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Multidimensional Poverty and Inequality in Urban Ethiopia[1,*]

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Abstract

Poverty reduction and ensuring fair distribution of resources have been among the core agenda of the Ethiopian government for decades. This study estimates the extents of urban monetary and multidimensional poverty and inequality at national and regional levels. The multidimensional poverty and inequality indices estimated constitute indicators grouped under four dimensions– education, health, living standards and monetary poverty. Associations to the micro-, community- and macro-level factors are made using simple simulations and econometric models. Data primarily come from ESS 2015/16. Results reveal large prevalence of food and nonfood poverty coupled with nonmonetary deprivations in housing and cooking fuels. Monetary poverty rates of incidence, gap and severity in 2015/16 are found to be higher than the official figures. Multidimensional poverty in urban Ethiopia is one of the highest, with more than half of it coming from monetary poverty followed by deprivations in living standards, health and education. Despite smaller values of multidimensional inequality index and inequality among the multidimensionally poor, disparities among regions exist. Deprivations, poverty and inequality seem to fall with urbanization and national rates are generally found to mask disparities among population groups. Besides demographic and geographic factors, receiving remittance, access to credit, availability of microfinance institutions and primary schools at community-level, and food price shocks are among the factors that are associated with various indicators of household welfare. Policy options include provision of basic public services, promoting access to microcredit, installment of fair distribution/redistribution systems and use of multidimensional approach to welfare measurement by the government.

Keywords: Multidimensional poverty, Multidimensional inequality, Welfare, Urban, Ethiopia.

JEL Classification: D63, I32, O18, P46.

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1. Introduction

Urbanization in poor countries has been viewed by some development theorists as an integral part of economic growth, poverty reduction and distributional change (Ravallion, Chen and Sangraula, 2007; Todaro and Smith, 2012). However, these claims are not well supported by empirical evidence so far. Fast urbanization in developing countries over the past few decades has led to more people worldwide living in urban than in rural areas since 2007. In 2020, over 56 percent of the world's population lived in cities/towns which is projected to reach over 68 percent by 2050 (UN, 2018). Countries in sub-Saharan Africa (SSA) register the highest recent urban growth rates averaging over 4.2 percent per annum in the last four decades (1980-2020). Over the same period, Ethiopia's urban population grew by over 4.7 percent per annum, making 21.7 percent of the total population to live in urban areas in 2020. This is projected to almost double to 39.1 percent (or 74.5 million people) in 2050 (UN, 2018).

Against expectation, the urbanization of SSA has rather been correlated with poverty and inequality. For example, the urban share of the money poor in the region grew from 24.3 to 30.2 percent during 1993-2002 when the urban population share rose from 29.8 to 35.2 percent (Ravallion, Chen and Sangraula, 2007). Showcasing inequality, growth in most cities and towns of SSA has also been associated with slum growth as evident from the change in their slum[3] household population between 1990 and 2014 by over 115 percent to reach about 201 million (UN-HABITAT, 2016). Besides the natural population growth, rural-urban migration is to blame for unregulated urban growth. Capacities of urban areas are pushed away from their limits of providing employment, housing, basic services (water, health, education, electricity), etc. These mean that urban dwellers may be deprived in multiple welfare indicators so that poverty and inequality analyses need to pursue a multidimensional approach. A very recent estimate using surveys done in 40 SSA countries over 2010–2018 shows that over 29 percent of urban residents live in acute multidimensional poverty, representing about 86 million of 326.5 million of the 2017 urban population in those countries (UNDP and OPHI, 2019). The same report shows for Ethiopia that 37 percent (or about 6 million of 16 million) of urban dwellers are poor multidimensionally.

[3] A slum household is defined as that lacking one or more of the following conditions: access to improved water, access to improved sanitation, sufficient living area, durability of housing, secure tenure (UN-HABITAT, 2016).

Income or expenditure has traditionally been used as a standard indicator of welfare, aggregated as indices such as FGT (Foster, Greer and Thorbecke, 1984) for poverty and Gini coefficient for inequality. A feature of this unidimensional approach is that it depends on market prices to compute the monetary values of goods consumed. However, the fact that markets are imperfect in many developing countries and that consumption includes public goods whose market prices are inexistent has put the approach under strong criticism, calling for a systematic inclusion of nonmonetary dimensions (Tsui, 2002). The multidimensionality of welfare is recognized by the SSF report (Stiglitz, Sen and Fitoussi, 2009), the 'Atkinson' report commissioned by the World Bank (World Bank, 2017), and very importantly by UN's Human Development Report through publication of multidimensional poverty and inequality indices (UNDP, 2010, 2015, 2019) and its Sustainable Development Goals (SDGs). A multidimensional approach is based on a shortfall from a threshold on indicators of someone's wellbeing (Bourguignon and Chakravarty, 2003) and summaries can be computed as a multidimensional poverty index (MPI) (Alkire and Foster, 2009, 2011) and inequality index (Seth and Alkire, 2014).

Poverty reduction and fair distribution of resources have been among the core agenda of the Ethiopian government for decades. These are at least reflected in its policy and strategy documents including Sustainable Development and Poverty Reduction Program (SDPRP) (MoFED, 2002), Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (MoFED, 2006), and Growth and Transformation Plan (GTP) I and II (MoFED, 2010; NPC, 2016). These and related efforts have helped declines in the proportion of people living in poverty in the last couple of decades. For example, over the 20-year period spanning 1995/96–2015/16, poverty headcount rate fell from 45.5 to 23.5 percent (NPC, 2017, Table 10). In urban areas, the reduction was slightly higher, from 33.2 to 14.8 percent. Other unidimensional poverty measures (poverty gap and severity indices) also dropped during the same period.

However, the absolute number of people living in poverty declined only slightly (from 25.6 to 21.4 million) over the reference period (1995/96–2015/16) (NPC, 2017, Figure 4). When nonmonetary dimensions are considered, the poverty situation in the country is even far higher as the percentage of the population in multidimensional poverty using 2016 survey data was 83.5 percent (or 85.5 million people) (UNDP, 2019). Over half of the overall multidimensional poverty is contributed by deprivations in living standards. Moreover, among all the countries considered for the global multidimensional poverty index (MPI), Ethiopia has the biggest difference between incidences of multidimensional poverty (83.5 percent) and monetary poverty (27.3 percent) based on the poverty line of $1.90 per person a day (UNDP and OPHI, 2019). Hence, poverty still is a concern in Ethiopia and a lot of work awaits ahead to achieve the Sustainable Development Goal (SDG) of ending poverty in all its forms by 2030.

Moreover, inequality in resource distribution has been rising in Ethiopia over the past decades. Official figures show that the Gini coefficient using unidimensional (expenditure) approach increased from 0.29 to 0.33 in the country and from 0.34 to 0.38 in urban areas between 1995/96 and 2015/16 (NPC, 2017). Though this indicator of monetary inequality among people in Ethiopia is still lower compared to that in other countries in East Africa (World Bank, 2020), the fact that it is getting higher over time is worrisome. Rising inequality not only constrains the country's efforts to meet SDG 10 of reducing inequality by 2030 and to maintain economic and social stability, but also severely undermines the poverty reduction role of economic growth. Therefore, reduction of poverty and inequality should continue as among the primary tasks of the Ethiopian government. This requires, among other things, timely assessments using state-of-the-art methods which this study takes on.

Recent empirical studies estimate poverty at national level in Ethiopia. These include MoFED (2012), NPC (2017), Sender (2019), Shimeles (2019), Woldehanna & Araya (2019), and World Bank (2010, 2016, 2020). The studies apply unidimensional indicators (income or expenditure levels) to determine welfare status. However, as noted earlier, welfare is multidimensional that income or expenditure is deficient in defining one's experience of poverty. Nonmonetary indicators capturing lack of capabilities need to be considered, including lack of education, health, housing, clean water, sanitation, electricity supply, empowerment, employment, personal security, information, etc. The multidimensional approach to poverty is well suited to analyze this. Yet, only few empirical evidences are available in Ethiopia at national level applying such a technique (World Bank, 2015; Bersisa and Heshmati, 2016, 2021; Seff and Jolliffe, 2016; Tigre, 2018; Goshu, 2019; Belete, 2021). For urban Ethiopia, no recent systematic evidence investigating poverty in this framework is available to our best knowledge.

With regards to inequality, previous studies in Ethiopia at national level (Geda, Shimeles and Weeks, 2009; Woldehanna and Araya, 2019) and subnational level (Nebebe and Rao, 2016; Teka, Woldu and Fre, 2019) primarily use unidimensional (expenditure-based) Gini coefficients. Despite the multidimensionality of inequality in resource distribution (UNDP, 2015), official inequality estimates are also unidimensional (MoFED, 2012; NPC, 2017). Some analyze inequality using a dashboard of monetary and nonmonetary outcomes (Kedir, 2015; Argaw, 2017). Only a couple of studies attempt to assess multidimensional inequality at national level (Goshu, 2019; Tigre, 2020). In fact, UNDP has recently started reporting multidimensional inequality indices alongside its MPI for over 100 countries including Ethiopia (UNDP, 2019; UNDP and OPHI, 2019). Apart from providing index estimates, these reports lack detailed contextual investigations and disaggregations by population groups and indicators.

This study seeks to assess multidimensional poverty and inequality thereby filling the existing evidence gaps and directing policy interventions in Ethiopia. Specifically, it seeks to answer: (i) What are the extents of monetary and multidimensional poverty and inequality at national, regional levels and other population group levels? and (ii) How are micro-, community- and macro-level correlate with multidimensional urban poverty and inequality? For answering these, the study employs available advanced methods in unidimensional and multidimensional welfare analysis. The estimated indices contain 12 indicators under four dimensions–education, health, living standards and monetary poverty. A mix of individual- and household-level characteristics are captured. Indicators in education and health dimensions contain capabilities of individuals which are then aggregated to the household. Indicators and their deprivation cut-offs are related to the wider literature, SDGs, the global MPI, national goals, and are also customized to the Ethiopian urban context. Unidimensional indices of poverty and inequality as well as their multidimensional extensions (Alkire-Foster index for poverty and Seth-Alkire index for inequality) are analyzed. Decompositions of results by selected population groups and dimensions/indicators and links to the macroeconomy and urbanization are also made. Simple simulations and econometric models are run to have an idea of the micro- and community-level factors that are associated with household welfare. The study primarily uses Ethiopia's LSMS-ISA dataset (ESS 2015/16) in addition to data and information collected from CSA, NPC, NBE, and other sources.

The remainder of the paper is organized as follows. The next section presents the research methods including the data. After results are presented and discussed in section three, the last section provides conclusions and policy implications.

2. Research Methods and the Dataset

2.1 The Dataset: Ethiopia Socioeconomic Survey

The study primarily uses the urban sub-sample of the 2015/16 wave of Ethiopia Socioeconomic Survey (ESS). Collected jointly by the World Bank and the Central Statistical Agency (CSA) as part of the Living Standard Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) project, ESS was initiated in 2011/12 in rural and small towns. Its 2013/14 and 2015/16 waves included samples from medium and large towns. ESS uses a stratified, two-stage design where regions of Ethiopia serve as the strata (CSA and World Bank, 2017). While the first stage involves selection of primary sampling units or enumeration areas (EAs), the second stage entails the selection of households using simple random sampling. In 2015/16, a total of 4,954 households were interviewed which host over 23,393 individuals. A third of them were sampled from urban areas (small, medium and large towns[4]) which this study focuses. Data cleaning produces a usable urban sample of 1,625 households (411 or 25% from small towns and 1,214 or 75% from medium and large towns) (Table A1 in the Appendix). As expected, the majority were drawn from the largest regions of Oromia (21%) and Amhara (18%). About 15% were also sampled from the city of Addis Ababa. As a multi-topic survey, ESS contains individual-, household- and community-level data. Individual data on demographics, education, health, expenditures, and time use are also collected while household data include expenditure, assets, shocks, non-farm enterprises, credit and farm production. Community-level data on various social services as well as on prices from local markets are available. Data for the dimensions of multidimensional poverty and inequality analysis are extracted from the various modules of ESS.

Although ESS is the principal data source, the study also used supplementary data and information from other sources. For example, data on

[4] CSA's definition of town size is used: Small town: less than 10,000 population; medium town: 10,000–100,000 & big town/city: more than 100,000 (CSA and World Bank, 2017). However, the ESS dataset used here does not discriminate between medium and large towns; we only have two groups: small town, and medium/large town.

urbanization are collected from CSA; information on microfinance come from the National Bank of Ethiopia; and government expenditure and related official statistics are obtained from the Ministry of Planning and Development.

2.1. Data Analysis Methods

The study follows procedures of the AF framework (Alkire & Foster, 2009, 2011) to identify households as multidimensionally poor. These tools provide raw (unweighted) deprivation headcount ratios for each indicator which are equivalent to the headcount ratio of the FGT family of indices. We then compute AF multidimensional poverty indices and undertake subgroup decomposition. Multidimensional poverty and inequality among the multidimensionally poor are also computed based on Seth & Alkire (2014). For the multidimensional analyses, the procedures also provide weighted deprivation count, censored multidimensional poverty headcount ratio, average intensity of deprivations, adjusted multidimensional poverty index and multidimensional inequality index. Regressions are lastly used to identify the correlates of multidimensional poverty and inequality in urban Ethiopia.

2.1.1. Dimensions and indicators

We use 12 indicators categorized in four dimensions that represent the welfare of the household. Some of the indicators capture access to and utilization of basic infrastructural services such as education, health, water, sanitation, electricity, housing. Others measure food and nonfood poverty as well as access to information. The fact that children's deprivations are considered through nutrition and education also helps capture the future welfare of the society. The dimensions, indicators and their deprivation cut-offs are chosen based on the literature, SDGs and global MPI. Yet, attempts are made to customize them to the Ethiopian urban context.

Table 1 provides the selected dimensions, indicators, weights, and deprivation thresholds for constructing multidimensional poverty and inequality indices.

The tool developed by Alkire & Foster (2009, 2011), implemented by (UNDP, 2010) since 2010 and Alkire & Santos (2014) for a host of countries and referred by many as the global MPI, is a widely accepted framework for multidimensional poverty analysis. The global MPI primarily uses Demographic and Health Surveys (DHSs) for its data needs but advises contextualizing choices of dimensions and indicators according to needs. Hence, this paper first opts for using LSMS rather than DHS dataset since the former contains income and expenditure data which DHSs lack. Second, given that housing is one challenge in many urban settings, we consider the number of people living per room above a certain limit (overcrowding) as one deprivation which is not available in the global MPI. Third, our indices contain a monetary poverty dimension. Yet, we keep eight indicators of the global MPI with little adjustment of moving drinking water and sanitation deprivations to the health dimension.

Table 1: Dimensions, indicators, weights and deprivation cut-offs for multidimensional welfare

Dimension (weight)	*Indicator (weight)*	*Deprivation cut-off*	*Indicator in Global MPI?*
Education (1/4)	Formal education (1/8)	Any household member has no formal education (SDG4.6).	Yes
	Child enrolment (1/8)	School-age child not currently attending school (SDG4.1).	Yes
Health (1/4)	Child nutrition (1/12)	Child (6-83 months-old) is stunted (height-for-age z-score<-2) (SDG2.2; WHO).	Yes
	Safe water (1/12)	Unsafe source of drinking water (SDG6.1; WHO).	Yes
	Sanitation (1/12)	Unimproved toilet facility (SDG6.2).	Yes
Living standards (1/4)	Electricity (1/20)	No access to electricity (SDG7.1).	Yes
	Cooking fuel (1/20)	No improved cooking fuels (SDG7.1).	Yes
	Overcrowding (1/20)	Over 3 people live per room (SDG11.1; UN-Habitat).	New
	Floor (1/20)	Floor is natural, non-permanent material (SDG11.1).	Yes
	Information (1/20)	No TV/ radio/mobile phone/ fixed phone.	New
Monetary poverty (1/4)	Food poverty (1/8)	Adult per-capita food expenditure is below the national food poverty line (SDG1.2; NPC).	New
	Nonfood poverty (1/8)	Adult per-capita nonfood expenditure is below the national nonfood poverty line (SDG1.2; NPC).	New

Note: WHO=World Health Organization. NPC=National Planning Commission. TV=Television. SDG=Sustainable Development Goal. SDG1.2: Reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions. SDG2.2: End all forms of malnutrition. SDG4.1: Ensure that all girls and boys complete free, equitable and quality primary and secondary education leading to relevant and effective learning outcomes. SDG4.6: Ensure that all youth and a substantial proportion of adults, both men and women, achieve literacy and numeracy. SDG6.1: Achieve universal and equitable access to safe and affordable drinking water for all. SDG6.2: Achieve access to adequate and equitable sanitation and hygiene for all and end open defecation, paying special attention to the needs of women and girls and those in vulnerable situations. SDG7.1: Ensure universal access to affordable, reliable and modern energy services. SDG11.1: Ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums. In 2015/16, official annual adult equivalent food, nonfood and overall poverty lines were birr 3772, 3412 and 7184 respectively (NPC, 2017).

Education is an important indicator of present and future capability. Two indicators–years of schooling and compulsory child enrolment–form the education dimension. Whether any household member has no formal education captures deprivation in years of schooling while deprivation in child enrolment is measured by presence of any school-age child not in school. Indicator of school enrolment for children of compulsory school-age, which is 7 to 17 years in Ethiopia, is widely used in the literature (Alkire and Santos, 2014; Seff and Jolliffe, 2016) and goes in line with national standards and SDG targets. The health dimension is represented by three indicators capturing lacks in human capital functioning and other health issues. The first is child nutrition measured in terms of stunting. Following Seff & Jolliffe (2016) and WHO (2006), we use two more indicators which are traditionally included in the standards of living dimension (access to safe drinking water[5] and sanitation) to strengthen the health dimension. Education and health dimensions represent the extent of access to and utilization of basic infrastructural services and contain a certain element of intrahousehold inequality.

The five indicators in the living standards dimension are similar for all members and capture the household public goods component of welfare. They primarily measure deprivations in other basic services including housing, electricity, cooking fuel and information. Housing is one of the major problems in urban Ethiopia where we capture it here as whether over three people live per room (Santos and Villatoro, 2018). Quality of the floor is another housing indicator. The choice of informational assets over all other assets is also motivated by the literature and applied on Ethiopian data (Plavgo *et al.*, 2013). Deprivation cut-offs of the indicators are chiefly taken from SDG targets and national ones.

As can be seen from Table 1, monetary poverty is incorporated as a fourth dimension. The monetary dimension may be considered as capturing both present and future capabilities. It is composed of two indicators: food poverty and nonfood poverty. In this paper, consumption aggregates into food and nonfood expenditure as done by the World Bank's LSMS team are used and compared with the country's official absolute poverty lines (NPC, 2017). Regional price differences are assumed away. One challenge of including a monetary indicator in a multidimensional index is its possible correlation with nonmonetary

[5] This is captured by improved water sources defined as consisting of water piped into a dwelling, water piped into a yard or plot, a public tap or standpipe, a tube-well or borehole, a protected dug well, a protected spring, bottled water, or rainwater (WHO, 2006).

indicators which may ultimately affect weights given to them. However, using similar dataset used here, Seff & Jolliffe (2016) find that monetary and multidimensional poverty are not correlated. There is growing research favoring the inclusion of a monetary dimension in multidimensional welfare measurement (Sen, 1999; Atkinson, 2003; Stiglitz, Sen and Fitoussi, 2009). For example, Sen notes that "the role of income and wealth has to be integrated into a broader and fuller picture of success and deprivation" (Sen, 1999, p.20). Recent works have also estimated multidimensional poverty indices with monetary poverty (Bersisa and Heshmati, 2016, 2021; Rippin, 2016; Burchi, Rippin and Montenegro, 2018; Santos and Villatoro, 2018; World Bank, 2018; Goshu, 2019; Belete, 2021). For instance, Bersisa & Heshmati (2016, 2021) and Goshu (2019) in their multidimensional poverty index for Ethiopia include a monetary dimension with an indicator taking 1 if the household's adult per-capita expenditure is below the national poverty line. World Bank's first multidimensional poverty indices for various countries also incorporate a monetary indicator that the household consumes below the international US$1.90 per day per person line (World Bank, 2018).

2.1.2. Identifying the poor and aggregating multidimensional poverty and inequality

We follow the AF framework (Alkire & Foster, 2009, 2011) to identify households as multidimensionally poor. The single indicator raw deprivation rates or headcount ratios (h_j) for each indicator j are computed as:

$$h_j = \frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}\left(y_{ji} \leq z_j\right)$$

where $I_{(0,1)}\left(y_{ji} \leq z_j\right)$ is an indicator function taking 1 if the expression in parenthesis is satisfied and 0 otherwise; y_{ji} is attainment by household i in indicator j; z_j is the cut-off in indicator j, also called indicator-specific poverty line; and N is the number of households. Note also that raw deprivations provide the proportion of households who are deprived in a specific indicator, regardless of whether they are deemed multidimensionally poor, i.e. they are not censored by the multidimensional deprivation status (Apablaza and Yalonetzky, 2012). These are equivalent to the poverty headcount ratio (P_0) in the FGT indices

(Foster, Greer and Thorbecke, 1984). The traditional FGT indices are used to estimate monetary poverty headcount (P_0), gap (P_1) and severity (P_2) rates.
The sum of weighted deprivations (C_i) for each household i, also called deprivation score, is

$$C_i = \sum_{j=1}^{D} w_j I_{(0,1)}\left(y_{ji} \leq z_j\right)$$

where w_j is the weight given to indicator j; and D is the total number of indicators. Censoring at the cut-off and averaging helps get the aggregate multidimensional poverty headcount ratio (H) as

$$H = \frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}(C_i \geq k)$$

where k is the multidimensional poverty cut-off. Optionally, once the poor are identified, this can be expressed as $H = \frac{q}{N}$ where q is the number of the multidimensionally poor. Following Alkire and Santos (2014) and (UNDP, 2019), a household is then identified as multidimensionally poor if it is deprived in at least a third of the weighted deprivations, i.e. $h_i = I_{(0,1)}(C_i \geq k)$ where $k = 0.33$. We also consider other thresholds to see the sensitivity of multiple deprivations to the choice of these cut-offs[6].

The average intensity of multidimensional deprivations (A) or average percentage of weighted deprivations (as a proportion of the maximum number of possible deprivations) suffered by the multidimensionally poor households is given by

$$A = \frac{1}{N*D*h_j}\sum_{i=1}^{N} I_{(0,1)}(C_i \geq k) * C_i.$$

The adjusted multidimensional poverty index (M) is then simply given by the product

$$M = H * A.$$

[6] UNDP (2019) considers people in the range 0.20–0.33 as vulnerable to multidimensional poverty while those with a deprivation score of 0.50 or higher are in severe multidimensional poverty.

For decomposing multidimensional poverty into dimensions/indicators and population subgroups, we proceed as follows. The percentage contribution (Q_j) of indicator j to the adjusted multidimensional poverty M is:

$$Q_j = \frac{1}{N * D * M} \sum_{i=1}^{N} I_{(0,1)}\left(y_{ji} \leq z_j\right) * I_{(0,1)}(C_i \geq k)$$

where the terms on the right-hand side are as defined previously. Such a decomposition provides information that can be useful for revealing the country's deprivation structure and can be helpful to policy (UNDP, 2019). If we have S number of population subgroups, the percentage contribution of each subgroup s (e.g. urban region) to the adjusted multidimensional poverty index M is extracted from the identity:

$$\frac{m_1(\frac{N_1}{N})}{M} + \frac{m_2(\frac{N_2}{N})}{M} + \cdots + \frac{m_s(\frac{N_s}{N})}{M} = 1$$

where m_s is the value of M in subgroup $s = 1, 2, \ldots, S$ and N_s is the number of households in each subgroup. Each element at the left-hand side of the equation is, therefore, the contribution of a specific subgroup.

As noted by Sen (1976), a measure of poverty needs to satisfy three important aspects– incidence, intensity and inequality. The AF counting approach to poverty based on ordinal indicators lacks the inequality aspect (Seth and Alkire, 2014; Rippin, 2016; Burchi, Rippin and Montenegro, 2018). A poverty measure that is insensitive to inequality does not provide incentives to the policymaker to prioritize the conditions of the poorest. In other words, we need a measure of inequality in order to understand whether a poverty alleviation policy has been equitable across the poor. Although multidimensional poverty index can still be decomposable, it is inconclusive regarding the disparity across socio-demographic subgroups.

This study employs the measure suggested by Seth & Alkire (2014) which Abeje *et al*. (2019) also applied to Ethiopian data. The traditional Gini coefficient (G) is also used to measure inequality in monetary terms (consumption expenditure). The multidimensional inequality index (I_h) among the multidimensionally poor suggested by Seth & Alkire (2014) is

$$I_h = \frac{4}{q}\sum_{i=1}^{q}[C_i - A]^2$$

where q is the number of multidimensionally poor households; C_i is the weighted deprivation score of households i; and A is the intensity of multidimensional poverty, as defined earlier. It can also be computed for the whole household population by using the overall average deprivation score and leaving the denominator q so that we denote the index by I.

Weighting of dimensions and indicators is important in multidimensional welfare analysis. We opt to provide equal weights to all dimensions, and each indicator in a dimension is similarly equally weighted. This is the tradition in most of the literature. However, depending on the availability of further information and assumptions made, one may also assign subjective weights (Decancq, Fleurbaey and Maniquet, 2019) or statistically-computed weights (Bersisa and Heshmati, 2016; Tigre, 2018). Besides basing our choices of dimensions and indicators on the literature and attempting to customize them to the Ethiopian urban context, we undertake a statistical procedure to test if the indicators and their weights are relevant following Goshu (2019). We estimate linear pairwise and nonlinear tetrachoric correlations between the chosen indicators and the computed multidimensional poverty and inequality measures whose results are summarized in Table A3, all the correlations with the weighted deprivation score and multidimensional poverty as well as with the multidimensional inequality (except one indicator) are highly significant confirming that our chosen indicators along with their weights are appropriate to analyze multidimensional poverty and inequality in urban Ethiopia.

2.1.3. Identifying correlates of multidimensional poverty and inequality

To gain an understanding of the significant correlates of single deprivations, monetary poverty, and multidimensional poverty and inequality, econometric models are estimated. Such analyses supplement non-parametric descriptive analyses on the links between multidimensional urban poverty and inequality and various micro-, community- and macro-level factors. They also help identify constraints, opportunities and policy implications for reducing poverty and inequality in urban Ethiopia. However, these estimations do not aim to find the determinants of multidimensional poverty and inequality.

The general model takes the form $Y_i = \boldsymbol{X\beta} + \varepsilon_i$ where Y_i measures the status of household i in monetary poverty, multidimensional poverty or multidimensional inequality; vector $\boldsymbol{X}$ represents the potential correlates with their parameters $\boldsymbol{\beta}$; and ε_i is the error term. Since multidimensional inequality is difficult to measure at the household level, we proxy it by a squared variation of the household deprivation score from the average deprivation score. For those related to monetary and multidimensional poverty, a binary logit is estimated while for multidimensional inequality, a simple ordinary least squares model is estimated.

3. Results

3.1 Characteristics of urban households

Table 2 provides the characteristics of households for the full urban sample and by town size. 41% are headed by females which is slightly higher in medium and large towns (43%). Head's average age is 42 years and 37% of them are younger than 35 years with those in medium and large towns significantly younger. Average household size is 3.9 persons. Over the year preceding the survey, 15% of the households took credit of at least birr 500. More than a third of them have at least one migrating member over the past two years for various reasons which reaches almost half in small towns. In a tenth of the households there exists some form of child labor and this is over thrice more prevalent in small towns (20%) than in medium/large towns (6%). While illiteracy is significantly higher in small towns (42%) compared to that in medium/large towns (23%), completing a certain level of education is not.

Overall, food and nonfood monthly expenditures are significantly higher among households living in medium/large towns than in small towns. About 1 in 10 urban households receive international remittances. Price and non-price shocks are also rampant in urban Ethiopia. For example, about 30% faced food price rises during the previous year with no significant disparities by town size. Health, primary school, and microfinance branches are reported to be available at community (enumeration area) levels in over two-thirds of the households where small towns are better than medium or large towns.

Table 2. Demographic and socioeconomic characteristics of urban households by town size

Variable	*All urban Ethiopia*		*Small town*	*Medium/large*	*Test for difference*
	Mean	*SD*	*Mean*	*Mean*	*p-value*
Household head is female	0.41	0.492	0.39	0.43	0.123
Household head's age	42.25	14.941	44.29	43.45	0.049**
Household head is young (<35y)	0.37	0.482	0.27	0.35	0.003***
Household size	3.88	2.127	4.35	3.84	0.000***
Household head is married	0.59	0.492	0.65	0.56	0.003***
Household head is Christian	0.82	0.387	0.73	0.82	0.002***
Household head is Muslim	0.18	0.384	0.26	0.18	0.002***
Household has migrant members	0.38	0.485	0.48	0.32	0.000***
Household head is working	0.58	0.493	0.57	0.57	0.926
Any child is working	0.10	0.297	0.20	0.06	0.000***
Share of females in working age (15-60y)	0.56	0.302	0.55	0.56	0.420
Head's education: illiterate	0.26	0.438	0.41	0.23	0.000***
Head's education: elementary	0.29	0.453	0.29	0.32	0.282
Head's education: high school	0.22	0.416	0.11	0.22	0.000***
Head's education: above high school	0.23	0.422	0.18	0.23	0.044**
Monthly expenditure (adult equivalent)	885.44	675.314	697.74	1027.43	0.001***
Monthly food expenditure (ad. eq.)	577.71	513.900	480.03	668.75	0.027**
Monthly nonfood expenditure (ad. eq.)	261.49	263.327	201.05	302.11	0.001***
Household owns the dwelling	0.48	0.500	0.66	0.42	0.000***
Taken credit of at least birr 500 in a year	0.15	0.353	0.14	0.15	0.550
Received international remittances	0.09	0.281	0.06	0.10	0.003***
Shock faced: food price rise	0.29	0.455	0.27	0.32	0.033**
Shock: non-price	0.11	0.309	0.11	0.10	0.443
Community has health clinic	0.76	0.428	0.85	0.74	0.000***
Community has public primary school	0.76	0.425	0.80	0.76	0.095*
Community has microfinance institution	0.69	0.464	0.74	0.68	0.028**

Notes: SD=Standard deviation. *, ** & *** show an estimate in small towns is statistically different from that in medium/large towns at 10%, 5% & 1% level, respectively. For categorical variables, proportion chi-square test is used. All observations are weighted to make estimates representative.

Source: Based on data from ESS 2015/16.

3.1 Unidimensional Deprivations, Poverty and Inequality

Measuring welfare using only monetary indicators gives FGT poverty incidence of 38%, intensity or gap at 13% and severity of 6% (Table 3). Corresponding official figures during the same year (2015/16) in urban Ethiopia are much lower at 15%, 4% and 1.4% (NPC, 2017)[7]. Although the incidence of monetary poverty does not significantly vary with head's sex, poverty gap and severity are higher among female-headed households. Households in small towns are worse off in all measures of monetary poverty. Unlike previous findings (NPC, 2017; Goshu, 2019), our estimates also show that urban monetary poverty measures are lower than national averages in Addis Ababa and regions with higher rate of urbanization such as Tigray. On the other hand, urban monetary poverty in the regions of Amhara and SNNP stay above the national averages. Monetary inequality measure (Gini coefficient) based on consumption expenditure in urban Ethiopia is estimated as 0.37 which contrasts with the official figure of 0.38 for the same year. Differences exist when disaggregated by town size and regions where the metropolitan Addis Ababa has the lowest Gini at 0.31 while urban areas of SNNP region are the most unequal at Gini of 0.46.

Table 3: Monetary poverty and inequality indices in urban Ethiopia: 2015/16

	Poverty headcount (P_0)	*Poverty gap (P_1)*	*Poverty severity (P_2)*	*Gini Coefficient (G)*
All urban Ethiopia	0.38	0.13	0.06	0.37
Head's sex				
Male	0.37	0.12**	0.05**	0.37
Female	0.41	0.15	0.07	0.37
City/town size				
Medium/large	0.33***	0.10***	0.04***	0.35
Small town	0.55	0.22	0.12	0.37
Urban region				
Addis Ababa	0.26	0.07	0.03	0.31
Amhara	0.50	0.17	0.08	0.35
Oromia	0.37	0.13	0.07	0.34
SNNP	0.39	0.14	0.07	0.46
Tigray	0.32	0.09	0.03	0.36
Other regions	0.37	0.15	0.08	0.34

[7] However, this should be taken carefully; ESS's food expenditure data are on selected items which may overestimate food and overall poverty rates.

Notes: *, ** & *** show an estimate of a group (e.g., male) is statistically different from that of the other group just below it (e.g., female) at 10%, 5% & 1% level, respectively.[1] In 2015/16, official annual adult equivalent poverty line was birr 7,184 (NPC, 2017). All observations are weighted to make estimates representative. SNNP=Southern Nations, Nationalities and Peoples. "Other regions" represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions.
Source: Based on data from ESS 2015/16.

Nonmonetary deprivation rates for the whole sample and for selected socioeconomic groups are presented in Table 4. Monetary food and nonfood poverty indicators are also reported. In general, there is considerable deprivation in indicators of living standards besides high prevalence of food and nonfood poverty. There also exist certain disparities in deprivations when disaggregated by head's sex and town size. Deprivations in education in urban Ethiopia are the lowest of all the deprivations measured. 6% of households have any member not receiving formal education with similar proportion reporting to host a school-age child not in school during the time of the survey. In a tenth of the households, their lives at least one under-seven child whose height-for-age is below WHO's standards (stunted). This child nutrition deprivation is substantially higher in male-headed households (13%) than in female-headed ones (5%). Drinking water is still not safe for 7% of the urban households in the sample and female-headed households are slightly worse off (9%). Sanitation constitutes the largest deprivation within the health dimension where 27% lack improved sanitation facilities, reaching as high as 39% among households in small towns.

Table 4: Unidimensional deprivations in monetary and nonmonetary welfare indicators in urban Ethiopia by head's sex and location: 2015/16

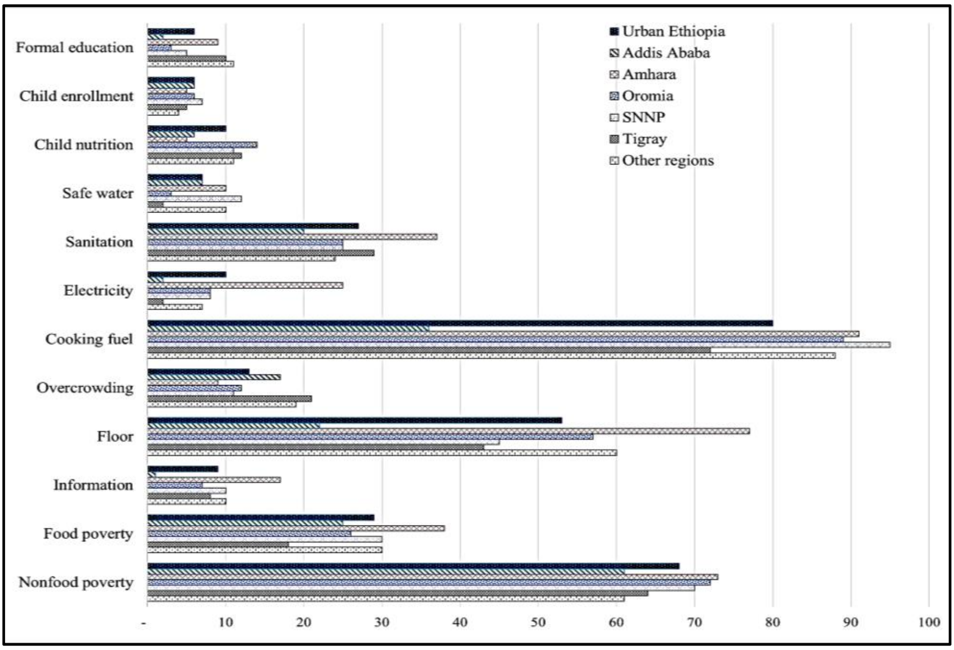
Dimension	*Indicator*	*All sample: urban Ethiopia*	*Head's sex*		*Town size*	
			Male	*Female*	*Medium/ large town*	*Small town*
Education	Formal education	0.06	0.04**	0.07	0.05	0.08
		(0.008)	*(0.010)*	*(0.012)*	*(0.008)*	*(0.020)*
	Child enrolment	0.06	0.05	0.06	0.06	0.06
		(0.006)	*(0.009)*	*(0.010)*	*(0.007)*	*(0.011)*
Health	Child nutrition	0.10	0.13***	0.05	0.09	0.12
		(0.012)	*(0.016)*	*(0.010)*	*(0.013)*	*(0.026)*
	Safe water	0.07	0.06*	0.09	0.08	0.06
		(0.016)	*(0.012)*	*(0.025)*	*(0.019)*	*(0.022)*
	Sanitation	0.27	0.26	0.29	0.23***	0.39
		(0.027)	*(0.029)*	*(0.034)*	*(0.030)*	*(0.053)*
Living standards	Electricity	0.10	0.07	0.15	0.09	0.14
		(0.032)	*(0.020)*	*(0.056)*	*(0.041)*	*(0.039)*
	Cooking fuel	0.80	0.80	0.80	0.75***	0.95
		(0.030)	*(0.033)*	*(0.034)*	*(0.039)*	*(0.019)*
	Overcrowding	0.13	0.15*	0.10	0.12	0.16
		(0.013)	*(0.018)*	*(0.017)*	*(0.015)*	*(0.031)*
	Floor	0.53	0.50	0.56	0.47***	0.73
		(0.036)	*(0.037)*	*(0.044)*	*(0.046)*	*(0.041)*
	Information	0.09	0.05***	0.15	0.07***	0.18
		(0.016)	*(0.012)*	*(0.026)*	*(0.020)*	*(0.027)*
Monetary poverty	Food poverty	0.29	0.27*	0.32	0.25***	0.42
		(0.023)	*(0.026)*	*(0.027)*	*(0.025)*	*(0.047)*
	Nonfood poverty	0.68	0.69	0.68	0.64***	0.81
		(0.023)	*(0.028)*	*(0.028)*	*(0.027)*	*(0.033)*

Notes: *, ** & *** show an estimate of a group (e.g., male) is statistically different from that of the other group just on the right (e.g., female) at 10%, 5% & 1% level, respectively. [1]In 2015/16, official annual adult equivalent food, nonfood and overall poverty lines were birr 3772, 3412 and 7184 respectively (NPC, 2017). Standard errors in parentheses. All observations are weighted to make estimates representative.

Source: Based on data from ESS 2015/16.

Deprivations in indicators of living standards are amongst the highest in urban Ethiopia. For example, 1 in 10 households has no electricity while an overwhelming 80% (95% in small towns) use unimproved cooking fuels. Partly proxying the housing problem, 13% of households have at least three of their members living in a single room. Over half of the houses have their floor made from natural, non-permanent material. This deprivation reaches about three quarters in small towns and is yet a major concern in medium and large towns (47%). About 1 in 10 households (as high as 1 in 5 in small towns) is disconnected from current information due to lack of information-providing assets. People in female-headed households are also highly deprived in information (15%). Food poverty is also high in urban Ethiopia where about 29% could not meet the national poverty line of birr 3772 per year per adult equivalent. Female-headed households (32%) and those living in small towns (42%) are the most affected in food poverty; and yet a quarter living in medium and large towns are food-poor. During the same period (2015/16), the official food poverty headcount rate in urban Ethiopia was reported as 15% while 28% in 2010/11 and 35% in 2004/05 (NPC, 2017). Nonfood poverty at 68% is over twice higher than food poverty which significantly varies by town size.

Figure 1: Deprivations in monetary and nonmonetary indicators in urban Ethiopia by region (%)



Notes: All observations are weighted to make estimates representative. SNNP=Southern Nations, Nationalities and Peoples. "Other regions" represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions.
Source: Based on data from ESS 2015/16.

Evidence on regional disparity in deprivations is depicted in Figure 1. Substantial variations exist in deprivations in almost all indicators across regions in urban Ethiopia. Compared with the national urban average (6%), deprivation in formal education is higher in Tigray (10%), Amhara (9%) and other less populated regions (11%) while Addis Ababa (2%) and Oromia (3%) are better performers. Deprivation in child enrolment is almost equally distributed in all regions. Nutrition deprivation measuring if any under-seven child is stunted in the household is the highest in Oromia followed by Tigray, SNNP and other regions. Concerning access to safe drinking water, SNNP (12%), Amhara (10%) and other regions (10%) have deprivations above the national average of 7%. Lack of sanitation is among the deprivations having big regional differences with Amhara region (37%) followed by Tigray (29%) performing poorly compared with Addis Ababa (20%).

Amhara region is also an outlier in terms lack of access to electricity with a quarter of urban households deprived while the national average is 10% and that in Addis Ababa is 2%. Use of unhealthy cooking fuels is the most widespread across all regions in urban Ethiopia. This deprivation ranges from 95% in SNNP region to 36% in Addis Ababa. Housing deprivation in terms of overcrowding (if more than 3 people live per room) also exhibits regional disparities ranging from 21% in Tigray to 9% in Amhara regions. However, housing quality is questionable where 77% of households in Amhara region live in houses whose floor are built with only natural and non-permanent materials. Oromia and other regions also have floor deprivations higher than the national average. Housing floor deprivation is expectedly the lowest in Addis Ababa (22%) compared with other urban areas in the country though still higher for a metropolitan city. This adds to the result that the City has one of the highest overcrowdings (17%). Information deprivation is the lowest in Addis Ababa and is the highest in urban areas of Amhara region. With regards to food poverty, except the outliers Amhara region (38%) and Tigray (18%), the headcount figures remain between 25% and 30%. Apart from worrisome higher incidences throughout, no substantial differences are noticed among regions on nonfood poverty.

Before analyzing the overall picture of poverty and inequality in a multidimensional context, it is worthwhile to see the deprivation score that is the weighted sum of deprivations in all indicators. This is depicted as a density curve in Figure A1 in the Appendix, disaggregated by town size and region. There exist large disparities in overall household deprivation across towns and regions. Notably, small towns and Amhara region have the highest accumulation of multidimensional deprivation in urban Ethiopia since their distribution curves remain atop of other comparison groups. In contrast, medium and large towns, and hence Addis Ababa, have the lowest cumulative deprivations.

3.2 Multidimensional Poverty and Inequality

Multidimensional poverty and inequality measures in urban Ethiopia are summarized in Table 5. There exists high incidence of multidimensional poverty (H) where 30% of the households lives below the multidimensional poverty line with high intensity (A) reaching 45% of the deprivations in weighted indicators. These make the adjusted multidimensional poverty index (M) 0.13. These compare with the estimates by UNDP & OPHI (2019) using DHS 2016 data for incidence, intensity and adjusted MPI in urban Ethiopia as 37%, 44% and 0.16 respectively although they do not include a monetary poverty dimension.

With regards to multidimensional inequality, the overall index in urban Ethiopia is estimated as 0.10 while the inequality among the multidimensionally poor is 0.048. An almost similar index for inequality among the multidimensionally poor for Ethiopia reported at the Human Development Report using DHS 2016 data is 0.024 (UNDP, 2019) whereas Seth & Alkire (2014) estimate a higher value of 0.129 for 2011, hinting that inequality among the poor rose between 2011 and 2016. In contrast, using a different approach and estimating for urban and rural areas, Goshu (2019) finds that multidimensional inequality increases with urbanization.

The issue of how multidimensional poverty and inequality vary with the choice of the multidimensional poverty cut-off is worth discussing. We estimate these measures at various cut-offs and summarize results in

Table A2 of the Appendix. At the worst extreme, i.e. if multidimensional poverty line is being deprived in at least 5% of the weighted indicators (*k=0.05*), we find 95% of households would be multidimensionally poor with an average intensity of 28% thereby making adjusted MPI of 0.26. Inequality among the multidimensionally poor stands at 0.094. At the other extreme cut-off of 0.80 or more, only 0.1% are multidimensionally poor with average intensity of 85% but almost none is in MPI. Inequality among the multidimensionally poor is 0.001 implying almost all at the highest deprivation cut-off are equally poor. UNDP (2019) defines that when the weighted deprivation score falls in the range 0.20–0.33 a household is vulnerable to multidimensional poverty; while at 0.50 or higher, severe multidimensional poverty sets in. Accordingly, another 30% of households is at risk of sliding into multidimensional poverty in urban Ethiopia while 7% lives in severe multidimensional poverty.

3.3 Decomposition of Multidimensional Poverty and Inequality

3.3.1 Decomposition by gender and location

Female-headed families are worse off in terms multidimensional welfare. Multidimensional poverty is significantly higher in households headed by females (0.15) compared to those headed by males (0.12) (Table 5). The difference comes from both incidence and intensity of poverty. Multidimensional inequality and the inequality among the multidimensionally poor are also substantially higher among female-headed households relative to the national urban average and male-headed households.

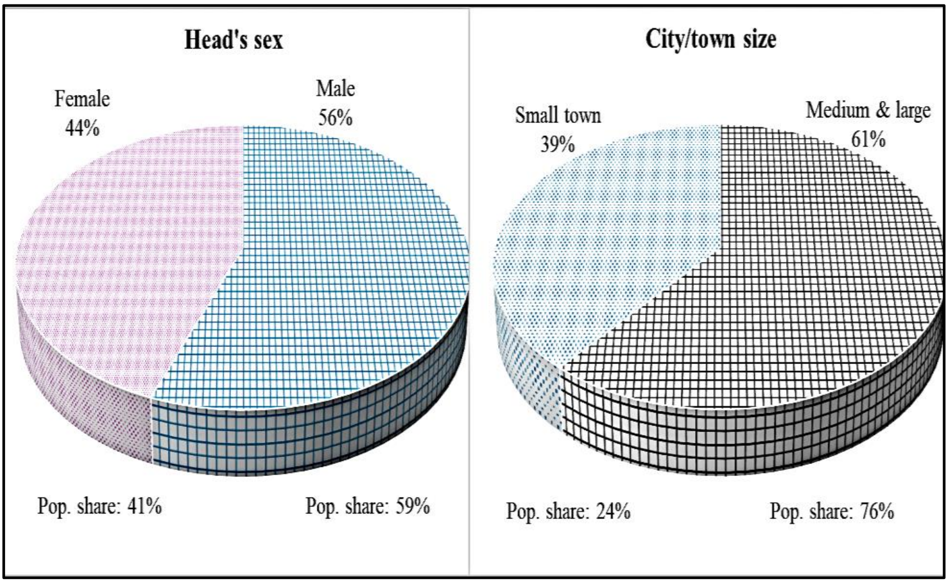
Table 5: Multidimensional poverty and inequality indices in urban Ethiopia: 2015/16

	Multi-dimensional poverty headcount	Average intensity of deprivations (A)	Adjusted multi-dimensional poverty index (M)	Multi-dimensional inequality (I)	Inequality among the multi-dimensionally poor
Urban Ethiopia	0.30	0.45	0.13	0.10	0.048
Head's sex					
Male	0.29*	0.44*	0.12*	0.09**	0.039**
Female	0.33	0.47	0.15	0.12	0.057
City/town size					
Medium/large	0.25***	0.45	0.11***	0.10	0.045
Small town	0.49	0.46	0.22	0.10	0.051
Urban region					
Addis Ababa	0.14	0.41	0.05	0.07	0.024
Amhara	0.43	0.46	0.20	0.11	0.045
Oromia	0.32	0.44	0.14	0.10	0.043
SNNP	0.31	0.46	0.14	0.11	0.057
Tigray	0.24	0.43	0.10	0.08	0.021
Other regions	0.30	0.46	0.14	0.12	0.086

Notes: k=0.33 is used as multidimensional poverty cut-off. *, ** & *** show an estimate of a group (e.g., male) is statistically different from that of the other group just below it (e.g., female) at 10%, 5% & 1% level, respectively. All observations are weighted to make estimates representative. Standard errors are not reported for brevity; they can be available upon request. SNNP=Southern Nations, Nationalities and Peoples. "Other regions" represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions. Source: Based on data from ESS 2015/16.

Regarding the distribution across regions, considerable disparities are observed particularly on the proportion of people living in multidimensional poverty. Like in the case of single and weighted deprivations, households in urban Amhara region at incidence, intensity and adjusted MPI of 43%, 46% and 0.20, respectively, are the most multidimensionally poor while those in Addis Ababa city are the least poor at 14%, 41% and 0.05. Urban areas in Oromia and SNNP regions are also other hotspots of multidimensional poverty. There is some regional variation in multidimensional inequality. A notable finding is that the most urbanized Tigray region and Addis Ababa city have the lowest overall multidimensional inequality and that among the multidimensionally poor.

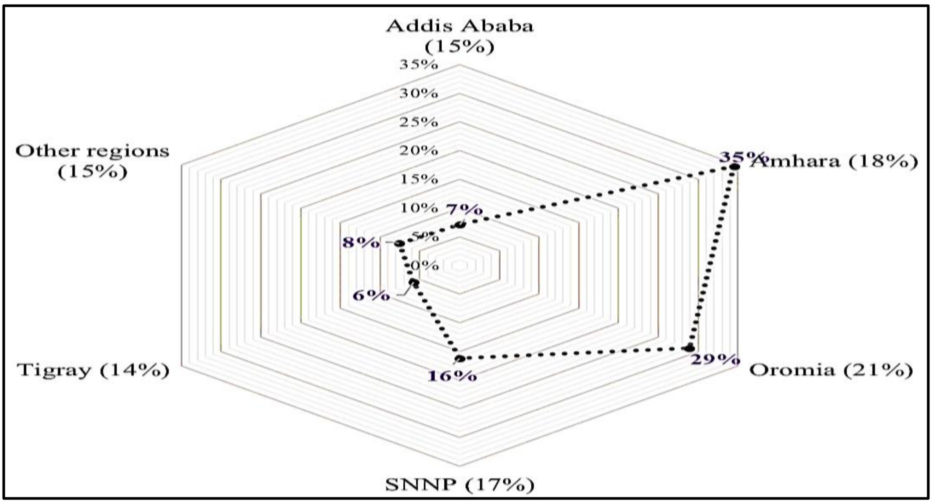
Figure 2: Contributions of population groups to multidimensional poverty in urban Ethiopia: 2015/16



Source: Based on data from ESS 2015/16.

After one considers their population shares, how do various population groups contribute to overall multidimensional poverty? Figure 2 contains results for selected groups using the AF decomposition procedure. It is found that female-headed households are slightly overrepresented in multidimensional poverty as they contribute 44% while their share in the urban population is lower at 41%. The contribution of households in small towns (39%) is also huge compared to their population share (24%).

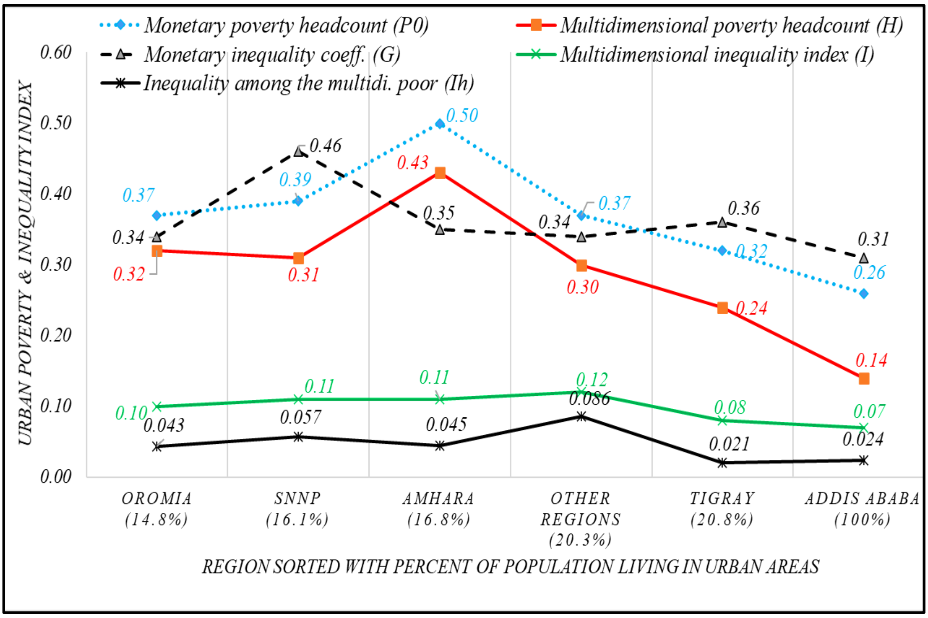
Figure 3: Contributions of regions to multidimensional poverty in urban Ethiopia 2015/16



Notes: Figures in parentheses represent percentage contributions of a region in the total urban population. SNNP=Southern Nations, Nationalities and Peoples. “Other regions” represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions. Source: Based on data from ESS 2015/16.

Regional contributions to adjusted multidimensional poverty is plotted in Figure 3. The county’s most populous regions, Oromia and Amhara, contribute much of the urban multidimensional poverty. However, Amhara region, with 18% share in the country’s urban population, contributes as much twice (35%) to adjusted multidimensional poverty. Oromia region still contributes more than its population (21%) to the MPI (29%). Urban population share and contribution to poverty almost match only for SNNP. Addis Ababa city and Tigray region are least contributors towards multidimensional poverty relative to their share in the country’s urban population.

Figure 4: Urban welfare indicators by region and urbanization rate: 2015/16



Notes: Regions are sorted in ascending order of their urbanization rate. SNNP=Southern Nations, Nationalities and Peoples. "Other regions" represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions.

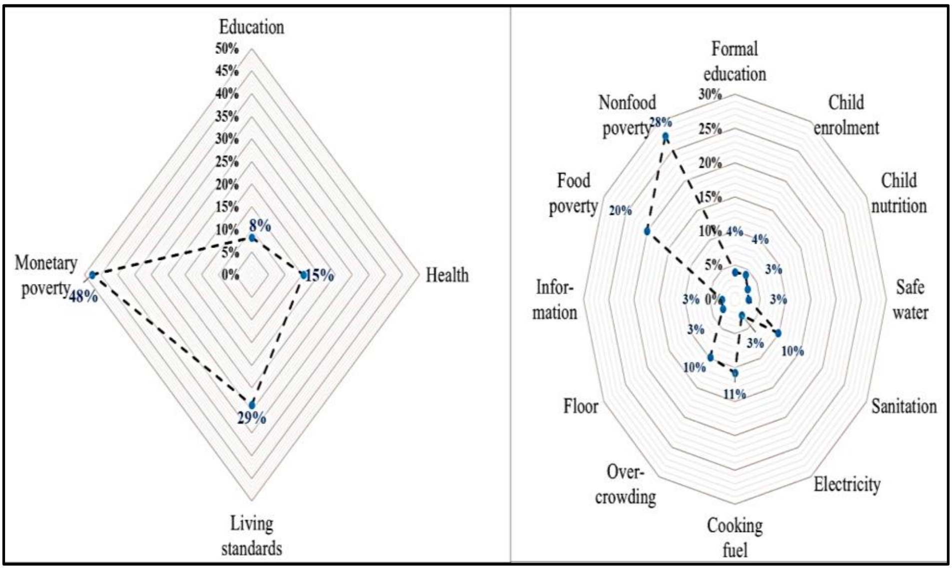
Source: Based on data from ESS 2015/16 and CSA (2013) Population Projections for 2016 (for urbanization).

Urbanization is widely thought to improve the welfare of people while some document that it did little to urban poverty particularly in SSA (Ravallion, Chen and Sangraula, 2007; Todaro and Smith, 2012). Our estimates seem to incline to the first hypothesis. We find that multidimensional poverty headcount in small towns is twice of that in medium/large towns with no significant difference in intensity (Table 5). Besides this evidence, we relate regional welfare estimates with corresponding regional urbanization rates (proportion of total population living in urban areas) obtained from CSA (2013). As depicted in Figure 4, the association urbanization has with multidimensional poverty and inequality as well as with monetary poverty takes the shape of an inverted-U while it generally seems to be inversely related to multidimensional inequality. These pro-urbanization findings contrast with those of Goshu (2019) that multidimensional poverty and inequality increase with urbanization.

3.3.2 Decomposition by indicators and dimensions

Figure 5 depicts the contributions of indicators and dimensions to adjusted multidimensional poverty in urban Ethiopia. As shown on the left panel, about half of the multidimensional poverty comes from monetary poverty dimension (48%), of which (right panel) 28% is contributed by nonfood poverty and the rest 20% by food poverty. This is followed by the dimension of living standards at 29% which is mainly contributed by deprivations in cooking fuels (11%) and floor of dwellings (10%). The health dimension contributes 15%, mainly due to sanitation deprivation (10%). Education is the least contributor at 8% with equal shares from its constituents (deprivations in a member's formal education and child enrolment). Large contributions of monetary and living standards dimensions in Ethiopia are also evidenced by Goshu (2019) estimating 44% and 16% respectively at country level. In the annual Human Development Reports, where multidimensional poverty index is estimated without a monetary dimension, the living standards dimension is always the dominant contributor, as high as 51% in 2016 (UNDP, 2019).

Figure 5: Contributions of dimensions and indicators to overall multidimensional poverty in urban Ethiopia: 2015/16



Source: Based on data from ESS 2015/16.

Table 6: Correlates of multidimensional poverty and inequality in urban Ethiopia: 2015/16

Variable	*Multidimensional poverty headcount (Logit)*			*Multidimensional Inequality (OLS)*			*Inequality among the multidimensionally poor (OLS)*		
	Urban Ethiopia	*Medium/ large*	*Small town*	*Urban Ethiopia*	*Medium/ large*	*Small town*	*Urban Ethiopia*	*Medium/ large*	*Small town*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Head is female	0.662***	0.717***	0.709*	0.027*	0.031*	0.010	0.018*	0.026*	–0.008
Head's age	0.018**	0.014*	0.045***	0.001*	0.000	0.002*	0.000	0.000	0.000
Household size	0.164***	0.161**	0.210***	0.001	–0.001	0.007	0.002	0.003	0.001
Any child is working	0.616*	0.645*	0.148	0.046	0.053	–0.007	0.010	0.028	–0.015
Females' share in working age	–0.58*	–0.528	–0.932*	0.015	–0.001	0.060	0.017	–0.008	0.065*
Owns the dwelling	–0.231	–0.213	–0.434	–0.004	–0.003	–0.016	0.000	–0.003	0.001
Taken credit of birr 500 or more	–0.639*	–0.555	–0.967*	–0.030*	–0.02	–0.055*	–0.025*	–0.01	–0.033
Has migrant members	–0.197	–0.06	–0.655*	–0.009	–0.006	–0.016	–0.003	–0.016	0.012
Received international remittances	–0.762**	–0.882**	–0.312	–0.016	–0.008	–0.062**	–0.03	–0.035	–0.030**
Shocks faced: food price rise	0.131	0.345	–0.309	0.027*	0.015	0.082*	0.035*	0.016	0.068*
Shocks faced: non-price	–0.105	–0.153	–0.018	–0.012	–0.013	–0.002	–0.018*	–0.018	–0.024*
Community: gov't primary school	–0.454*	–0.599*	0.007	–0.016	–0.031*	0.046	–0.003	–0.014	0.020
Community: microfinance institution	–0.478*	–0.388	–0.343	–0.003	0.001	0.003	–0.003	–0.016	0.013
Community: daily/weekly market	0.052	0.286	–1.349	–0.006	0.005	–0.166	0.014	0.018	–0.048*
Living in small town	1.009***	-	-	0.014	-	-	0.005	-	-
Region: Amhara[1]	1.389***	1.296***	1.398	0.026	0.027*	0.161	0.008	0.006	0.024
Region: Oromia[1]	0.806*	0.748*	0.768	0.009	–0.004	0.147	0.003	–0.016	0.034
Region: SNNP[1]	0.596	0.388	1.054	0.023	0.002	0.190*	0.023	–0.02	0.060
Region: Tigray[1]	0.538	0.626	0.405	–0.013	–0.005	0.116	–0.011	–0.02	0.013
Region: All others[1]	0.623	0.426	-	0.025	0.058	-	0.057	0.113*	-
Constant	–2.384***	–2.421**	–1.283*	0.054	0.080**	–0.073	–0.007	0.019	–0.016
Number of observations	1,625	1,214	411	1,625	1,214	411	504	288	216

Notes: *, ** & *** show statistical significance at 10%, 5% & 1% levels, respectively. [1]Comparison group is Addis Ababa. Multidimensional inequality is proxied by a squared variation of the household deprivation score from the average. SNNP=Southern Nations, Nationalities and Peoples. All observations are weighted to make estimates representative. Standard errors are not reported for brevity; they can be available upon request.
Source: Based on data from ESS 2015/16.

3.4 Factors Associated with Multidimensional Poverty and Inequality

Answering the question of what factors at household, community and macroeconomic levels could be associated with welfare is among the crucial steps to getting closer to policy implications. We run several regressions of monetary and multidimensional poverty, and inequality for the whole urban sample, small towns, and medium/large towns. Relevant diagnostic tests were done and passed before the final regressions were run.

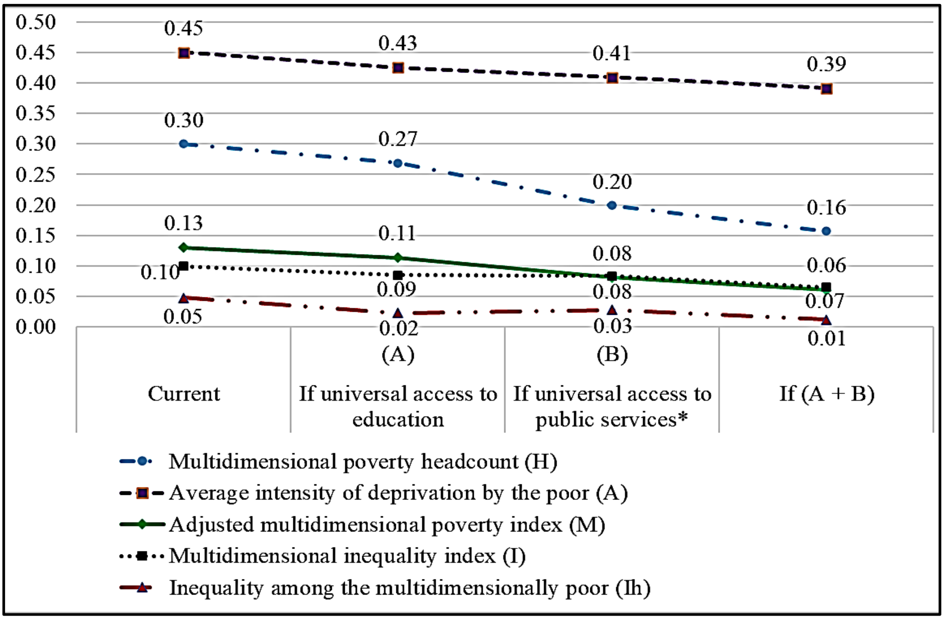
Table 6 summarizes results on the factors that have associations with households' multidimensional poverty status and inequality. Demographic factors such as female headship, increasing head's age and large household size increase the probability of being multidimensionally poor. Using 2011 and 2014 rounds of ESS that sample only rural and small towns of Ethiopia (excluding large and medium towns), Bersisa and Heshmati (2021) similarly find that households with more members and female heads have higher multidimensional poverty incidence. Our estimates show that multidimensional poverty is positively associated with child labor and negatively with higher share of working female adults. Financial factors are also found to be important where those having access to credit, receiving remittances and living closer to microfinance institutions report lower multidimensional poverty. Presence of a primary school in the community is also correlated negatively with multidimensional poverty. The previous finding that multidimensional poverty is higher in small towns and in regions of Amhara and Oromia (relative to Addis Ababa) is also confirmed when other factors are controlled in the regressions. This is also corroborated by Bersisa and Heshmati (2021) in rural and small towns, relative Dire Dawa.

We proxy multidimensional inequality at the household level by a variation of that household's deprivation score from the average weighted deprivation score. Apart from certain demographic and geographic factors, taking credit and receiving international remittances and a nearby primary school are found to reduce overall multidimensional inequality and that among the multidimensionally poor. In contrast, shocks in the form of food price rises worsen inequality.

Correlates of monetary poverty are presented in Table A4 in the Appendix. After controlling for demographic and geographic factors, monetary poverty is found to be lower in households headed by those with at least primary education. Bersisa and Heshmati (2021) likewise find for rural and small towns of Ethiopia that households with literate heads are less likely to be monetarily poor. Our estimates also reveal that living in places where microfinance institutions are available and access to credit are associated with lower monetary poverty.

Besides those micro- and community-level factors, there are numerous macroeconomic opportunities and constraints associated with urban multidimensional poverty and inequality in Ethiopia. As one opportunity, there seem to be overall government commitment and policy framework. Governments in Ethiopia have a history of preparing development plans aiming at addressing poverty and inequality. Recent ones include SDPRP (2006–2006), PASDEP (2006–2010), GTP I (2010/11–2014/15) and GTP II (2014/15–2019/20). The current government also unveiled the Ten-year Development Plan (2020/21–2029/30). Besides policy frameworks, commitment in terms of spending has also been noticed. For example, recent trends in poverty-targeted expenditures (education, health, agriculture, roads, water) over the period 2011/12–2015/16 averaged over two-thirds of total government expenditure (NPC, 2017). However, there are related constraints, including, among others (i) lack of efficiency by government agencies including implementation of policies at lower tiers of government; (ii) poor expenditure and project management coupled with corruption which not only increase the public debt but also result in inflation when projects take too long to give outputs while billions of funds are pumped into them; and (iii) poor provision and distribution and/or high cost of public infrastructure such as electricity, safe water and improved cooking fuels.

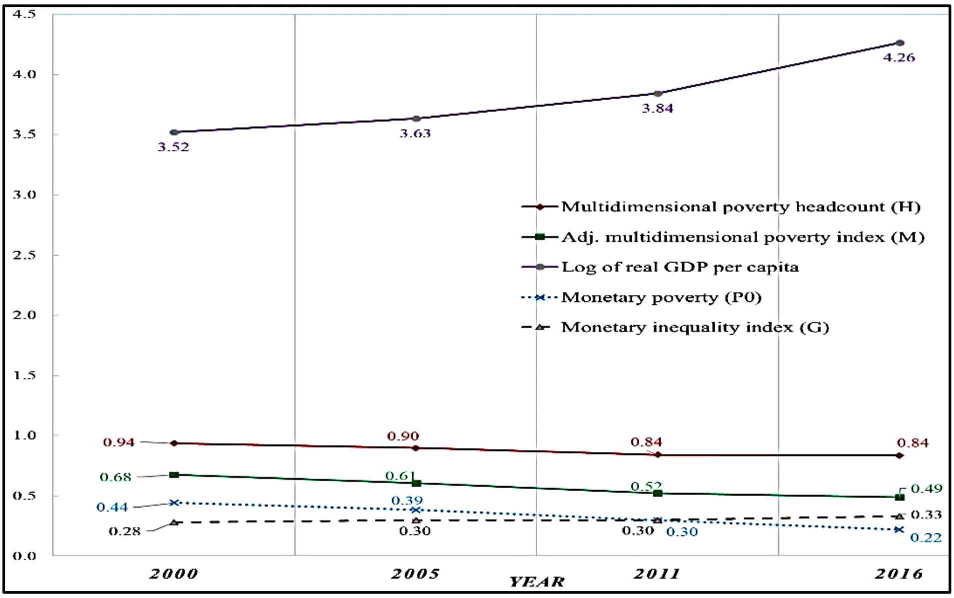
Figure 6: Universal coverage of publicly provided basic services and multidimensional welfare in urban Ethiopia: simulated



Notes: *Refers to universal access to water, electricity and improved cooking fuel. Standard errors in parentheses. All observations are weighted to make estimates representative.
Source: Based on data from ESS 2015/16.

The second opportunity is that there has been economic growth over the past decades, and this is expected to continue in the years to come. However, the quality of the recent past growth is questionable. Since 2000, four Demographic and Health Surveys and Household Income Consumption and Expenditure (HICE) surveys were conducted that helped estimate both monetary and multidimensional welfare measures in Ethiopia. Collecting these estimates from various sources and corresponding real per-capita GDP growth data from the National Bank of Ethiopia (NBE), we plot trends in Figure 7. A result that stands out is that the association between micro-level welfare and macro-context in terms at least of real per-capital GDP has not been uniform. Over 2000–2016, while monetary poverty headcount was halved, multidimensional poverty headcount fell only by 10 percentage points. In the five years spanning 2011–2016, during when economic growth was the fastest, multidimensional poverty headcount was virtually flat. The entire fifteen years were also characterized by a rise in expenditure inequality as measured by the Gini coefficient.

Figure 7: Recent trends of economic growth and monetary and multidimensional poverty and inequality in Ethiopia: 2000–2016



Source: Based on Alkire & Roche (2013), NPC (2017), NBE (2017), UNDP (2010, 2015, 2019).

As a third opportunity, a fairly large number of microfinance institutions exist in Ethiopia. According to the National Bank of Ethiopia, 46 microfinance institutions have been in operation in the country as of July 2020, and some are big and experienced. Moreover, 70% of urban households live in communities having a microfinance institution. However, ESS 2015/16 data show that household credit comes primarily from informal sources with formal or microcredit covering only 27% in urban areas. This is despite our findings that taking credit by households as well as availability of a microfinance institution at community level have desirable correlations with monetary and multidimensional poverty and inequality.

4. Conclusions and Policy Implications

4.1 Conclusions

This study aims at analyzing Ethiopia's urban multidimensional and monetary poverty and inequality levels, their sources, links to the macro-context, constraints, opportunities and policy issues. Multidimensional poverty and inequality indices use four dimensions, namely, education, health, living standards and monetary poverty, represented by twelve indicators relevant to Ethiopian's contexts and yet related to the literature and SDGs. Data primarily come from the urban sub-sample of ESS 2015/16 which is a LSMS-ISA project of the World Bank. Supplementary data and information also come from various sources.

Findings reveal large prevalence of food and nonfood poverty as well as substantial nonmonetary deprivation particularly in indicators of living standards such as housing and cooking fuels. National deprivation and poverty rates generally mask substantial variations across male-female headship, small town-medium/large town and region. Notably, many of the deprivations are found to be higher in female-headed households, small towns and Amhara region. Estimated monetary poverty incidence, gap and severity are higher than the official figures. Multidimensional poverty in urban Ethiopia is one of the highest with a larger proportion found at a risk of sliding into the same. About half of the overall multidimensional poverty comes from monetary poverty followed by deprivations in living standards, health and education. Overall multidimensional inequality index and the inequality among the multidimensionally poor may be lower but inequalities among regions and within female-headed households are large.

Poverty and inequality seem to fall with urbanization while regional differences are large. The most urbanized, Addis Ababa city and Tigray region, have the lowest deprivation, multidimensional poverty and inequality rates. Households in urban Amhara region have the highest incidence and adjusted multidimensional poverty rates. Given their population shares, small towns and those in Amhara and Oromia regions contribute more to urban multidimensional poverty. Although there seem to be overall government commitment, policy framework and economic growth as opportunities, numerous constraints challenge efforts of reducing poverty and inequality. Despite economic growth over the past decade seemingly halving monetary poverty, multidimensional poverty declined very steadily, and monetary inequality slightly rose. Besides demographic and geographic factors, receiving remittance, access to credit, availability of microfinance institutions and primary schools at community-level, food price shocks are among the factors that are correlated with various indicators of household welfare in urban Ethiopia. For instance, shocks in the form of food price rises worsen multidimensional inequality.

4.2 Policy Implications

The finding of substantial deprivation particularly in indicators of living standards dimension, which ranks as the second most contributor to overall multidimensional poverty, clearly needs intervention. As these deprivations include publicly provided infrastructural services such as electricity and drinking water, it is crucial that the government pursues a policy of affordable provision. Given that lack of improved cooking fuels is always among the top deprivations in Ethiopia, it requires special intervention. Relating it to universal access to electricity and promoting use of alternative sources of clean household energy may be of paramount help. Addressing the housing problems in urban areas, besides reducing household level overcrowding, is expected to have multiplier welfare effects. Strategies to address housing and related issues need to consider regional contexts and town sizes; one-size-fits-all strategy may not bring required results.

Large incidences of food and nonfood poverty, jointly contributing the largest share of overall multidimensional poverty, also call for interventions. Results imply policies advocating gendered interventions, family planning, and provision of education, credit and employment opportunities. On the other hand, the findings of notable disparities among regions and higher rates of deprivation, poverty and inequality in small towns inevitably call for installing fairer redistribution systems. Given that poverty and inequality are found to fall with urbanization, a policy direction towards planned urbanization is also recommended.

Promoting household access to microcredit and other sources of finance is also another vital strategy. The National Bank of Ethiopia needs to promote innovative forms of microcredit access to the poor by the financial institutions under its supervision. Stabilizing prices, especially of food, has effects on all forms of poverty and inequality. As the link between economic growth and poverty reduction is not perfect and with undesirable effects on inequality, redistribution policies including social protection programmes for those in severe welfare deprivations may also useful. We also suggest use of a multidimensional approach to welfare measurement, rather than only a monetary one, by the Ministry of Planning and Development for assessment of the country's progress towards reduction of poverty and inequality. As welfare is multidimensional, such a comprehensive approach which also reports monetary welfare measures helps monitor progress from various dimensions, align to the SDGs and improve targeting of the poor. Future research may use panel data and advanced econometric methods which consider endogeneity issues to identify the factors that determine multidimensional welfare in Ethiopia.

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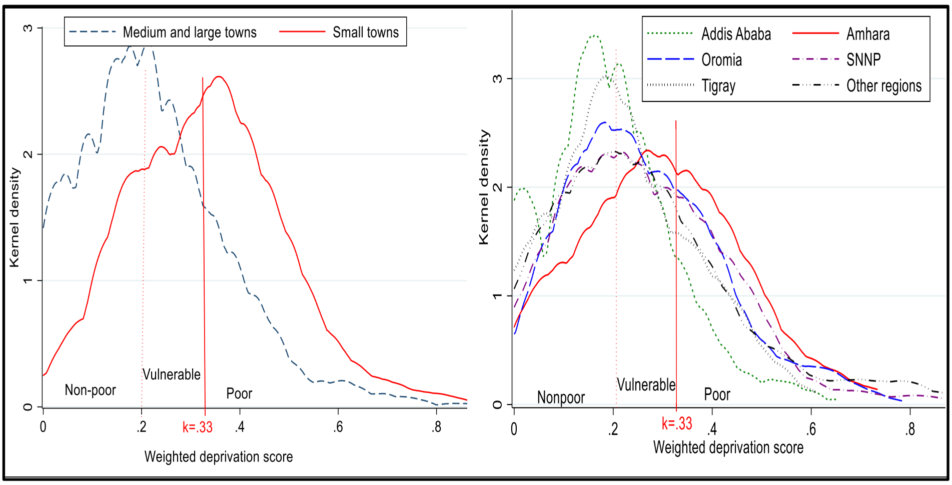
Appendix

Table A1: Distribution of urban households interviewed in ESS 2015/16 by region and town size

Region	*Distribution of households interviewed in urban areas*			
	Small towns	*Medium and large towns*	*Urban total*	*% of urban total*
Addis Ababa	*-*	*241*	*241*	*14.8*
Amhara	*103*	*193*	*296*	*18.2*
Oromia	*106*	*236*	*342*	*21.0*
SNNP	*97*	*180*	*277*	*17.0*
Tigray	*43*	*189*	*232*	*14.3*
All other regions	*62*	*175*	*237*	*14.6*
Urban total	*411*	*1,214*	*1,625*	*100.0*
% of urban total	*25.3*	*74.7*	*100.0*	

Notes: SNNP=Southern Nations, Nationalities and Peoples.
Source: Extracted from ESS 2015/16.

Figure A1: Density curves of weighted deprivation scores in urban Ethiopia by town size



Notes: SNNP=Southern Nations, Nationalities and Peoples. "Other regions" represents the regions of Afar, Benishangul-Gumuz, Gambella, Harari and Somali, and Dire Dawa city administration. ESS data are not separately representative in these regions. According to UNDP (2019), households with weighted deprivation cut-off of 0.33 or higher are identified as multidimensionally poor, those in the range 0.20–0.33 are vulnerable and those with 0.50 or higher are in severe multidimensional poverty.
Source: Based on data from ESS 2015/16.

Table A2: Multidimensional poverty and inequality at various cut-offs in urban Ethiopia: 2015/16

Multidimensional welfare measure	***Multidimensional poverty cut-off (k)***						
	k=0.05	***k=0.10***	***k=0.20***	***k=0.33***	***k=0.50***	***k=0.67***	***k=0.80***
Multidimensional poverty headcount	0.95	0.87	0.60	***0.30***	0.07	0.01	0.001
(H)	*(0.011)*	*(0.016)*	*(0.029)*	*(0.024)*	*(0.011)*	*(0.005)*	*(0.001)*
	0.28	0.30	0.36	***0.45***	0.62	0.75	0.85
Average intensity of deprivation (A)	*(0.009)*	*(0.008)*	*(0.007)*	*(0.008)*	*(0.011)*	*(0.016)*	*(0.003)*
Adjusted multidimensional poverty	0.26	0.25	0.21	**0.13**	0.04	0.01	0.00
index (M)	*(0.010)*	*(0.011)*	*(0.013)*	*(0.012)*	*(0.007)*	*(0.004)*	*(0.001)*
Inequality among the	0.094	0.083	0.063	***0.048***	0.028	0.012	0.001
multidimensionally poor (I_h)	*(0.007)*	*(0.006)*	*(0.006)*	*(0.007)*	*(0.006)*	*(0.004)*	*(0.000)*

Notes: Standard errors in parentheses. All observations are weighted to make estimates representative.

Source: Based on data from ESS 2015/16.

Table A3: Correlations between indicators and multidimensional poverty and inequality measures in urban Ethiopia: 2015/16

Dimension	Indicator	Correlation with Weighted deprivation score	Correlation with Multidimensional poverty status	Correlation with Multidimensional inequality
Education	Formal education	0.3753***	0.6188***	0.3676***
	Child enrolment	0.2836***	0.5901***	0.1900***
Health	Child nutrition	0.2132***	0.3241***	0.0910***
	Safe water	0.2621***	0.3768***	0.3260***
	Sanitation	0.5101***	0.5897***	0.2112***
Living standards	Electricity	0.4033***	0.6087***	0.3816***
	Cooking fuel	0.3955***	0.6167***	–0.0271
	Overcrowding	0.2857***	0.4140***	0.0729***
	Floor	0.5255***	0.6772***	0.1131***
	Information	0.4387***	0.6786***	0.3853***
Monetary poverty	Food poverty	0.5942***	0.8294***	0.2333***
	Nonfood poverty	0.6043***	0.7296***	–0.1087***

Notes: *** denotes correlation is significant at 1% level. The correlation with multidimensional poverty status is tetrachoric (nonlinear) while other correlations are linear pairwise.

Source: Based on data from ESS 2015/16.

Table A4: Correlates of monetary poverty in urban Ethiopia in 2015/16: logit marginal effects

Variable	Urban Ethiopia	Medium/ large town	Small town
	(1)	*(2)*	*(3)*
Head is female	0.081*	0.111**	0.008
Head's age	–0.002	–0.002	0.001
Household size	0.045***	0.041***	0.062***
Has migrant members	–0.021	0.019	–0.135*
Received international remittances	–0.066	–0.105*	0.136
Head's educ: elementary[1]	–0.122**	–0.172**	–0.033
Head's educ: high school[1]	–0.206***	–0.261***	–0.057
Head's educ: >high school[1]	–0.337***	–0.377***	–0.271**
Any child is working	0.091	0.085	0.019
Females' share in working age	–0.171**	–0.187**	–0.112
Owns the dwelling	–0.018	–0.035	0.020
Taken credit of birr 500 or more	–0.096*	–0.064	–0.220**
Shocks faced: food price rise	–0.007	0.021	–0.047
Shocks faced: non-price	0.031	0.007	0.108
Community: gov't primary school	–0.076*	–0.128*	0.100
Community: microfinance institution	–0.100*	–0.094	–0.165
Community: daily/weekly market	0.069	0.052	0.128
Living in small town	0.167**	-	-
Region: Amhara[2]	0.133*	0.108	0.102
Region: Oromia[2]	–0.014	0.010	–0.119
Region: SNNP[2]	–0.014	–0.059	0.044
Region: Tigray[2]	–0.023	–0.056	0.016
Region: All others[2]	–0.051	–0.040	-
Expenditure quintile: poor[3]			
Expenditure quintile: middle[3]			
Expenditure quintile: rich[3]			
Expenditure quintile: richest[3]			
Constant	0.531***	0.638***	0.377
Number of observations	1,625	1,214	411

Notes: *, ** & *** show statistical significance at 10%, 5% & 1% levels, respectively. [1]Comparison: illiterate. [2]Comparison: Addis Ababa.[3] Comparison: poorest. Multidimensional inequality is proxied by a squared variation of the household deprivation score from the average. SNNP=Southern Nations, Nationalities and Peoples. All observations are weighted to make estimates representative. Standard errors are not reported for brevity; they can be available upon request.

Source: Based on data from ESS 2015/16.

Determinants of Smallholder Farmers' Market Orientation for Small-Scale Crop Commercialization in West Gojjam Zone, Amhara Region, Ethiopia[1]

Lijalem Abebaw[2, 3,*], Worku Tuffa[2], and Dawit Alemu[4]

Abstract

The study examines the determinants of smallholder farmers' market orientation considering agro-ecology and transaction costs. Multistage sampling procedure was used to collect quantitative data from 405 randomly selected smallholder farmers. Qualitative data were collected through key informant interview and focus group discussions. Descriptive statistics, one-way ANOVA and zero-inflated beta regression were used to analyze quantitative data while narration data analysis used to analyze the qualitative data. The results have revealed that smallholder farmers in the lowlands and midlands are more market oriented than they are in the highlands. Education increases the probability and proportion of market orientation. Farmland size and farmland rental contracts positively influence the probability of market orientation. Distance from home to nearby markets negatively affect the proportion of smallholder farmers' market orientation. Mobile possession positively influences the probability of market orientation. Membership to farmers cooperatives enhances extent of market orientation. The findings have suggested that human capital, physical resource endowments and arrangement, transaction costs, cooperatives, and agro-ecological endowment affect smallholder farmers' market orientation. Therefore, education, farmland rental contracts, infrastructure development, and soil fertility improving technologies are needed to increase market orientation and promote small-scale commercialization.

Keywords: market orientation; agro-ecology; transaction cost; zero-inflated beta regression

JEL Code: Q12, Q13, Q15, Q18

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1. Introduction

Crop production in Ethiopia has dominant role in the agriculture sector of the economy. It is a source of livelihood for large number of populations, which contributes for food and nutrition security, and export earnings. The smallholder farmers cultivate more than 96 percent of the cultivated farmland (Taffesse et al., 2011). This implies commercialization of smallholder farmers crop production have vital role to transform the economy. The Ethiopian government in its Agriculture Development Led Industrialization (ADLI) economic development policy and consecutive Growth and Transformation strategic plans give due attention for smallholder farmers crop commercialization.

Crop commercialization leads to greater market orientation of farm production which is manifested through increase in purchase of traded inputs and decline in utilizing non-traded inputs and the decline of mixed farming system to specialized production (Pingali, 2001; Pingali and Rosegrant, 1995). Small-scale crop commercialization necessitates product choice and input use decisions, and allocation of resources based on market signals (Abafita et al., 2016; Gebremedhin and Jaleta, 2010; Pingali, 1997; Pingali and Rosegrant, 1995). In other words, it is market-orientation, which can be defined as production decision manifested through a relative choice of crop products and allocation of inputs to meet the market demand. It is higher input allocation for marketable products than households' food products. Consequently, market orientation of smallholder farmers implies decisions towards the production of marketable crop species and the allocation of more agricultural land and other inputs.

Market orientation is commonly affected by socio-demographic characteristics, physical resource endowments, commodities productivity, and input and output markets (Gebremedhin and Jaleta, 2010; Micheels and Gow, 2008; Pingali and Rosegrant, 1995). The resource endowments comprise farm households′ socio-demographic characteristics such as household head, age, education, family size, and labor. Physical resource endowments contain farmland size and equines. Institutional services include access to market information, credit and agricultural extension services. Commodity production is affected by agro-ecological endowment (Behera et al., 2007; Eledu et al., 2004). Agro-ecology induces diversity of agro-ecosystem services, which affects crop types production because, certain type of agro-ecosystem services is suitable for production of specific crop type (Behera et al., 2007). Therefore, agro-ecology affects crop production and revenue (Taffesse et al., 2012). Access to market is affected by transaction costs (Alene et al., 2008; Baraka et al., 2019; Holloway et al., 2000; Olwande et al., 2015; Williamson, 1981). Thus, the transaction cost associated with exchange of inputs and outputs in markets increases, leading to the inefficiency of input and output markets (Baraka et al., 2019; de Janvry et al., 1991).

The previous literature focuses on the theoretical explanations in factors affecting market-oriented farming with less attention to empirical analysis to smallholder farmers. The exception is the work by Gebremedhin and Jaleta (2010) who analyzed the determinants of market orientation. The previous literature has explained that agro-ecology affects crop production and revenue; however, it does not reveal its association with smallholder farmers decision in resource allocation to marketable crop types based on market signal. Moreover, the literature employs Ordinary Least Square (OLS) and Tobit regressions, which assume normal distribution. However, the market orientation is an index that has both Bernoulli and beta distributions. Thus, zero-inflated beta regression enables better treatment of beta and Bernoulli distribution. Lastly, from practical point of view, understanding the factors affecting smallholder farmers market orientation focusing on agro-ecology and transaction costs plays an important role in turning smallholder mixed production systems into specialized and market-oriented production thereby enhance small-scale commercialization.

2. Literature Review

Market orientation is smallholder farmers' production decision manifested through a relative choice of crop products and allocation of inputs to meet the market demand. In practical terms, market orientation is decisions towards the production of marketable crop species and the allocation of more agricultural land and other inputs. Resource endowments, the productivity of commodities and output markets are considered important determinants of the market-oriented decision of smallholder farmers (Gebremedhin and Jaleta, 2010; Micheels and Gow, 2008). Resource endowment such as farmland and labour affect crop type choice (Behera et al., 2007; Donovan and Poole, 2014; Hitayezu et al., 2016). The smallholder farmers cultivate multiple crops. The relative allocation of farmland size for mix of crops is affected by farmland size and farm household labour. Farm household labour constrains cultivation of crop types demand intensive labour for management practices where as larger farmland size encrourages production of marketable crop types (Donovan and Poole, 2014). Commodity productivity and market price, on the other hand, are key criteria for resource allocation (Micheels and Gow, 2008), which is a response to changing market prices, comparative advantage, and economic opportunity (Rosegrant et al., 1995). Farmers' decision on the relative allocation of farmland to the product mix to be produced is often based on considerations that could maximize benefits. In this regard, empirical evidence shows that market-oriented producers consider both the productivity of commodities and the market price to maximize profits (Micheels, 2010; Micheels and Gow, 2008; Suh and Moss, 2018).

On the other hand, crop production varies by agro-ecology, as differences in agro-ecological endowments increase the production of specialized commodities increases (Timmer, 1997). Agro-ecology refers to the interaction of the ecology, agronomy, local knowledge and social settings of a particular community that creates an agro-ecosystem suitable for a local context (Hazard et al., 2017). The agro-ecosystem affects the diversity, interaction and synergy of crop and livestock species (Conway, 1983; Tittonel, 2015). Diverse agricultural systems include diverse agricultural practices, landscapes and species diversity (Kremen et al., 2012). The interaction process stimulates the function of the agro-ecosystem, which increases resource use efficiency and commodity production potential (Tittonel, 2015).

Transaction cost is the cost of carrying out transaction of goods and services between the buyer and seller (Fischer and Qaim, 2012). Transaction cost includes costs for searching of a trading partner with whom goods or services are exchanged, negotiating a price and bargaining with potential trading partner, and transferring the product (Fischer and Qaim, 2012; Holloway et al., 2000). Transaction cost is classified in to fixed and proportional transaction cost (Key et al., 2000). Fixed transaction costs are costs that are invariant based on the volume of traded good or service. Whereas proportional transaction costs are variable costs that differ based on the volume of traded good or service. Markets in developing countries are characterized by poor infrastructure and limited access to information (Ingenbleek et al., 2013). As a result, the transaction cost associated with exchange of input and outputs in markets increases, leading to the inefficiency of input and output markets (Baraka et al., 2019; de Janvry et al., 1991). With this regard, transaction cost is expected to affect smallholder farmers' market orientation but still there is a need to analyze the empirical data.

3. Methodology

3.1 Description of the study area

West Gojjam zone is one of the 13 administrative zones of Amhara region. It is located in north west of Ethiopia. Its capital, Finote Selam, is 385 km far from Addis Ababa, on the other hand, 171 kms far from the Amhara region capital, Bahir Dar. West Gojjam zone has fourteen woredas and six town administrations. The total population is 2,758,806 and the population density is 158.25 persons per square kilometer (CSA, 2008). The rural and urban dwellers are 2,306,999 and 451,807, respectively (ibid). The zone covers an area of 13,311.94 square kilometers. Elevation ranges from 684 to 3656 masl[5] (meter above sea level) (West Gojjam zone plan commission, 2013).

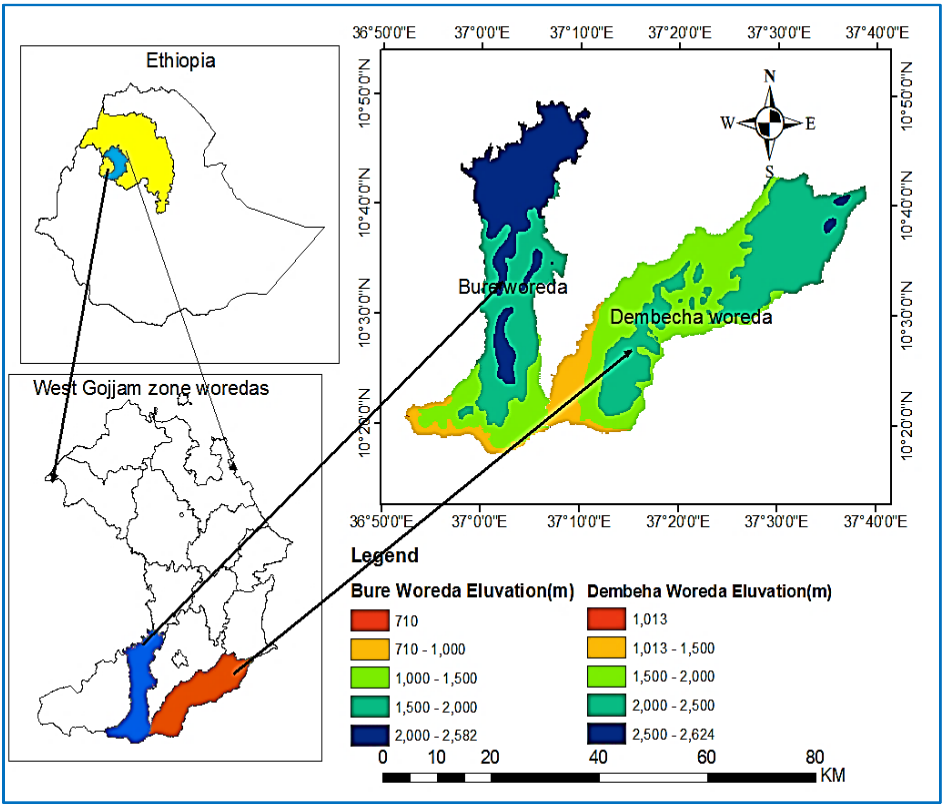
Crop production is unevenly distributed throughout the study area in line with the altitude, soil type and fertility, temperature, rainfall, infrastructure and market access. Altitudes, rainfall, and average temperature ranging from 1700 to 3000 masl, 1057 to 1657 millimeter and 15 to 27.5 degree Celsius, respectively (Amede et al., 2017; Deressa et al., 2010). The area has a favorable environment for the production of different crops (Amede et al., 2017); consequently, the study area is potential producer of diversified crop types such as cereals, pulses, oilseeds, vegetables and fruits. According to Central Statistical Authority (CSA, 2014), in west Gojjam zone, the cultivated farmland size is estimated to be 612, 297.16 hectare covered by teff, maize, wheat, pepper, millet, barely, potato, onion, beans, peans, chickpea, grass pea and niger seed and vegetables and fruits. The annual crops covered more than 93 percent of the total crop cultivated farmlands (Gebremedhin and Jaleta, 2010b; Taffesse et al., 2011). To this effect, the study analyzes smallholder farmers' annual crop types market orientation. The per capita farmland holding size in the study area ranges from a minimum of less than 0.1 to a maximum of 10 hectares and average of 1.23 hectares. The study area has also a strong livestock component, dominated by cattle, followed by sheep, goats and equines, which supports crop production through providing draft power and market access.

Market oriented production to transformation the agriculture sector is the major development strategy in the last more than 20 years, which have effect on smallholder farmers market-oriented production. The institutions responsible in commercial transformation of agriculture are Amhara Region Agriculture

[5] above sea level

Bureau, Amhara Region Research Institute (ARARI), Farmers' cooperatives and unions, and Amhara Credit and Saving Institute (ACSI). The institutions involve in assisting the smallholder farmers in technology generation, provide extension advisory and credit services, and supply improved agricultural technologies such as improved seeds, chemical fertilizer, herbicides, and pesticides. Thus, the study area is purposively selected as the region is more prone to crop production and there have been efforts by public and private organizations to enhance market-oriented crop productions to transform the economy.

Figure 1: Map of the study area



3.2 Research Design

A mixed research design combines quantitative and qualitative research design (Creswell, 2013; Graff, 2013; Howe, 1988). The mixed research design is useful if quantitative or qualitative research approach is inadequate to understand the research problem (Creswell, 2009). In other words, the purpose of using mixed methods is for triangulation and complementarity (Greene et al., 1989). Triangulation is seeking convergence of research findings using multiple methods. Complementarity is using different methods to assess different study components or phenomenon. Quantitative research is used to quantify the resource endowments, biophysical and institutional variables and its association with market orientation. The qualitative research is used to collect qualitative data through individual interview and focus group discussions to conceptualize the market orientation. and also, justify why and how the explanatory variables affect the market orientation. A variety of qualitative and quantitative methods give deeper insights and clear picture of the complexity of research problems in the local context (DFID, 1999; Mushongah and Scoones, 2012). Thus, mixing quantitative and qualitative research approach are in-deed compatible in investigating the research problem (Howe, 1988).

3.3 Sampling Procedure, Sample Size, Data Collection and Analysis

Sampling procedure:- proportion to the size and multistage random sampling strategy were employed to select respondent farmers. Accordingly, Dembecha zuria and Burie Zuria woredas were selected through lottery method among fourteen woredas administered in west Gojjam zone. Dembecha zuria and Burie Zuria woreda has 31 and 21 kebeles, respectively. Woreda agriculture offices clustered the number of kebeles as lowland, midland and highland based on their altitude and crop production system. Accordingly, a kebele from each agro-ecology for both districts were randomly selected. Hence, seven kebeles[6] namely Zeyushewen, Wadera and Ambaye from Burie Zuria district; and Astevoch, Egziabhierab, Yesheboch and Gelila from Dembecha Zuria district were selected randomly from list of highlands, midland and lowland kebeles, respectively. Proportion to size sampling strategy was employed to select sampled farmers from each *kebele* (Table 1).

Sample size:- Cochran sample size determination formula was used as the study area has large population size (Israel, 1992). Cochran formula make the sample size 385 and then, we add contingency 5 percent making the total sample size 405 respondents. Since we do not have much information about market orientation of the population, to get maximum variability we assumed 50% of the

[6] Kebele is the lowest administrative unit in the government structure

population was market oriented and also, employ 95% confidence interval with 5 % precision.

$$n_0 = \frac{z^2pq}{e^2} \quad \textbf{(1)}$$

Where: z is 1.96, p is the estimated proportion of the population who is market oriented (0.5) q= (1- p) =0.5 and e is the precision level (0.05).

Data collection method: Quantitative and qualitative data were collected to analyze the determinants of smallholder farmers' market orientation. Quantitative data were collected using structured questionnaires through personal interview. The questionnaire, translated to Amharic, contains farm households' socio-demographic characteristics, physical and financial assets, agro-ecology, crop production, input-output markets, transaction costs and access to institutions. Qualitative data were collected using checklist through individual interview and focus group discussions to substantiate the quantitative data, which is moderated by the first author.

Data analysis: quantitative data analysis is done through descriptive statistics, inferential statistics such as chi-square test, one-way ANOVA and zero-inflated beta regression. Qualitative data was analyzed through narration method of analysis.

3.4 Conceptualizing Market Orientation

As it is discussed earlier, market orientation is about smallholder farmers' economic decision-making in the allocation of resources to the mix of crops produced for both household consumption and market. In the livestock-crop mixed farming system of the study area, the farmers produce different types of food and high-value crops both to meet their household consumption and marketed surplus. The annual crops types produced by the farmers, in the study area and used for analysis, are pepper, maize, teff, wheat, millet, barely, faba bean, chickpea, field pea, niger seed, potato, and onion. Market orientation entails people's allocation of farmland to the mix of crop types produced to maximize benefit based on productivity and market price. In this process of farmers' decision, the smallholder farmers' want to maximize their expected utility in deciding the allocation of resources to produce both for household consumption and marketable surplus.

Market orientation is calculated as the smallholder farmland allocation to each type of crop cultivated, weighted by the marketability of each crop at farmer level, divided by the total area cultivated per crop. In previous studies, market orientation is calculated as the smallholder land allocation to each type of crop cultivated, weighted by the marketability of each crop in a specific location divided by the total area cultivated per crop (Abafita et al., 2016; Gebremedhin and Jaleta, 2010; Tefera, 2014). This study, however, employs the marketability index of smallholder farmers, which weighs the allocation of land that can measure variability at the farmer level, for fear that the location specific marketability index may overestimate or underestimate the marketability index of the farmer. Therefore, it is calculated that market orientation as the sum of farmland allocated for each crop cultivated, weighted by the marketability of the same type of crop at the farmer level, divided by the total cultivated land in a given production year. The higher the allocation of farmland for marketable crops, the higher the farmer market orientation index will be. No market orientation means that the smallholder farmer do not market produced crop(s) in a particular production year, while Market Orientation Index (MOI) equals one means that a farmer allocated the total farmland for a single crop production and has marketed the total quantity produced.

$$MOI_i = \sum_{i=1}^{n} \frac{l_{ji}}{l_{ti}} * M_{ji} \qquad 0 \leq MOI < 1 \qquad \textbf{(2)}$$

Where;

MOI_i Market orientation index of farmer i

l_{ji} farmland size (hectare) allocated to crop j by the farmer i

l_{ti} total farmland size cultivated for crop production by the farmer i

M_{ji} Marketability index of crop j of the farmer i

Marketability index is the amount of crop j marketed divided by the total crop j produced by the farmer i, in a specific production year.

$$M_{ji} = \frac{c_{mji}}{c_{pji}} \qquad \textbf{(3)}$$

Where;

c_{mji} amount of crop (quintal) j marketed by the farmer i

c_{pji} amount of crop j produced by the farmer i

M_{ji} marketability index of crop j of the farmer i

3.5 Econometric Model: Application of Zero-Inflated Beta Regression

The empirical MOI data is continuous proportion contains zero (0≤MOI<1). Linear regression is not appropriate in the restricted proportional, indexed and rate of dependent variables between 0 and 1 (Ferrari and Cribari-Neto, 2004). This is because, the same source states that proportions are asymmetry and the predictions based on normality assumption are misleading. Zero-inflated beta regression assumes that the dependent variable has mixed continuous-discrete distribution with a probability of mass at zero (Ospina and Ferrari, 2012). Cognizant to this fact, the empirical MOI contains zero values that make a mixed continuous-discrete distribution. The discrete distribution is Bernoulli distribution at a farmer did not allocate farmland to cultivate crop for market in the production year (MOI=0). The beta distribution parameterized in terms of smallholder farmers' market orientation mean and precision parameter, and Bernoulli distribution is the probability of farmers that do not allocate farmland to cultivate crop commodity for sale in a production year. Thus, zero-inflated beta regression computes the smallholder farmers market orientation mean and the precision parameter of beta distribution and the probability of smallholder farmers' do not allocate farmland to cultivate crop commodity for sale in the production year. The precision parameter shows the dispersion of the distribution of smallholder households' market orientation index. As the precision parameter increases dispersion of the distribution of smallholder farmers' market orientation (MOI) decreases. Zero-inflated beta regression is specified as the probability and conditional mean function of a response of households' market orientation is:

$$b_{ic}(MOI;\ \alpha, \mu, \phi\ ) = \begin{Bmatrix} \alpha & if\ MOI = 0 \\ (1-\alpha)f(MOI; \mu, \phi) & if\ MOI\ \varepsilon(0,1) \end{Bmatrix} \qquad \textbf{(4)}$$

$(1-\alpha)$ is the conditional mean of smallholder farmers market orientation when its value is between zero and one, in a beta density function; α is a probability mass at smallholder market orientation index is zero.

The mean of MOI and its variance is computed as:

$$E(MOI) = \alpha c + (1-\alpha)\mu \quad \textbf{(5)}$$

$$var(MOI) = (1-\alpha)\frac{\mu(1-\mu)}{\phi+1} + \alpha(1-\alpha)(c-\mu)^2 \quad \textbf{(6)}$$

$E(MOI)$ is the weighted average of the mean of the Bernoulli distribution at c or MOI=0 and beta distribution $B(\mu,\phi)$ with weights α and $(1-\alpha)$ and also $E(y/y\, \varepsilon\, (0,1)) = \mu)$; $var\ (y/y\ \ \varepsilon\ (0,1) = \frac{\mu(1-\mu)}{\phi+1}$

Zero-inflated beta regression functional form is the market orientation index as the probability at zero and conditional mean (Pereira and Cribari-Neto, 2010).

The probability of smallholder farmers output commercialization at zero functional form:

$$h(\alpha_t) = \gamma_0 + \gamma_1 z_{t1} + \varepsilon \quad \textbf{(7)}$$

The output commercialization conditional means functional form:

$$g(\mu_t) = \beta_0 + \beta_1 x_{t1} + \varepsilon \quad \textbf{(8)}$$

The precision parameter function is

$$b(\phi_t) = \lambda_0 + \lambda_1 s_{t1} + \varepsilon \quad \textbf{(9)}$$

Where: $h(\alpha_t)$ the probability of household output commercialization at zero function; $g(\mu_t)$ the smallholder farmers output commercialization conditional mean function; $b(\phi_t)$ the households output commercialization precision parameter function. γ_1, β_1 λ_1 Vector of parameters to be estimated. z_{t1} x_{t1}, s_{t1} Vector of explanatory variables. The explanatory variables are socio-demographic characteristics, resource endowments, transaction costs, and agro-ecology. ε random errors distributed as normal distribution with zero mean and unitary variance

Equation 4 to Equation 6 provides interesting features. The variance of MOI is a function of (α_t, μ_t, ϕ_t) and the consequence of the covariate values (Ospina and Ferrari, 2012). The covariates and the parameters influence the precision of the conditional distribution of MOI. Therefore, zero-inflated beta regression offers the effect of the heterogeneity among market-oriented farmers and nonmarket oriented farmers on the extent or probability of market orientation, respectively.

3.6 Hypthesized Determinants of Market Orientation

Smallholder farmers' market orientation varies due to heterogeneity in socio-demographic characteristics, resource endowments, transaction costs and access to institutional services. The theoretical and empirical review reveals the association between heterogeneity among smallholder farmers and its influence on market orientation.

Socio-demographic characteristics such as education, sex and dependency ratio could affect market orientation. Education enables the smallholder farmers access to market information and process it (Gebremedhin and Jaleta, 2010). For instance, education increases the ability of the farmer technology and innovation adoption (Admassie and Ayele, 2011; Yigezu et al., 2018), and also, it might enable them have inputs for optimum allocation for production of marketable crops. Therefore, education is expected to increase resource allocation to produce marketable commodities. Men and women headed farm households have difference in production efficiency and selection of marketable crop types. Teklu (2005) documented that male-headed farm households are more efficient in production than women-headed farm households. This might be due to the cultural taboo that women are incapable to plough farmland (ibid); and women access to productive farmland is limited (Ali et al., 2016), which limits allocation of farmland to marketable crops. In addition, women have less access to market information, which affect the allocation of resources for marketable crop types. Thus, male-headed farm households are expected to increase market orientation more than their counterparts.

Household consumption demand could affect market orientation because household consumption requirements reduce the investment to improved technologies and make more risk averse. Real-dependency ratio is a proxy for consumption demand, which shows the proportion of unproductive household members over productive household members. It measures the dependency of the household based on labour capacity of the household. Sharp (2003) calculated real dependency ratio as:

$$real\ dependency\ ratio = \frac{family\ size - labor\ capacity}{labor\ capacity}$$

The higher the real-dependency ratio demands the higher the amount of food crops for consumption and the lower the income gain and investment on marketable crop types.

Smallholder farmers' physical resource endowments and arrangements affect the decision to allocate resources (Poole et al., 2013; von Braun, 1995). These are owned farmland size, farmland fragmentation and farmland rented contract. In the study area, farmland is undoubtedly the most important input for crop production. Larger farmland size increases the relative allocation of farmland size to marketable crops because the household food consumption demand is expected to be less elastic. Thus, the smallholder farmers' allocation of farmland size for marketable crops expected to increase. Land fragmentation refers to the number of parcels of farmlands an individual farmer owns. Farmland fragmentation increases the production costs and reduce productivity (Latruffe and Piet, 2014) thereby reduces smallholder farmers allocation of resources for marketable crops. In other words, the smallholder farmers try to allocate more farmland for food crop types to meet household food consumption demand while reducing investment on marketable crop. Simpson index takes in to account the number of parcels and the size of the parcel in estimating land fragmentation (Wu et al., 2005). The index increases as the number of parcels increases. Similarly, it increases when the size of the parcels tends to be similar; it decreases when the plot size increases,

$$SI_i = 1 - \frac{\sum_{j=1}^{k} a_{ij^2}}{(\sum_{j=1}^{k} a_{ij})^2} \qquad 0 \leq SI < 1 \qquad \textbf{(10)}$$

Where;

SI_i is Simpson land fragmentation index of farmer *'i';*

a_i the area of parcel '*j'* of farmer *'i'* , where *'j'* ranges from *1* to *k;*

$SI=0$ means the farmer have one parcel of land (land consolidation).

As the household owns large farmland fragmentation index, market orientation is expected to reduce.

Scarcity of farmland is an important constraining factor for crop cultivation accompanied by legal prohibition of land selling and buying by the government (Alemu, 2009). To alleviate this, the community have a practice of farmland rental contracts7 for crop production for specific production seasons (Zeng et al., 2018). The rented farmland increases the cultivated farmland size and thus, the smallholder farmers are expected to allocate large farmland size for marketable crops. Moreover, irrigation enhance cash crop production (Pender and Alemu, 2007); thus, it is expected that irrigation would increase smallholder farmers production of marketable crops.

Transaction cost imped market access (Dillon and Barrett, 2017; Janvry et al., 1991); thereby reduce specialized crop production (Omamo, 1998). Transaction costs are difficult to measure (Alene et al., 2008). Thus, smallholder farmers transaction cost measured in proxies such as residence distance to the all-weather roads and nearby market places and access to mobile phones. Thus, as the smallholder farmers' residence distance from the nearby markets and all-weather roads, the smallholder farmers are expected to reduce allocation of resources to marketable crop types. Moreover, smallholder farmers access to cell phone would able them to get market information, used for market entry thereby the smallholder farmer allocation of resources for marketable crops enhances.

Last but not least, access to institutional services such as agricultural extension, cooperatives and credit services can enhance smallholder farmers access to technologies, market and finance that would enhance smallholder farmer's capability in market-oriented production (Timmer, 1997; von Braun, 1995; Woldey and Peck, 2010).

[7] Farm land rental contracts is a land tenure arrangement which includes share-in and rented-in farmland sizes cultivated by the smallholder farmer in the crop production season. Rented-in and share in arrangements are made between the landowner and the land renter in cash and in-kind, respectively.

4. Result and Discussion

4.1 Market Orientation and Smallholder Farmers' Characteristics by Agro-Ecology

Table 3 depicts that the sampled respondents' average market orientation index was 0.150. Among the sampled respondents 18.68% is non-market oriented while 81.32% are market oriented at varied extent. Market orientation significantly varies among the lowland, midland and highland farmers. The farmers in the lowland are higher than the midland, and the midland ones are higher than the highland. The farm household heads average educational status was grade 1.290. The farm households’ average real-dependency ratio was 0.433.

Regarding physical resource ownership and characteristics, the smallholder farmers average owned farmland size was 1.286. The lowland farmers owned farmland size is greater than the midlands and highlands; and also, the midlands farmland size is greater than it is in the highlands. Land fragmentation was significantly lower in the lowlands than it is in midlands and highlands. Smallholder farmers’ average farmland rental contract size is 0.471 hectare. The average farmland rental contract size is significantly larger in the lowlands than it is in midland or highland agro-ecology. It implies farmland rental contract is important for crop cultivation. Moreover, smallholder farmers who have an access to a small-scale irrigation varied among agro-ecologies. The proportion of sampled smallholder farmers who have an access to a small-scale irrigation in the highlands, midlands and lowlands were 45.2, 22.7 and 3.74 percent respectively. The small streams in the highlands have an access for small-scale irrigation whereas, in the lowlands rivers flow in the deep gorges makes inaccessible for irrigation.

The smallholder farmers travel on average 42.425 minutes to reach to the nearby market place. Smallholder farmers’ residence from the all-weather road takes on average 26.129 minutes. The farmers’ residence distance to all-weather road was significantly lower in the lowlands than it is in the highlands. The proportion of mobile owned farmers was significantly varied among highlands, midlands and lowlands. These suggest the farmers in the lowlands incurred less transaction cost relative to the farmers in the midlands or highlands. The smallholder farmers’, who are members of the cooperatives, accessed public extension services, and accessed formal credit service varied among agro-ecologies.

The results generally indicate that farmers in the lowlands endowed with resources and have access to infrastructures that increase crop productivity and reduce transaction costs. Consequently, smallholder farmers' market orientation in the low land is higher in comparison with their counterparts in the midland and highland agro-ecologies.

4.2 Crop Production and Marketability by Agro-Ecology

Table 4 depicts there is significant variations in farmers' all crop types (pepper, maize, teff, wheat, barely, millet, niger seed, fababean, chickpea, field pea, potato and onion) average crop produced value among the three agro-ecologies. The average crop produced value in lowlands (126256.4), midlands (51341.14) and highlands (34641.31) in Ethiopian Birr (ETB) shows the smallholder farmers' average income gain from crop production in the lowlands was larger than the other agro-ecologies. This is in line with the view that agro-ecology affects crop production and revenue (Taffesse et al., 2012). Similarly, the area's agricultural production potential affects the smallholder farmers' commercialization (Bernard et al., 2008; Gebremedhin and Jaleta, 2010). Based on the agro-ecologies, crop types and productions are varied in lowlands, midlands and highlands. For instance, in the highlands, potato, barley and field pea production are higher than midlands and lowlands. In the midlands, almost all crop types are produced and the average production is in between the highlands and lowland productions. Nevertheless, teff (*Eragrostis Teff*) production, in the midlands, excel the other agro-ecological zones production potential. In the lowlands, farmers' average pepper, maize and wheat production are higher than midlands and highlands; whereas, barley and field pea are not produced. This result has revealed that potato, barley and field pea are accessed better agro-ecosystem service in the highlands than other agro-ecologies; whereas the lowlands agro-ecosystem services are favorable for pepper, maize and wheat production but not favorable for field pea and barley. In line with this, all farmlands are not favorable for all crop species production (von Braun and Kennedy, 1994). This is, therefore, the smallholder farmers' market orientation in the lowlands is greater than the other agro-ecologies (Table 3).

The crop marketability has varied among agro-ecologies. The smallholder farmer's average marketability of crops in the lowland is greater than the midland and highland. The proportion of paper, maize and wheat sold in the lowland is greater than in the midland and highlands. However, the proportion of teff and potato sold in the highland is greater than they are in the lowland. Furthermore, the proportion of millet, niger seed, faba bean, chickpea and bean were negligible though there is variation among agro-ecologies. This means that agro-ecology affects the production of crop species and their marketability, thereby affecting the market orientation of smallholder farmers.

4.3 Determinants of Market Orientation: Estimates of Zero-Inflated Beta Regression

Prior to zero-inflated beta regression estimation, specification tests were done. Variable inflation factor (VIF-test) has shown maximum 2.29 and contingency test depicted the correlation coefficients are less than 0.5. Therefore, there is no multicollinearity among the covariates. Breusch-Pagan / Cook-Weisberg test have shown there is heteroscedasticity problem (chi-square, 62.67 and p=0.000); which is alleviated through robust estimation. Market orientation is estimated using zero-inflated beta regression shows among 380 (MOI) sampled farmers included in the model, 337 (88.684 percent) are correctly estimated. The link test, *_hatsq* was not statistically significant (p=209), reveals the model is correctly specified. In addition, the precision parameter estimate shows there is significant variation in conditional distribution of market orientation index at 1% significance level.

The results of the zero-inflated beta regression are presented in Table 5. As the results indicate, being male-headed farm households indicates higher probability of market orientation decision with no significant influence in the proportion of market orientation. Indeed, focus group discussion and key informant interview revealed that female-headed farm households are more involved in small businesses, such as the manufacture and sale of *Katikala*[8] and the informal market in onions and potatoes. Similarly, female-headed farm households have greater chance to participate in non-farm activities (Oxfam, 2013). In this way, female-headed farm households make money to cover their living expenses and focus less on income from selling regular crops that are produced unlike those of their male-headed counterparts.

[8] Katikala is a local beverage manufactured from cereal crops, buckthorn (rhamnus prinoides) and water.

As expected, educational status of the farm household head increases the extent and probability of market orientation. Similarly, education enhances smallholder farmers market orientation Gebremedhin and Jaleta, 2010). This suggests that the degree of market orientation requires a good understanding of the separation of production and consumption needs of farm households, and then, helps to allocate more farmland size to marketed crops.

If the smallholder farmers owned farm size increase by one hectare, the probability of a farmer to be market-oriented increase by 11.99 percent while the increase has no a significant effect on the proportion of market orientation. High cost of inputs[9] purchase can limit the production of marketable crops in large farmland size. Similarly, farmers who owned less farmland size apply chemical fertilizer and intensive crop management practices more than those who owned large farmland size (Pender and Gebremedhin, 2008). On the other hand, high cost of input purchase forces the farmers to rented-out their owned farmland. This suggests there is input market imperfections (Barrett et al., 2010; Sen, 1962) that increase production costs forced the farmers cultivate less productive crop varieties otherwise, rent-out their owned farmland.

A-one-hectare land increases in farmland rental contract size increases the probability of the farmer market orientation by 17.8 percent while it does not have a significant effect on the proportion of market-oriented. The smallholder farmers who have little or no small owned farmland have a practice of farmland rental contract to meet subsistence household consumption demand (produce for household food consumption and marketed surplus to generate cash income for subsistence needs) thereby, the farmland allocation for marketable crops reduces. On the other hand, the smallholder farmers may not afford to buy the recommended quantity of purchased inputs to cultivate marketable crops, which demands improved technology package; thereby, allocation of farmland size for marketable crops diminishes. Similarly, as the farmland size increases the farmers less intensify agricultural production (Pender and Gebremedhin, 2008). Therefore, farmland rental contract size enables smallholder farmers to allocate small portion of farmland to marketable crops; however, the smallholder farmers unable to allocate more as the rental farmland size increases due to household consumption demand and less affordability of purchased inputs.

[9] Inputs are improved crop varieties, chemical fertilizer and labor which are used for intensive crop production.

Smallholder farmers' access to irrigation positively affects the probability of market-oriented decision while it could not affect the degree of market orientation. Because smallholder farmers use small streams for irrigation and thus, water scarcity affects allocation of large farmland size for marketable crops (Abebaw, 2013).

As expected, smallholder farm households' residence distance from the nearby market place negatively affects the proportion of market-orientation due to high transaction costs, and consequently reduces profitability. Owning mobile phone positively affects the probability of market-oriented decisions but insignificant on the proportion of market orientation. This suggests market information is quantity invariant transaction cost (Alene et al., 2008).

Smallholder farmers' membership to farmers' cooperatives increase the extent of their market orientation. Since there is scarcity of chemical fertilizer and improved seeds supply, the members of the cooperatives have the opportunity to access more quantity of chemical fertilizer and improved seed in comparison with non-members of the cooperatives.

The farmers who live in the midland agro-ecological zone relative to highland farmers positively influence the probability farmers market orientation. In the same vein, the farmers farming in the lowlands in comparison with farming in the highlands agro-ecological zone positively affected both the farmer decision and the conditional mean of market orientation. According to the focus group discussants and key informant interview data, the undulated topography and amount of rainfall in the highland is higher than it is in the midland and lowland and also, the midland undulated topography and amount of rainfall are higher than it is the lowland. This results in severe soil degradation in the highland in comparison with the midland and lowland; and also, the midland soil degradation is higher than the lowland. Thereby, the soil fertility status in the highland, midland and lowland affects cultivated crop types, productivity, and production. Accordingly, the empirical analysis in Table 4 states that cultivated crop types, productivity, and marketability varied among the highland, midland and lowland agro-ecologies. Therefore, agro-ecology affects the relative farmland allocation to marketable crops. Similarly, agro-ecological resource endowments increase the production of specialized commodities (Timmer, 1997).

5. Conclusion and Policy Implications

The study has sought to contribute to the understanding of determinants of market orientation by focusing on agro-ecologies and transaction costs. Results from the empirical analysis show physical resource endowment and arrangement, agro-ecological favourability and access to market infrastructure enhance crop production, marketability, and reduce transaction costs. The agro-ecologies such as lowland followed by midland are favourable for the high production of crop types relative to the highlands. The crop types marketability is higher in the lowlands followed by midlands and highlands. The lowlands and midlands have better market infrastructure in comparison with the highlands thereby reduce transaction costs in the lowlands and midlands than highlands. Moreover, resource endowments and arrangements such as owned farmland size and farmland rental contracts are higher in the lowlands followed by midlands and highlands. The econometric analysis shows lowland and midland agro-ecologies enhanced market orientation in comparison with highlands while transaction costs harmed market orientation. On the other hand, owned farmland size and farmland rental contract size increase the probability of market orientation but not the extent of market orientation. This might be due to households' consumption demand and imperfect factor markets that hinder expansion of market-oriented production. Cognizant to these facts, the agro-ecology, infrastructure development, and physical resource endowment and arrangement accompanied with imperfect factor markets caused significant variation in smallholder farmers' market orientation.

The result provides pathway to explain the smallholder farmers' market orientation. Though smallholder market orientation is affected by socio-demographic characteristics, resource endowments, transaction costs and access to institutional services; agro-ecologies and transaction costs are important determinants in the smallholder farmers′ decision. The smallholder farmers′ relative farmland allocation to the mix of crop types to maximize the benefit is varied by agro-ecologies, access to market infrastructure and factor market imperfections. Therefore, investment in smallholder households′ education, developing all-weather roads and interventions in soil fertility improving technologies in the highland and midland that enhance crop productivity and production, are important intervention areas to enhance market orientation thereby prompt small-scale commercialization.

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Appendix 1

Table 1: Sample size by agro-ecology and kebele

Woreda	Agro-ecology	Selected kebele	Population	Sample size
Burie zuria	Lowland	Zeyushewen	696	51
	Midland	Wadera	814	59
	Highland	Ambaye	1238	86
Dembecha zuria	Lowland	Astevoch and Egziabhirab	1160	76
	Midland	Yesheboch	580	43
	Highland	Gelila	944	90
Total			5432	405

Table 2: Summary of variables description, measurement and expected hypothesis

Explanatory variables	Variable description	Measurement	Expected hypothesis
Socio-demographic characteristics			
Sex	Household head sex	Dummy1 if male; 0 otherwise	+
Education	Household head education	Continuous	+
Dependency	Household real-dependency ratio	Continuous	-
Physical resource endowments and arrangements			
Farmland	Farmland size in hectare	Continuous	+
Farmland fragmentation	Farmland fragmentation index	Continuous	-
Rented-in farmland	Rented-in farmland size in hectare	Continuous	+
Irrigation	Access to irrigation	dummy 1 if access; 0 otherwise	+
Transaction costs			
Distance from all-weather road	Residence distance from the all-weather road in minutes	Continuous	-
Distance from nearby market	Residence from distance from nearby market minutes	Continuous	-
Mobile	Mobile owned	dummy 1 if owned; 0 otherwise	+
Access to institutional services			
Cooperative	Membership to cooperative	dummy 1 if member; 0 otherwise	+
Credit service	Access to formal credit service	dummy 1 if accessed; 0 otherwise	+
Extension service	Access to agricultural extension service	dummy1 if accessed; 0 otherwise	+
Agro-ecology	Highland agro-ecology	dummy 1 if highland; 0 otherwise	+/-
	Midland agro-ecology	dummy 1 if midland; 0 otherwise	+/-
	Lowland agro-ecology	dummy 1 if lowland; 0 otherwise	+/-

Table 3: Market orientation and smallholder characteristics by agro-ecology

Variables	Obs(n)	Total mean (std. Error)	Mean (standard errors) by agro-ecology			F /X^2 test
			Lowland	Midland	Highland	
Dependent variable						
Market orientation index (continuous)	380	0.150(0.008)	0.249 (0.017)[a]	0.144(0.013)[b]	0.077(0.008)[c]	51.83 ***
Socio-demographic characteristics						
Household head sex (dummy=1 male,0 otherwise)	405	0.931(0.014)	0.925 (0.025)	0.898(0.032)	0.957(0.017)	3.1841
Household head education (continuous)	404	1.290(0.123)	1.29 (0.206)	1.136(0.205)	1.388(0.214)	0.78
Real-dependency ratio	402	0.433(0.030)	0.522 (0.0575) [a]	0.381(0.061) [bc]	0.397(0.040) [c]	3.89 **
Physical resource endowment and arrangement						
Mobile owned (dummy= 1owned; 0= otherwise)	405	0.683(0.026)	0.794 (0.039)	0.761(0.046)	0.547(0.042)	23.6007***
Farmland size owned in hectare	405	1.286(0.044)	1.641 (0.095) [a]	1.328(0.070) [b]	0.986(0.050) [c]	28.12***
Land fragmentation index	376	0.571(0.012)	0.526 (0.023) [c]	0.615(0.021) [ab]	0.579(0.02)[b]	2.39*
Farmland rental contract size in hectare	404	0.471(0.036)	0.720 (0.083) [a]	0.504 (0.067) [bc]	0.259(0.032) [c]	16.53***
Access to irrigation (dummy 1 if access; 0 otherwise)	404	0.261(0.024)	0.0374(0.0184)	0.227(0.045)	0.453(0.042)	59.0291***
Transaction cost						
Residence distance from the all-weather road in minutes	405	26.129(2.262)	16.897 (1.749) [c]	28.182(6.980) [bc]	31.935(2.772) [a]	5.54***
Residence from distance from nearby market minutes	405	42.425(1.841)	43.477(3.274)	38.148(3.216)	44.324(3.012)	1.83
Mobile owned (dummy= 1owned; 0= otherwise)	405	0.683(0.026)	0.794 (0.039)	0.761(0.046)	0.547(0.042)	23.6007***
Access to services						
Membership to cooperative (1 member; 0 otherwise)	397	0.692(0.0253)	0.729(0.0432)	0.818 (0.041)	0.583(0.042)	17.8488***
Access to credit service (1 accessed; 0 otherwise)	402	0.521(0.027)	0.626 (0.047)	0.489(0.054)	0.460(0.042)	6.7627**
Access to extension service (1accessed; 0 otherwise)	402	0.895(0.017)	0.916(0.0269)	0.955(0.022)	0.842(0.031)	8.6283**
Agroecology (highland =base)						
Midland agro-ecology (dummy=1 midland; 0 otherwise)	405	0.264(0.024)				
Lowland agro-ecology (dummy=1 midland; 0 otherwise)	405	0.320(0.026)				

Note: [a,b,c,] shows there is significant variation among the categories; ab, bc and ba shows no significant variation between the two categories. Observation(n) variation is due to unit non-response, the data is missed completely at random (MCAR) and also which is less than 10 percent of the sample size 385, thereby represents the population. Thus, "list wise deletion" of missing data and "complete-case analysis" lead to unbiased parameter estimates (De Leeuw et al., 2003; Howell, 2007; Kang, 2013; Little, 1988; Pampaka et al., 2016) Standard errors in parentheses, *** significant at 1%, ** at 5%, * at 10%.

Table 4: Sampled smallholder farmers average crop production (in kilograms and ETB) and marketability by agro-ecology

Crop species	Crop production: mean (standard errors)				Marketability: mean (standard errors)			
	Highland	Midland	Lowland	F-value	Lowland	Midland	highland	F(p-value)
Crop produced value (ETB)	34,641.31 (3092.317)	51,341.14 (4239.131)	126,256.4 (9165.567)	72.61***	0.324 (0.022)[a]	0.204 (0.017)[b]	0.174 (0.015)[c]	18.98***
Pepper	182.632(42.240)	319.279(58.292)	1168.107(138.53)	39.63***	0.29 (0.0336)[a]	0.1490 (0.03)[bc]	0.131 (0.023)[c]	9.45***
Maize	768.129(47.947)	2027.404(128.184)	4101.639(248.349)	134.49***	0.334 (0.023)[a]	0.2 (0.022)[b]	0.046(0.009)[c]	76.80***
Tef	143.567(12.060)	227.837(23.547)	166.967(19.391)	5.89 ***	0.011(0.005)[c]	0.071(0.018)[a]	0.0570(0.014)[ba]	5.05***
Wheat	128.216(16.975)	343.75(38.809)	1205.738(110.85)	82.07 ***	0.086(0.016)[a]	0.078 (0.018)[ba]	0.013(0.004)[c]	12.00***
Barely	243.86(20.75)	88.942 (21.245)	0((omitted))	51.68***	0(0 omitted)	0.0009 (0.001)	0.007 (0.003)	2.51*
Millet	160.526 (18.55)	270.192(25.513)	37.295(12.785)	27.61***	0(0 omitted)[c]	0.016 (0.007)[a]	0.005(0.003)[ba]	3.70**
Niger	0(omitted)	61.635(12.145)	4.918(2.629)	31.90***	0.002 (0.0023)[b]	0.087 (0.025)[a]	0(0 omitted)[cb]	16.54***
Bean	102.193(10.844)	50.240 (9.927)	100.902(19.854)	3.96**	0.044(0.0172)[ba]	0.002(0.002)[c]	0.047 (0.012)[a]	3.56**
Chickpea	3.509(3.509)	6.25(3.463)	172.336(30.593)	32.76***	0.019 (0.0079)	0(0 omitted)	0.006 (0.006)	2.36
Field pea	5.760 (1.968)	1.442 (1.071)	0(omitted)	3.94**	0(0 omitted)	0(0 omitted)	0.01(0.005)	2.70*
Potato	698.538(70.755)	198.077 (56.603)	36.885(21.342)	37.93***	0(0 omitted)[cb]	0.028(0.015)[b]	0.083(0.015)[a]	11.27***
Onion	30.702(10.535)	17.309(14.681)	0(omitted)	2.45*	0(0 omitted)	0.012 (0.009)	0.012(0.007)	1.05

N.B Standard errors in parentheses, *** significant at 1%, ** at 5%, * at 10%

Table 5: Zero-inflated beta regression model of smallholder farmers' market orientation

Dependent	Market orientation			
	Delta-method			
Explanatory variables	Marginal effects on probability of having value 0			
	Proportion	Zero-inflate	Dy/dx	ln_phi
Socio-demographic characteristics				
Household head sex (dummy=1 male,0 otherwise)	0.0571(0.234)	-1.273**(0.576)	-.1417035	
Household head education (continuous)	0.0900***(0.0202)	-0.212**(0.0913)	-.0236254	
Real-dependency ratio(continuous)	-0.0682(0.0914)	-0.559(0.564)	-.0622544	
Physical resources and arrangements				
Farm size owned in hectare(continuous)	-0.0756(0.0752)	-1.078***(0.403)	-.1199557	
Land fragmentation index(continuous)	-0.176(0.240)	0.881(0.888)	.097996	
Farmland rental contract in hectare(continuous)	-0.0459(0.0804)	-1.600***(0.529)	-.178025	
Access to irrigation (dummy 1 if access; 0 otherwise)	-0.103(0.130)	-0.933**(0.402)	-.1038005	
Transaction costs				
Residence distance from the all-weather road in minutes(cont.)	-0.0943(0.00113)	-0.00413(0.00380)	-.0004594	
Residence from distance from nearby market minutes (cont.)	-0.0270*(0.0161)	-0.00760(0.0517)	-.0000845	
Mobile owned (dummy= 1owned; 0= otherwise)	0.0281(0.122)	-0.832**(0.358)	-.0925661	
Access to services				
Membership to cooperative (dummy = 1member; 0 otherwise)	0.242**(0.116)	0.538(0.366)	.0599068	
Access to credit service (dummy =1 accessed; 0 otherwise)	-0.0926(0.0994)	0.446(0.354)	.0495836	
Access to extension service (dummy= 1 accessed; 0 otherwise)	-0.0549(0.188)	-0.589(0.498)	-.0654899	
Agro-ecology				
Midland agro-ecology (dummy = 1 midland; 0 otherwise)	0.207(0.142)	-1.749***(0.491)	-.1946032	
Lowland agro-ecology (dummy = 1 lowland; 0 otherwise)	0.820***(0.155)	-1.897***(0.562)	-.2111428	
Constant	-1.744***(0.314)	2.923***(0.865)		2.123***(0.0859)
Observations	337	337		337

Note: highland is the base agro-ecology, robust standard errors in parentheses, *** significant at 1%, ** at 5%, * at 10%

Table 6: Variable Inflation Factor (VIF)

Variable	VIF	1/VIF
Lowland	2.10	0.476610
Rainfed farm size	1.71	0.584743
Midland	1.51	0.660121
Farmland fragmentation index	1.40	0.715415
Farmland rental contract size	1.36	0.736336
Access to irrigation	1.26	0.796285
Mobile owned	1.23	0.809839
Access to extension service	1.23	0.812999
Household head sex	1.23	0.813280
Member to farmers' cooperative	1.20	0.836021
Distance to all-weather road	1.19	0.838725
Distance to nearby market	1.18	0.849519
Real dependency ratio	1.15	0.872827
Household head education	1.07	0.935046
Access to credit service	1.06	0.941193
Mean vif	1.32	

Table 7: Contingency coefficient test

	Household head sex	**Access to irrigation**	**Mobile owned**	**Member to cooperative**	**Access to credit services**	**Access to extension**	**Midland**	**Lowland**
Household head sex	1.0000							
Access to irrigation	0.1486	1.0000						
Owned mobile	0.1873	-0.0589	1.0000					
Member to cooperative	0.1969	-0.0281	0.2380	1.0000				
Access to credit service	0.1213	-0.0014	0.0739	0.0358	1.0000			
Access to agricultural extension service	0.2503	-0.0530	0.2007	0.1923	0.1286	1.0000		
Midland	-0.0832	-0.0552	0.1030	0.1378	-0.0429	0.0635	1.0000	
Lowland	0.0616	-0.3242	0.1584	0.0928	0.1294	0.0956	-0.4027	1.0000

Omitted variable test

Ramsey RESET test using powers of the fitted values of MOI

Ho: model has no omitted variables

F (3, 309) = 8.29

Prob > F = 0.142

Table 8: Model fitness test (linktest)

MOI	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]
Proportion					
_hat	0.0326575	0.2540496	0.13	0.038	-0.4670979 0.5324129
_hatsq	2.870757	0.7226387	3.97	0.209	1.449214 4.292301
_cons	0.0574479	0.0191943	2.99	0.235	0.0196896 0.0952062

Estimating the Impact of Agricultural Technology Adoption on Teff Productivity: Evidence from North Shewa Zone of Amhara Region, Ethiopia[1]

Mesele Belay Zegeye[2]

Abstract

This study aims to examine the impact of agricultural technology adoption on Teff productivity in the North Shewa Zone of the Amhara region, Ethiopia. The analysis is based on household-level data covering 395 households collected in 2021. Multinomial logit and multinomial endogenous switching regression models were used for analysis. The results of the study showed that agricultural technology adoptions are affected by the education level of the household head, off-farm employment, livestock ownership measured in tropical livestock units, access to credit, household's saving, access to extension service, farm size, and distance from the market. The results have also pointed out that the adoption of fertilizer and/or improved seed have increased teff productivity significantly. Furthermore, the adoption of a combined fertilizer and improved seed has provided higher productivity than adoption in isolation. Therefore, supporting agricultural technology adoption by increasing access to fertilizer and/or improved seed have significantly increased agricultural productivity.

Keywords: technology adoption, multinomial logit, multinomial endogenous switching regression, teff productivity, Ethiopia

JEL Classification: Q16: C21

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1. Introduction

In Ethiopia, agriculture is the main motor for the economy which accounts for about 80% of living. Its average share to the GDP is about 34.1%, employs about 79% of the population, accounts for 79% of foreign earnings. It is the major backbone of the raw material and capital for the investment and market (National Planning and Development Commission, 2018; Diriba, 2020). However, the sector still is characterized by lower productivity, subsistent production, and traditional farming systems. Thus, an increase in agricultural productivity is the primary requirement for overcoming problems of poverty, food insecurity, low income of the farm households, and low economic development of the country. Accordingly, the adoption of improved agricultural technology is one of the way for which agricultural productivity increased (Jayne et al., 2017; Admassie and Ayele, 2010). In Ethiopia, agricultural technology adoptions are strongly recommended to improve agricultural crop productivity. This is because in the countries with land paucity and rising problems of land degradation and population growth, agricultural production cannot be persistent without the application of agricultural technologies (De Janvry et al., 2000, 2017; Mohammed, 2014; Habtewold, 2018; Jayne et al., 2017).

Considering the importance of agricultural technologies in raising agricultural productivity, maintaining food security and reducing poverty, the government of the country has been promoting and implementing different agricultural technologies. For example, the adoption of tractor, machinery, improved seed, harvester, irrigation, pesticides, threshing grain, fertilizers, and sorting and packaging the products as well as new farming practices (Admassie and Ayele, 2010) are some to name a few. Although lots of efforts and investments have been made by the government of Ethiopian to promote, and disseminate the adoption of agricultural technologies, the agricultural technology adoption rate remains very low, resulting in lower agricultural productivity (Jayne et al., 2017; Abay et al., 2017; Natnael, 2019; Asmare et al., 2019). Therefore, the actual lower productivity of the sector is caused by the lower adoption rates of agricultural technologies. To this end, to gain more insight on the factors that determine the adoption and how adoption possibly increases productivity, this study looks at the determinants of the adoptions of fertilizer and/or improved seed and the implied impact on teff productivity in North Shewa zone. The author uses the adoption of fertilizer and/or improved seed adoption because the adoption of these technologies is widely used and have higher adoption rate in the study area compared to other technology packages.

Teff is one of the most extensively cultivated cereal crops in Ethiopia. It is the most dominantly consumed crop in the country (CSA, 2019). Recently, the crop is receiving worldwide attention for its nutritional and health-related benefits (Lee, 2018). It is providing the livelihoods for the majority of smallholder farmers and a strategic crop with the potential to enhance commercialization of smallholder agriculture and improve food security. In the country, the crop accounts more than 3 million hectare of grain crop area and as to production it accounts more than 54 million tones (CSA, 2019). Amhara region is the second largest Teff producer next to Oromia region in the country. The average productivity of Teff in the region is 2.29 tones per hectare which is very low (Minten et al., 2013). According to the report of National Teff Research Commodity Strategy 2016-2030, the productivity of Teff can be increased by 4.34 tones per hectare if farmers could adopt agricultural technologies (Abewa et al., 2020). Therefore, considering what factors affect smallholder farmers not to fully adopt the agricultural technologies and the motivations for such adoption is critical to accelerate the adoption process.

Besides, the use of agricultural technologies increases agricultural productivity and thus reduces poverty (De Janvry et al., 2000). There are few researches conducted so far on the impacts of agricultural technology adoption on Teff productivity in Ethiopia. For example; Abewa et al. (2020), Negussie (2020), Wolde (2021), Tamirat (2020), Natnael (2019), Vandercasteelen et al. (2016) and Berhe (2014) found that the adoption of agricultural technologies significantly raises Teff productivity.

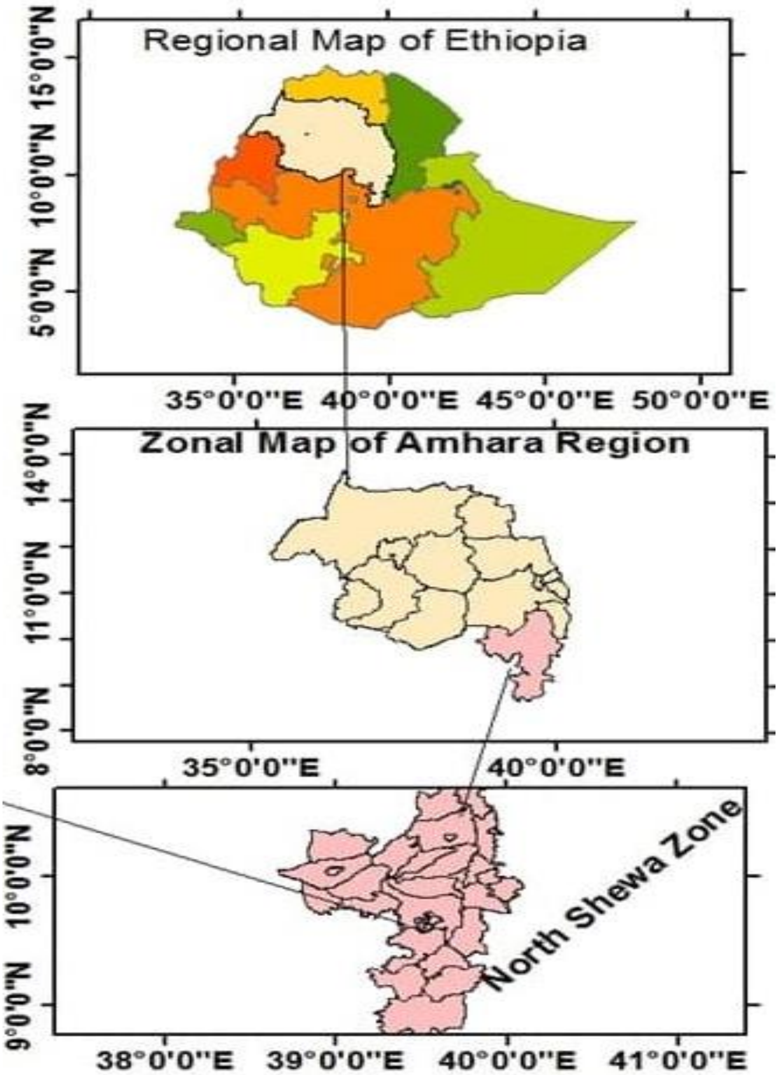
The contribution of the study to the current literature is three-fold. First, many studies have been conducted previously on the area examining the impacts of single agricultural technology adoption on Teff productivity (example, Vandercasteelen et al., 2016; Negussie, 2020; Wolde, 2021; Tamirat, 2020). However, this study examines the impact of multiple technology adoption on the productivity Teff because farmers adopt more than one technology in their crop fields. Second, most previous studies examined the impact of agricultural technology adoption on Teff productivity by employing ordinary least square (OLS) and Propensity Score Matching (PSM) models (for example, Abewa et al., 2020; Wolde, 2021; Tamirat, 2020; Natnael, 2019). However, these models do not show the true effect of agricultural technology adoption on Teff productivity because these models fail to form sufficient counterfactuals to capture the treatment effect, and assume no selection bias due to unobserved factors. But, in non-experimental studies of this kind, examining the impact of adoption on productivity is challenging mainly because of the existence of selection bias due to observed and unobserved factors (Belay and Mengiste, 2021). Therefore, this study used multinomial endogenous switching regression (MESR) model which solves the problem of selection bias, possible endogeneity, and counterfactual situations. Thirdly, researches on the impact of agricultural technology adoption on Teff productivity is less clearly documented in the study area. Therefore, this study aims to examine the impact of agricultural technology adoption on Teff productivity in North Shewa zone, Amhara region, Ethiopia.

2. Methodology

2.1 Study Area Profile

The study was conducted in North Shewa zone of the Amhara region of Ethiopia. The zone is one of the 10 zones in the region. It is bordered by the Oromia Region on the south and west, by South Wollo on the north, by the Oromia Zone on the northeast, and on the east by the Afar Region. On average, the yearly rainfall fluctuates between 400 – 700 mm and the yearly average temperature varies between -8 - 35.7oC. About 88.34% are rural inhabitants, of which 0.01% is pastoralists. Agriculture is the main livelihoods of the peoples of the zone. Among the major crops grown in the zone, teff, wheat, barley, maize, sorghum, millet, and pulse different types of Beas, pea, and lentil crops are the dominant product of the farmers (North Shewa Zone administrative office, 2020).

Figure 1: Geographical Location of North Shewa Zone



2.2 Data and Sampling Description

The study focused on teff farming households randomly selected from the two major teff growing districts of the zone. The study was conducted based on a household-level cross-sectional data collected from north Shewa zone farmers. The data for analysis were collected through a questionnaire that would allow the collection of demographic, socio-economic, and institutional characteristics. To select sample households, the study used the multi-stage sampling method. Firstly, from the total districts of the zone two districts specifically Minjar Shenkora and Moretna Jiru were selected purposively due its high potential to agricultural practices, the dominant teff producing districts of the zone and its topographical similarity. Following this, according to north Shewa zone administration office (2019), there are a total of 50640 households in the selected districts (Minjar Shenkora = 29359 households and Moretna Jiru =21281 households). For the second stage where simple random sampling method was used, the sample size (n) was determined as described in Yamane (1967) using the following formula:

$$\mathrm{n} = \frac{N}{1+N(e)^2} = \frac{50640}{1+50640(0.05)^2} = 397$$

Where n is the sample size, N is the total household size and e is level of precision. Hence the total sample size n = 397 was allocated to Minjar Shenkora ($n_1 = \frac{397}{50640} * 29359 = 230$) and to Moretna Jiru ($n_2 = \frac{397}{50640} * 21281 = 167$). As a result, 397 households were drawn as sample size in this study. Thirdly, from the total Kebeles of the selected districts, 15 Kebeles were randomly selected and lastly simple random sampling was used to select each sample respondent from each selected Kebeles. Due to missing information, 2 observations were dropped. Thus, 395 households were considered for the analysis.

2.3 Analytical Framework

The study employed descriptive and econometric approaches for data analysis. Descriptive analysis like mean and standard deviation were used to gain a better understanding of the demographic characteristics, socio-economic and institutional characteristics of the farm households. An econometric method such as an endogenous switching regression model was used to examine the impact of agricultural technology adoption on teff productivity in the study area.

2.4 Estimation Strategy and Model Specification

In the adoption theory, farm households' adoption of the technology is expected to be based on their expected profit/gain from adoption of a specific choice given his/her constraints. This implies adoption occurs if the utility of the chosen package is higher than the utility of the other alternatives. However, the utility that is gained from adopting agricultural technology is not observed but only it's a choice of technology, one can assume a random utility model which states conditional probability choice given farmers' choice (Verbeek, 2005).

Measuring the impact of fertilizer and/or improved seed adoption on teff productivity requires controlling for endogeneity problem, possible selection bias and unobserved heterogeneity issues. In response to this, the MESR model is potential to solve these problems. Following Kassie et al. (2015, 2018), Tesfay (2020), Mohammed (2014), Danso-Abbeam & Baiyegunhi, (2018) and Teklewold et al. (2013) farm households' decision to adopt alternative agricultural technologies and its impact on outcome variable (yield in this case) was modeled using Multinomial Endogenous Switching Regression model (MESR). The model is estimated in two stages. In the first stage, the farm households' decision to adopt alternative technology packages was estimated using multinomial logit selection model (MNL). In the second stage, the impact of each alternative technology packages on teff productivity were estimated using ordinary least squares (OLS) with a selectivity correction term from the first stage due to time-varying unobserved heterogeneity.

Assume that farm households aim to maximize their utility (U_i) – such that productivity in this case, by comparing with alternate package h. For the i^{th}farm household faced with J alternative technology sets, choice of alternative technology j over any alternative package h implies that $U_{ij} > U_{ih}\ for\ all\ other\ h \neq j$. The expected utility of the farm households from adopting technology package j (U_{ij}^*) is a latent variable determined by observed household, plot, and institutional characteristics (X_i) and unobserved characteristics (ε_{ij}):

$$\boldsymbol{U_{ij}^* = X_i\beta_j + \varepsilon_{ij}} \qquad (\mathbf{1})$$

Where X refers to a set of observed explanatory variables determine technology adoption and ε_{ij} is error term. Let T_{ij} be an index that indicates the choice the farmer has made - it equals 1 if the household has adopted the fertilizer, equals 2 if the household has adopted the improved seed and equals 3 if the household has adopted a combination of fertilizer and improved seed technology and 0 if non-adoption, such that:

$$T_{ij} = \begin{cases} 0 \text{ iff } & U_{i0}^* > \max_{h \neq j}(U_{ih}^*) \quad \text{or} \quad \mu_{i0} < 0 \\ . & . \qquad\qquad . \\ . & . \qquad\qquad . \\ . & . \qquad\qquad . \\ J \text{ iff } & U_{iJ}^* > \max_{h \neq j}(U_{ih}^*) \quad or \quad \mu_{iJ} < 0 \end{cases}$$

Where μ_{ij} is the expected difference in utility (productivity) between alternative technology packages j and h. Hence, i^{th} farm households will adopt alternative technology package j if (and only if) $\mu_{ij} = \max_{h \neq j}(U_{ij}^* - U_{ih}^*) > 0$.

It is assumed that the error terms ε_{ij} are independent and identically distributed that is under the assumption independence of irrelevant alternatives (IIA) hypothesis in the MNL. The MNL model can be specified as:

$$P_{ij} = Pr(\varepsilon_{ij} < 0 | X_i = j) = \frac{\exp(X_i \alpha_i)}{\sum_{j=1}^{3} \exp(X_i \alpha_i)} \qquad (\mathbf{2})$$

Where i indicate an individual farm household; j represents the technology choice set; Xi represents is a set of observed household demography, socioeconomic, plot, institutional and locational factors that affects the decision of adopting; and β_j are unknown parameters to be estimated. The parameters of the latent variable are estimated with maximum likelihood estimation.

Secondly, the outcome equation, the impact of agricultural technology adoption on teff productivity (productivity measured as quintal per hectare) is estimated using MESM. The model runs a separate regime for the adopters of alternative technologies and non-adopters so as to accounting for endogeneity and selection biases. Suppose agricultural productivity is specified Pij for adopters of alternative technologies and Pi0 for non-adopters. Thus, the outcome equations for each regime are stated as follows:

$Regime\ 0\ (not\ to\ adopt)$:

$$P_{i0} = \alpha_0 X_{i0} + e_{i0} \quad if\ T_i = 0 \tag{3}$$

$Regime\ j\ (to\ adopt)$:

$$P_{ij} = \alpha_{ij} X_{ij} + e_{ij} \quad if\ T_i = 1, 2, 3 \ldots \text{m} \tag{4}$$

Where Pij, the outcome variables, represents teff productivity for non-adopter and adopters - observed if and only if package j is adopted, where $U_{ij} > U_{ih}\ for\ all\ other\ j \neq h.$, X_i denote a set of explanatory variables that influence teff productivity; α_i are parameter to be estimated, and e_i represents error terms. If the error terms in equations (1) (3) and (4) are not independent and identically distributed, a consistent OLS estimate of parameters needs the addition of the selection correction terms of the alternative choices in equations (2) and (3). Given this, consistent estimates can be found by adding the selectivity correction terms (mills ratio) generated from the adoption equation (Teklewold et al., 2013). Then the consistent estimates of the MESR can be specified as:

$Regime\ 0\ (not\ to\ adopt)$:

$$P_{i0} = \alpha_0 X_{i0} + \gamma \hat{\lambda}_{i0} + \varphi_{i0} \quad if\ T_i = 0 \tag{5}$$

$Regime\ j\ (to\ adopt)$:

$$P_{ij} = \alpha_{ij} X_{ij} + \gamma \hat{\lambda}_{ij} + \varphi_{ij} \quad if\ T_i = 1, 2, 3 .. \text{m} \tag{6}$$

Where γ_i is the covariance between ε's and φ's, λ_j is the inverse Mills ratio computed from the estimated probabilities in Eq. (2) as follows:

$$\hat{\lambda} = \sum_{j}^{m} \rho_j \left(\frac{\hat{P}_{im} \ln(\hat{P}_{im})}{1 - \hat{P}_{im}} + \ln(\hat{P}_{ij}) \right)$$

Where ρ is the correlation coefficient of ε and φ. In the multinomial choice setting, there are $J - 1$ selection correction terms. Practically, the models in equations (5) and (6) has heteroscedasticity problem that arise from the computation of inverse mills ratio λ_j. Hence, standard errors are bootstrapped to account the problem.

According to Di Falco et al. (2010) and Belay and Mengiste (2021), for the MESR model to be adequately identified, it is important to use exclusion restriction due to the endogenous nature of technology adoption decisions. Exclusion restriction test refers to in excluding explanatory variables that affect the selection equation directly but not the outcome equation. The reason for this is that the inverse Mill's ratio is a non-linear function of the explanatory variables in the adoption equation. Thus, the second stage equation is identified because of this non-linearity. But, the non-linearity of the inverse Mill's ratio is not normally tested or justified. Hence, so as to make the source of identification clear, it is worthwhile to have an explanatory variable in the adoption equation, which is not included in the outcome equation. Therefore, this study used variables of extension visit, farmers' cooperative, distance from the road and from the market as instruments to correct for selection. The result demonstrates that the selected instruments are insignificant on the outcome equations at a 1% level. This approves the validity of the selected instruments and the model is adequately identified, as reported in Appendix 1.

2.4.1 Treatment Effects of Adoption

The MESR model allows us to estimate the average treatment effects of adoption under actual and counterfactual scenarios; and can be specified as follows:

Adopters with adoption (actual):

$$E\left[P_{ij} \mid T = 1,2,3\right] = \alpha_{ij}X_{ij} + \gamma_{ij}\varepsilon\hat{\lambda}_{ij} \tag{7}$$

Non-adopters without adoption (actual)

$$E[P_{i0} \mid T = 0] = \alpha_{i0}X_{i0} + \gamma_{i0}\varepsilon\hat{\lambda}_{i0} \tag{8}$$

Adopters had they decided not to adopt (counterfactual)

$$E\left[P_{ij} \mid T = 0\right] = \alpha_{i0}X_{ij} + \gamma_{i0}\varepsilon\hat{\lambda}_{ij} \tag{9}$$

Non-adopters had they decided to adopt (counterfactual)

$$E[P_{i0} \mid T = 1,2,3] = \alpha_{ij}X_{i0} + \gamma_{ij}\varepsilon\hat{\lambda}_{i0} \tag{10}$$

The difference between eq. (7) and eq. (9) yields the average treatment effect of teff productivity on the treated (TT); and specified as:

$$ATT = E\left[P_{ij} \mid T = 1,2,3\right] - E\left[P_{ij} \mid T = 0\right] = X_{ij}\left(\alpha_{ij} - \alpha_{io}\right) + \hat{\lambda}_{ij}\left(\gamma_{ij}\varepsilon - \gamma_{i0}\varepsilon\right) \quad (\mathbf{11})$$

On the other way, the difference between eq. (10) and eq. (8) gives the average treatment effect of teff productivity on the untreated (TU); and defined as:

$$ATU = E[P_{i0} \mid T = 1,2,3] - E[P_{io} \mid T = 0] = X_{i0}\left(\alpha_{ij} - \alpha_{i0}\right) + \hat{\lambda}_{i0}\left(\gamma_{ij}\varepsilon - \gamma_{i0}\varepsilon\right) \quad (\mathbf{12})$$

The difference between eq. (11) and eq. (12) provides in transitional heterogeneity (TH) that shows whether the effect of adoption is higher or lower for the adopters than the non-adopters.

Table 1: Description and measurement of variables and hypothesis of the study

Explanatory Variables[19]	Description and measurement	Expected Sign
Sex	Sex of the household head = 1 if male; 0 if female	+/-
Education	Education level of the household head = 0 if illiterate; 1 if grade 1-8; 2 if grade 9-12; 3 if above grade 12	+
Access to credit	=1 if the farm household had taken loan; 0 otherwise	+
Off-farm Employment	=1 if the farm household had participated; 0 otherwise	+/-
Saving	=1 if the farm household had saving in formal financial institution; 0 otherwise	+
Extension visit	=1 if a household had an extension visit during their practice; 0 otherwise	+
Farm cooperative	=1 if the household is a member of farm cooperative; 0 otherwise	+
Age	Age of the household head, measured in years	+/-
Family size	The total number of household size	+/-
TLU	Total Livestock herd size of the household measured in Tropical Livestock Unit (TLU)	+/-
Farm size	Total farm size of the household in hectare	+
Distance from market	Distance from home to the nearest market (in kilometers)	-
Distance from all-weather road	Walking distance from home to all road centers (in kilometers)	-

[19] Selection of the variables used in this study are based on previous studies (e.g. Admassie and Ayele 2010; Sebsibe et al. 2015; Mohammed 2014; Kassie et al. 2018; Ayenew et al. 2020; Belay and Mengiste 2021).

3. Results and Discussion

This section provides results of the determinants of agricultural technology adoption (adoptions of fertilizer and/or improved seed) and their implied impact on the productivity of Teff crop of the zone.

3.1 Descriptive Statistics

Table 2 summarizes the possible alternative technology adoptions used in the study. Out of the total 395 sampled farm households, about 21.27% are non-adopters (F0I0), whereas 26.08% and 15.95% of them adopted fertilizer (F1I0) and improved seed (F0I1), respectively, and finally, about 36.71% of them have adopted a combination of fertilizer and improved seed (F1I1).

Table 2: Alternative technology adoption and their frequency

Choice	Binary package	Fertilizer		Improved seed		Frequency	Percentage
		Fo	F1	Io	I1		
1	F0I0	√		√		84	21.27
2	F1I0		√	√		103	26.08
3	F0I1	√			√	63	15.95
4	F1I1		√		√	145	36.71

Note: Each element in the combination is a binary variable and for fertilizer (F) and improved seed adoption (I), and the subscripts represent 1 = adoption and 0 = non-adoption.
Source: Author's estimate, 2021

Table 3 provides the summary of explanatory variables for the adopters and non-adopters. The result shows that most of the household heads in the adopters' group are male-headed households, household heads in the adopters' group are older, and have higher educational level as compared to the non-adopters. On average, adopters have higher farm size and livestock assets than the household heads in the non-adopters' group. Moreover, the farm households from the adopters' group are more likely to engage in off-farm activities, have higher rates of saving, higher rates of access to credit, extension visits and farm cooperatives than the households from the non-adopters' group. Additionally, on average, farm households in the adopters' group are located near to the market and urban centers than the non-adopters. Therefore, the result confirms that the household, socio-economic and institutional characteristics are relatively high for adopters as compared with the non-adopter ones.

Table 3: Summary of Variables used for the Regressions

Explanatory Variables	Category	Adopters			Non-Adopters
		F1I0	F0I1	F1I1	F0I0
Sex	Male	95(92.23)	56(88.89)	135(93.10)	79(94.05)
	Female	8(7.77)	7(11.11)	10(6.90)	5(5.95)
Education	Illiterate	46(44.66)	24 (38.10)	43(29.66)	44(52.38)
	1-8	46(44.66)	30 (47.62)	73(50.34)	30 (35.71)
	9-12	11(10.68)	8(12.70)	21(14.48)	8 (9.52)
	>12	0	1(1.59)	8(5.52)	2(2.38)
Access to credit	Yes	61(59.22)	29 (46.03)	71(48.97)	37 (44.05)
	No	42(40.78)	34 (53.97)	74(51.03)	47 (55.95)
Off-farm Employment	Yes	67(65.05)	44 (69.84)	91(62.76)	44 (52.38)
	No	36(34.95)	19 (30.16)	54(37.24)	40 (47.62)
Saving	Yes	93(90.29)	58 (92.06)	122(84.14)	69 (82.14)
	No	10(9.71)	5 (7.94)	23(15.86)	15 (17.86)
Extension visits	Yes	94(91.26)	61 (96.83)	314(95.15)	70 (83.33)
	No	9(8.74)	2 (3.17)	16(4.85)	14 (16.67)
Farm cooperative	Yes	192(84.21)	40 (75.47)	141(97.24)	142 (76.76)
	No	36(15.79)	13 (24.53)	4(2.76)	43 (23.24)
	(Percents' in parenthesis)				
Age	Mean	42.203	41.539	43.841	44.142
	SD	(11.12)	(11.85)	(11.18)	(13.00)
Family size	Mean	4.941	5.0	4.875	5.0
	SD	(2.09)	(1.75)	(2.18)	(2.24)
TLU	Mean	6.466	6.21	6.022	5.353
	SD	(4.55)	(3.94)	(3.88)	(3.58)
Farm size	Mean	1.463	1.465	1.876	1.294
	SD	(.551)	(.403)	(.822)	(.522)
Distance from market	Mean	5.232	5.283	4.807	5.998
	SD	(5.16)	(5.78)	(5.74)	(5.51)
Distance from all-weather road	Mean	3.489	3.592	3.246	3.703
	SD	(3.78)	(4.20)	(4.98)	(5.83)

3.2 Empirical Analysis

3.2.1 Determinants of Agricultural Technology Adoption

Table 4 presents the estimated results of the multinomial Logit model. The reference or base category of the model is non-adopter (F0I0). Before the estimation, the author performed different tests. The result of the Wald test has shown that we reject the null hypothesis that all regression coefficients are jointly equal to zero (Chi2(45) = 1118.23: P > chi2 = 0.000). The Hausman test result for test of IIA assumption shows that all the alternative packages are unique with respect to the variables in the model, as presented in Appendix 2. The results of the test of multicollinearity problem have indicated that there is no serious multicollinearity problem across the explanatory variables, see Appendix 3. And finally, robust regression is used to control for the heteroscedasticity problem.

The result have shown that the coefficient of the education level of the household head is positive and significant for the adopters of fertilizer (F1I0) and a mix of fertilizer and improved seed (F1I1) as it is expected, implying that educated farmers are more likely to adopt a combination of fertilizer and improved seed technology (F1I1) simultaneously more than the non-educators one. This is because education enables people to acquire, analyze and evaluate information on modern technology, market opportunity and its implied benefits. This finding is in line with the works of Belay and Mengiste (2021).

The coefficient of off-farm participation is positive and significantly influences the adoption of F0I1 and F1I1 packages as it is expected, implying that those farmers joining in off-farm activities are more likely to adopt (F1I1) than the non-adopter. This is because farm households can generate additional income, and used to solve the problem that the farm household's faces while intending to purchase farm technologies. The finding is similar with the finding of Sebsibe et al. (2015). The coefficient of saving is positive and significant on the adopters of F1I1 as it expected, indicating that households who had saved money are more expected to adopt F1I1 adopters. This is because saving serves as a means of overcoming liquidity constraints and a means of buying inputs for agricultural production. This is consistent with Belay and Mengiste (2021), and Natneal (2019).

The coefficient of TLU is significant and indicates that TLU is positively associated with the adoption of fertilizer (F1I0) and improved seed (F0I1), as it is expected. This is because farm household's having livestock asset is more likely to adopt F1I0 and F0I1 than those who do not have. This is because of farmers who possess a flock of livestock are more likely to adopt than the have-not as it helps to get improved technologies as it serves as a source of income and inputs for fertilizer. This finding is in line with the findings of Admassie & Ayele (2010). Farm size is another important factor that has a positive and significant influence on adopting all technology packages used in the study, implying that households owing large farm sizes are more expected to adopt than households who have less. This is true because as operated farm size increases, the likelihood of farmers considering farming activity as full time or way of life increases: and hence more likely motivated towards adopting agricultural technologies. This implies that greater land size serves as a security against the risk of crop failure. The result is parallel to the works of Feyisa (2020).

The coefficient of credit access is positive and significant for the adoption of F1I0 and F0I1 as it is expected, implying that households who get credit service are more likely to adopt F1I0 and F0I1 technologies than their counterparts. This is because getting credit significantly reduces liquidity constraints that households could face while they want to purchase agricultural technologies (Mohammed, 2014; Belay and Mengiste, 2021). The coefficient of extension visit is positive and significant for the adoptions of all combinations used in the study. As it is expected, having an extension visit during the adoption practice of agricultural technologies are more likely to adopt F1I0, F0I1 and F1I1 than those who do not have. This is because an extension visit provides the required information to the farm households regarding the characterization, sources, application, and importance of the technology. This is in line with Ayenew et al. (2020), Admassie and Ayele (2010).

Lastly, the coefficient of distance from the market is negative and significant for the adoption of all technology packages used in this study as it is expected, implying that households living nearer the market places are more likely to adopt F1I0, F0I1 and F1I1 technologies than their counterparts. This is because farmers may have higher access to information on improved agricultural technologies, and also could lead to timely adoption, and lower production cost, and hence are likely to adopt. The finding of the study is consistent with (Sebsibe et al., 2015; and Mohammed, 2014).

Table 4: Maximum Likelihood Estimates for the multinomial Logit model

Base category: Non-adopters	**Adopters of**		
	F1I0	**F0I1**	**F1I1**
Variables	**Coefficient (SE)**	**Coefficient (SE)**	**Coefficient (SE)**
Sex	-0.570 (0.678)	-0.846 (0.641)	-0.404 (0.681)
Age	-0.014 (0.016)	0.020 (0.017)	0.009 (0.014)
Family size	0.026 (0.068)	0.003 (0.093)	0.039 (0.089)
Education (base: illiterate)			
Grade 1-8	0.180 (0.350)	0.524 (0.388)	0.822(0.340)**
Grade 9-12	-0.033 (0.551)	0.529 (0.587)	0.873 (0.531)
Grade >12	1.386 (0.079)***	0.660 (1.192)	2.663 (0.930)***
Off-farm employment	-0.017 (0.038)	0.738 (0.369)**	0.352 (0.028)***
TLU	0.111 (0.042)**	0.030 (0.014)**	0.328 (0.039)
Saving	0.110 (0.516)	0.648 (0.565)	0.616 (0.304)**
Distance to market	-0.114 (0.024)***	-0.110 (0.043)**	-0.106(0.018)***
Distance to all-weather road	-0.017 (0.038)	-0.011 (0.041)	-0.005 (0.042)
Extension visit	0.661 (0.051)***	1.834 (0.892)**	2.767 (0.910)***
Credit access	0.661 (0.330)**	0.046 (0.013)***	0.166 (0.317)
Farm cooperative	0.784 (0.626)	-0.468 (0.607)	0.437 (0.640)
Farm size	0.665 (0.348)*	0.634 (0.350)*	1.648 (0.349)***
Constant	-1.353 (1.208)	-3.662 (1.372)***	-5.196 (1.390)***

Obs. 395; Wald Chi2 (45) = 1118.23; *P* > chi2 = 0.000; Log pseudolikelihood = -467.40809; Robust regression

Note: ***significant at 1% level; **significant at 5% level; *significant at 10% level; Standard errors in parenthesis.

Source: Author's estimate, 2021

3.2.2 Impact of Agricultural Technology Adoption on Productivity

This section discusses the impact of agricultural technology adoption on teff productivity in the study area. In response to the impact evaluation pitfalls, a multinomial endogenous switching regression model is employed. The model results show that the self-selection problem is apparent in the data. Specifically, the mills' ratio values are significant, implying that using the model is appropriate. The falsification test results show that (Prob > F = 0.2808) the selected instruments are valid and the model is adequately identified, as they are highly insignificant at 1% level, see Appendix 1.

Table 5 presents the conditional average treatment effects of adoption of a combination of alternative packages on teff productivity. The study compares the value of teff productivity under the actual case that have adopted with the counterfactual case which had not adopted. The true average treatment effect of adoption of fertilizer and/or improved seed on teff productivity is estimated by comparing the actual productivity with the respective counter-factual scenario. The results show that adopters have significantly larger productivity per quintal than the non-adopters. That is to say, actual adopters have increased their productivity and actual non-adopters if they decided to adopt, their productivity would increase as well. Specifically, the adoption of mix of fertilizer and improved seed (F1I1) results in high productivity (21.31 quintals per hectare) followed by the adoptions of fertilizer package only (F1I0) productivity (17.10 quintals/ha) and by the adoptions of improved teff seed only (F0I1) productivity (15.95 quintals/ha). The average treatment effect has shown farm households increased their productivity by 9.227, 7.042 and 5.709 quintals/ha from adopting full technology (F1I1), fertilizer only (F1I0) and improved seed only (F0I1) respectively.

Conversely, the average treatment effect on the non-adopters is 9.48 quintal per hectare, which will increase by 11.994, 7.063 and 5.692 quintals per hectare if they decide to adopt full technology (F1I1), fertilizer only (F1I0) and improved seed only (F0I1) respectively. Therefore, the result confirms that the adoptions of fertilizer and/or improved seed significantly increase teff productivity in the study area. The negative significant values of transitional heterogeneity effect (TH) for the adoption of fertilizer and improved seed (F1I1), would mean that the effect of adoption would be significantly lower for the farm households who adopted than those who did not adopt.

Thus, the results of the study demonstrate that the adopters of fertilizer and/or improved seed significantly increases teff productivity than non-adopters. Moreover, full technology adopters are more productive than single technology adopters. The finding of the study is similar to previous works of Abewa et al. (2020), Wolde (2021), Tamirat (2020), Natnael (2019) and Tiruneh and Bizuayehu (2021).

Table 5: Estimation of Conditional Expectations and Treatment Effect using MESM

Alternative		Decision stage		
		To Adopt	**Not to adopt**	**Adoption Effect**
Adopters of	F1I0	17.10 (.297)	10.06" (.243)	TT1 = 7.042***
	F0I1	15.95 (.278)	10.24" (.300)	TT2 = 5.709***
	F1I1	21.31 (.075)	12.08" (.300)	TT3 = 9.227***
Non-adopters	F0I0	16.54" (.332)	9.48 (.289)	TU1= 7.063***
	F0I0	15.17" (.274)		TU2= 5.692***
	F0I0	21.47" (.085)		TU3= 11.994***
				TH1 = -.0205
				TH2 = .0169
				TH3 = -2.766***

Notes: TT = Adoption effect for adopters, TU = Adoption effect for non-adopters, TH (TT-TU) = transitional heterogeneity

Standard errors in parenthesis, and ***, ** denotes significance level at 1% and 5% respectively.

Source: Authors' estimates, 2021

4. Conclusion

The study has examined the impact of the adoption of fertilizer and/or improved seed on teff productivity in the North Shewa zone of the Amhara region of Ethiopia. The study has used multinomial endogenous regression model to estimate the determinants of agricultural technology adoption and the implied impact on the productivity. The results of the selected equation show that the adoption of fertilizer and/or improved teff variety decision by households is positively and significantly influenced by the education level of the household head, off-farm participation, livestock ownership measured in tropical livestock units, credit access, and saving and extension visit. Furthermore, the adoption of fertilizer and/or improved teff variety decision by households is negatively and significantly affected by distance from the market. The results of the outcome equation have indicated that the adoption of fertilizer and/or improved seed technologies has a direct impact on increasing teff productivity in the study area. Thus, finding has also confirmed the potentially positive role of agricultural technology adoption in raising crop productivity. Besides the study suggests that the concerned bodies or policymakers need to support and promote the adoption of fertilizer and/or improved seed technologies to exploit the productivity effects of agricultural technology adoption.

More specifically, it is recommended that policies that aim to encourage and expand the adoption of new or improved alternative agricultural technology and a combination of agricultural technologies will have a substantial impact on improving crop productivity. The government at Zone, region and federal level should strengthen the local policy level interventions and increase access to credit and agricultural extension services. With regard to distance from market, the concerned body should have to provide/create the necessary input/output markets near to the farm households. Moreover, education will help the farm households learn about the potential merits and demerits of adopting agricultural technologies without any intermediary. Therefore, government should invest heavily to increase the literacy rate among the rural farmers.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix 1: Falsification Test (OLS Regression)

Linear regression

Productivity	Coef.	St.Err	t-value	p-value	[95% Conf.	Interval]	Sig
Distance from all-weather road	.19	.199	0.96	.342	-.205	.585	
Farm cooperative	-1.077	2.318	-0.46	.644	-5.69	3.537	
Distance from market	.13	.146	0.89	.376	-.16	.419	
Extension visit	-1.21	1.727	-0.70	.486	-4.648	2.228	
Constant	10.135	2.569	3.94	0	5.021	15.249	***

Mean dependent var	9.481	SD dependent var	5.767
R-squared	0.061	Number of obs	84
F-test	1.291	Prob > F	0.281
Akaike crit. (AIC)	536.433	Bayesian crit. (BIC)	548.587

*** p<.01, ** p<.05, * p<.1

Appendix 2: Hausman IIA specification Test

	Coef.
Chi-square test value	0.000
P-value	1.000

Appendix 3: Multicollinearity test

Variance inflation factor

	VIF	1/VIF
Distance from market	1.742	.574
Distance from all-weather road	1.692	.591
Family Size	1.313	.762
Age	1.303	.768
TLU	1.092	.915
Total land Size	1.006	.994
Mean VIF	1.358	.

Matrix of correlations for categorical variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) SeX	1.000						
(2) Education	-0.033	1.000					
(3) Saving	-0.001	0.071	1.000				
(4) off-farm partici~n	-0.006	0.179	0.138	1.000			
(5) credit	0.096	0.031	0.157	0.007	1.000		
(6) EXtenSion	0.029	-0.043	0.117	0.021	-0.048	1.000	
(7) farm cooperativ~r	0.066	-0.018	0.345	-0.019	0.049	0.032	1.000

Appendix 4: Multinomial Endogenous Switching Regression Result
Dependent variable: Teff Productivity (Quintal/hectare), inverse Mills ratio

Variable	F0I0	F1I0	F0I1	F1I1
	Coffe.(SE)	Coffe.(SE)	Coffe.(SE)	Coffe.(SE)
M0		-4.006***(1.168)	-.057 (.541)	-2.205**(1.050)
M1	-1.728(1.772)		-.544 (1.52)	-3.771***(1.277)
M2	.185(.481)	3.171**(1.369)		4.382**(1.695)
M3	1.607(1.657)	1.484 ***(.301)	.560 (1.013)	

*** p<.01, ** p<.05, * p<.1

Debt Sustainability and Economic Growth: Evidence from Low Income Sub-Saharan African Countries[1]

Nitsuh Mengist[2]

Abstract

The purpose of this study is to examine the effect of external public debt on economic growth and to examine the debt sustainability of twenty-four SSA countries over the period 2000-2017 using panel data analysis in which a fixed effect model is estimated. The study found out that external public debt, external public debt service, and trade openness have a negative and significant effect on the economic growth of the selected SSA countries. However, investment and domestic debt have a positive and significant impact on the economic growth. Additionally, the inflation rate and population growth have no significant effect on economic growth. For the purpose of examining the debt sustainability of the chosen countries, various tests were undertaken. The study has concluded that the external debt is unsustainable. In light of the findings, selected SSA countries should adopt an optimal balance between external and domestic debt to ensure sustainable economic growth. They should also implement measures to promote export and expand domestic investment.

Keywords: Sub-Sahara Africa, Panel data regression, Fixed Effect Model, Debt Sustainability, Hausman test

JEL Classification: H63

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1. Introduction

Many African countries have problems in finance all of their development spending with the revenues they collect from domestic sources. As a result, they consider borrowing as a substantial source of financing to realize sustainable economic growth[3].Governments' debt financing can help in this regard by channeling resources to projects where the rates of returns are at least sufficient to service the debt incurred (Irwin, 2015). Governments borrow either from domestic or external sources or both. Domestic debt includes funds raised through financial assets such as Treasury bills, bonds, and money borrowed from other locally-owned financial institutions. While, external debt is generated from bilateral and multilateral sources.

In the 1980s, the world experienced a debt crisis in which, highly indebted Latin American and other developing regions were unable to repay their debt. The problem exploded in August 1982 as Mexico reported the failure to service its international debt, and a similar problem immediately expanded to the rest of the world (Harl, 1990). In the 1980s and 1990s, SSA debt burden increased to higher levels, and they have become unable to pay back their debt. Most of them have been granted relief and reduction schemes following the massive debt-forgiveness campaigns of the 1990s. The subsequent fall in debt levels reduced worries about debt-related problems in these countries (Kelbesa, 2014).

Following the 1980s debt crisis, debt relief has been one of the issues on the policy agenda of governments and international institutions. Donors and the international community have agreed to further debt cancellation to the Highly Indebted Poor Countries (HIPC). Accumulated debt has an effect on SSA countries' macroeconomic performance, political, and institutional aspects. High debts could threaten the effectiveness of structural reforms aimed at enhancing growth and poverty reduction (Moss and Chiang 2003). Therefore, SSA countries' situation towards debt servicing and debt accumulation raises the issue of debt sustainability[4].

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[3] Sustainable economic growth is economic development that attempts to satisfy the needs of humans but in a manner that sustains natural resources and the environment for future generations. Sustainable economic growth is a sole and most important factor to change the living standard of peoples (Buscemi and Alem, 2012).

[4] Debt sustainability is the ability of a country to meet its debt obligations without requiring debt relief or accumulating arrears.

The fragile financial and economic environment poses serious challenges for developing country debt sustainability. While the bulk of global debt is still held in developed countries, emerging and developing countries debt rose from 40 per cent of global GDP in 2008 to 93.2 percent in 2017. For developing countries as a whole, total external debt stocks had reached $7.64 trillion in 2017, having grown at an average yearly rate of 8.5 percent between 2008 and 2017, or more than 80 per cent over the period. Over the same period, total external debt stocks increased from $155 billion to $293.4 billion in the least developed countries, representing an average annual growth rate of 7.4 percent. Emerging economies registered a slightly higher average growth rate at 9.5 per cent of their external debt stocks. As a result, high debt levels can be problematic as the countries may require debt restructuring and forgiveness which is disruptive and costly and the burden of a debt overhang may undermine urgent progress on policy reform (UNCTAD 2018).

External debt-servicing difficulties have historically afflicted SSA countries, as it is hampering the continent's economic growth as servicing external debt diverts scarce fiscal resources from crucial areas of spending for development and growth. AFRODAD's (2016) report shows, in 1999 it was estimated that "the Highly-Indebted Poor Countries (HIPCs) spent one third of their tax revenues in servicing their debts.

As a result, many researchers are interested in identifying the effect of external debt on growth and have reached different conclusions. Greene (1989), Elbadawi et al. (1996), UNECA (1998), Iyoha (1999), Mwaba (2001), Reinhart et al. (2012), and Panizza and Presbitero (2014) conclude that accumulated external debt works against growth. On the other hand, a study by Tunde (2012), Matiti (2013), Zeaud (2014), Spilioti and Vamvoukas, (2015), Cassimon et al. (2015), and Njangang (2018) revealed a positive relationship between external debt and growth. These inconsistency of results suggest an ensuing controversy in the literature and there is a need for further empirical investigation into the subject matter.

There are three features distinguishing this study from much of the substantial empirical literature on the field. Firstly, the existing studies did not distinguish between public and private external debt. But this is crucial given that the transmission channels are substantially different. Hence, this paper gives an analysis of the impact of external public debt (public and publicly guaranteed) on the economic growth of selected SSA countries.

Secondly, the study examines the debt sustainability situation of low-income SSA countries[5]. The existing empirical literature focuses on the debt crises of SSA countries where middle-income countries of the region are also included. But the concept of debt sustainability in low-income countries is different from that in middle-income countries. Low-income countries have weak policy records to relatively middle-income countries that have some access to private capital inflows. Thirdly, the study incorporates the issues of both the effect of external public debt on economic growth and external debt sustainability of low-income SSA together.

The general objective of the study is to test debt sustainability and to examine the relationships between external public debt and economic growth of low-income SSA countries. While, the specific objectives are; to investigate the effect of external public debt on the economic growth of low-income SSA countries; to analyze the trend of external public debt and economic growth and to examine the effects of other macroeconomic variables on economic growth.

Generally, the finding from this study contributes to the countries by identifying the relationship between external public debt and economic growth in accordance with the debt servicing capacity of the nations. This paper also contributes to other researchers to give insight for further studies as a source of a document. Moreover, it would be useful to explore the above-mentioned issues by updating data and come up with results that are expected to have insightful implications for policy.

2. Survey of the Literature

Foreign debt with the presence of good economic policies encourage the development process that will definitely improve investment climate and help to improve the governance quality by removing the constraints regarding the low tax revenues (Qayyum and Haider, 2012). External debt helps a capital deficient nation to develop its productive activities and infrastructures. Government investments are financed by an additional resource from external debt and this contributes to economic growth (Saifuddin, 2016).

[5] Low income SSA countries are Benin, Burkina Faso, Burundi, Central African Republic, Chad, Comoros, Congo Democratic Republic, Eritrea, Ethiopia, Gambia, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Mozambique, Niger, Rwanda, Senegal, Sierra Leone, Somalia, South Sudan, Tanzania, Togo, Uganda, Zimbabwe.

External debt affects economic growth through capital-accumulation and total factor productivity growth channels. The capital-accumulation channel implies when external debt grows large, investors lower their expectations of returns in anticipation of higher taxes needed to repay debt, so that new domestic and foreign investment is discouraged, which, in turn, slows capital-stock accumulation (Pattillo, Poirson and Ricci, 2004). The other consideration is that high debt levels may also constrain growth by lowering total factor productivity growth. Governments may be less willing to undertake difficult and costly policy reforms if it is perceived that the future benefit in terms of higher output will accrue partly to foreign creditors. The poorer policy environment, in turn, is likely to affect the efficiency of investment and productivity (Ricci, 2004).

High levels of uncertainties and instabilities related to the debt overhang are likely to hinder incentives to improve technology or to use resources efficiently (Pattillo and Ricci, 2004). The adverse effect of external debt can be reduced or even reversed in the presence of sound macroeconomic policy. The policy measures include reducing the budget deficit, lowering inflation rate, and achieving trade openness (Presbitero 2005). The debt relief initiatives should focus on creating fertile ground for macroeconomic stability (Ramzan and Ahmad 2013).

SSA countries face a severe and growing external debt problems. External debt as a ratio to GDP or exports of goods and services for SSA countries has risen more than threefold since 1980 and exceeds the comparable ratios identified in the Baker initiative (Greene 1989). Investors have the willingness to lend a country's government depends on the country's suspected primary surplus, the level, and volatility of its rate of growth, and the amount of debt government expects to be able to propose in the future for the purpose of servicing the debt it seeks to raise today (Collard et al. 2015).

3. Materials and Method

The study used panel data for 24 SSA countries that are classified as low income which is based on a measure of national income per person, or GNI per capita. The data covers the period between 2000 and 2017 for all variables included in the study. The study employed data from the World Bank's World Development Indicator (WDI) database, Global Development Finance database (World Bank), and supplemented with data from the World Economic Outlook database (IMF). The study employed external public debt, external public debt service, investment, population, inflation, trade openness, and domestic debt as explanatory variable.

Econometric tests of debt sustainability consist of investigating whether export, import, and other debt sustainability indicators are co-integrated. The theoretical framework of this study is based on the Husted (1992) framework. Husted (1992) provides a simple small-economy framework in which a representative household is able to borrow and lend freely in international financial markets at a given world rate of interest. The representative agent's budget constraint derived as follows:

$$\mathbf{Y_0 = C_0 + I_0 + NX_0 \quad where: NX_0 = X_0 - M_0} \qquad \mathbf{(1)}$$

Husted (1992) considers the above equation as a small open economy that produces and exports a single composite of good.

The agent is able to borrow and lend in international markets using one-period financial instruments, faces a given world rate of interest, and is assumed to maximize lifetime utility subject to budget constraints. The current period budget constraint of this agent is given in equation (2).

$$\mathbf{C_0 = Y_0 + B_0 - I_0 - (1 + r_0)B_{-1} \quad where: NX_0 = (1 + r_0)B_{-1} - B_0} \qquad \mathbf{(2)}$$

Where C_O is current consumption; Y_O is output; I_o is an investment; r_o is the one-period world interest rate; B_0 is international borrowing; and $(1 + r_O) B_{-1}$is the initial debt of the representative agents, corresponding to the country's external debt.

Husted (1992) suggested that equation (2) holds true for every time period. Iterating equation (2) forward provides the economy's inter-temporal budget constraint.

$$\mathbf{B_0 = \sum_{t=1}^{\infty} \delta_t NX_t + \lim_{n\to\infty} \delta_n B_n} \qquad \mathbf{(3)}$$

Where NXt is the trade balance in period t which equals $\mathrm{NXt} = \mathrm{Xt} - \mathrm{Mt} = \mathrm{Yt} - \mathrm{Ct} - \mathrm{It}$, Xt equals export and $\mathrm{Mt}$is import, and δt is the discount factor or $\delta t = 1/(1 + r)t$.

A necessary and sufficient condition for external debt sustainability is that as $n\to\infty$, the discounted value of the external debt converges asymptotically to zero. This transversal condition can be expressed as:

$$\lim_{n\to\infty} \boldsymbol{\delta}_n B_n = 0 \tag{4}$$

Equation (4) implies that a country cannot borrow (lend) indefinitely in global capital markets to finance its trade account deficit (surplus). If this transversal condition holds, then the amount that a country borrows (lends) in international financial markets equals the present value of the future trade surplus (deficits). Thus, a test for the sustainability of the external debt can check for the co-integration of Mt and Xt. If they are I (1) this co-integration regression takes the following form:

$$\mathbf{X}_t = \mathbf{a} + \boldsymbol{\delta}\mathbf{M}_t + \mathbf{U}_t \tag{5}$$

Formally, if M_t and X_t are I (1), the null hypothesis is that M_t and X_t are co-integrated and $\delta = 1$. If the null hypothesis is not rejected, then the external debt is said to be sustainable.

The study uses panel data analysis with annual datasets from 2000 to 2017 and aims to show the impact of external public debt on the economic growth of low-income SSA countries. The theoretical foundation is the augmented Solow model and endogenous growth model with a modification that extends the basic production function framework to permit human capital as an additional input into the production function following Romer (1996) and debt burden following Cunningham (1993). As implied by the Solow’s formulation, economic growth is a function of capital accumulation, labor force, and exogenous technological progress which makes physical capital and labor more productive. According to the endogenous growth model, human capital influences economic growth as:

$$\mathbf{Y} = \mathbf{f}\,(\mathbf{K}, \mathbf{HK}, \mathbf{LF}, \mathbf{A}) \tag{6}$$

Where Y is a proxy for economic growth; K is capital stock; HK represents Human capital; LF denotes labor force and A is technology. Although the endogenous growth model explains variables which affect economic growth, the model does not consider the impact of debt burden on economic growth. But Cunningham (1993) revealed debt burden is a vital determinant of economic growth especially, for those who are developing and highly indebted economies. Then after including debt burden as a new variable, the growth model can be expressed as:

$$\mathbf{Y = f\ (K, HK, LF, DB, A)} \quad \mathbf{(7)}$$

Where: DB is debt burden. Based on economic theories this study modeled GDP growth as a function of external public debt (EPD), external public debt service (EPDS), investment (INV), population growth (POP), trade openness (TOP), Domestic debt (DOM), and inflation rate (INF). This relationship is expressed as:

$$\mathbf{GDP = \beta_0 + \beta_1 lnEPD_{it} + \beta_2 lnEPDS_{it} + \beta_3 lnINV_{it} + \beta_4 POP_{it} + \beta_5 lnTOP_{it} + \beta_6 lnDOM_{it} + \beta_7 lnINF_{it} + U_{it}} \quad \mathbf{(8)}$$

4. Empirical Results and Discussion

The first step in the econometric analysis is to carry out a unit root test on the variables of interest. The test examines whether the variables are stationary or not. Non-stationary data has often been regarded as a problem in the empirical analysis. The results from the test are presented in Table 1 below and all the variables except external public debt and external public debt services are stationary in level. External public debt and external public debt services are stationary at first difference. Hence, all the variables are integrated of order zero and one the basic conditions for the applications of other test are met and can move to the next step of the analysis.

Table 1: Unit Root test result

Var	Levin-Lin-Chu		Im-Pesaran-Shin	
	t-statistic	P-value	t-statistic	P-value
lnGDP	-6.1094	0.0000*	-5.1539	0.0000*
lnEPD	-1.5728	0.0579	-1.3276	0.0922
lnEPDS	0.4910	0.6883	-0.1473	0.4415
lnINV	-3.0759	0.0010*	-2.3998	0.0001*
POP	-8.2349	0.0000 *	-2.3212	0.0101*
lnINF	-5.9949	0.0000*	-3.2777	0.0000*
lnTOP	-5.6768	0.0000 *	-6.0009	0.0000*
lnDOM	-2.8025	0.0025*	2.4748	0.0005*
lnEPD	-4.7403	0.0000**	-8.5440	0.0000**
lnEPDS	-9.5041	0.0000**	-9.8945	0.0000**

Source: Authors computation from the WDI (2018). The null hypothesis is non-stationarity and the alternative hypothesis is stationarity* and ** indicates statistical significance at I (0) (level) and I (1) (first difference), respectively.

There are three types of tests applied on debt sustainability indicators (external public debt to GDP ratio and external public debt service to export ratio), export and import to check the status of countries regarding their external debt sustainability. Those are univariate unit root tests, panel unit root tests, and panel co-integration tests. The univariate unit-root test statistics for all series (ADF and PP) fail to reject the unit-root null at the level at the 5% significance level while; all series are stationary at first difference. As a result, the researcher turns to test panel unit root, and panel co-integration between the selected variables. The result of panel unit root test is presented in Table 2 below and declares that external debt is unsustainable and similar to the test result of the univariate unit root test; and leads to the third step of panel co-integration test.

Table 2: Panel Unit Root test result of debt sustainability indicators

Specification		Levin-Lin-Chu		Im-Pesaran-Shin	
		t-statistic	P-value	t-statistic	P-value
lnEPD	1st difference	-4.7403	0.0000	-8.5440	0.0000
lnEPDS	1st difference	-9.5041	0.0000	-9.8945	0.0000
lnEXP	1st difference	-5.6579	0.0000	-8.5516	0.0000
lnIMP	1st difference	-10.5485	0.0000	-6.1226	0.0000

Source: Authors computation from WDI (2018). All the variables are stationary at first difference.

The third step in analyzing public debt sustainability is a panel co-integration test. The test is employed to investigate whether the debt sustainability indicators, export, and import are cointegrated; cointegration implies that the *I* (1) series are in a long-run equilibrium; they move together, although the group of them can wander arbitrarily. Cointegration between these variables is a necessary condition for debt sustainability. The Kao (1999) panel co-integration test result is presented in Table 3 below and the test accepts the null hypothesis of no cointegration between variables.

Table 3: Kao Residual cointegration test result

	Statistic	Prob.
DF	-1.359955	0.0869
Residual variance	0.107172	
HAC variance	0.120998	

Source: Authors computation from WDI (2018)

From the Table 4 below we have seen that out of seven explanatory variables five of them significantly affect economic growth of low-income SSA countries from 2000 to 2017. Both external public debt to GDP ratio and external public debt service to export ratio have a negative and significant effect i.e. similar to the expected sign. Thus, on average, 1 percent increases in external public debt to GDP ratio and external public debt service to export ratio of the countries results in 34.9 and 17.4 percent reduction in economic growth, respectively. This result is consistent with the classical and monetarist theory of public debt.

Similarly, the coefficient of population growth is negative but insignificant. Unlike the expected sign, trade openness has a negative and significant effect on economic growth, similar with Rodriguez and Rodrik (1999), Vlastou (2010), and Jawaid (2014) findings that trade restrictions in the form of tariffs, as well as trade-related taxes, are positively associated with economic growth. Relying on a large sample of both developing and developed countries the relationship between trade openness and growth is negative even if it depends on the level of development and size of the economy.

However, gross investment (similar with the findings of Firebaugh (1992), Borensztein et al. (1998) and Asiedu (2002)) and domestic debt have a positive and significant effect on economic growth. The funds generated through domestic borrowing have been used partially to finance those expenditures of governments that contribute to the growth of GDP and long-term development purposes.

Table 4: Fixed Effect model estimation test result

lnGDP	Coefficient	Robust Std. Err	t-value	P-value
lnPED	-.3492947	.0544624	-6.41	0.000***
lnPEDS	-.1743913	.0552937	-3.15	0.004***
lnINV	.2596801	.0978064	2.66	0.014**
POP	-.1534773	.0757545	-2.03	0.055*
lnINF	.0015258	.0205354	0.07	0.941
lnTOP	-.4740249	.1282074	-3.70	0.001***
lnDOM	.2080128	.0609789	3.41	0.002***
CONS	16.10268	2.009333	8.01	0.000

Source: Authors computation using WDI data (2018). ***, ** and * represents significant variables at 1%, 5% and 10% significant level, respectively.

Government with large recurrent budget deficit may be forced to tap into domestic savings including through the issuance of domestic debt, to close their budget gap. In addition to this, domestic debt can also be used to achieve monetary policy target. This is particularly the case in countries with a large balance of payment surpluses, created by large aid inflow and this increases liquidity which could undermine macroeconomic stability and central banks often are decide to intervene by selling government or central bank bills to stem inflationary pressure from excess liquidity (Christensen 2004). Finally, the inflation rate has a positive but insignificant effect in this study.

5. Conclusions and Policy Implications

The econometrics test result indicates that a significant and negative effect of external public debt to GDP and external public debt service to the export ratio on economic growth. A higher debt burden leads to a significant portion of government revenue being devoted to debt servicing instead of being channeled to productive investment. This is a constraint condition to improve economic growth. As a result of which, GDP growth declines. A significant increase in external public debt also discourages investments by increasing uncertainty concerning government policies. An increasing external public debt stock often creates expectations that the government is likely to increase tax to meet its debt obligations. Due to this, the private sector investors are likely to postpone their investment, which in turn reduces economic growth.

The coefficients of population growth and inflation rates are not statistically significant in the selected countries. Similarly, gross investment has a positive and significant effect on the economic growth of low-income SSA countries from 2000 to 2017. An increase in investment involves increased spending of the countries savings' on capital goods that are necessary for production and is likely to increase labor productivity. The resulting increase in aggregate output leads to an improvement in GDP growth and standards of living.

Furthermore, domestic debt has a positive and significant effect on economic growth. Domestic debt is better for low-income countries of SSA for two reasons. First, the payment is made by domestic currencies and this reduces the problem of foreign currencies shortage. Second, the domestic debt interest rate is low compared with external debt. Unlike the expected positive coefficient, trade openness has a negative and significant effect. Trade liberalization reduces the productivity of the infant industry. For a newly created industry to survive, the government needs to protect it from foreign competition until its production process becomes more efficient and cost-effective.

In this study, the researcher has applied econometric techniques useful to assess the sustainability of external debt. Various univariates and panel unit root test have been applied to 24 Sub Saharan low-income countries with 18 years of data. Three different techniques were applied. The first was the univariate unit root tests (ADF and PP) to know the external debt sustainability of individual countries and the result depicted nonstationary series of external public debt stock to GDP, external public debt service to exports ratios, export, and import. Thus, all the countries are facing the unsustainable level of external public debts. Panel unit root tests (LL and IPS) was the second type of test and applied on low-income SSA countries as a whole to assess their external debt status. The test found that the external debt of the selected countries' economies as a whole was unsustainable.

The third type of tests includes time series and panel cointegration based approaches and found out that there was no long-run relationship observed between external public debt, external public debt service, export and import for each of the selected countries (unsustainable external public debt) and panel cointegration approach declared external debt was unsustainable as a whole. Based on the results, it can be said that the increased external debt is leading the low-income SSA countries' economies toward the low level of growth and retarding development in the economies.

Based on the empirical results the following measures are recommended. First, there is a need to implement an appropriate policy measure in order to adopt a balance between external and domestic debt so as to maintain steady economic growth. Countries with a narrow export base needs export diversification in order to widen the revenue base and reduce external borrowing for the countries to move out of debt distress.

Second, to avoid unsustainable levels of external debt, all low-income SSA countries should reallocate their resources in the development heads. They can utilize their externally borrowed resources in production and development purposes so that the profits and better repayment capacity can make the debt sustainable. The countries may create the economic environment attracting foreign direct investment which supplements not only the countries capital stock by filling the saving-investment gap but also removes fiscal and current account deficits. The countries should export more and try hard to stable general price level, adopt measures to increase the domestic saving and investment rates, borrow from the sources having the less volatile and low-interest rate.

Finally, appropriate debt management mechanisms should be adopted and implemented to keep debt levels within sustainable limits. To be more specific, the Government should invest the borrowed money on productive investments, reduces unnecessary expenditures, and try to reduce corruption.

List of Acronyms

AFRODAD	African Forum and Network on Debt and Development
ARDL	Autoregressive Distributed Lag model
DSA	Debt Sustainability Analysis
DSF	Debt Sustainability Framework
FDI	Foreign Direct Investment
FE	Fixed Effect
GNI	Gross National Income
HIPC	Highly Indebted Poor Countries
IBC	Intertemporal Budget Condition
IMF	International Monetary Fund
MDRI	Multilateral Debt Relief Initiatives
MSD	Maximum Sustainable Debt
PD	Probability of Default
PNG	Private Non-Guaranteed debt
PPG	Public and Publicly Guaranteed debt
PV	Present Value
RE	Random Effect
SSA	Sub-Saharan Africa
UNCTD	United Nations Conference on Trade and Development
UNECA	United Nations Economic Commission for Africa
VIF	Variable Inflation Factor
WB	World Bank
WDI	World Development Indicator

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The Existence and Structure of Rural Households' Income Mobility: Evidence from Panel Data in Ethiopia (2011-2016)[1]

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Abstract

Ethiopia's economic reports on income inequality, poverty, and other welfare indicators have been promising for the last two decades. It is quite relevant to understand how rural households from different income classes perform over time, income mobility. Income mobility can be regarded as a transformation between two income vectors over a period of time where some are expected to climb or may slide down and moves from one step to another at different rates. This study investigates the existence and structure of households' income mobility in Ethiopia using three waves of the household panel survey for the period of 2011to 2016. It employs Shorrock's rigidity index, transition probability matrix, and Field and Ok (1999) methods for the analysis. The finding of the study points out that income mobility exists with a higher rate of both relative and absolute income mobility. The result of decomposition of income sources have showen that income obtained from nonfarm sources have positively contributed to the difference in income mobility between rural households whereas the decomposition of income effects have revealed that growth effect is the leading factor compared to transfer effect. Hence, the finding shows the need to implement policies targeting income growth to shorten mobility gaps.

Keywords: Income Mobility, Field and Ok, Shorrock's Index, Transition Matrix, Ethiopia

JEL classification: I31, I32, I38

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1. Introduction

In the year 2010-2020, Africa has made remarkable progress in economic growth indicators. Recent data shows that African countries' gross domestic product has reached 3.4 percent in 2019 and 3.9 percent in 2020 (ADB, 2020). Africa's real GDP is projected to grow by 3.4 percent in 2021, after contracting by 2.1 percent in 2020. This projected recovery from the worst recession in more than half a century will be underpinned by a resumption of tourism, a rebound in commodity prices, and the rollback of pandemic-induced restrictions (ADB, 2021).

When we look at Ethiopia's economic progress, the poverty levels fell by around 20% between 2011 and 2016. The headcount poverty rate declined from about 93% in 2000 to 45.5 % in 2017 and 5.3 million people have lifted out of poverty in 2017 (WB, 2018). Compared with other East Africa countries, Ethiopia is registered to be the lowest level of extreme poverty, at 15.9 percent from 2020 to 2021; however, income inequality also has increased slightly from 0.30% in 2011 to 0.33 in 2016.

One of the most important factors is believed to be related to economic progress is the issue of income change. Studies have recommended investigating the relevance of examining how people are moving along the income distribution using welfare indicators such as income, consumption, and asset by providing a wider perspective of how the distribution of income evolves (Corak, 2013; Lambert and Rossi, 2016; Alesina et al., 2017; Dabla-Norris et al.,2015; Alvaredo and Gasparini, 2015).

The measurement of income change is an essential component to know where we stand to use for policy-making. For instance, a society's progress or socio-economic development is often gauged by how much people's well-being or living standards have improved and by how much socio-economic deprivation has been reduced over time which allows identifying priorities that will put the needs of the people first and will address the challenges that societies face ahead (Martinez, 2017; Nolan, 2018; Atkinson *et al.*, 2017).

The extent to which households move across different economic positions (income over time in our case), income mobility, is a central issue in a variety of public policy discussions today. Income mobility, in this regard, is seen as indicative of the opportunities afforded by society to escape one's origins where most policymaking is gauged by how much people's well-being or living standards have improved/ deprived of over time that allows identifying priorities and challenges in the society (Krebs et al., 2012; Efa Gobena and Bizualem, 2017; Martinez, 2017; Atkinson et al., 2017; Nolan, 2018).

Understand how income evolves, often seen as examining equality of opportunity (Shorrock, 1978; Fields, 2010; Jenkins, 2011). This is because different income mobility levels such as upward movers and downward movers can call for a different mix of policies. Thus, understanding income mobility supports policymaking to be efficient in terms of resources and time allocation (Martinez, 2017).

The existing literature has proposed that several measures to evaluate income mobility such as expenditure and income. Income is preferred to analyze sources of mobility. In some contexts, income might actually be more accurate than expenditures in cases where consumption instrument is overly complex and undergoes changes over time. On the other hand, expenditures are typically a better guide to long-term well-being of the household or its ‘permanent income’ as household will exercise some consumption smoothing. In most cases, expenditures are more accurately captured particularly among the poor who have relatively constant and well-known expenditures on relatively few items while their incomes can be very erratic and unpredictable. The study has access to income and expenditure data and uses both.

Although there has been vast research on income mobility in most of the advanced economies and little is found in developing countries, there is no evidence in the face of Ethiopia on income mobility to date. An issue is particularly relevant because most policy designed to reduce poverty and disparities among households, aiming to increase mobility in the process deserves closer scrutiny. Having these concerns, this study intends to evaluate the existence and structure of the households' income mobility, further disaggregating relative and absolute household income mobility in Ethiopia.

2. Data and Methods

2.1 Data Sources, Collection Method, and Type

The study has used panel data collected by the World Bank in collaboration with the Ethiopia Central Statistics Agency (CSA) as the Living Standard Measurement Survey-Integrated Agricultural Survey (LSMS-ISA). The survey has three rounds collected in 2011/2, 2013/4, and 2015/6 as the first wave, second wave, and third wave, respectively. The panel dataset is a nationwide survey collected using multistage probability samples of households. First, the domains of the study are identified (regions, urban/rural) using a stratified random design. Second, enumeration areas (EAs) were selected with probability proportional to size. Third, the primary sampling units (PSU) are geographically defined area units selected with probability proportional to size based on the last population census in the country. Finally, once the PSUs have been selected, an enumeration of these PSUs is carried out to ensure that an accurate and up-to-date listing of all dwellings and households is available. With a complete current list of all dwellings in the PSU, the secondary sampling units (households) are selected using systematic random sampling in both rural and small towns. The first wave collected includes only rural and small-town areas; however, the second and third waves expanded to include urban areas (Table 1).

Table 1: The sampling frame and sample distribution of the survey

	Wave One				Wave Two				Wave Three			
	Rural		Small town		Rural	Small towns	Large towns		Rural	Small towns	Large towns	
	EAs	HHs	EAs	HHs	EAs	EAs	EAs	HHs	EAs	EAs	EAs	HHs
National	280	3466	43	503	280	42	73	5262	280	42	73	4954
Tigray	30	360	4	48	30	4	15	633	30	4	15	633
Afar	10	120	2	24	10	2	1	159	10	2	1	159
Amhara	61	728	11	127	61	10	15	1077	61	10	15	1077
Oromiya	55	656	11	125	55	10	20	1080	55	10	20	1080
Somali	20	237	3	36	20	3	3	321	20	3	3	321
Benishangul	10	120	1	12	10	1	0	132	10	1	0	132
SNNP	74	885	10	119	74	10	15	1233	74	10	15	1233
Gambella	10	120	1	12	10	1	1	147	10	1	1	147
Harari	10	120	0	0	10	1	3	177	10	1	3	177

Note: HHs = households interviewed, EAs= Enumeration area numbers

Sources: Author’s calculation using ESS data 2011/12, 2013/13 and 2015/16 waves

A total of 3969 households from wave one, 5262 households from wave two, and 4954 households from wave three were interviewed with a total of 6.8 attrition rate for rural households. As the study is based on rural households, large towns were considered only in the second and third waves, those samples from urban were automatically excluded from the analysis. The study further imposes a restriction on the sample size due to missing information in the consumption data, and households with zero total consumption (Table 2).

Table 2: Sample size and excluding criteria

No.	Excluded the household due to	Wave-one		Wave-Two		Wave-Three	
		Total	Excluded	Total	Excluded	Total	Excluded
1	The domain of the study	3969	-	5262	1,486	4954	1,255
2	Lost to Attrition	3969	270	3776	77	3699	-
3	Missing information on consumption aggregate*	3669	67	3699	145	3699	146
4	No food consumption reported	3632	70	3554	168	3553	164
5	Not Matched in both waves	3562		3386		3389	
Final Sample size (9,717)		3239		3239		3239	

Note: *missing information refers to the purchased items with no valid conversion factor to convert food items to monetary values

Sources: Author's calculation using ESS data 2011/12, 2013/13, and 2015/16 waves

The comparisons were conducted between the full sample, the subsample, and the balanced sample with measures of central tendency and dispersion of using household income and consumption data. It can be seen in Appendix Table 1 that the balanced subsample did not underestimate and the trend is consistent in both full sample and unbalanced samples. Thus, the study used a balanced subsample for the analysis.

2.2 Method of Data Analysis

2.2.1 Shorrock's rigidity index

The vast majority of income dynamics studies have focused on how the existence of mobility is measured in economies. The study uses Shorrock's rigidity index to analyze the existence of income mobility, in relative terms (Shorrock, 19870). Shorrock index, one of the single-stage indexes, is constructed using Gini of the average income between the periods with the weighted average of the Gini in each period as follows;

$$R = \frac{G(x+y+z)}{\mu_x G_x + \mu_y G_y + \mu_z G_{yz} / \mu_x + \mu_{y+} \mu_z} \quad \textbf{(1)}$$

Where; R is rigidity index, Gx refers to the GINI coefficient and μ_x refers to mean income in the first period; Gy refers to the GINI coefficient and μ_y refers to mean income in the final period. The result of the rigidity index is interpreted as one would mean no mobility, while zero would indicate perfect mobility. In general, the larger the value rigidity index means the lesser mobility and larger permanent component of inequality measures and smaller the value of rigidity index means the higher mobility and smaller permanent component of inequality measure.

2.2.2 Transition probability matrix

There are cases where a single-stage index such as the Shorrock index may not capture a more disaggregated mobility. This is because the Shorrock rigidity index may reach no mobility if all income is increased at a constant proportion factor that only captures the variation in income share and ranks over time. In this case, a two-stage index has been suggested and this study uses a transition probability matrix to analyze the existence of income mobility, in absolute terms. The transition probability matrix is constructed by dividing into endogenously determined income/consumption groups of equal sizes (quintile in our case). This matrix is used to capture the growth dimension of income dynamics where immobility, upward mobility ratio, and downward mobility are described.

The result from this transition matrix can be interpreted as follows. The household experiencing change in income/consumption groups over three waves, from lowest to higher or vice versa are called 'mobiles', and those who does not experience change referred to as 'immobile'. From mobiles, those who experience change from lower-income/consumption groups to higher-income/consumption groups are referred to as 'upward income mobiles', and those who experience change from higher-income/consumption groups to lower-income/consumption groups are referred to as 'downward income mobiles'.

2.2.3 Structure of income mobility

The study also assesses the structure of income mobility by decomposing income mobility by sources and effects. The decomposition of income sources has been analyzed using GINI coefficient approach proposed by Lerman and Yitzhaki (1985). The method decomposes the income sources between and within total income, farm income, and non-farm incomes and stated as follows;

$$\mathrm{G} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{S_K}\,\mathrm{RG_K R_K} \tag{2}$$

Where; the GINI coefficient is the product of three components including share of income from a given total income (Sk), the GINI coefficient of income gap within each income category (Gk), and the GINI correlation between income from the given activity and total income (Rk). The decomposition of income mobility into growth and transfers effect were also analyzed using Fields and Ok [1999] method that measures changes in income between two periods. It is being stated with a single stage and axiomatic form as follows;

$$FO_n\,(x,y) = \left(\frac{1}{n}\sum_n^1 |lny_i - lnx_i|\right) + \left(\frac{2}{n}\sum_n^1 |lnx_i - lny_i|\right) \tag{3}$$

Where; $\mathrm{x} = \mathrm{x_1}, \mathrm{x_2}, \mathrm{x_3} \ldots\ldots\ldots \mathrm{x_n}$ and $\mathrm{y} = \mathrm{y_1}, \mathrm{y_2}, \mathrm{y_3} \ldots\ldots\ldots \mathrm{y_n}$, the initial and final income, n is the number of households and FO is the change in expenditure/income from x to y. The first term on the left-hand side has represented welfare change due to the growth effect whereas the second captures the transfer effect.

3. Results and Discussion

3.1 Relative Income Mobility

The study has used Shorrock's rigidity index to estimate the relative income mobility of households based on adult equivalent consumption with per capita income for comparisons. A summary of the results of Shorrock's rigidity was presented in Table 3. The result showed that estimate from income data is higher than consumption data. This is because of two reasons. First, consumption smoothing makes expenditure less erratic, and secondly, respondents' behavior in reducing inequality. For instance, in the case of expenditure, the poor are reported very well whereas the rich usually forget it, in case of Income, the rich tend to have predicted and stable income source more than the poor do as the result the poor tend to understate the income (Bound et al. 1991; Deaton, 1997).

The result also has shown that Ethiopia's rural households have a Shorrock's rigidity index of 0.97 which implies that a higher rate of income mobility exists in both income and expenditure data. A study in Egypt found that Shorrock's rigidity index was 0.95 for income and 0.934 for consumption and it concluded that Egypt is characterized by high mobility (Marotta and Yemtsov, 2010). Another study by Woolard & Stephan Klasen (2005) in South Africa indicated that the rigidity index for incomes and expenditures indicates a fairly high degree of mobility.

Table 3: Shorrock's rigidity index using income and expenditure, 2011-2016

GINI coefficient and Income/Consumption	Income-based		Consumption-based	
	Per capita	Total	Per adult equivalent	Total
GINI 2011	0.41162	0.427	0.75575	0.77502
GINI 2013	0.33746	0.36529	0.54975	0.54526
GINI 2016	0.34459	0.36384	0.76837	0.77897
Average GINI	0.36356	0.38409	0.69129	0.69975
Average Income/consumption 2011	5059.69	19430.37	2609.03	13445.68
Average Income/consumption 2013	5071.12	19538.02	2617.11	13639.9
Average Income/consumption 2016	5640.59	21537	5587.91	35226.19
Shorrock Rigidity Index	0.9993	0.9987	0.9703	9626

Sources: Author's calculation using ESS data 2011/12, 2013/13, and 2015/16 waves

3.2 Absolute income mobility

The result of relative income mobility already points a lot. However, it is essential to unpack mobility further and turn it into a transition matrix for a further disaggregated look. This is because relative income measurement does not show the difference in income due to the increase of proportion factor which only captures the variation of income shares or rank over time. The transition matrix for both expenditure and income were presented in Table 4 and Table 5. The transition matrix first, allocated household into income/expenditure groups, income quintile in our case where Quintiles are numbered from 1 for the poorest to 5 for the richest, then examines the mobility between these income/expenditure quintiles groups.

It can be seen that 45% of the household who are in the richest quintile in 2011 remained there in 2013 and another 22% moved down just one quintile. Likewise, 52% of those who began in the poorest quintile were still there 3 year later and another 21% had moved up just one quintile. In the same manner, 40% of the household who are in the richest quintile in 2013 remained there in 2016 and another 24% moved down just one quintile. Likewise, 46% of those who began in the poorest quintile were still there 3 year later and another 24% had moved up just one quintile. This indicates that there is less mobility in the bottom and top quintiles than in the middle of the distribution. This can also be confirmed using the number of elements found in the diagonal section of transition matric. The number of elements in the transition matric found in the right of the diagonal section is slightly less than the element in the left. That is expecting slighter income mobility experience indicating there is less mobility in the top and bottom quintile than in the middle of the distribution. This is because the bottom (top) quintiles can only stay in the same quintile in which the income especially the right-hand tail is particularly large which is the reason why persistence in that group is particularly high (Table4).

Table 4: Transition Matrix by quintile using expenditure (Percentages), 2011-2016

		Wave 2							Wave 3				
		1	**2**	**3**	**4**	**5**			**1**	**2**	**3**	**4**	**5**
Wave 1	1	51.46	20.97	13.40	7.570	6.6	**Wave 2**	1	46.36	24.03	14.57	10.39	4.65
	2	25.59	23.96	24.68	16.94	8.83		2	24.36	24.87	24.19	17.67	8.92
	3	18.33	22.75	22.27	22.43	14.22		3	16.11	22.74	21.84	23.49	15.81
	4	11.77	16.28	23.26	28.63	20.06		4	7.14	18.54	25.23	26.29	22.8
	5	4.83	10.14	18.51	21.93	44.58		5	6.53	12.48	16.69	24.24	40.06
Total		19.91	18.0	20.50	20.31	21.27			19.76	20.35	20.41	20.56	18.93

Sources: Author's calculation using ESS data 2011/12, 2013/13, and 2015/16 waves

Note: the estimate is based on annual adult equivalent consumption

As a robustness check, the study further analyzed the rate of transition between waves (2011-2013, 2011-2016) using income data. The result indicated that 22% of the household who are in the richest quintile in 2011 remained there in 2013 and another 23% moved down just one quintile. Likewise, 22% of those who began in the poorest quintile were still there 3 year later and another 4% had moved up just one quintile. In the same manner, 28% of the household who are in the richest quintile in 2013 remained there in 2016 and another 22% moved down just one quintile. Likewise, 37% of those who began in the poorest quintile were still there 3 year later and another 21% had moved up just one quintile. This indicates that the matrix for both income and expenditure are remarkable similar (Table5).

Table 5: Transition Matrix by quintile using income (Percentages), 2011-2016

		Wave 2							Wave 3				
		1	2	3	4	5			1	2	3	4	5
Wave 1	1	21.77	23.990	21.47	17.44	15.32	Wave 2	1	36.700	21.100	14.91	14.45	12.840
	2	12.48	25.340	28.03	22.03	12.12		2	20.270	28.480	21.44	17.76	12.060
	3	7.760	16.300	23.91	31.37	20.65		3	12.690	20.190	22.37	26.33	18.420
	4	7.190	6.130	18.60	31.71	36.36		4	9.740	10.530	18.29	27.63	33.820
	5	10.86	5.750	15.65	17.57	50.16		5	9.540	5.470	9.960	19.35	55.680
Total		13.46	18.430	22.63	23.46	22.01			15.930	16.330	17.51	21.92	28.310

Sources: Author's calculation using ESS data 2011/12, 2013/13, and 2015/16 waves
Note: the estimate is based on annual income per capita

3.3 Structure of Income Mobility: Decomposition by Sources and Effects

From the above sections, it is understood how rural households from different income classes perform over time, income mobility. So, if need arises, the overall picture of improvements can be verified by knowing which income sources have led the mobility that happened in now rural Ethiopia. Thus, decomposing income sources, as well as income effects, are widely used in welfare studies to understand the contribution of each income source and its effects on income mobility. The decomposition is used either by the income sources such as farm income, nonfarm income, total income and by the effect including growth effect, and transfer effect. This study employed a STATA user-writing program 'descoGini' for decomposing income sources developed by L'openz-Feldman (2006) which allows the estimation of bootstrapped standard errors, confidence intervals and marginal effect and 'fokmob' for decomposing effects developed by Phillip Van Kerm (2002).

2.2.4 Decomposition by Sources

Rural households in Ethiopia have different sources of income including nonfarm income and farm income (including crop income, livestock income and agricultural wage). Table 56 presents the result of decomposition by income sources between and within for total income, farm income and non-farm income.

For brevity, it is possible to start from between total income, farm income and non-farm income sources. The result of farm income shows that a one percent increase, all else being equal, decrease the Gini coefficient of total income by 0.27percent and it is unequally distributed (0.89%), and the Gini correlation between farm income and total income is 0.91 percent, indicating farm income is disfavoring the rich more than any other sources.

On the contrary, the result of nonfarm income shows that a one percent increase, all else being equal, increases the Gini coefficient of total income by 0.27percent and its Gini coefficients are higher than 1 reflecting the two notable findings. The first is the presence of some negative values where it is consistent with previous studies which argue that the ability to handle negative incomes is an advantage of the Gini coefficient over Atkinson's index (Lerman and Yitzhaki, 1985; Wodon and Yitzhaki, 2002). On the other side, the Gini coefficients of nonfarm income result showed that it may be overstated and appear to be larger than they appear in reality (Brenda, 2013). The Gini correlation between nonfarm income and total income is 0.92 percent, indicating nonfarm income is favoring the rich more than any other sources. Overall, the income derived from farm income has a higher share of total income (about 77 percent) and nonfarm income has a 23 percent share of total income with a positive effect. This is consistent with the fact that the majority of rural household income was derived from farm income.

Within income sources estimated under the last column of category four where total income is decomposed into a crop, livestock, agricultural wage, non-agricultural wage, self-employment/business, transfers and all other income. The result from this category has revealed that total income is highly unequally distributed among rural households with the highest Gini coefficient from crop income and the lowest from self-employment. In terms of share in total income livestock income, crop income and the non-agricultural wage have the top share of about 50 percent, 25perecnt and 20 percent respectively. The highest correlation between income sources and total income is observed for self-employment income, while the lowest is observed for transfer income. To conclude, a percentage change in the overall Gini coefficient indicates that, an increase in self-employment income results in an increase in total income and a decrease in the gap between income mobility of rural households, while other income sources have a decrease in total income and increase the gap between income mobility of rural households.

The result in Table 6 below shows that decomposed farm income into the crop, livestock and agricultural wage incomes with 32 percent, 66 percent, and 2 percent share in total income respectively. The household farm income is highly unequally distributed among rural households. A ten percent increase in the income obtained from livestock and agricultural wage, result from a decrease in a gap of income mobility between rural households by 43 percent and 26 percent, respectively, while, a ten percent increase in the income obtained from the crop, resulting in an increase in the gap of income mobility between rural households by 70 percent. This is due to the factor involvement of households in farming activities such as far size and related arrangements, which explain the gap between rural households. This is consistent with the previous study of Efa (2017).

Regarding nonfarm decomposition, it is observed that non-farm income is decomposed farm income into self-employment/business, non-agricultural wage, transfer and all other income with 21, 89, 13, 17 percent share in total income respectively. The household nonfarm income is unequally distributed among rural households. As a single percent increase in the income obtained from non-agricultural wage, transfer and all other income, result decreases in the gap of income mobility between rural households by 61, 10 and 15percent respectively. Similarly, a single percent increase in the income obtained from self-employment/business results an increase in the gap of income mobility between rural households by 86 percent. The reason for this is that income obtained from non-farm income in general and self-employment, in particular, is the main inequality increase in sources of income.

Table 6: Decomposition of income sources: Farm, Nonfarm and total income components

Category	Income Source	S_k	G_k	R_k	Share	% Change
Total Income	Non-Farm	0.2291	2.9382	0.9192	0.4991	0.2699
	Farm	0.7709	0.8886	0.9068	0.5009	-0.2699
	Total Income		1.2400			
Farm Income	Crop	0.3220	1.0198	0.8902	0.3289	0.0070
	Livestock	0.6560	0.9398	0.9393	0.6517	-0.0043
	Ag.wage	0.0221	0.9904	0.7899	0.0194	-0.0026
	Farm		0.8886			
Non-farm Income	Self-Employ	-0.2057	-9.5988	0.9780	0.6573	0.8630
	NonAg. wage	0.8951	0.9725	0.9394	0.2783	-0.6168
	Transfer	0.1242	0.9390	0.6742	0.0268	-0.0974
	All Other	0.1865	0.9499	0.6252	0.0377	-0.1488
	Nonfarm		2.9382			
Total Income	Crop	0.2482	1.0198	0.7539	0.1539	-0.0943
	Livestock	0.5057	0.9398	0.8809	0.3376	-0.1681
	Ag.wage	0.0170	0.9904	0.6940	0.0094	-0.0076
	Self-Employ	-0.0471	-9.5988	0.9236	0.3370	0.3841
	NonAg. wage	0.2051	0.9725	0.8615	0.1386	-0.0665
	Transfer	0.0285	0.9390	0.4096	0.0088	-0.0196
	All Other	0.0427	0.9499	0.4483	0.0147	-0.0281
	Total Income		1.2400			

Source: author's calculation using ESS data 2011/12, 2013/13, and 2015/16 waves
Note: S_k: represents the share of income from a given in total income
G_K: represents the Gini coefficient of income gap within each income category
R_K: represents the Gini correlation between income from the given activity and total income % Change: represents

3.3.2 Decomposition by effects

As shown above, absolute and relative income mobility, as well as the structure of income of households, are experiencing both negative and positive income mobility. The mobility are caused by either of the two effects including the growth effect in which the household relative income position in the population has not to change and the transfer effect caused by the relative position change. Field and Ok (1996) suggested that income mobility may be due to the transfer effect if income transfers from one household to another household while the growth effect occurs when the household gain from economic opportunities when there is an economic growth.

The decomposition result in Table 7 showed that the total effect on relative mobility (based on expenditure) was 52 % in 2011 to 2014, 50% in 2014 to2016 and 58% 2011 to 2016 which the total effect on relative mobility in income mobility is like “U” type processing. The total effect on absolute mobility based on expenditure showed that there is a slight income growth from 2011-2016 (absolute percentage index of 3.95 percent from 3.45 percent). This is because households can participate in diversified income sources and other income-generating activities. The result of the effect on relative mobility and absolute mobility is similar when considering income and consistent with previous studies (Jiang et al., 2016; Melcah, 2020).

The Growth Effect, Fields & Ok (1999) Absolute income Mobility has indicated upward income mobility with an absolute percentage index of 1.10 percent from 5.86 percent while Fields & ok (1999) relative income mobility has indicated downward income mobility with a relative percentage index of 84 percent from 83 percent in terms of expenditure. On average from 2011-2016, there is 5.76 percent growth effect in absolute terms and there is 41.7 percent growth effect in relative terms. Thus, the growth effect has shown an upward effect in absolute terms while a downward effect in relative terms.

The transfer effect can be seen that, on average from 2011-2016, there is 3.38 percent transfer effect in absolute terms and there is 17 percent transfer effect in relative terms (Table 6). Overall, the result is consistent with studies that argue that income growth contribution is better than the transfer where income growth is the main source for income mobility (Jiang et al., 2016; Melcah, 2020).

Table 7: Decomposition of income mobility: transfer and growth effect

Mobility Type	Time Periods	Expenditure Based			Income-Based		
		Total effect	Growth effect	Transfer effect	Total effect	Growth effect	Transfer effect
Fields & Ok (1999) Absolute Mobility Index	2011-2014	3.45	1.10	3.44	6.18	2.38	5.94
	2014-2016	3.33	5.86	2.74	8.69	3.11	5.57
	2011-2016	3.95	5.76	3.38	9.95	3.27	6.68
Fields & Ok (1999) Relative Mobility Index	2011-2014	0.519	0.084	0.436	1.176	0.567	0.608
	2014-2016	0.504	0.083	0.420	0.981	0.024	0. 579
	2011-2016	0.583	0.417	0.166	1.332	0.574	0.758

Sources: Author's calculation using ESS data 2011/12, 2013/13 and 2015/16 waves

4. Conclusions and Recommendations

A recent estimate of income inequality, poverty, and other welfare indicators has shown an improvement in Ethiopia. These key economic development indicators cannot answer two questions. One, 'Are the richer getting rich and the poor getting poorer?' 'Who are winners and looser during the economic process?' To answer these questions, it is important to conduct income mobility analysis, tracking the households' income over time. Analysis of income mobility provides a broader picture of the income distribution dynamics which leads to sub-optimal intervention. The overall objective of the study was to generate evidence on the existence and structure of households' income mobility in Ethiopia using balanced panel data that has three waves collected in 2011/2, 2013/4, and 2015/6.

The study used Shorrock's rigidity index, transition probability matrix, Field and Ok (1999) methods for analysis. Overall, there is a fairly high degree of mobility in both income and expenditure in Ethiopia. The transition matrix result, for stayer/non-mobile, has revealed that there is less mobility in the top and bottom quintile than in the middle of the distribution. For upward mover, the result has indicated that those households who were in the first income status were likely to experience an income increase.

To sum up, Shorrock's rigidity index and the transition probability matrix has showed the sampled households have experienced slighter income mobility and proved the existence of relative and absolute income mobility in Ethiopia. Thus, the finding from relative and absolute income has two main important points. First, is used as the roadmap for other parts of the study where is used to differentiate the income mobility distribution. Second, the findings of bottom-level households that have experience of income mobility are an important area for policy targeting. The decomposition result has also showed that the income mobility difference among rural households in Ethiopia was embodied in the nonfarm income and growth effect. As the result, it is relevant to target income growth effect and income-generating activities to shorten the income mobility gaps.

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