life-chances (Nolan et al., 2006). As Allen (2011) indicates, if children grow up in poverty all too often they become the parents of the next generation to live in poverty. This is especially true in developing countries where market is inefficient, poverty could be triggered by various socio-economic factors, and the majority of the population is easily vulnerable. This suggests the significance of focusing on child poverty to sustainably reduce its long-term impact in the coming generation. Child poverty reduction may have instrumental effect on improving societal well-being including efficiency of resource use, stock of human capital and extent of social problems (Micklewright, 2004).

Deprivation indictors used to measure child poverty can be child specific or household level indicators. However, measuring child poverty mainly on child specific indicators has different advantages than lumping together with household level measurements. This is because the existence of variations between the needs of children and other household members, mostly less consideration is given to children in different aspects, and unequal share of resources within the household (Gordon et al., 2003). Thus, sometimes despite the level of households' income or social wellbeing, children may be in poverty while the households in general are not. Moreover, what applies to adult members of household or the family may not be assumed automatically applied to children. This indicates that poverty measure at household level may underestimate or overestimate the level of child poverty, suggesting focusing mainly on child specific indicators may provide better information for policy than aggregate household level indicators.

Researchers have been following various approaches to characterize the nature and aspects of child poverty in both developed and developing countries. However, broadly speaking, based on the poverty indicators used, previous researches could be classified as unidimensional and multidimensional approaches. Although, the unidimensional approaches use single deprivation indicator like income or consumption as a proxy, it is still the most commonly used approach by researchers around the globe. This approach identifies children into poor and non-poor by using relative or absolute poverty thresholds. Nevertheless, as indicated by UNICEF (2012), using single indicator like income or expenditure has many drawbacks due to the following main reasons: lack of reliable income data; inability of household income to represent real household expenditure; and availability of subsidy for some services such as health and education that cannot be captured with household income. Moreover, Alkirea and Foster (2011) have also identified unattainable assumption on the existence of markets for all goods and services, limited ability of monetary indicators to guarantee the utilization of all necessary goods and services, and the possibility of getting flawed income or consumption data due to missing observation as major challenges of using the unidimensional approach. Due to these challenges, recently most researchers recommend using the multidimensional approaches (Ortiz et al., 2012, UNICEF, 2007). On the other hand, the multidimensional approach would help to incorporate different child specific and household level indicators including child access to basic services, household assets, child nutrition, and other social indicators. Compared to the uni-dimensional approach, this approach has advantages to influence policy dialogues on poverty reduction, social sector spending, and identify indicators that capture children socio-economic needs and major factors that trigger children into deprivations (Ortiz et al., 2012). However, as indicated by various empirical findings, this approach has also its own limitation that needs to be addressed especially during identification and aggregation stages (Alkire and Foster, 2011).

The issue of time is also one of the most important aspect in poverty analysis. Addison et al. (2009) have pointed out that poverty dynamics, multidimensional concepts and measures, and cross-disciplinary research on poverty as the three main fronts on which progress must be made if researchers want to deepen understanding on poverty and significantly improve the effectiveness of poverty reduction strategies and policies. Based on time of analysis, poverty measures can also be broadly classified as static and dynamic approaches. The static approach mainly examines poverty status at a specific point in time to show the snapshot of incidence during a specific period. Nevertheless, using this approach it is not possible to understand the changes in poverty over time that would possibly provide more information for policies and intervention design (Addison et al., 2009, Cellini et al., 2008). On the other hand, the dynamics approach helps to measure the change in poverty over a period of time and the associated factors with the change. Using the dynamic approach, it possible to understand how and why individuals move into or out of poverty within a range of time and design appropriate policies and strategies that would address the persistence nature of poverty (Bradbury et al., 2001). In general, according to (Bradbury et al., 2001), focusing on the dynamic nature of child poverty has the following justifications. First, individual child living condition this year mostly depends on previous year poverty status and children who have already been poor for a long time are likely to be worse off than those who are newly poor. Second, the poverty history of each children in different periods would tell us whether poverty is a onetime event observed among a small group of children or an experience that is widely shared in different societies for longer durations. Third, child poverty has impacts that last beyond childhood into adulthood and the future effects depend on the nature of poverty experienced now. Fourth, focusing on movements into and out of poverty is useful for explaining the extent and intensity of poverty and major causes associated with the movement. For instance, a rising child poverty rate may come either because of the number of children entering into poverty is increasing or because of the number of poor children who leave poverty is decreasing. Fifth, and finally, mostly policy design aimed to reduce the number of poor children depends on the nature of movements into and out of poverty. If turnover in child poverty is low, then the policy can concentrate on the relatively unchanging group of poor families that experience long periods of low living standards. Therefore, based on various empirical findings and current debates on poverty it is possible to conclude that examining the dynamic nature of poverty for a range of spells can provide additional information on events associated with the prevalence and persistence of poverty than the static aspects (Finnie and Sweetman, 2003, Lindquist and Lindquist, 2012, Andriopoulou and Tsakloglou, 2011)

2.2.2 Determinants of poverty dynamics

Using either of the above approaches, researchers have tried to identify household socio-economic, institutional, and environmental factors as the major possible causes of poverty in different countries. For instance, using household monetary indicators, various studies show that living with single parent, employment status, and level of education have significant effect on entry or exit from poverty (Buddelmeyer and Verick, 2008; Cellini et al., 2008; Corak et al., 2008; Corcoran and Chaudry, 1997; Fertig and Tamm, 2009; Lindquist and Lindquist, 2012). Similarly using multidimensional indicators, other researchers have also indicated that family size, unemployment, social integration, and level of education have strong effect on the likelihood of households exit from poverty (Bastos and Machado, 2009; Martinez and Perales, 2015; Roelen, 2014). Furthermore, especially in developing countries, change in herd size, land size, agricultural shocks, help from friends, income diversification, and employment in formal sectors have found to have significant contribution on households exit from poverty (Kristjanson et al., 2010, Kijima et al., 2006). These suggest that causes of poverty could be associated with multiple factors including household demographic characteristics, capital (human, physical and social), structural issues such as employment, household and economic shocks, and other social and behavioral constraints. The diversity of empirical evidences on the possible causes of poverty may indicate the multifaceted nature of poverty and the need for considering different factors to understand fully the real cause of poverty. Focusing on either of these factors would be only a partial view of the problems that may not help to design policies that could sustainably address the root causes of the problem.

To sum up, issues raised above would tell us multidimensional and dynamic approaches of measuring child poverty can provide substantial information on the type and nature of deprivation than uni-dimensional and static approaches. Moreover, from the available few studies it is evident that empirical evidences on the dynamic nature of multidimensional child poverty are almost non-existent. In view of these limitations, this paper tries to provide additional insight on the available body literatures by using both of these approaches especially in the context of developing countries. More importantly, unlike to other previous studies, different explanatory factors on the causes of poverty are included based on most common theories of poverty and the recently suggested interdisciplinary analysis approaches that would help to explore the complex nature of poverty causes.

3. Methodological issues and data

3.1 Panel data and source

The study uses three waves (2002, 2007, and 2009) data from Young Lives panel Survey that has been jointly conducted by Oxford University and Ethiopian Development Research Institute (Young Lives Ethiopia, 2013). The Young Lives study is an international child poverty assessment that has been implemented in four countries including Ethiopia, Peru, India, and Vietnam to generate policy relevant information on child poverty in the study countries and around the globe. The survey in Ethiopia covers five regions including Addis Ababa, Amhara, Oromia, SPNN, and

Tigray and sample households were selected from both urban and rural dwellers. Even though so far four waves of data were collected, in this paper we used only the first three waves (2002, 2007, and 2009) data collected on 1000 older cohort children. The data contains household and child level information on education, health, socio-economic changes, livelihood, social capital, and others.

3.2 Constructing poverty index and identification of the poor

Multidimensional poverty status of children and factors associated with child poverty dynamics were identified using the following five steps. Firstly, 11 child level deprivation indicators were identified based on recent child poverty status indicators suggested by different empirical findings (Table 1). These are education, health, shelter, safe drinking water, sanitation facilities, information, electricity, nutrition, material, care, and freedom. The indicators are selected mainly based on the first internationally agreed definition of child poverty assessment guidelines that include issues of child rights, adequate nutrition, decent living condition, and access to services and information (United-Nations, 2007). Using these indicators is considered as innovative and informative approach to develop a good measure of child poverty, especially to quantify both the extent and depth of poverty. For each indicator equal weight is assigned and threshold measure or deprivation cutoff point is defined using severe deprivation definition (Gordon and Nandy, 2012). However, to make the estimation more consistent and reliable the best sets of deprivation indicators were again identified using Cronbach's Alpha measure of scale reliability, as suggested by Gordon and Nandy (2012). As a result, two indicators, care and freedom, were found to be inconsistent with other indicators and removed from the index. Cronbach's Alpha for the three years is found to be greater than 0.6, which could be considered as modest based on some empirical findings (Loewenthal, 2004; Nunnally and Bernstein, 1994). The results of inter-item correlation matrix also indicate the absence of any strong correlation between the remaining nine indicators.

Table 1: Deprivation indicators used and definition for severe deprivation thresholds

Indicators	Definition for severe deprivation threshold
Education	Children who have never been school or not currently enrolled in school or their grade achievement is below the median grade level of the sample
Health	Children who did not receive treatment for major recent illness or who perceives their health status is worse than others or who has faced long term health problem
Sanitation	Children who has no access to a toilet facility of any kind or live in a dwelling where the household share the toilet facility with other households
Shelter	Children living in a dwelling with 5 or more people per room or with no floor material
Drinking Water	Children using unprotected surface water such as rivers, ponds, streams, lakes, and others
Electricity	Children living in a household without access to electricity
Material	Children living in a household who does not hold at least one of the most common household assets such as refrigerator, sofa, table chairs, bed, sewing machine, water pump, tractor, car, motor cycle or bicycle
Nutrition	Children who are below three standard deviations of the international reference for stunting (height for age) or wasting (weight for height) or underweight (weight for age)
Information	Children who has no access to a radio, television, telephone, newspaper or computer (i.e. any forms of media)
Care	Children where the mother is not the primary caregiver
Freedom	Children participated in household chores for more than 2.5 hours per day

Secondly, based on the methodology suggested by Alkirea and Foster (2011), multidimensional poverty index was constructed using the selected nine indicators for the three periods. Then multidimensional poverty status of each child was determined by choosing appropriate cutoff point or poverty line in the three periods. In this case, mostly researchers' either randomly assign the cutoff point based on their intuition on the society socio-economic status or simply take cutoff points suggested by previous similar studies. For instance, according to Gordon et al. (2003), a child is considered as under absolute poverty if he/she suffers from two or more severe deprivation of basic human needs. Similarly, Alkier recommended using 33% deprivation from selected indicators as the optimum level. However, applying such type of generic approaches may not be rational for different countries with different economic, social, and political situations especially in the context of developing countries where most the basic needs are still not fully met. A as a result, the poverty line identifications approaches mentioned above are considered as scanty and unscientific by various researchers.

Consequently, considering the limitation of the above approaches Gordon et al. (2003) and his colleagues have suggested using a combined identification approach using statistical procedures that may include income/expenditure and deprivation indicators simultaneously. According to them, a good combined multidimensional poverty line should maximize between sums of squares and minimize within sum of square when the continuous poverty measure run with the discrete deprivation indicator using one of general linear models (GLM). Since this looks more scientific than the other approaches, analysis of variance (ANOVA) and logistic regression model were used in this paper to determine the appropriate poverty cutoff point.

However, due to the absence of complete income or expenditure data for the three periods we used wealth index as a proxy for income or household consumption expenditure in the ANOVA model. Wealth index, which is one of the traditional indicators to measure household poverty, is a composite indicator constructed from housing quality index, consumer durable index, and service index. In additions to its simplicity for measurement, it is believed that wealth index can indicate more permanent position of households poverty status than either income or expenditure measures. In the ANOVA model while wealth index was used as dependent variable, multidimensional poverty indicators constructed from different cutoff point were used as independent variables. Similarly, in the logit model, while multidimensional poverty indicators were used as dependent variables, wealth index, total adult equivalent, and dependent children under 18 years of age were used as independent variable. Finally, both models suggest cutoff point four and more as the optimum threshold for the multidimensional poverty, as it maximizes the between group variation than other possible cutoff points (Table 2). Therefore, in all of the three periods, children who are deprived at least in four of the deprivation indicators from the finally selected nine indicators are considered as multidimensional poor.

Table 2: ANOVA and Logit Model results to identify optimum position of the poverty threshold

Cutoff point	F Statistic for corrected ANOVA Model	Logistic Regression Model Chi-square	Sig.
Deprivation score for 1 or more	152.14	334.98	0.000
Deprivation score for 2 or more	553.00	1189.77	0.000
Deprivation score for 3 or more	1000.29	1863.66	0.000
Deprivation score for 4 or more	**1179.99**	**2152.51**	0.000
Deprivation score for 5 or more	971.35	2038.30	0.000
Deprivation score for 6 or more	580.21	1520.00	0.000

Thirdly, based on the Alkirea and Foster (2011) approach, multidimensional poverty status of children was determined and disaggregated by region and site (rural/urban) of children. Three different poverty measures including Head Count Ratio (H), Average Intensity (A) and Adjusted Head Count Ratio (M_o) were estimated to capture the overall and regional multidimensional poverty status of children. The head count ratio indicates the proportion of poor children from the total sample and it is obtained by dividing the number of multidimensional poor children by the total number of children. The average intensity of deprivation indicates the average numbers of deprivations a poor child suffer and it is simply obtained by dividing the sum of total number of deprivations each poor child suffer by the total number of poor children. Adjusted head count ratio, the multidimensional poverty indicator in our case, is calculated by simply multiplying the 'headcount ratio' and 'average intensity' (HA).

With a given cutoff vector C, vector D representing the number of dimensions on which an individual child is deprived, and n-dimensional vector of deprivation Q, the above poverty indicators can be specified as follows (Alkirea and Foster, 2011):

$$q_{i=} \begin{cases} 1 & if\ d_i \geq c_0 \\ 0 & otherwise \end{cases} \quad \dots\dots (1)$$

Then the head count ration 'H' is estimated by:

$$\mathrm{H} = \frac{1}{n}\sum_{i=1}^{n} q_i \dots\dots (2)$$

Subsequently the average of deprivation 'A' experienced by poor children can be estimated by:

$$A = \frac{\frac{1}{d}\sum_{i=1}^{n}\sum_{j=1}^{d} g_{ij}^{0}}{\sum_{i=1}^{n} q_i} \quad \text{…………………………………………………………………….…} (3)$$

Where $g_{ij}^{0} = \begin{cases} g_{ij}^{0} & if\ q_i = 1 \\ 0 & otherwise \end{cases}$

Finally, the adjusted head count ratio M_0 is calculated by:

$$M_0 = A \times H = \frac{1}{nd}\sum_{i=1}\sum_{j=1} g_{ij}^{0} \quad \text{…………………………………………………………} (4)$$

3.3. Dependent and independent variables of poverty dynamics model

For the poverty dynamics model, a binary dependent variable that indicates the multidimensional poverty status of the child is generated using cutoff point four. It is constructed from the nine equally weighed child deprivation indicators as mentioned above. Therefore, a child is considered as multidimensional poor if he/she is deprived in four or more of these deprivation indicators and non-poor otherwise. The variable is coded as binary and it takes 1 if the child is multidimensional poor at period 't' and '0' otherwise.

The independent variables are selected based on the above-mentioned different theories of poverty and results of previous similar empirical findings. Accordingly, variables such as household demographics characteristics, household capitals (human, physical, and social), employment sector, household shock, and household location indicators are included. Since the main purpose of the study is to assess factors associated with dynamics of multidimensional poverty, more attention is given to time varying variables in the three periods although other time invariant variable such as sex of the head is also included. The description and hypothesized effect of selected independent variables on the dependent variable are given in table 3 below.

Table 3: Description of explanatory variables and their expected effect on multidimensional poverty

Explanatory Variables	Description	Expected sign
Household demographics		
Age of household head	A continuous variables that shows the age of the household head	+
Household Head Sex	The sex of household head: 1= Male; 2 = Female	Unknown
Household size	The total number of household members	Unknown
Dependency ratio	It refers to the ratio of the total number of dependent household members on the working age members. Dependent is defined here as the persons below age 18 years or greater than 64 years living in the same household	-
Social capital and social network		
Has some helper	A dummy variable that takes 1 if the household has somebody to help in time of need and 0 otherwise	+
Political party membership	A dummy variable takes 1 if the household is a member of any political party and 0 otherwise	+
Structural/Economic		
Main Employment sector	A categorical variable that indicates the main employment sectors of household head. It represents 1 = Agriculture; 2 = Non-agriculture; 3 = Both	
Ag./Non-Ag working months	A continuous variables constructed from the ratio of average working months the household participated in agricultural to non-agricultural activities	Unknown
Intensity of remittance	A continuous variable constructed from total sources of household remittance. It indicates the average number of remittance sources the household had previously	+
Household Shocks		
Lone parent	A dummy variable that takes 1 if the child has single parent and 0 otherwise	-
Unmanageable Debt	It is a dummy variable that takes 1 if the household owed unmanageable debt and 0 otherwise	
Experience Job Loss	A dummy variable that takes 1 if the household has experienced job loss and 0 otherwise	-
Experience Crop Failure	A dummy variable that takes 1 if the household has experienced crop failure and 0 otherwise	-
Household Capital		
Education of Head	A continuous variable that shows the highest educational level of the household head	+
Education of Caregiver	A continuous variable that shows the highest educational level of the caregiver	+
Total Livestock Unit (TLU)	A continuous variable constructed from the total number of livestock owned by the household using FAO approaches	+
Total land size (Ha)	A continuous variable that indicates the total amount land owned by the household (hectare)	+
Own house	A dummy variable takes if the household owns a house and 0 otherwise.	
Household location		
Site : Rural	A dummy variable that indicates the location of the household and it takes 1 for rural and 0 for urban	-

3.4 Econometric model and model specification

Poverty transitions can be modelled using different approaches based on various theoretical assumptions and their practical implications. Researchers have been using different models to understand the dynamics nature of poverty. For instance, Jenkins (2000) and Aassve et al. (2006) identified income variance component models, longitudinal poverty pattern models, transition probability models, structural models as the four different types of models that can be used to understand the dynamic nature of poverty. As Jenkins pointed out, transition probability models are considered as the most commonly models used to understand poverty dynamics. The dependent variables in these models are the probability of exiting, entering, or re-entering poverty while the explanatory variables may include observed individual and household characteristics. These models belong to multivariate time hazard or duration model and allow variability of transition rate with both selected household characteristics and time (Dagum and Costa, 2004).

However, in most national level surveys, sample households may not come from homogenous population and mostly households are nested in different clusters, which violate the most common assumption of independence in transition probability models. In this case, using the usual regression models may not give the correct parameter estimates and standard errors as there might be structural variation among different clusters of samples. This is mainly true for longitudinal studies, where variables of interest are measured on the same observations in different times and samples selected from different clustering units or groups of heterogeneous population. For such type of data, multilevel models could give better explanation than others could, as it uses information from individual and cluster level differences (Gelman and Hill, 2007). These models are simply an extension of most common regression models that incorporate cluster level variations at different levels and they have been increasingly used for the analysis of data having hierarchical and grouping structures including panel and repeated measures (West et al., 2007, Hamilton, 2013). Since they are mix of fixed and random effect models, multilevel models are mostly called as mixed effect models, which we use this name in the rest of this paper.

The comparative advantages of mixed models over poled regression, fixed and random effect models is documented in different empirical researches. Most importantly, they help to understand two effects', fixed and random, simultaneously especially when observations are nested in one or more clusters. While the fixed effect model, like to other regression models, has an intercept and slops for different parameters that allow explaining the effect of independent variables on the outcome indicator, the random effect helps to describe the effect of group level unobserved heterogeneity on the outcome indicator. Even though the primary interest is estimating, the covariate associated with the fixed effect, considering the variations among different clusters as random effect mainly give better estimates than either fixed or random effect models could give. In general, according to Guo and Zhao (2000), using mixed effect model for multilevel data has the following advantages. First, since structural differences may exist between clusters, the model allows incorporating the effect of cluster level covariates in estimating individual level differences. Second, including cluster level variation helps to minimize any possible source of bias which would be resulted due to cluster level difference, as households in the same cluster tend to be similar than households in other clusters and ignoring this clustering effect would lead to bias in parameter estimates. Thirdly, compared to others, it provides correct standard error and significant tests, as households in a given cluster may be dependent in various ways. Fourth, it helps to estimates the random effect variance and covariance estimates and decomposes the total variance in the outcome variable in to individual and clustering level. Moreover, it also helps to generalize the finding of the study to other similar clusters in the same country or in other developing countries.

Similarly, using mixed effect model for this particular dataset may be justified by two main reasons. Firstly, since sample households are nested in communities, clusters, and regions, the data has obviously multilevel structure. However, based on the result of descriptive statistics and considering its relevance for policy purpose, we only considered region as the higher-level clustering variable in this paper. In Ethiopia, there are nine regions and two chartered cities and these regions are mainly established based on ethnicity and language of the population, which may have its own implication on dynamics of poverty. There are social, economic, and cultural differences among these regions and people in the same region tend to share similar cultural and socio-economic behaviors than other people in different regions (Heck and Thomas, 2009). The level of development, access to institutions, infrastructures, and socio-cultural setting varies from region to region. Moreover, in line with the country social and economic development priorities, each regional states and charter cities are expected to have their own development policies and strategies to address issues related with social and economic development challenges. These would have noticeable differential effect on the poverty status of children among regions. Therefore, lumping together such type of regional variations would ultimately lead to biased estimates. Secondly, children used in this study are observed in three panels, which indicate violation of the independence assumption, as children in one cohort are similar with other cohort. In such type of data, the usual regression models may not give accurate estimate of coefficients and standard errors and mixed effect models would give unbiased estimates than others.

Mixed effect logistic regression model

To accommodate within child variation, within region variation, and effect of region simultaneously, three level mixed effect model, where repeated observations nested in individual children and individual children are nested in regions, is used in this paper. Level one refers to the repeated observations represented by time 't', level two the subject children nested in a region 'i' and level three the clustering effect regions 'j'. Level one indicates variation in poverty status due to time, which may be associated with different household level characteristics and represents the fixed effect of the model. This helps to test the effect of different variables on child poverty status. Level two and three indicators are included as random effect. In level two, we test the effect of different variables on child poverty status relative to the regional level poverty, it indicates if the within region level effect is different from zero. Children living in the same region with better socio-economic status may have better probability to exit from poverty than children in other region with poor socio-economic status. The highest-level region, level three, indicates region level variation in relation to the overall variation in all regions. It tests if between region effects is different from zero.

Since the dependent variable, multidimensional poverty status of the child is binary variable that takes 1 if the child is identified as multidimensional poor or 0 otherwise, the non-linear mixed effect model with the logit link function is used to estimate the probability of being multidimensional poor (Gelman and Hill, 2007, StataCorp, 2015). Accordingly, the three level model can be specified as follows. Level one can be specified using different explanatory variables as indicated below:

$$\text{logit}\,[P(y_{tij} = 1|\chi_{tij,}\upsilon_{ij})] = \beta_{0ij} + \beta\chi_{tij} + \varepsilon_{tij}(\text{l}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

Where, y_{tij} represents the probability of a child 'i' being poor in time 't' of a given region 'j', ε_{tij} represents individual time specific deviation from the predicted outcome and χ_{tij} is a column vector of explanatory variables. Then the level two model, child level random effect can be given as:

$$\beta_{0ij} = \delta_{00j} + \upsilon_{0ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where, υ_{0ij} represents the child specific deviation from the predicted region level outcome. Similarly, level three, the regional level variation, can be specified as:

$$\delta_{00j} = \gamma_{000} + \upsilon_{00j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where, γ_{000} is the overall intercept and υ_{00j} is region level random effect that indicates region level deviation from the overall predicted outcome. **Then the composite equation can be given as follows:**

$$\text{logit}\left[P(y_{tij} = 1 \left|\left|\chi_{tij,}\upsilon_{0ij},\ \upsilon_{00j}\right)\right] = \gamma_{000} + \beta\chi_{tij} + \upsilon_{0ij} + \upsilon_{00j} + \varepsilon_{tij} \ldots\ldots\ldots\ldots\ldots\ldots (8)\right.$$

It is assumed that the random effects are independent and normally distributed with,

$$\upsilon_{0ij} \sim N(0, \sigma_2^2\ )$$

$$\upsilon_{00j} \sim N(0, \sigma_3^2\ )$$

Where, σ^2 denotes a vector of variance component at child and region level.

4. Results and discussion

4.1 Summary of selected deprivation indicators by regions

Table 4 presents the proportion of child deprivation in different indicators disaggregated by regions. Compared to 2002, in 2007 the proportion of children deprived in the all dimension showed significant reduction. However, the relative change in 2009 was lower than the relative change observed in 2007, which indicates more number of children again experienced deprivation in 2009. Moreover, in 2009 almost in all regions more numbers of children were deprived in education and health than before. For instance, compared to 2007, in 2009 the proportion children deprived in education was creased by 13%. This is because more number of children dropped their schooling in 2009 and more number of children who had grade level below the median grade level of the sample children. For example, compared to 2007, in 2009 both the proportion of children who dropped their schooling and those achieved below the median grade level were increased by 8% .This could mostly happen in developing countries especially where teenage children are expected to be involved in different household and other income generating activities. Similarly, after 33% reduction in 2007 the proportion of children deprived in heath was also raised to the same level what it was in 2002. This could be associated with various social and economic factors including access to health services and limited financial capacity. For example, from the total children who were ill in 2009, 65% of them reported that they did not visit any health center because the cost associated with treatment. Unlike to health and education, the overall reduction in sanitation, drinking water, material, information, and electricity deprivation are very significant. Similarly, even though the change seems small, the overall decreases for shelter and nutrition were also positive.

Table 4: Summary of child deprivation indicators in different regions

Region	Year	EDU	HEAL	SANIT	SHEL	DRINK	ELEC	MATE	NUTR	INFO
Addis Ababa	2002	0.09	0.17	0.88	0.71	0.20	0.01	0.48	0.06	0.28
	2007	0.07	0.11	0.88	0.62	0.00	0.01	0.11	0.09	0.06
	2009	0.21	0.18	0.80	0.57	0.00	0.03	0.07	0.10	0.04
	AC%	12	1	-8	-14	-20	2	-41	4	-24
Amhara	2002	0.32	0.30	0.89	0.99	0.36	0.79	0.84	0.21	0.73
	2007	0.28	0.16	0.61	0.97	0.29	0.76	0.45	0.29	0.62
	2009	0.45	0.35	0.56	0.97	0.18	0.58	0.43	0.37	0.56
	AC%	13	5	-33	-2	-18	-21	-41	16	-17
Oromia	2002	0.43	0.14	0.71	0.96	0.45	0.81	0.86	0.16	0.50
	2007	0.46	0.11	0.48	0.90	0.13	0.49	0.30	0.10	0.27
	2009	0.55	0.17	0.28	0.9	0.08	0.31	0.12	0.15	0.22
	AC%	12	3	-43	-6	-37	-50	-74	-1	-28
SNNP	2002	0.42	0.15	0.78	0.90	0.59	0.66	0.59	0.44	0.60
	2007	0.46	0.12	0.42	0.85	0.18	0.61	0.17	0.14	0.41
	2009	0.63	0.22	0.22	0.87	0.10	0.61	0.21	0.17	0.35
	AC%	21	7	-56	-3	-49	-5	-38	-27	-25
Tigray	2002	0.39	0.26	0.75	0.96	0.52	0.81	0.95	0.25	0.70
	2007	0.33	0.18	0.81	0.94	0.24	0.67	0.73	0.23	0.56
	2009	0.43	0.11	0.28	0.91	0.18	0.65	0.82	0.34	0.46
	AC%	4	-15	-47	-5	-34	-16	-13	9	-24
	2002	0.34	0.20	0.80	0.91	0.44	0.65	0.75	0.24	0.58
	2007	0.34	0.13	0.62	0.87	0.18	0.54	0.36	0.17	0.40
	2009	0.47	0.21	0.4	0.86	0.11	0.46	0.34	0.23	0.34
Overall	AC%	13	1	-40	-5	-33	-19	-41	-1	-24

Note: AC%=Absolute percentage change; EDU=Education; HEAL=Health; SANIT=Sanitation; DRINK=Drinking Water; ELEC=Electric City; MATE=Material; NUTR=Nutrition; INFO=Information

Looking in to the regional disaggregated deprivation measure would give us better insight on the level and extent deprivation in each region. For instance, shelter and sanitation deprivations look the most important deprivations that need greater attention in all of the regions than other deprivation indicators. On the other hand, relatively SNNP region in nutrition deprivation and Tigray regions in health deprivation have shown better progress than other regions. Furthermore, education deprivation in Oromia and SNNP, information deprivation in Amhara, and material and electricity deprivation in Tigray regions look the most important dimensions that need targeted intervention. Likewise, while Amhara region seems the most deprived region in most of the deprivation indicators, except in sanitation, Addis Ababa region is the least deprived region in most of the deprivation indicators. Largely, the disaggregated information could provide specific evidences on the most important dimensions and the type of deprivation in each region that have significant implication to fine tune intervention to efficiently reduce poverty in each regions and in the country as a whole.

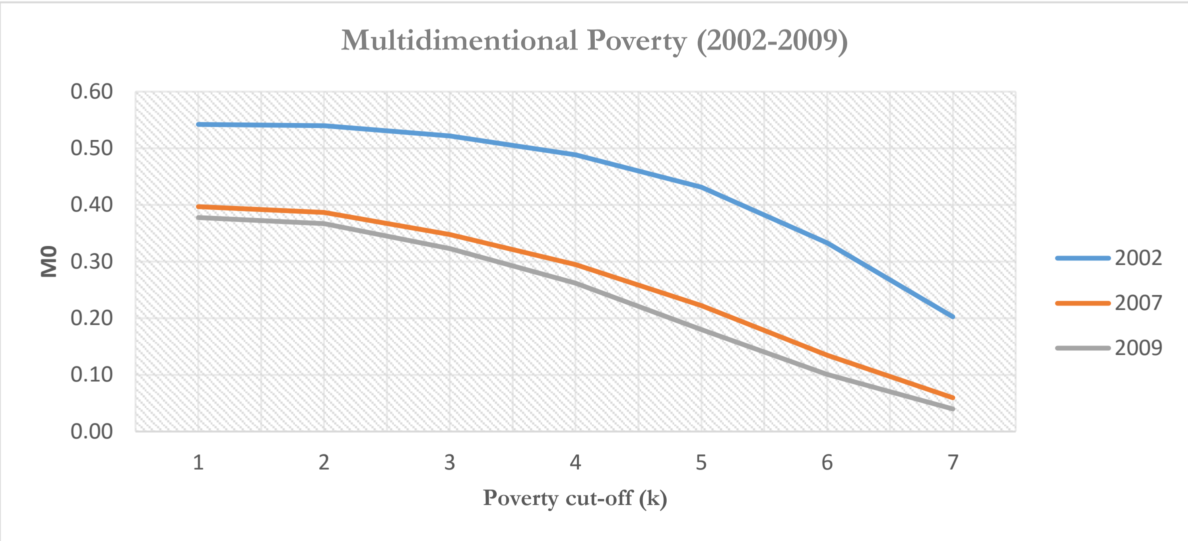
4.2 Multidimensional poverty measures by region and site of children

Summary of poverty trend in the three periods indicates, compared to 2002, multidimensional poverty was decreased in 2007 and 2009 (Table 5 and Figure 1). Both the head count ratio (H) and intensity of deprivation (A) indicate that the proportion of children under multidimensional poverty has decreased during the study periods. For instance, with cutoff point four, in 2002, the head count ration was about 75% but in 2009, it was decreased to 46%, which shows 39% relative change. Similarly in 2002 the average amount of deprivation that the poor children experienced was about 65% (about 6 dimensions) but this amount was reduced to 56% (about 5 dimensions) in 2009, with also indicates a relative change of 14%. With the same cutoff point, compared to 2002, in 2007 and 2009 adjusted head count ratio (M_0) prevalence showed 41% and 47% reduction respectively. Correspondingly, compared to 2007, in 2009 the reduction in adjusted head count ratio was about 11%. The simultaneous change in head count ratio and intensity of deprivations indicates the observed reduction in multidimensional poverty (M_0) is the result of both decrease in the proportion of children who were poor (H) and decrease in the intensity of deprivation (A).

Table 5: Multidimensional poverty incidence by different cutoff point

Poverty Cutoff (k)	Multidimensional Headcount (H)			Intensity of Deprivation (A)			Multidimensional Child Poverty Index (M0 = HA)		
	2002	2007	2009	2002	2007	2009	2002	2007	2009
1	0.99	0.97	0.97	0.55	0.41	0.39	0.54	0.40	0.38
2	0.93	0.84	0.83	0.58	0.46	0.44	0.54	0.39	0.37
3	0.84	0.67	0.66	0.62	0.52	0.49	0.52	0.35	0.32
4	0.75	0.50	0.46	0.65	0.58	0.56	0.49	0.29	0.26
5	0.62	0.35	0.28	0.70	0.64	0.64	0.43	0.22	0.18
6	0.44	0.19	0.14	0.75	0.72	0.72	0.33	0.13	0.10

Figure 1: Change in multidimensional child poverty during 2002 to 2009



The regional disaggregated measures of multidimensional poverty prevalence, which shows the proportion of multidimensional poor children in each region, are presented in Table 6 and Figure 2. In general, the relative changes between 2002 and 2009 seem significantly higher in all sample regions of the country. The highest proportions of children who exit from multidimensional poverty are observed in Addis Ababa region mainly due to decrease in the head count ratio (82%). As indicated above, the smallest proportion of exit is observed in Amara region (28%), which is because of the smallest change observed both in the head count ratio and average deprivation. On the other hand, compared to others the highest reduction in percentage of average deprivation is observed in SNNP region (23%) while the lowest reduction is observed in Addis Ababa and Amhara regions (6%).The overall poverty reduction in Amhara and Tigray regions, is significantly lower than the average reduction in the country. Moreover, it looks that child poverty in Amhara region is the worst as both the proportion of deprived children and the depth of their deprivation is the highest.

Table 6: Multidimensional poverty indicators by region (with cutoff point 4)

Region	H			A			Mo		
	2002	2007	2009	2002	2007	2009	2002	2007	2009
Addis Ababa	0.34	0.06	0.06	0.49	0.46	0.46	0.17	0.03	0.03
Amhara	0.87	0.70	0.68	0.65	0.59	0.61	0.57	0.41	0.41
Oromia	0.78	0.47	0.30	0.66	0.53	0.52	0.51	0.25	0.16
SNNP	0.75	0.48	0.50	0.69	0.56	0.53	0.52	0.27	0.27
Tigray	0.92	0.73	0.69	0.65	0.62	0.56	0.60	0.45	0.39
Overall	0.75	0.50	0.46	0.65	0.58	0.56	0.49	0.29	0.26
Percent Change (%)*		-33.3	-8.0		-10.7	-3.5		-40.5	-11.2

*=*Change with previous years*

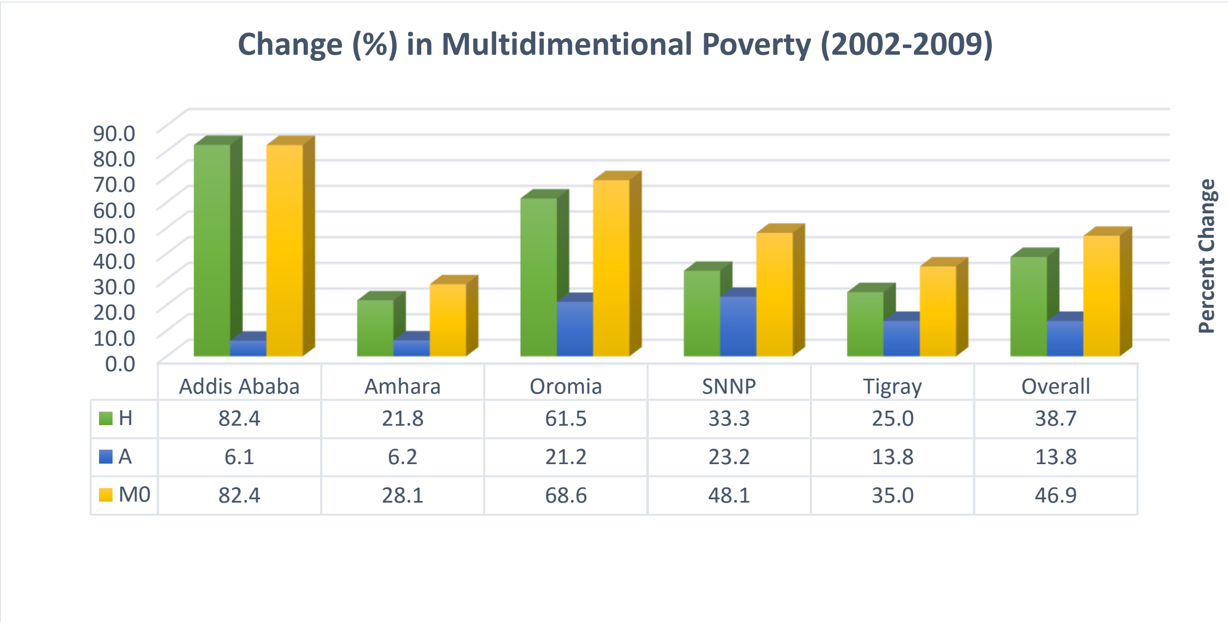


Figure 2: Change in multidimensional poverty between 2002 and 2009

Similarly, as it is expected the urban-rural disaggregated measure of poverty also shows that the prevalence of poverty in rural area is higher than in urban areas (Table 7). Between 2002 and 2009, in rural areas, the prevalence of multidimensional poverty was decreased by 39% while in urban area it was decreased by 60%. The overall change in both areas is associated with both the change in the proportion of children who are poor and intensity of deprivation. Nevertheless, while the head count ratio reduction accounts 58% and 27% in urban and rural areas respectively, average deprivation accounts 2% and 16% of the change in urban and rural areas respectively. High prevalence of poverty in rural areas would be associated with the social, economic, and geographic factors. In rural areas, children have limited access to education and health services not only because of economic factors but also because of the availability of limited infrastructures in these areas.

Table 7: Multidimensional poverty indicators by site (with cutoff point 4)

	H			A			Mo			Absolute**
Site	2002	2007	2009	2002	2007	2009	2002	2007	2009	Variation
Urban	0.39	0.17	0.16	0.52	0.50	0.51	0.20	0.09	0.08	-60.00
Rural	0.94	0.74	0.68	0.68	0.59	0.57	0.64	0.44	0.39	-39.06
Overall	0.75	0.50	0.46	0.65	0.58	0.56	0.49	0.29	0.26	-46.94
Relative Change (%)*		-33.33	-8.00		-10.77	-3.45		-40.51	-11.17	

**=Change with previous years; **=Change between 2002 and 2009*

4.3 Multidimensional poverty transition by region

Table 8 presents summary of poverty transition by region. Between 2002 and 2009, 36.8% and 41.4% of the sample children experienced chronic and transient poverty respectively. Children who have never experienced poverty account only 21.8%. This indicates that almost 79.2% of the children have experienced poverty at least in one period, signifying the majority of the children have experienced poverty at least once. The proportion of children who moved out of poverty in 2007 accounts 26.4% while those who entered are only 1.8%, which indicates higher rate of exit than entry. Even though the gap is narrow, the proportion of exit and entry in 2009 was also similar. The regional disaggregated measure also indicates the presence of unbalanced transition among different regions. In Addis Ababa region, the highest proportion (64.1%) of children has never experienced poverty. On the other hand, the highest proportion of children who have experienced persistent poverty is found in Tigray region. Compared to others, in Oromia region the highest proportion of children has moved out of poverty. The chi-square test for independence of poverty transitions status and location of the child also confirms the presence of statistically significant relationships between locations of the child and poverty transition. For instance, the proportion of children who never experienced poverty in Addis Ababa is significantly ($P < 0.05$) different from the proportions in all other regions and relatively higher proportions of children were moved out of poverty in Addis Ababa and Oromia regions than other regions (Table 8). However, the insignificant relationship between moving into poverty and location of the child depicts that the proportions of children who moved into poverty were almost similar in all regions.

Table 8: Summary of poverty transition (%) by region and site

	Region					Site		overall
Poverty Status	Addis Ababa	Amhara	Oromia	SNNP	Tigray	Urban	Rural	
Never poor	64.1_{a}	$9.3_{b,d}$	$19.1_{b,c}$	21.8_{c}	6.5_{d}	55.2_{a}	4.1_{b}	21.8
Chronic poor	0.7_{a}	56.0_{b}	21.6_{c}	33.3_{c}	63.0_{b}	6.5_{a}	52.9_{b}	36.8
Transient down -2009	0.7_{a}	1.6_{a}	1.0_{a}	1.6_{a}	0.5_{a}	2.4_{a}	0.5_{b}	1.1
Transient down -2007 & Stay there	0.0^{2}	1.0_{a}	0.5_{a}	1.2_{a}	0.5_{a}	0.9_{a}	0.6_{a}	0.7
Transient up -2009	5.6_{a}	$11.4_{a,b}$	21.6_{b}	11.1_{a}	8.5_{a}	6.2_{a}	15.0_{b}	11.9
Transient up -2007 and stay there	$22.5_{a,c}$	10.9_{b}	27.3_{a}	$17.7_{a,b}$	$15.5_{b,c}$	21.1_{a}	17.2_{a}	18.5
Transient down -2007 & Transient up -2009	1.4_{a}	$1._{a}$	1.5_{a}	0.8_{a}	0.5_{a}	2.7_{a}	0.3_{b}	1.1
Transient up -2007 & Transient down -2009	4.9_{a}	8.3_{a}	7.2_{a}	12.3_{a}	5.0_{a}	5.0_{a}	9.4_{b}	7.9

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $P < .05$ in the two-sided test of equality for column proportions.

The urban/rural disaggregated measure of poverty transition also indicates that chronic poverty is experienced mainly in rural areas than urban areas and the proportion of children under chronic poverty in urban area is significantly ($P< 0.05$) different from the proportion in rural area. On the other hand, compared to rural area, higher proportion of children have never experienced poverty in urban area in the two periods, suggesting very significant ($P< 0.05$) difference in the nature of poverty prevalence between the two locations. Moreover, the proportion of children who moved out of poverty in both urban and rural areas was greater than those who moved into poverty during these three periods. The significant different in the nature of poverty, chronic/transient, in rural vs urban areas indicates the need for different targeted intervention in the two areas mainly by using specific indicators as suggested by Barrett (2005) .

4.4 Descriptive summary of independent variables

Results of Chi-square test that summarizes the relationship between categorical independent variables and poverty status of children is presented in table 9. Except for sex of the head, significant relationship is observed between most of the categorical variables and multidimensional poverty status of children. For instance, the proportions of non-poor children who lives in households who have some help during challenges or members of political party are higher than the proportion of poor children in these households. On the other hand, the proportion of poor children who live in households who experienced crop failure or who are lone parents are higher than the proportion of non-poor children. Similarly, the proportion of poor children who live in households mainly employed in the agricultural sector is by far greater than those children who live in households employed in non-agricultural sector. The chi-square test for most of these variables has also confirmed the presence of statistically significant relationships between these variables and the multidimensional poverty status of children.

Table 9: Descriptive summary and chi-square test for categorical explanatory variables

Explanatory variables	Response Category	Non-poor	Poor	Chi-square test
Sex of household head	Male	74.3^{a}	74.0^{a}	0.034
	Female	25.7^{a}	26.0^{a}	
Lone parent	Have partner	89.5^{a}	84.7^{b}	14.794***
	Lone parents	10.5^{a}	15.3^{b}	
Member of political group	No	92.1^{a}	94.8^{b}	9.048***
	Yes	7.9^{a}	5.2^{b}	
Has help during a problem	No	12.7^{a}	15.6^{b}	4.954**
	Yes	87.3^{a}	84.4^{b}	
Own unmanageable debt	No	68.1^{a}	60.7^{b}	16.60***
	Yes	31.9^{a}	39.3^{b}	
Experience job loss	No	84.6^{a}	89.6^{b}	16.418***
	Yes	15.4^{a}	10.4^{b}	
Experience crop failure	No	83.6^{a}	54.7^{b}	269.93***
	Yes	16.4^{a}	45.3^{b}	
Household own house	No	42.0^{a}	19.1^{b}	182.580***
	Yes	58.0^{a}	80.9^{b}	
Main employment sector	Agriculture	6.1^{a}	23.1^{b}	528.523***
	Non-agriculture	65.8^{a}	24.2^{b}	
	Both	28.1^{a}	52.7^{b}	
Urban or Rural	Urban	70.4^{a}	15.7^{b}	899.473***
	Rural	29.6^{a}	84.3^{b}	

Likewise, test results for mean and medians difference for the continuous explanatory variables between multidimensional poor and non-poor children is presented in table 10. The results indicate the presence of statistically significant difference on the mean values of indicator variables and children poverty status. For instance, non-poor children live in households who have higher mean value for some of the variables such age of head, total livestock unit, education of household head, and education of caregiver, number of remittance sources, and household size than poor children. On the other hand, poor children live in households with higher mean values of dependency ratio, working months in the agricultural sector, total livestock holding, and total land holding than non-poor children. Both the mean and median difference tests between the values of poor and non-poor children households show almost similar results for all of the variables. For example, except for age of head and household size, statistically significant difference is observed in the mean and median values of household remittance, relative number of working months in agricultural sector, dependency ratio, total land, and livestock holding, and education of the head and caregiver. This implies the presence of possible relationships between these explanatory variables and multidimensional poverty status of children that would affect poverty transition of children.

Table 10: Descriptive summary, mean, and median test continuous explanatory variables

Explanatory variables	Non-poor					Poor					Median Test (P-value)
	Mean	Med	Std.D	Min	Max	Mean	Med	Std.D	Min	Max	
Age of Head	46.40_a	45.00	11.37	17.00	87.00	45.68_a	45.00	11.73	15.00	90.00	0.050
Household size	6.46_a	6.00	2.13	2.00	16.00	6.42_a	6.00	2.10	1.00	13.00	0.911
Dependency ratio	0.97_a	0.75	0.78	0.00	5.00	1.28_b	1.00	0.86	0.00	6.00	0.000
Sources Remittance	0.75_a	1.00	0.93	0.00	6.00	0.52_b	0.00	0.73	0.00	4.00	0.000
Ag./Non-Ag working months	0.20_a	0.00	0.41	0.00	2.67	0.50_b	0.00	0.82	0.00	12.00	0.000
Total household land size (ha	0.46_a	0.02	0.80	0.00	4.00	0.87_b	0.75	0.78	0.00	4.00	0.000
Total Livestock Unit	1.55_a	0.00	2.48	0.00	15.95	2.28_b	2.00	2.33	0.00	16.80	0.000
Education of Head	5.17_a	4.00	4.65	0.00	16.00	1.90_b	1.00	2.82	0.00	16.00	0.000
Education of Caregiver	3.61_a	3.00	4.13	0.00	16.00	0.97_b	0.00	2.24	0.00	12.00	0.000

4.2 Triggers of poverty transitions

Multilevel mixed effect model was run to identify possible triggers of poverty transition during the study period. The first step in running the multilevel model was to check whether including the random intercepts child (CHID) and region (Region) provide additional information or not. Accordingly, the null model, with the random intercept only was run and the result was checked for the presence of statistically significant effects of clustering variables (Table 11). The reported likelihood test for the presence of regional difference in variance component model shows that there is strong evidence against the null hypothesis that $u_{ot\ j}=0$ and the log odds of being multidimensional poor of a child in a given time 't' on average region 'j' is estimated to be 0.341. The intercept for any region 'j' for a time't' can be written as $0.341 + u_{otj}$ with an estimated variance of $u_{ot\ j} = 2.45$. The between child effect of within the same region is also very significant as it can be observed from the estimated variance and confidence interval. The variance is about eight standard deviation from zero.

Similarly, figure 2 visualizes the importance of including the random intercept region to differentiate the multidimensional poverty status of children in different regions. Considering SNNP as a reference region and keeping other things constant, the probability of being multidimensional poor in Addis Ababa region is two times lower than the reference region. On the other hand, in Tigray and Amhara regions the probability of a given child to become multidimensional poor is 116% and 93% higher than in SNNP region. This clearly indicates the effect of regional variations on poverty status of children that would obviously resulted from difference in social, cultural, and economic conditions of households in each region. This strongly suggests that any econometric modeling without considering this variation would lead to biased parameter estimates and higher standard errors for some of the parameters.

Table 11: Summary of two level random intercept model

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Constant	0.341	0.704	0.48	0.628	-1.039	1.721
Random-effects	Estimate	Std. Err.	[95% Conf. Interval]			
Region: Var(_cons)	2.446	1.583	0.688	8.696		
CHID: Var(_cons))	3.200	0.419	2.476	4.137		
Chi2(2) = 742.40***						

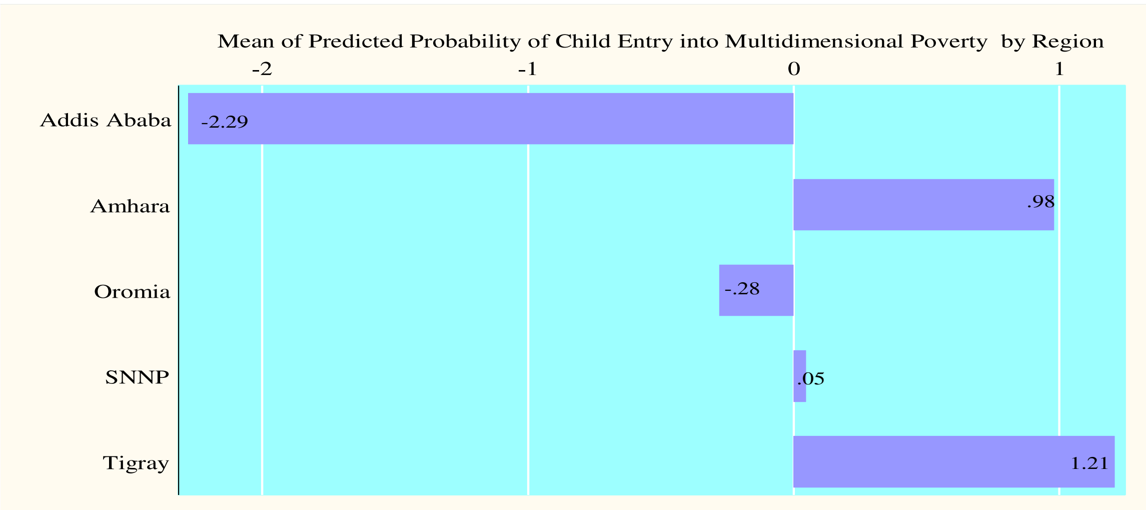


Figure 3: Mean of Predicted Probability for Entry into Poverty of the Random Intercept only Model

Table 12 presents the result of mixed effect model for the effect of different household level factors on the dynamics of multidimensional child poverty. It shows that most of the variables that include household demographic, household capital, economic/structural changes, household shocks, and location related variables have significant effect on the dynamics of child poverty. This implies that the probability of a child being chronically poor or moving into or out of poverty can be a function of these observed or other unobserved household and environmental shocks experienced by households. The likelihood ratio test reported at the end of table 12 indicates the random intercepts have made significant improvement over the logistic model, which also indicates the predictors as a set reliably distinguish for moving into or moving out of multidimensional poverty (Chi-square = 295, P < .000 with Df = 22).

After including the covariates, the results of total variability decomposed by the random intercepts and ICC (Interclass Correlation) are presented at the end of table 12. As it can be seen from the estimated variances and confidence intervals, the effect of the two levels, region and child level repeated measures, are also found very significant. Similarly, the ICC results show that there is strong correlation between children in the same region and within child observations in different panels, which confirms the presence considerable clustering effect at region and child level. In the following section, the results of the model are discussed.

Table 12: Result of mixed effect logit model on triggers of poverty transition

Dependent variables	Coef.	Std. Err.	z	[95% Conf. Interval]		OR
Household demographic						
Age of household head	-0.0194	0.0073	-2.66***	-0.0338	-0.0051	0.9805
Female headed with partner	-0.0159	0.2333	-0.07	-0.4728	0.4728	0.9841
Male headed without partner	0.0979	0.4442	0.22	-0.7727	0.9686	1.1028
Female headed without partner	0.4659	0.2664	1.76*	-0.0527	0.9847	1.5935
Household size	-0.1214	0.0415	-2.92***	-0.2029	-0.0399	0.8856
Dependency ratio	0.2051	0.0926	2.21**	0.0236	0.3667	1.2277
Social capital and social network						
Has some helper	-0.3538	0.1956	-1.81*	-0.7373	0.0295	0.7019
Member of Political Party	-0.6633	0.2505	-2.65***	-1.1542	-0.1723	0.5151
Economic/Structural						
Sector: Non-agricultural	-0.9654	0.3045	-3.17***	-1.5624	-0.3618	0.3808
Sector: Agriculture and Non-agriculture	-0.3405	0.2606	-1.31	-0.8515	0.1703	0.7113
Agri./Non-agri. Working Months	0.3240	0.1898	1.71*	-0.4815	0.6962	1.3826
Number of Remittance Sources	-0.2915	0.0874	-3.34***	-0.4628	-0.1202	0.7471
Household capital						
Total amount of land owned (ha)	-0.0656	0.1168	-0.56	-0.2946	0.1633	0.9364
Household own house	-0.2276	0.2163	-1.05	-0.6517	0.1964	0.7964
Total livestock Unit (TLU)	-0.1664	0.0375	-4.38***	-0.2377	-0.0906	0.8485
Head Education	-0.1614	0.0293	-5.50***	-0.2190	-0.1039	0.8508
Caregiver Education	-0.1156	0.0325	-3.55***	-0.1795	-0.0517	0.8907
Household Shocks						
Unmanageable Debt	0.2047	0.1495	1.37	-0.0883	0.4979	1.2272
Job loss	0.2364	0.2064	1.15	-0.1680	0.6410	1.2667
Crop Failure	0.2799	0.1604	1.74*	-0.0345	0.5945	1.3231
Change in location						
Rural	2.8089	0.2745	10.23***	2.2707	3.3470	16.5917
Year						
2007	-1.9590	0.2032	-9.64***	-2.3574	-1.5605	0.1409
2009	-2.0764	0.2121	-9.79***	-2.4922	-1.6605	0.1253
Constant	3.6209	0.6847	5.29***	2.2789	4.9630	33.3742

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Region: var(_cons)	0.62448	0.42385	0.16511	2.36184
CHID: var(_cons)	2.05120	0.40732	1.38988	3.02717
LR test vs. logistic model: chi2(2) = 163.06		Prob > chi2 = 0.0000		

Inter class correlation conditional on fixed effects

Level	ICC	Std. Err.	[95% Conf. Interval]	
Region	0.104	0.063	0.030	.304
CHID/Region	0.447	0.057	0.338	.561

Household demographics

The effect of demographic characteristics of households' on child poverty transition looks highly significant. Age of household head, marital status, household size, and dependency ratio have significant impact on the dynamics of poverty. Children who are living with younger aged household heads have higher risk of moving into multidimensional poverty than children living with older aged household heads. A unit increases in the age of the head decreases the likelihood of children to move into multidimensional poverty by 2%. This could be associated with lower household asset accumulation and other capitals in the younger households' heads than older household heads. Similar results have been reported by various researchers both in developed and in developing countries (Valletta, 2006; Andriopoulou and Tsakloglou, 2011; Muyanga et al., 2013). According to other findings, households headed by young individuals have higher risk of staying longer in poverty than others. Finnie and Sweetman (2003) have also observed compared to the reference age groups, younger families have volatile poverty status with higher entry rate.

Dependency ratio has positive and significant association with children entry into multidimensional poverty. A unit increases in the number of dependent person would increase the probability of child moving into poverty by 22%. In other words, children who are living in households with more numbers of dependents have more likelihood to move into multidimensional poverty than others. Of course, high dependency ratio implies lower household per capita earning which may affect the overall household consumption expenditures. Other researchers have also reported similar results (Chaudhry et al., 2009).

The widely accepted view on the presence of positive correlation between household size and poverty status appears different in this paper. Unlike to dependency ratio, household size has negative and significant association with the probability of entry into multidimensional poverty. The odd ratio indicates a unit increase in family size would decrease the likelihood of entry by 12%. This may be due to the interaction effects of dependency ratio and household size. Large sized households with lower dependency ratio may be in a better position to generate household income and may have the possibility to involve in different productive activities than large sized households with more number of dependents (Lanjouw and Ravallion, 1995). Other researchers such as Woolard and Klasen (2005) also reported that having large household size with more number of dependent children would increase the risk of moving into poverty. From the descriptive statistics, it is also possible to see that the average numbers of household size in the poor and non-poor children households are almost the same (Table 10). However, the dependency ratio in poor children households is 31% higher than non-poor children households. Because its possible effect on estimation, other empirical studies have also suggested the need for adjusting household size during poverty analysis (White and Masset, 2003).

Empirical studies also documented the presence of high risk of moving into poverty for children living with lone parents (Bradbury et al., 2001; Callens et al., 2009; EU, 2008; Lindquist and Lindquist, 2012). This depicts that children who are living in divorced, widowed or single families have very high probability to move into poverty than others. To see if there is any variation between being with male or female lone parent on the poverty transition, the interaction terms for lone parent and head of household variables are included in the model. Taking male-headed household with partner as a reference, children living with lone female-headed households have 59% more likelihood to enter into multidimensional poverty than the reference group. Likewise, even though it is not significant, living with lone male-headed households has also positive effect in multidimensional poverty entry, signifying the presence higher risk for being with female-headed lone parents than male-headed lone parents. This shows the importance of household marital status in defining the poverty status of children and especially the need for intervention in minimizing family dissolution (Valletta, 2006). For instance Lindquist and Lindquist (2012) argues that children who had single parents that marry have the highest chance of leaving poverty, and children with divorcing parents have a lower chance of leaving poverty than children in stable families. Policy options in this regard need to focus on establishing institutions either supporting family ties or providing targeted support for lone parent households. Unfortunately, available policies on family support and targeted intervention on family issues are almost non-existent.

Social capital and network

The z tests for statistically significance contribution of social capital and network related predictor variables demonstrate that participation in political leadership and availability of informal help after crisis have negative contribution on children entry into multidimensional poverty. The odd ratio for political party membership indicates that children living in households where the heads are members of political party has 49% less risk to enter into multidimensional poverty than others. Households who are member of political party have better opportunities to create networks and norms that govern interactions among individuals, households, and communities than others. In additions, political party membership improves household access to information, increase their participation in collective actions, and facilitate household welfare and access to different resources by linking physical, social, and human capital (Grootaert and Bastelaer, 2002). Moreover, participation in politics and high form of social interaction within families and communities are among the domains social cohesions and capitals that have positive contribution on the livelihoods of households (Forrest and Kearns, 2001). Based on the social capital and social exclusion theories social capital capitalizes individual economic opportunities by creating linkages and connections with others. The finding of this study is in line with other similar studies conducted by different researchers (Kristjanson et al., 2010).

Availability of help after any crisis or problem has also significant ($P < 0.05$) contribution on children movement out of multidimensional poverty. The odd ratio indicates that children who are living in households who have somebody that can provide help after any problem or crisis are 30% less likely to move into multidimensional poverty than others who do not have. In the absence of strong institutional support, the most important strategy to cope up with crisis and some unexpected shock is support from family members or relatives. Especially in developing countries, its role is highly important, as there is no well-organized and established social security and support systems. Similar findings were also reported in developed countries that designate poor households who have strong social network with families have more probability to get help and cope up with unexpected challenges than others (Matthews and Besemer, 2015). In general, the above findings highlight the contribution of social capital and networks in poverty alleviation and suggest the need for designing alternative support strategies especially after unexpected challenges and establishing a culture that would strengthen households' social capital and networks.

Economic/Structural changes

Explicitly, higher household income has positive contribution to move out of poverty. However, mostly the incomes of households depend on the type of livelihood activity where households are mainly engaged in, as the productivity of labor varies from sector to sector especially in the developing countries context. In this paper, due to the absence household income data for all panels we used households' employment sector as a proxy for households earning and livelihood activities. Household's employment sectors are categorized mainly into agriculture, non-agriculture and both agriculture and non-agriculture. This would help to see if there is any structural association between employment sector of the household members and multidimensional poverty status of children. Considering the agricultural sector as a reference, working in non-agricultural sector has negative effect on children entry into multidimensional poverty. In other words, children living in households where their livelihood is mainly depend on non-agricultural sector have lower risk of moving into multidimensional poverty than those who are solely depend on agriculture. The odds ratio for this variable indicates that children living in non-agricultural based livelihood households have 38% less risk to enter into multidimensional poverty than the reference category. Similarly, even though it is not statistically significant, negative relationship is also observed between working in both sectors and multidimensional poverty entry status of children. However, higher proportion of involvement in the agricultural activities also seems to increase the likelihood of children transition into multidimensional poverty. This is mostly expected especially in the context of developing countries where most of the farming households are smallholders and subsistence operating in a very small amount of land, which is also true in this dataset. The most important policy implication from the above indicators could be improving the productivity of the agricultural sector and creating other non-farm employment opportunities to diversify households' livelihood especially in the agricultural sector. The multiple role of enhancing agricultural productivity in poverty reduction has been documented in various empirical researches (Schneider and Gugerty, 2011, Nyankori, 2009).

Remittance, intensity of household financial support sources in our case, has significant ($P < 0.05$) and negative effect on children movement into multidimensional poverty. The odd ratio shows that a unit increase in remittance or support sources would decrease the probability of moving into multidimensional poverty by 25%. Likewise, as highlighted on the availability of help above, this also suggests that the presences of diverse support from different sources would decrease the likelihood of a child movement into multidimensional poverty. This is mainly because remittance could be associated with households' investment in socio-economic activities such as health, education, business, and others, which are directly related with children need and welfare in the households (Ratha, 2013). For instance, a study conducted in Ghana have shown that children living with households who are receiving remittance had better access to education and health services than others (Jr and Cuecuecha, 2013).

Household capital

Capital has been reported as one of the important factors that determine poverty status of households in various empirical researches. We have also found that household educational status and ownership of productive assets such as livestock size and land holding have negative effect on children movement into multidimensional poverty. The odd ratio indicates a unit increase in education of household head and the caregiver would decrease the risk of children entry into multidimensional poverty by 15% and 11% respectively. Different theories of poverty including the classical and neo-classical theories also recognize the significant contribution of human capital in poverty reductions at it can enhance individuals' silks that in turn improve their productivity. Moreover, educated individuals have better access to information that contributes to their decisions on economic and other social issues. Empirical findings on poverty dynamics have also reported similar findings both in developed and in developing countries (Jung and Smith, 2007; Kristjanson et al., 2010). Targeted educational intervention such as adult education for caregivers and households heads in the rural area may be considered as a good policy option.

In developing countries, where agricultural activities are the most important contributors of household livelihood strategies, household livestock and land ownership has momentous contribution to define the poverty status of households. Mostly they have positive effect on households exit from poverty. Results from the multilevel model also show that household livestock ownership has statistically significant and negative effect on children entry into multidimensional poverty. A unit increase in total livestock unit would decrease the probability children entry into multidimensional poverty by 16%. The role of livestock ownership on household livelihood and poverty is well documented in various empirical findings (Randolph et al., 2007, Millar and Photakoun, 2008). Although it is not statistically significant, the effect of land size and house ownership on poverty entry is also negative.

Household shocks

Shock has been reported as one of the driving forces that lead households into poverty. Similarly, in this paper children who live in households who experienced one or more shocks such as job loss, crop failure, and unmanageable debt appear to have higher risk to enter into multidimensional poverty than others do. The odd ratio for crop failure indicates that household's crop failure experience would increase the likelihood of children to move into poverty by 32%. Crop failure has multiple effects on the livelihood of households mainly by affecting household income and consumption pattern. The effect would be worst especially in the context of subsistence smallholder farmers where their livelihood is primarily depend on crop production from their smaller parcel of land. Children and pregnant women are the most vulnerable part of the society during crop failures and the risk of school dropout would become high, as households could not properly provide food and other necessary expenditures. Even sometimes, children may be sent to be hired somewhere and generate income to support the family. Similarly, children access to health services would also become low due to inadequate income.

Though not significant, the effect of other household shock related indicators, job loss and unmanageable debt, on multidimensional poverty entry of children is positive. Statistically significant positive effects have also reported by other researchers (Kijima et al., 2006, Daoud et al., 2016). The big lesson from this finding is the need for strengthening the social security system such as crop and livestock insurances that would provide support during various unintended shocks. Moreover, child level targeted support programs that could make children to stay in school and healthy would have significant contributions.

Household geographical disparities

Poverty is not only a factor of household demographic, economic, and social factors but it is also highly associated with geographic factors. The statistically significant association of poverty and site related indicator (rural/ urban) indicates the spatial characteristics of poverty that may have strong implication for designing targeted policies and interventions. The odd ratio for site indicates that children who are living in rural areas have significantly higher likelihood (1569%) to enter into multidimensional poverty than others who live in urban areas. Among others, the main reason behind intensified multidimensional child poverty in the rural areas could be associated with poor infrastructures like road, education and health facilities, water, and electric services and investment in these areas have significant return in reducing both the extent and depth of child poverty. Of course, the contribution of infrastructures on poverty reduction is well known and documented in various studies (Parikh et al., 2015) Moreover, as it is indicated above the productivity of labor in the rural area is significantly lower because of limited access and use of technologies in the agricultural sector. Therefore, enhancing agricultural productivity in rural areas may have greater contribution in poverty reduction by improving household income and food security status.

5. Conclusion

This paper contributes to the empirical literature on child poverty dynamics using panel data from Ethiopia. It uses multidimensional poverty analysis approaches to describe the extent and depth of child poverty in different geographic and cultural settings of the country. The paper tries to incorporate various methodological and analytical limitations identified by previous researches and present additional insights on child poverty analysis. It uses multilevel mixed effect model to identify factors associated with dynamics of multidimensional child poverty by considering both time and cluster level effects. Our paper shows that multidimensional child poverty has decreased during the study period both in headcount ratio and intensity of deprivation, although the change in head count ratio is greater than the change in intensity of deprivation. The regional disaggregated measure of multidimensional child poverty also illustrates the presence of significant variation in the extent and depth of multidimensional poverty among different regions, which signposts the role of geographic and cultural variation on child poverty status. Similarly, the rural/urban disaggregated results also indicate that children in rural areas are under chronic multidimensional poverty with relatively lower transition rate than their counterpart children in urban areas. Moreover, the results of multilevel mixed effect model indicate that multidimensional child poverty is driven by multiple factors including household demographic, social capital and network, economic or structural changes, household capitals, household shocks and location or geographic related factors. Furthermore, the multilevel mixed effect model suggests the need for considering cluster level differences when assessing poverty in heterogeneous population, which would have significant contribution to understand the extent of poverty at different clustering levels that would help to design targeted interventions. From the results of this paper, it is possible to conclude that major policy options and intervention strategies that opt to address child poverty should first consider if either targeted or generic policy is required and need to identify the best entry point that may possibly address multiple deprivation.

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