Ethiopian Journal of Economics

Volume XXIX Number 2 October 2020

A Publication of
THE ETHIOPIAN ECONOMICS ASSOCIATION
(EEA)

VOLUME XXIX NUMBER 2 OCTOBER 2020

Published: October 2021

Consumption-based and Multidimensional Poverty Dynamics in Ethiopia: Evidence from Spatiotemporal Approach[1]

Aemro Tazeze Terefe,[2] Mengistu Ketema Aredo,[3] Abule Mehare Workagegnehu,[4] and Wondimagegn Mesfin Tesfaye[5]

Abstract

Consumption-based and multidimensional poverty comparison provides a conceptually meaningful, empirically informative and more precise image for policy decisions. This study is a deep drive of consumption-based and multidimensional poverty dynamics and the decomposition of disparities among rural and small towns in Ethiopia. Data from three rounds of the Ethiopian Living Standard Measurement Survey (LSMS) was used to compute the Foster-Greer-Thorbecke index for consumption-based poverty and the Alkire-Foster index for multidimensional poverty. The study considered a balanced sample of 3220 households every three rounds with the corresponding sample weight for the post-stratification adjustments to ensure all regions are represented. Though consumption-based poverty has been moderately declining over time, multidimensional poverty has exhibited inconsistent changes over time. The transition probability of non-poor into poor and/or change to non-poor and poor was relatively high. Multidimensional indicators exhibit backwards or forward

1 Manuscript received: 7 July 2021
Accepted: 19 August 2021
[2] PhD fellow in Agricultural Economics at Haramaya University, Ethiopia; corresponding author. Email: aemrot@gmail.com.
[3] Professor of Agricultural and Resource Economics at Haramaya University and Chief Executive Officer (CEO) of the Ethiopian Economics Association (EEA), Ethiopia. Email: mengistuket@gmail.com.
[4] Assistant Professor in Agricultural Economics and Head School of Agricultural Economics and Agribusiness at Haramaya University, Ethiopia. Email: abulemehare@gmail.com.
[5] Economist Consultant, World Bank Group, Ethiopia. Email: wtesfaye@worldbank.org.
Acknowledgements:
The authors are grateful to the Haramaya University, School of Agricultural Economics and Agribusiness, German Academic Exchange Service (DAAD), and African Economic Research Consortium for generous funding assistance.

movers of deprivations. Specifically, malnutrition and years of schooling showed a high transition probability for households to keep household status. Southern Nations Nationalities and Peoples (SNNPs), Oromia and Amhara regions have the highest relative contribution for both poverty measurements. Female-headed households had a low relative contribution for consumption-based poverty but a high contribution for multidimensional poverty. Moreover, rural areas also contribute more to consumption-based and multidimensional poverty. There is a significant difference in consumption-based poverty based on drought and shortage of rainfall shocks, but no significant change in rainfall shocks in multidimensional poverty. It implies that short-term shocks are more reflected in consumption poverty while simultaneous shocks are significant in multidimensional poverty. Considering both monetary and multidimensional measures is vital to get a complete picture of welfare decomposition and transition. Therefore, it is necessary to design policy interventions that reduce poverty in rural areas, SNNPs, Oromia and Amhara regions and male households with the highest relative contribution of poverty to improve social-economic welfare in Ethiopia.

Keywords: Foster-Greer-Thorbecke index, Alkire-Foster index, decomposition, and transition.
JEL Codes: I27, O19, Q12

1. Introduction

Achieving sustainable and inclusive economic growth is the key focus area of development goals across the globe. These goals include improving welfare, reducing inequality, and setting indicators of multidimensional well-being (Ravallion, 2017; Kim and Heshmati, 2019). World Bank's sustainable development goal is to end extreme global poverty and reduce the poverty headcount ratio from 10.7% in 2013 to 3% by 2030 (UNDP, 2014). According to the World Bank (2018), between 1990 and 2015, the percentage of the world's population living in extreme poverty fell from 37.1 to 9.6 percent. Nevertheless, the money metric approach in measuring poverty is not human-centred, which defines poverty as a scarcity of economic resources or incomes to meet minimum basic needs for a decent life (Mekonnen and Amas, 2021). Though measuring well-being has involved considerable efforts by scholars, policymakers, and social planners for an extended time (Mekonnen and Amas, 2021), no uniquely agreeable measurement has been overextended so far.

Over the past three decades, the Ethiopian economy has exhibited substantial gross domestic product growth. Reducing monetary poverty is attributed to reform-based government policies and heavy private and public investments. Despite all these steps, the Ethiopian government reported that around 25 percent of the population lives under the poverty line (GTP-II, 2016). This is considering money metric measurements of poverty only. The use of a monetary measure of poverty assumes that markets and prices exist for all goods and services. Hence, this measurement is subject to incompleteness, bias, narrow conceptualizations of the reality on the ground, and eludes precise measurement to address poverty reduction policies. Due to the limitation mentioned above of income and expenditure as a measure of poverty, the multidimensional approach is becoming the traditional method today (Alkire, 2018; Samuel *et al*., 2018; Santos and Villatoro, 2018; Bourguignon and Chakravarty, 2019).

The contemporary empirical and conceptual literature admits that poverty is a multidimensional phenomenon, and measurements that account for various socio-economic aspects of the subject under investigation are prominent. Substantially multidimensional poverty in Ethiopia has decreased between 2002 and 2009, despite a relatively high baseline condition (Mwanakatwe and Barrow, 2010). Disregarding the baseline and relative population growth, Ethiopia has been cited as one of the world's lowest-income countries. According to a global Multidimensional Poverty Index (MPI) report for 2018, Ethiopia seconds Niger in the number of multidimensionally poor people in Africa (Alkire *et al*., 2017; OPHI, 2018). Despite the promising progress, a record of multidimensional poverty is still a deep-rooted societal problem in Ethiopia.

Previous empirical studies have focused on measuring poverty in Ethiopia using monetary and multidimensional approaches. Monetary-based poverty analysis has been used by Kashi *et al*. (2016), Oumer (2016), and Birhan and Tesfahun (2017). Some researchers also conducted multidimensional poverty analysis (Dean and Jolliffe, 2016, Bersisa and Heshmati, 2016; Tigre, 2018, Misganaw *et al.*, 2019; Degye, 2020; Tigre, 2020; Bantayehu and Singi, 2021; Galgalo *et al.*, 2021; Tsegaye, 2021; Desawi *et al*., 2021). Nevertheless, these studies have ignored some indicators and dimensions; either use specific groups or locations, restrict their analysis to single outcomes, focus on cross-sectional data disregarding dynamism over time, and lack decomposition in subpopulation groups. Others used a short panel and cross-sectional data and examined consumption-based and multidimensional poverty (Dean and Jolliffe, 2016; Tigre, 2018; Tigre, 2020; Megibaru, 2020; Mekonnen and Almas, 2021). These studies are also limited in their coverage, weighting and the data usage.

Consumption-based and multidimensional poverty comparison provides a conceptually meaningful, empirically informative and more precise image for policy decisions. Therefore, the integrated nature of well-being is essential for evaluating poverty levels and reveal the true picture of social problems, capabilities, functioning and distribution. It is also crucial for poverty targeting to advance the distribution of non-market goods, especially in the country that follows developmental state policy. Furthermore, methodologies for a distributive measurement analysis have advanced considerably in recent years and created new possibilities for measuring decomposition. The results of this study would inform policy interventions targeting poverty reduction by considering both consumption-based and multidimensional wellbeing dynamics in conjunction. Additionally, the results would help policy-makers tailor their programs and plans for resource allocation based on specific location and social groups and create a more comprehensive policy formulation. Estimating inequality across regions helps to design anti-poverty interventions. Therefore, this study has adopted and used the integrated theoretical approach of welfare and multidimensional poverty theories to examine the trends, transition, decomposition, and inequalities.

Generally, the contribution of the body of literature in this study is four-fold. First, it uses the recent three rounds of panel data from 2012 to 2016 for measuring consumption-based and multidimensional poverty. Second, it helps a new empirical perspective to compare the dynamics and suggest informed decisions of poverty measurements. Third, it makes decompositions based on location and different social groups. Lastly, it also considers drought reports as a shock and downscaled rainfall at the household level and decomposed rainfall shocks by taking shortage of annual rainfall as a proxy variable for rainfall shock. To the best of the researchers' knowledge, this is the first study to estimate the comparison of consumption-based and multidimensional poverty at the country level using panel data and applying the Foster-Greer-Thorbecke (FGT) and Alkire–Foster (AF) methodologies by employing Distributive Analysis for Stata Package (DASP).

2. Methodology

2.1 Data Description

The research has used the Living Standard Measurement Survey (LSMS) data, which is conducted by the World Bank in collaboration with the Central Statistical Agency (CSA) of Ethiopia. This comprehensive dataset consists of samples from all regions in the country (nine regional states and two city administrations) representing the national population of Ethiopia. A total of 290 Enumeration Areas (EAs) and 43 EAs from small-towns[6], 12 households in each EAs were selected in the first wave. During the second and third waves, 100 urban EAs were added. The addition also included one more region to the sample, Addis Ababa. In each EA, 15 households were selected. The addition of urban EAs increased the sample size from 333 to 433 EAs. The first wave had a low non-response rate of 0.7 percent; the final interviewed sample was 32025 individuals and 3.969 households; the second wave attrition rate was 4.9 percent producing a sample size of 33147 individuals and 3,776 households. The third wave was about 43785 individuals and 5466 households. However, maintaining the balanced panel sample for this analysis and restricted the final analysis by excluding households missing information related to multidimensional indicators. Restricting households with such item non-response resulted in 2012 and 2014 a loss of 18.87 percent of the sample and in 2016 a loss of 41perecent of sample for both attrition rate and due to excluding unbalanced data. Finally, the study has considered a balanced sample of 3220 households in each round with the corresponding sample weight for the post-stratification adjustments to ensure that all regions are represented.

[6] Operation definition on this research it means all town included in the first wave of LSMS data which was included Addis Ababa city administration.

2.2 Empirical Strategy

Household consumption-based poverty was estimated using the formula given in Haughton and Khandker (2009).

$$P_{ot} = \frac{1}{N}\sum_{i=0}^{N} I(Y_{it} < Z) \qquad \textbf{(1)}$$

Where, P_{ot} is the headcount poverty over time, N is the total sample households, Y_{it} is adult consumption expenditures of a household in different period i, Z is consumption-based poverty, and $I(.)$ is the indicator function which is 1 if the expression $Y_{it} < Z$ is true, 0 otherwise. Additionally, the researchers have used a more general class of poverty measures proposed by Foster-Greer-Thorbecke (FGT) (2010) to examine the incidence and depth of poverty since it is decomposable across locations sub-groups climate-induced shocks. As one of the measures proposed by Foster and Thorbecke (2010), it is defined as

$$P_{at} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{G_{it}}{z}\right)^{at}, \ at \geq 0 \qquad \textbf{(2)}$$

Where αt is a measure of the index's sensitivity to poverty and the poverty line at period t. When parameter αt = 0, P_{0t} is simply the headcount index at time t and when αt = 1, the index is the poverty gap index P_{1t} at period t. For all αt > 0, the measure is strictly decreasing in the living standard of the poor. *G* is the number of population subgroups, and Z is the poverty line.

The FGT poverty index (P_t) decomposed population subgroups following Duclos and Tiberti (2016) by regions, sex, residences and shocks in a different time:

$$\hat{P}_t(Z_t, \alpha_t) = \sum_{g_t=1}^{G_t} \hat{\phi}(g_t)\hat{P}_t(Z_{tz}; \alpha_t \ g_t) \qquad \textbf{(3)}$$

Where G is the number of population subgroups, $\hat{P}(z,\alpha,g)$ is the estimated FGT index of subgroup g, $\hat{\phi}(g)$ is the estimated population share of subgroup g, $\sum_{g=1}^{G}\hat{\phi}(g)\hat{P}(z;\ a\ \ g)$ is the estimated relative contribution of subgroup g to total poverty.

For multidimensional poverty measurement, three core dimensions and ten indicators developed by Alkire (2011) and Alkire and Santos (2014) have been used with corresponding weights (see in detail Table 1). There are different axiomatic approaches to measuring multidimensional poverty. The dashboard approach is a starting point to estimate the level of deprivation in the dimensions separately (Alkire *et al*., 2011; Ravallion, 2011). This approach helps see the impact of specific policies but does not precisely reflect the joint distribution of deprivations across the population (Alkire *et al*., 2015). The second is the intersection approach if a person can be considered poor if each dimension's achievement is less than the poverty threshold set for that dimension but produces weakly low poverty estimates. The last is the union approach considers an individual to be poor only if the achievement in one of the dimensions falls below its respective threshold. The union approach is very commonly used but leads to exaggerated estimates of poverty. In between these two extremes, MPI is widely used recently (Duclos and Younger, 2006). MPI uses different dimensions and indicators. A poverty cut-off is set for each indicator. Finally, the multidimensional poverty cut-off is developed by combining all the indicators based on the weight assigned to each indicator (Alkire and Foster, 2011).

Table 1: Multidimensional poverty dimensions and indicators

Dimensions of poverty	Indicator	Deprived if…	Weight		Poverty line
Education	Years of schooling	No households' member has completed five years of schooling	1/6	1/18	1/3
	Child school attendance	Any school-aged child is not attending school up to class 8	1/6	1/18	
Health	Child mortality	Any child has died in the family	1/6	1/18	1/3
	Nutrition	Any child for whom there is nutritional information is malnourished	1/6	1/18	
Living standard	Electricity	The household has no electricity	1/18	1/54	1/3
	Improved sanitation	The household's sanitation facility is not improved, or it is improved but shared with other households	1/18	1/54	
	Improved drinking water	The household does not have access to improved drinking water, or safe drinking water is more than a 30-minute walk from, round-trip	1/18	1/54	
	Quality of floor	The household has a dirt, sand, or dung floor	1/18	1/54	
	Cooking fuel	The household cooks with dung, wood, or charcoal	1/18	1/54	
	Assets' ownership	The household does not own more than radio-TV, telephone, bike, motorbike, or refrigerator and does not own a car or truck	1/18	1/54	
MPI(1.00)		MPI poor if deprivation at or above	1/3		1/3

Source: Alkire and Foster (2011); Alkire (2014), and Alkire and Santos (2014).

By following Nawaz and Iqbal (2016) and Nawaz and Iqbal (2021), the household assigned a deprivation score (S_i) based on the weighted deprivations experienced in each indicator. The deprivation score of each household lies between 0 and 1. The deprivation score of each household (S_i) calculated by:

$$S_{it} = (W_1 I_{1t} + W_2 I_{2t} + W_3 I_{3t} + \cdots + W_c I_{ct}) \quad \textbf{(4)}$$

Where, $I_{it} = 1$ if the household is deprived in indicator i; and 0 otherwise, at time t period, and W_i is the weight attached to indicator I with $\sum_{it=1}^{c} W_i = 1$. A column vector $S_{it} = (S_{1t}, \dots, S_{ct})$ of the deprivation, the score reflects the breadth of each household's deprivation at different period t. A household is deemed to be poor if its deprivation score is equal to or greater than the poverty cut-off, $S_{it} \geq K$. A household is identified as poor if it has a deprivation score greater than or equal to 1/3 (33%) (OPHI, 2014; Dotter *et al.*, 2017).

According to OPHI (2010), adjusted headcount (M0) for multidimensional poverty has decomposability and monotonicity properties, applicable for categorical, ordinal or cardinal indicators. Therefore, the LSMS data were fitted to rigorous examination using the distributive analysis strata package (DASP) developed by Duclos and Araar (2013). The headcount ratio (H0), the intensity of poverty (A), and adjusted headcount ratio (M0) (Alkire and Santos, 2010) were estimated. The multidimensional poverty headcount ratio (H), therefore,

$$H0 = {}^{n}/_{N} \quad \textbf{(5)}$$

Where n stands for the number of multidimensional poor households and N is the total number of sample households. The headcount ratio measures the incidence of multidimensional poverty of the households. The average intensity of multidimensional poverty (A) reflects the proportion of the weighted component indicators (WDS), in which, on average, poor people are deprived of (dn). This measure is called the breadth of multidimensional poverty. Technically,

$$A = \sum_{1}^{n} \frac{WDS}{dn} \quad \textbf{(6)}$$

$$MPI = M0 = H0 \times A = \sum_1^n \frac{WDS}{dN} \quad \textbf{(7)}$$

Headcount ratio (H0) is simple to compute and easy to understand. It violates dimensional monotonicity in that the overall multidimensional poverty remains the same if the deprivation of a person increases (Saboor *et al*., 2015). The headcount ratio (H0) is adjusted by multiplying it with the intensity or depth of deprivations (A) being experienced to address the violation of dimensional monotonicity. The inclusion of A in the formula for M_o ensures that both the incidence of MDP and the intensity of deprivations are determined simultaneously (Feeny and McDonald, 2016). The decomposability of multidimensional poverty into sub-populations and dimensions is expressed as;

$$M_0(MDP) = \frac{N_1 M_0(MDP_1)}{N} + \frac{N_2 M_0(MDP_2)}{N} + \cdots \frac{N_k M_0(MDP_k)}{N} \quad \textbf{(8)}$$

Where $N1$, N2 and Nk are different sub-groups of population N, and $MDP_{1,}$ MDP_2 and MDP_k are different sub-group matrices of the indicator matrix. Therefore, the share/contribution of each sub-group for the overall poverty was:

$$S(MDP_1) = \frac{N_1 M_0(MDP_1)}{NM_0(MDP_1)} \; S(MDP_2) = \frac{N_2 M_0(MDP_2)}{NM_0(MDP_2)} \; S(MDP_k) = \frac{N_k M_0(MDP_k)}{NM_0(MDP_k)} \quad \textbf{(9)}$$

Where (MDP_1) is the share of sub-group MDP_1, (MDP_2) is the share of sub-group MDP_2 and (MDP_k) is the share of sub-group MDP_k of the overall poverty. The contribution of each group for the general poverty level at a time will be:

$$SD_j = \frac{\sum_{i=1}^{n}(W_i g_{ij})}{\frac{nd}{M_0}} \quad \textbf{(10)}$$

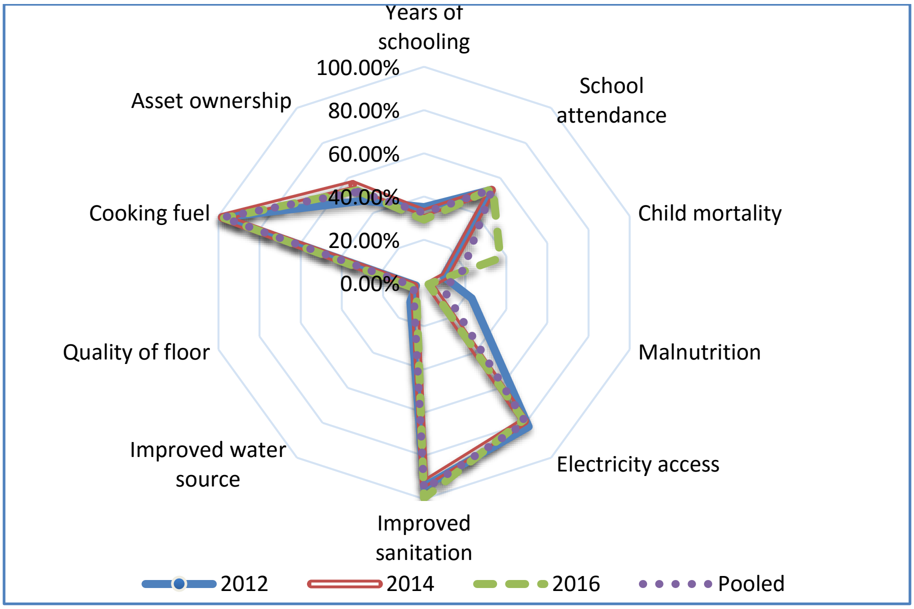
Where, SD_j is the contribution of each dimension for the overall adjusted headcount ratio ($M0$).

3. Results and Discussion

3.1 Comparison of Multidimensional and Consumption-based Poverty

The number of deprived households with the respective percentage of deprivation for each multidimensional poverty indicator is presented in Figure 1 below. These are the percentages of poor individuals in one indicator, regardless of whether the household is deemed multidimensional poor or not.

Figure 1: Multidimensional poverty indictors' deprivation over time



Source: Computation based on ESS[7] (2012, 2014, 2016).

Table 2 shows the level of consumption poverty in Ethiopia using FGT measures of incidence (P0), poverty gap (P1), and severity of poverty (P2) for 2012-2016. Since 2012 Ethiopia has had 38 percent of poverty incidence (P0), 13.1 percent poverty gap (P1), and 6.3 percent severity of poverty rates (P1). In 2016, households experienced a remarkable improvement in consumption-based poverty. The country has witnessed a 25.8 percent of poverty incidence (P0), 8 percent poverty gap (P1) and 3.4 percent severity of poverty (P2). This shows a

[7] Ethiopian Socioeconomic Survey

12.2 percent reduction in the share of the population living in poverty within the year 2012. The decline in P0, P1, and P2 have continued between 2012 and 2016. For instance, the population below the poverty line's share decreased from 38 percent in 2012 to 25.8 percent in 2016 (Table 2). Generally, consumption-based poverty indicators (P0, P1 and P2) have exhibited a declined trend over time in all rounds. According to World Bank (2020a), this progress has been underpinned by robust and sustained economic growth averaging 10.9 percent annually, despite being adversely affected by climate variability and other factors.

Most indicators registered decreases across the three waves except improved sanitation, flooring made, cooking fuel, and asset ownership. Child nutrition and year of schooling exhibited 21.03 percent and 12.02 percent decline, respectively, between 2012 and 2016. The nutrition indicator also registered a declining trend of 31 percent. UNDP (2015) also confirmed that child mortality is declined by 59 percent between 1990 and 2015 in Ethiopia. Though the electricity source shows minimal improvement across time, it is almost effectively stagnant and non-existent. This is in line with the CSA (2016) report where about 80 percent of the sample population is deprived of access to electricity, and more than 95 percent of the population are deprived of cooking fuel and improved sanitation in 2012-2016 (CSA, 2016). Similarly, World Bank (2018) and Migbaru and Zerayehu (2020) reported that the supply of electricity, clean energy for cooking, and improved sanitation are not adequate and contribute to living standards.

Table 2: Consumption-based and multidimensional poverty indices over time in Ethiopia

Consumption-based poverty				Multidimensional poverty		
Year	**P0**	**P1**	**P2**	**H0**	**A**	**M0**
2012	0.38	0.131	0.063	0.750	0.454	0.341
2014	0.314	0.092	0.039	0.681	0.426	0.290
2016	0.258	0.08	0.034	0.776	0.452	0.350
Pooled	0.312	0.099	0.044	0.736	0.445	0.327

Note: P0=incidence of poverty; P1=poverty gap; p2 = severity of poverty; H0=headcount ratio; A= intensity of deprivation; M0=adjusted headcount ratio.

* Observations weighted to make results representative of all individuals in Ethiopia.

Source: Computation based on ESS (2012, 2014, and 2016)

As depicted in Table 2, relative poverty incidence was higher in 2012, but the gap slightly decreased in terms of incidence, depth, and severity of consumption-based poverty during 2012-2016. It is interesting to footnote that the level of average incidence dropped, showing that poor households were progressively concentrated above the poverty line over time so that the burden of falling poverty chop somewhat. MoFED (2016) also confirmed that poverty in rural Ethiopia had declined consistently in rural areas related to improved agricultural technologies and rural infrastructure. Furthermore, according to Mohammed (2020) and Osabohien *et al*. (2020), the Ethiopian national poverty incidence was 23.5 percent, on the total population in 2015 and 30.8 percent for the international poverty line.

As shown in Table 2, in Ethiopia, multidimensional poverty indices (H0, A, and M0) were declined from 2012 to 2014, but in 2016, it was more significant than before. In 2012-2014 the multidimensional poverty decreased by around 6 percent. Educational dimension (years of schooling life), health dimension (child nutrition), and living standard (access to electricity, improved sanitation, and improved source of water) significantly contributed to the decline of national headcount ratio (H0) and adjusted headcount ratio (M0). This decline mainly can be due to the efforts that the government undertook to improve access to education, health, and living standard, particularly in improved schooling life and school attendance, and improving nutrition, improved water and sanitation (see above Figure 1), even if the change is not that much substantial. This finding is similar to the World Bank (2018) report and UNDP (2015) that the Ethiopian government was implementing development strategies for the last couple of years, enabling the decline of multidimensional poverty.

Within three waves, the headcount ratio (H0) increased by 2.6 percent, and the adjusted headcount ratio (M0) increased by 1.6 from 2012 to 2016. The trend between those statistically significant indicators and dimensions that shows improvement of deprivation over time was less than that declined deprivation. This leads to increases in the deprivation of aggregate multidimensional poverty quietly. However, the level of multidimensional poverty in this result is higher than that reported by UNDP (2018) and OPHI (2018). This is probably due to the sampling weight and the rigorous estimation techniques of Distribute Analysis for Stata Package (DASP). Furthermore, this analysis only focused on rural and small-town areas, making this significant difference compared with previous studies. In 2014-2016, increasing H0 and M0 could be due to drought shocks in 2015 in Ethiopia, seriously affecting different indicators (child mortality, improved water and housing quality) of multidimensional poverty throughout the nation. World Bank (202b) also supports these arguments that adverse climate affects the livelihood in general and specifically child mortality due to lack of food and coping mechanisms forcing people to sell their fixed assets.

Different dimensions of poverty have contributed differently to multidimensional poverty. Living standard has contributed the most in all-round (around 58 percent, 52.7 percent and 66.9 percent in rounds respectively) followed by education (42 percent, 47 percent and 39 percent in rounds respectively) and health (around 15 percent, 7 percent and 27 percent in all rounds respectively (Table 2). Seff and Jolliffe (2016), Tigre (2018) and Migbaru and Zerayehu (2021) found living standard contributes the most to poverty indices then follows education, but health dimension has the most negligible contribution. The contribution of health (child mortality and nutrition) is the lowest in the panel year compared to other dimensions. This can be due to the improvements in the health service, mainly in child mortality though slightly increase in 2012-2016, and nutrition which decreased by around 23 percent between 2012 and 2016. This finding is similar to that of UNDP (2015) and CSA (2016) in 2012-2014, and Tigre (2018).

When comparing the consumption-based and multidimensional poverty measures at a household level, an appealing question is: "Is it possible to identify the same household as non-poor or poor poverty?" The poverty status match was between 29.13-37.33 percent of sample households between two measures (Table 3).

The percentage of non-poor and poor in consumption-based poverty and non-poor and poor in multidimensional poverty measurements difference is quite significant in all years. Multidimensional poor households are not poor in consumption-based poverty and this paints a different picture of poverty in Ethiopia.

Table 3: Consumption and multidimensional poverty, percentage of households in Ethiopia

		Consumption-based poverty											
	Status	2012			2014			2016			Pooled		
		Non-poor	Poor	Total	Non-poor	Poor	Total	Non-poor	Poor	Total	Non-poor	Poor	Total
MDP	Non poor	22.64	2.39	33.39	29.01	2.89	31.89	20.59	1.83	22.42	24.08	2.37	26.45
	Poor	63.48	11.49	74.97	59.78	8.32	68.11	69.04	8.54	77.58	64.10	9.45	73.55
	Total	86.12	13.88	100	88.79	11.21	100	89.63	10.37	100	88.18	11.82	100
Poverty status match*				34.13			37.33			29.13			33.53

* Status match is the percentage of households with similar poverty status in both measures.

Source: Computation based on ESS (2012, 2014, 2016).

Over time the contribution for some dimensions is not the same. The contribution of education decreased by around 3 percent in 2012-2016. Years of schooling, deprivation had a statistically significant contribution to the decline of their contribution to education in multidimensional poverty (see Appendix Table 1). Nonetheless, living standard dimensions, their contribution decreased in 2014, but it increased in 2016 even if the overtime change in living standards' contribution is not that much bigger. This may be due to an increase of deprivation (indicators except for electricity and improved drinking water) on living standard dimensions (refer above Figure 1).

According to World Bank (2020b), the increment of deprivation for sanitation and diarrhea incidence were directly related to drought shocks. Consequently, the household should sell any asset for coping mechanisms, and mobility leads to an increase in the flooring's deprivation.

Generally, poverty estimates based on consumption-based poverty are lower than multidimensional poverty in all rounds. For example, consumption-based poverty was estimated at 38, 31.4, and 25.8 in 2012, 2014, and 2016 respectively, while the multidimensional poverty estimated for the same period was 74.97, 68.11, 77.58, respectively (see Table 2). Furthermore, estimates suggest that about 8.32-11.49 percent of households were poor in both consumption-based and multidimensional poverty between 2012 and 2016 in Ethiopia. Despite using different approaches to estimating poverty, these results are approaching the national estimates MoFED (2015) suggested. Ilana Seff and Dean Jolliffe (2016) also found significant differences in the poverty estimates between well-being measures based on consumption and multidimensional poverty measurement. The consumption-based poverty trend is more consistently compared to the official poverty result than the multidimensional poverty result.

3.2 Poverty Transition

With this information and through transition matrices, researchers have observed changes in households' different states over time by both measurements of poverty. Consumption-based poverty shows a transition in ascending and descending over time. The transition probability of non-poor into poor and or change into non-poor and poor was relatively high. Regarding multidimensional indicators of exhibits transitions in and out/backward or forward movers of deprivations. Looking at each of the multidimensional poverty indicators, the transition probability for malnutrition and years of schooling show a high probability for households to keep their status of non-deprivation or change into non-deprivation if they deprived in the initial condition from 2012 to 2016, from 2014 to 2016 and from 2012 to 2014 (Appendix Table 2). The school attendance, source of fuel for cooking, and access to electricity indicators have a relatively low transition probability of a household staying deprived or moving into non-deprivation if initially deprived. In contrast, indicators of access to improved drinking water, quality of housing, and improved sanitation show different trends. Access to drinking water exhibits persistency in deprivation and a higher probability of changing into deprivation if a household is not initially deprived. This suggests that not much welfare improvement was observed for households in terms of improved sanitation, access to electricity, cooking fuel, and housing quality. All are being indicators for a standard living dimension of the multidimensional poverty indicators.

About 77.02 percent of households were always poor or non-poor in all waves (Table 4). Measurement of consumption-based poverty exhibits relatively high transitions in and out/backward or forward movers of poverty compared with chronic poverty. This is consistent with the findings of Bruck and Sindue (2013), Dercon, and Krishnan (2000), who found relatively high transitions in and out of poverty (22.98 percent). Ilana Seff and Dean Jolliffe (2016) also found the changes in consumption and relatively easy for a household to move substantially up or down the consumption gradient over a short period. Furthermore, World Bank (2015b) also reported that around 14 percent of non-poor households are estimated to be vulnerable to falling into poverty in Ethiopia. About 49.99 percent of households were multidimensional poor in either one or two waves (Table 4). More than half of the households are persistently poor in all waves. Researchers found that most households are persistent in multidimensional poverty, both consistently poor and never poor (58.01). Multidimensional poverty analysis was found to depict high persistent nature over time. Because households get most public services and facilities through governments, some of the facilities and services do not have market prices.

Table 4: Movement of households in and out of poverty in the percentage of households

	Consumption-based poverty	Multidimensional poverty
Always poor (three times)	1.96 (63)	50.99 (1642)
Twice poor	6.61 (213)	25.68 (827)
Once poor	16.37 (527)	16.3 (525)
Never poor (always non poor)	75.06 (2417)	7.02 (226)
Persistence status*	77.02(2480)	58.01 (1868)
Transient status**	22.98(740)	41.99 (1352)
Total	100% (3200)	100% (3200)

*Persistent status is the sum of the percentage of households who were never poor and always poor.

**Transient status is the sum of the percentage of households who were poor once or twice.

Source: Computation based on ESS (2012, 2014, and 2016).

For instance, sanitation, electricity, and improved water source lead to multidimensional poverty's persistent nature. This result is plausible as a household is less likely to change some indicators than living standard indicators when facing certain shocks. Ilana Seff and Dean Jolliffe (2016) was reported some multidimensional poverty indicators a part of a structural problem. Additionally, in Ethiopia, a large proportion of the services, infrastructure, and facilities have limited engagement in the formal market and multidimensional poverty indicators not provided by private sectors.

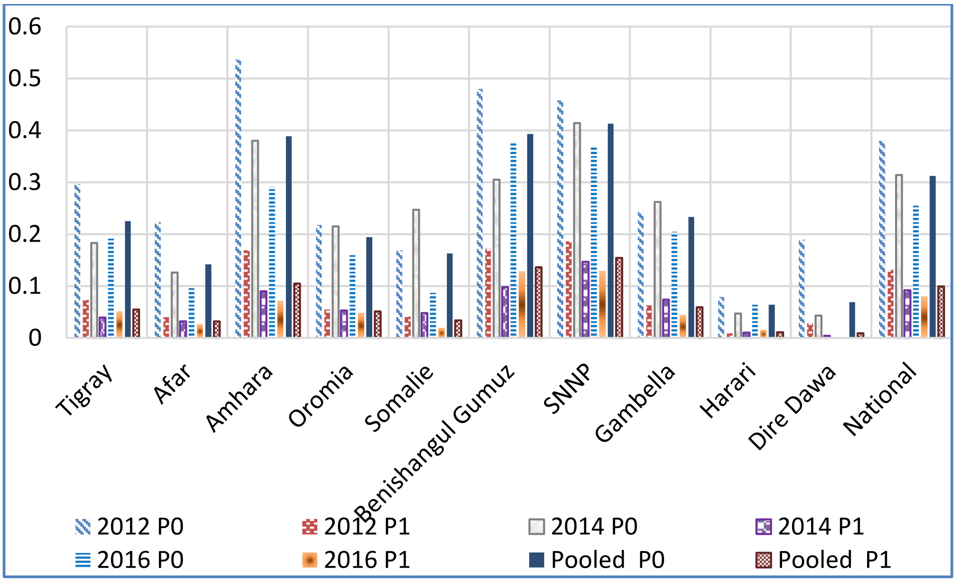
3.3 Decomposition

3.3.1 Decomposition by region

The results of the consumption-based poverty incidence and gap of poverty declined over time in different regions. However, poverty incidence is moderately high (Figure 2). Because of the subsistence, a farming system in all Ethiopia regions and the livelihood of the rural population is a mainstay on rained agriculture; poverty is primarily still a rural phenomenon (Alemayehu *et al*., 2015; GTP-II, 2016). In 2012, poverty incidence is very high in Amhara (0.536), Benishangul Gumuz (0.48), and SNNP (0.458); whereas poverty incidence was lower in Harari, Dire Dawa, and Somalie. In 2014, the highest poverty incidences were in SNNP, Amhara, and Benishangul Gumuz; and in 2016 were Benishangul Gumuz, SNNP, and Amhara.

As shown in Figure 2 though poverty incidence was very high relatively in Amhara regional state, there was a tremendous improvement over time compared with SNNP and Benishangul Gumuz. Poverty incidence, poverty gap, and severity were slightly lower in Somalie, Harari, and Dire Dawa and steadily declined. Especially in 2016, poverty incidence, poverty gap and severity of poverty in Dire Dawa almost was null.

Figure 2: Trend of incidence and gap of poverty in regions and Ethiopia



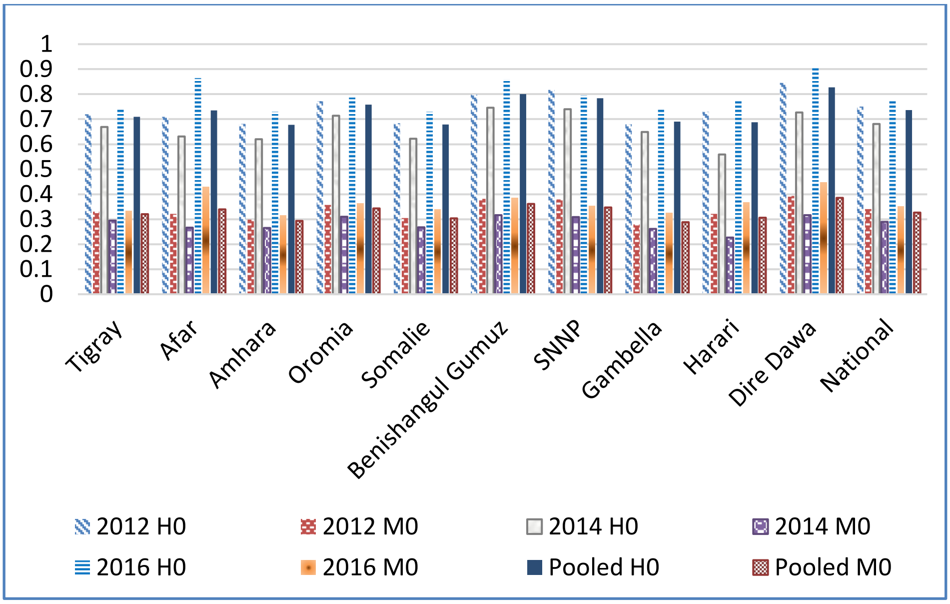
*Observations weighted to make results representative of all regional individuals in Ethiopia. Standard errors are adjusted for stratification and clustering.

Source: Computation based on ESS (2012, 2014, 2016)

Figure 3 shows the estimates of the headcount (Ho) and adjusted headcount ratio (M0) of the nine regional states of Ethiopia and one city administration (Dire Dawa) over three rounds by Alkire and Foster (2007) method.

Some regions showed progress change in H0 from 2012 to 2016, yet the patterns differ across regions. For instance, the headcount and adjusted headcount ratio (poverty profiles) in Dire Dawa, SNNP, and Benishangul Gumuz were very high in 2012, 2014, and 2016 though they showed incrementally in 2014 and a decline in 2016. Amhara, Somalie, and Gambella had a low MPI profile in 2012 compared with the other regions. In these regions, H0 showed further reduction in 2014, but a clear increment occurred in 2016. In 2016, H0 was very high as compared to 2014. Dire Dawa, Benishangul Gumuz and Afar had the least multidimensional poor in 2016.

Figure 3: Trends of multidimensional poverty indices across the region



*Observations weighted to make results representative of all regional individuals in Ethiopia. Standard errors are adjusted for stratification and clustering.

Note: Based on Alkire and Foster (2017), H0=Headcount ratio; M0=Adjusted headcount ratio)

Source: Computation based on ESS (2012, 2014, and 2016)

Though the level of H0 was high in 2016, the rest regions were relatively better compared with Dire Dawa, Benishangul Gumuz, and Afar. The trends for H0 are similar to those for M0: progress in 2012 to 2016 but not always monotonic (for example, SNNP faced higher H0 in 2014 than Benishangul

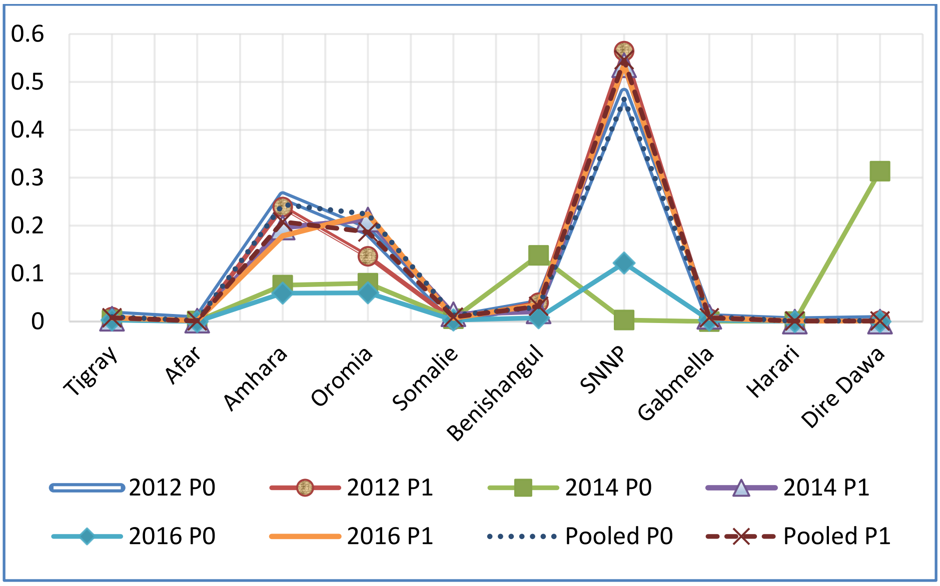
Gumuz, but SNNP had less in M0 (adjusted headcount ratio) as compared with to Benishangul Gumuz. It implies that the intensity of multidimensional poverty is severe in Benishangul Gumuz.

Comparisons of regional multidimensional poverty show that even though there were some differences over the years, the multidimensional poverty (M0) level was high in 2016 in almost all country regions. Particularly adjusted headcount ratio was relatively highest in Dire Dawa, Benishangul Gumuz, and SNNPs regions in 2012, respectively (Figure 3). Generally, the multidimensional poverty indices steadily fluctuate and declined inconsistently over time in Ethiopia. The different trends in multidimensional poverty could be linked to the fact that most multidimensional poverty indicators are service provisions such as health, education, and living standards even though the government has improved provisions via efforts to achieve the 2015 Millennium Development Goals (MDGs). However, this continuing service provision vs population growth rate in the nation is not proportional.

Figure 3 presents a nationally representative picture of absolute and relative consumption-based poverty in different regions. This part goes beyond to assess how widespread relative and absolute poverty has been. In general, the difference in the absolute and relative contribution of poverty among different regions is insignificant over time. Both absolute and relative contribution for prevalence and gap of poverty levels are highest in SNNP, Amhara, Somalie, and Oromia in 2012-2016, where the lowest absolute and relative contribution of prevalence, gap, and severity of poverty recorded in Dire Dawa, Harari, and Afar.

In all regions, the relative contribution of incidence and gap consumption-based poverty has declined over time. There was remarkably little difference in relative poverty in Dire Dawa Harari and Afar, but Oromia is the only region that showed a decline of the absolute and relative incidence of poverty in 2012-2016 predominantly. The relative contribution of SNNP, Oromia, and Amhara for H0 and M0 was very high in all waves. The relative contribution of SNNP declined over time, but in Oromia and Amhara regions, the relative contribution for H0 and M0 increased in 2012-2014. In 2016, the relative contribution for H0 in Amhara was higher than the Oromia region, but the relative contribution for M0 was lower for Amhara compared with Oromia. Gambelia, Harari, Afar, Benishangul Gumuz, and Dire Dawa had a less contribution for H0 and M0 respectively in 2012-2016.

Figure 4: Relative contribution of consumption-based poverty indices by regions

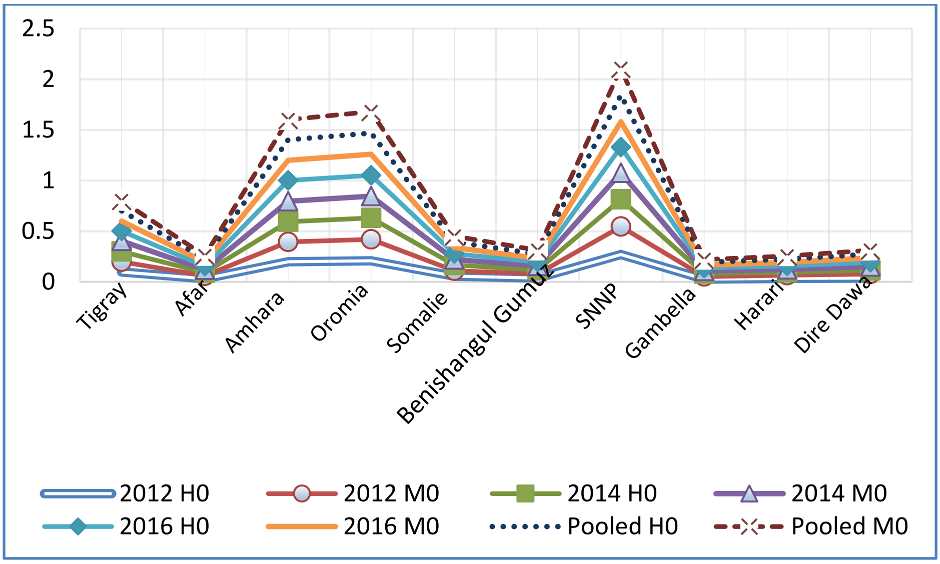


*Observations weighted to make results representative of all regional individuals in Ethiopia. Standard errors are adjusted for stratification and clustering.
Note: P0 is poverty incidence, and P1 is Poverty gap
Source: Computation based on ESS (2012, 2014, and 2016)

Out of the nine regions in Ethiopia and one city administration SNNP, Oromia and Amhara regions constituted about 67.5% of H0 and 67.2 percent of M0 of the country's total population in 2012-2016.

This finding was also similar to the CSA (2010), which stated that the three regions (SNNPs, Oromia and Amhara) had contributed more for relative contribution for multidimensional poverty. Hence, a poverty analysis of these regions can give us a good picture of Ethiopia's multidimensional poverty. Multidimensional poverty relative contribution is very high in regions with large populations while emerging regions contribute less (Figure 5).

Figure 5: The relative contribution of regions to the national multidimensional indices



*Observations weighted to make results representative of all regional individuals in Ethiopia. Standard errors are adjusted for stratification and clustering after constructing the weighted sum of all three dimensions.
Source: Computation based on ESS (2012, 2014, and 2016)

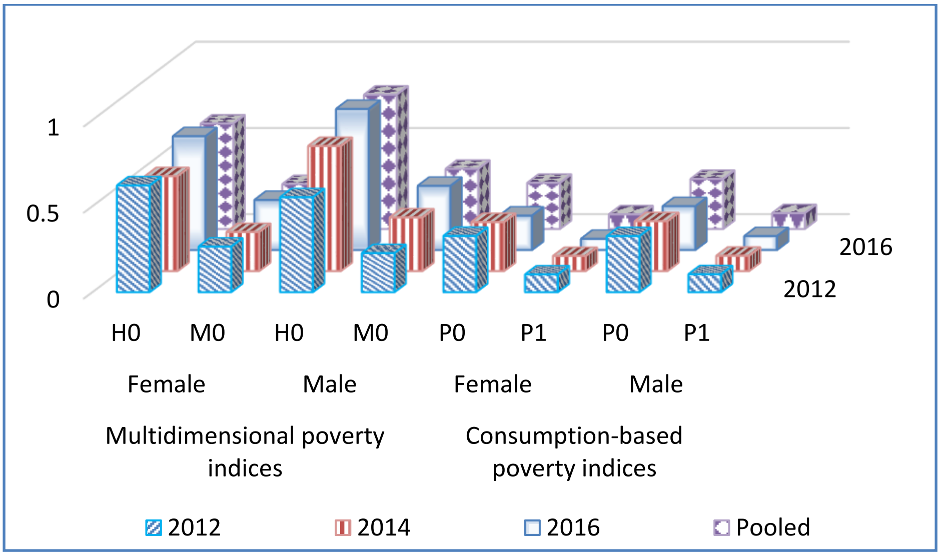
3.3.2 Decomposition by sex

Figure 6 depicted the disaggregation of consumption-based and multidimensional poverty indices by the sex of household heads. Consumption-based poverty by sex of household heads was almost similar across female and male-headed households. Compared to the national level of incidence and depth of poverty, female-headed households incidences were slightly lower than that of male head households. Prevalence and poverty gap for female-headed households were 0.37 and 0.103, respectively, in 2012 and more significant than that of male-headed households (0.326 and 0.104).

Over time, consumption-based poverty for both female- and male-headed households in Ethiopia decreased moderately. Consumption-based poverty in female and male populations was almost similar in 2012, whereas there was a relative improvement in the female population over time. Specifically, the reduction in poverty incidence and the gap was particularly strong over time for female heads compared with male-headed households. This may be because female-headed households may be more likely to access different social programs, public services, better preference, and test towards consumption instead of saving than male-headed ones.

The trend of multidimensional poverty indices shows that it is high in Ethiopia in general and in female subpopulation households in particular (Figure 6). Probably the female populations, most livelihoods are vulnerable and have less resource ownership or endowments than the male population. In 2012, 2014, and 2016, the share of poor female individuals in the population for H0 was 0.846, 0.928, and 0.934, respectively. There were increments in the percentage of poor female individuals between 2012 and 2014, whereas they slightly declined between 2014 and 2016.

Figure 6: Decomposition and trends of poverty indices by sex of households



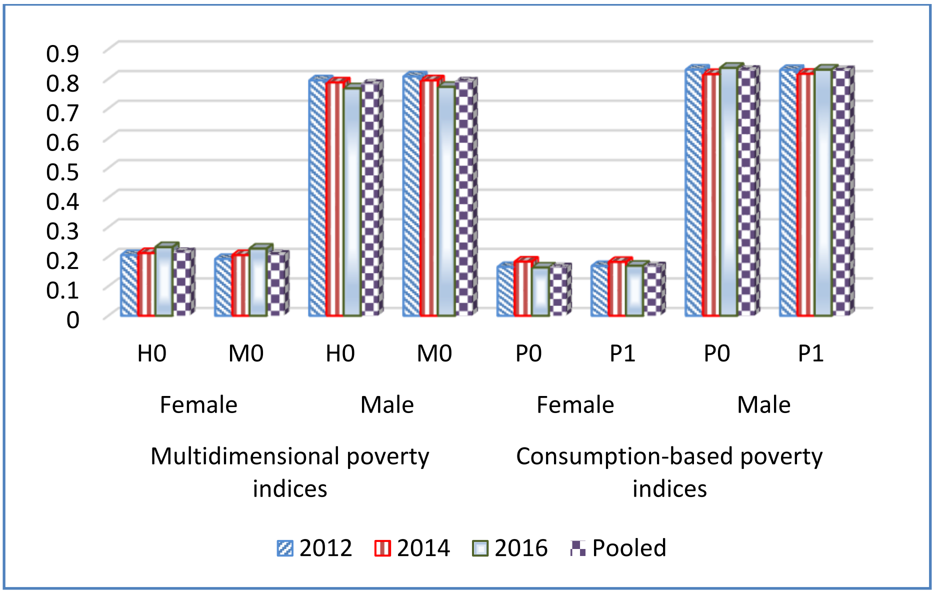
*Observations weighted to make results representative of all regional individuals in Ethiopia.

Note: H0: headcount ratio; M0: Adjusted headcount ratio; P0: Poverty incidence; P1: poverty gap

Source: Own computation based on ESS (2012, 2014, and 2016).

There was a proportional increment in the headcount ratio (H0) of poor female households and the adjusted headcount ratio (M0) between 2012 and 2014 but not in 2016. Multidimensional indices (H0 and M0) have not been decreasing consistently over time; instead, they have been significantly increasing between 2014 and 2016 and slightly declined between 2012 and 2014. Ethiopia was committed to attaining the MDGs by 2015. It developed the first Growth and Transformation Plan (GTP-I) and (GTP-II), designed to maintain rapid and broad-based growth and eventually end poverty. This may be because female-headed households are associated with more climate-sensitive resources and access to land or the credit market and information on risk-coping techniques. This argument is also revealed by Huynh and Resurreccion (2014), and World Bank (2020b) reports. However, this evidence is not generalizable as the social norms gender embedded may determine an advantaged or disadvantaged condition.

Figure 7: Relative contribution of sex household groups for poverty indices



Note: H0: headcount ratio; M0: Adjusted headcount ratio; P0: Poverty incidence; P1: poverty gap

Source: Computation based on ESS (2012, 2014, and 2016)

Although female-headed households relatively had low consumption-based poverty and high multidimensional poverty indices compared with male-headed ones, the relative contribution for both consumption-based and multidimensional poverty indices is significantly low, but the contribution increased over time. In consumption-based poverty, female-headed households' relative contribution increased for incidence and poverty gap in 2012-2014 but eventually declined in 2016. In 2012-2014, male-headed households' relative contribution for poverty incidence declined though the relative contribution is high, and the poverty gap was increased. Female-headed and male-headed households' relative contribution for multidimensional poverty indices declined in 2012-2014 but increased in 2014-2016, as shown in Figure 7. This finding is also similar to that of Tigre (2020), which indicated gender-based decomposition incidence of consumption poverty is high for male-headed households compared to female-headed households in Ethiopia.

3.3.3 Decomposition by residence

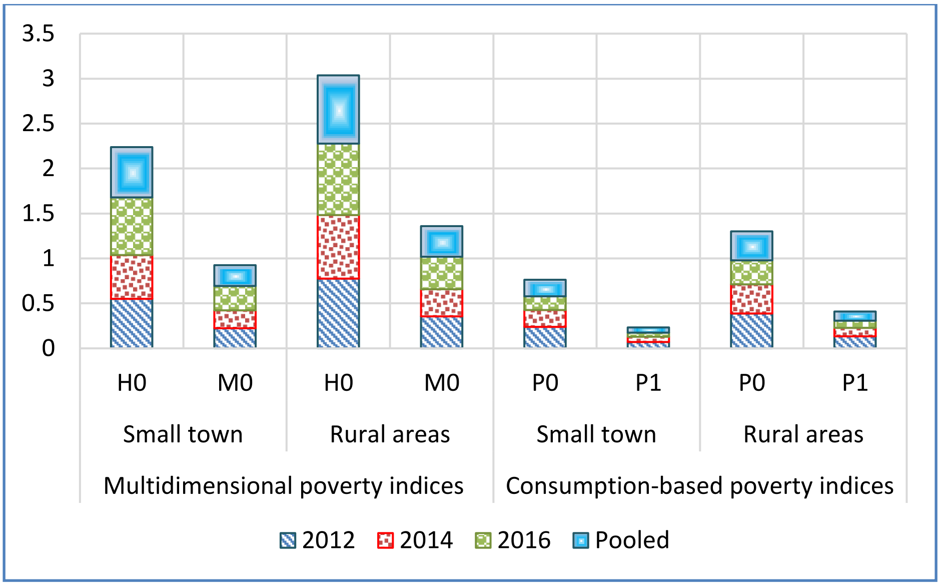
Figure 8 depicted the distribution of multidimensional and consumption-based poverty indices over rural and small towns. Consumption-based poverty showed that the relative majority of the population are above the poverty line in rural areas. The prevalence and gap of rural poverty indices were higher (0.297 and 0.094) than that in small-town (0.185 and 0.055) areas in 2012-2016. However, poverty is relatively more prevalent in rural areas of the country. This is comparable to Ethiopia's poverty, where rural areas are relatively worse-off in poverty than their small-town counterparts. According to World Bank (2020b), poverty decreased from 30 percent in 2011 to 24 percent in 2016 in rural areas and from 26 percent in 2011 to 15 percent in 2016 in urban areas despite adverse climatic conditions of poverty reduction in Ethiopia. In rural areas of Ethiopia, the poverty reduction was relatively slow, with the poverty rate decreasing by four percentage points compared with the reduction of poverty rate tumbling by 11 percent in urban areas.

Generally, over time, poverty in rural and small-town areas has decreased moderately, but the poverty reduction was particularly strong in small-town areas. It implies the poverty reduction was particularly strong in small-town areas. This is probably because participating in non/off-farm activities would be very high, and better awareness of quality life is better in small towns than in rural areas. This is clear evidence that suggests the need to design policy interventions to reduce poverty in rural areas where poverty is worse than in small-town areas. This finding is similar to the work of Tigre (2018), Tigre (2020) and World Bank (2020a).

As Figure 8 depicted, the decomposition of consumption-based poverty and multidimensional poverty indices are high in rural areas than counter-intuitive. A steady pattern has been observed in the relative contribution of consumption-based poverty indices in rural and small-town areas in 2012-2016. The relative contribution of poverty in rural areas was very high compared with the small town over time. Poverty reduction in rural areas was relatively subdued, and this result is similar to the World Bank (202b) report. This is mainly because the government was focusing on towns, and the rural areas did not get equal attention. This finding was in line with Alemayehu *et al*. (2015), GTP-II (2016), and Tigre (2018). As expected in both measurements, poverty indices are high in rural areas. Because of the traditional farming system followed in the rural population, the livelihood is dependent on agriculture. Inherently agricultural farming is most vulnerable to different shocks and risks. Furthermore, different infrastructures and services are relatively minimal in rural areas.

Over time, small-town and rural areas multidimensional poverty indices are not consistently declining, whereas consumption-based poverty incidence and poverty gap in small towns and rural Ethiopia decreased moderately (Figure 8). Increment in multidimensional poverty indices between 2014-2016 maybe because of the improvement in social infrastructure and public service, access to electricity, water and health services, and other services are not proportional to population growth in the country and due to the adverse effect of extreme poverty climate events. This has also been revealed by Tigre (2018) and World Bank (2020a). Education, health, and living standard dimensions of poverty were improved alongside over time but remained at a low level (World Bank, 2020b)

Figure 8: Decomposition and trends of poverty indices by residence

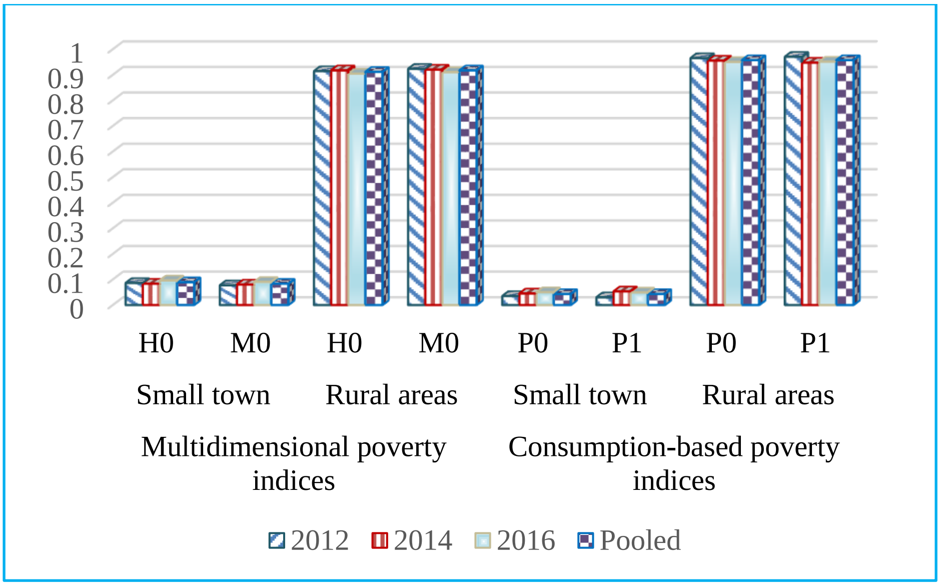


Note: H0: headcount ratio; M0: Adjusted headcount ratio; P0: Poverty incidence; P1: poverty gap

Source: Own computation based on ESS (2012, 2014, and 2016).

As shown in Figure 9, the relative contribution of small-town for total multidimensional poverty indices is low compared to rural areas. Over time, relative contributions of the rural areas have changed inconsistently. For instance, declined in 2014-2016 but slightly increased in 2012-2014. For small towns drops in 2012-2014 but did not fall in 2014-2016. It implies that the Ethiopian government has given attention to rural areas, though the contribution is still by far higher compared with small towns.

Figure 9: Contribution of subgroups to indices (percentage)



Note: H0: headcount ratio; M0: Adjusted headcount ratio; P0: Poverty incidence;
P1: poverty gap

Source: Own computation based on ESS (2012, 2014, and 2016).

3.3.4 Decomposition by shocks

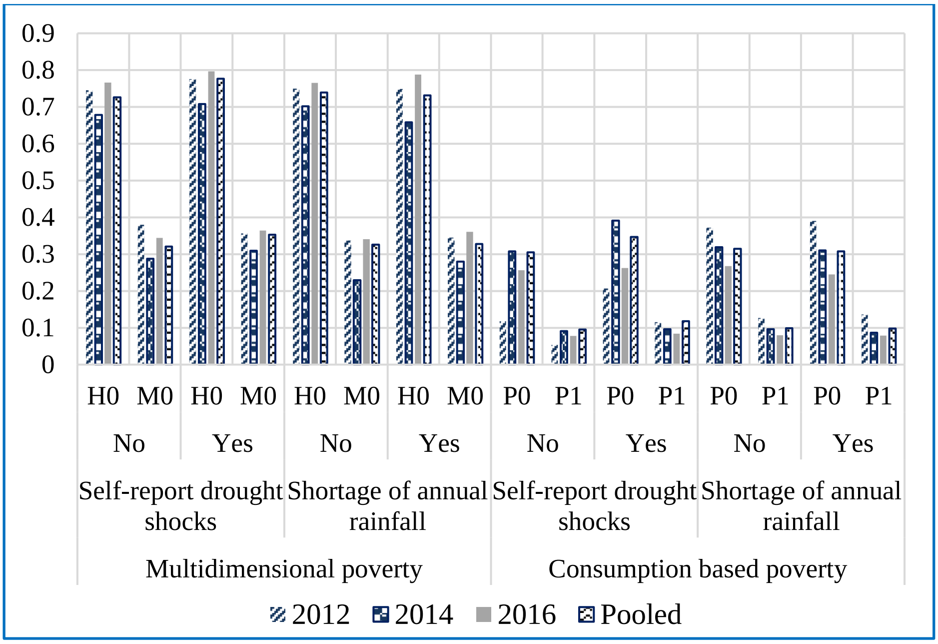
Figure 10 also reports the decomposition of multidimensional and consumption-based poverty indices by different climate-induced shocks over time—the result of comparison between who reported the existence of drought socks or not by using shortage of rainfall[8] and self-report drought[9]. There is a significant negative impact of (self-reported) drought exposure on consumption when using a self-reported indicator of drought exposure. For consumption-based poverty, both incidence and gap of poverty somehow vary over time

[8] The estimated rainfall has been taken as shocks as normalized deviations in a single annual rainfall from the expected yearly historical rainfall over the 17 years (2001–2017). Shortage of rainfall is identified as one standard deviation away from the historical mean rainfall and is then coded as a binary dummy variable (=1 if the household experienced drought at time t and 0 otherwise).

[9] It is dummy variables that measured the perception of households about the drought occurrence. Suppose the answer is yes/one if the households perceived a drought; otherwise, no/zero.

inconsistently between two groups, and the difference is not significant. This is likely due to the endogeneity problem. That is for households who reported the drought shocks, the headcount ratio and adjusted headcount for multidimensional poverty and the incidence and gap of poverty for consumption-based poverty were relatively higher than those who did not report drought shocks over time. Bachewe *et al*. (2017) found that actual cereal prices increased during the drought, consistent with a story of high agricultural impacts of the drought, consequently affecting consumption. In consumption-based poverty, such climate-induced shock could seriously affect the households' absorptive capacity by selling liquid assets and if the government develops social protection programs. The study has used data on a sample of Ethiopian households observed before (2014) and after/during the drought (2016).

Figure 10: Multidimensional and consumption-based poverty indices by shocks



Note: H0: headcount ratio; M0: Adjusted headcount ratio; P0: Poverty incidence; P1: poverty gap

Source: Computation based on ESS (2012, 2014, and 2016) and CHIPS[10]

[10] Climate Hazards Group InfraRed Precipitation with Station

World Bank (2020b) also reported that climate-related variables positively affect multidimensional poverty in Ethiopia. Researchers have found a clear negative impact of the drought on household welfare. Using drought indicators based on remote sensing data, Sohnesen (2019) did not see an impact of rainfall on consumption.

Regarding multidimensional poverty, drought has adversely affected improved water, electricity access, and improved sanitation due to shortage of water. However, households with a shortage of mean annual rainfall had almost similar H0 and M0 in 2012, better H0 and M0 in 2014, and less H0 and M0 in 2016. It implies that rainfall shortage did not affect multidimensional poverty in the short run. The evidence suggesting that shocks can drive changes in consumption-based poverty in the short run and multidimensional poverty indices, in the long run, implies that deprivation can be a useful indicator for monitoring adverse shocks reactions. People who have had a bad year are more likely to report exposure to shocks. Similarly, Hirvonen *et al.* (2020) found that the drought did not lead to a widespread increase in the health dimension of poverty but an adverse impact in areas with a limited road network.

4. Conclusion and Policy Implications

Consumption-based and multidimensional poverty assessments based on household-level panel data provide a complete picture of wellbeing dynamics. In the overall survey year, the incidence of consumption-based poverty was very small compare with multidimensional poverty. Furthermore, most of the large portions of sample respondents who are multidimensional poor are not poor by consumption. The poverty status match found between 29.13-37.33 percent of sample households between two measures. This result shows that the two poverty measurement methods are relatively not comparable and had no similar status. The minimal overlap between consumption-based and multidimensional poverty implies that the two poverty measures portray and paint a different picture of poverty in Ethiopia. Measurement of consumption-based poverty exhibits relatively high transitions of poverty as compare with chronical poor. Consumption-based poverty shifts more substantially. Most households are persistently multidimensional poor in all waves, and depict high persistent nature over time.

The results of the consumption-based poverty indices declined over time in different regions. However, poverty incidence is relatively high in Amhara, Benishangul Gumuz and SNNP over time. However, there was a tremendous improvement in poverty incidence in Amhara over time compared with SNNP and Benishangul Gumuz. In all regions, the relative contribution of consumption-based poverty has declined over time, but Oromia is the only region that predominantly declined absolute and relative poverty. The trend of multidimensional poverty steadily fluctuated and declined inconsistently over time in Ethiopia. The different trends in multidimensional poverty indices could be linked to the fact that most of the multidimensional poverty indicators with population growth rates in the nation are not proportional and comparable. Specifically, multidimensional poverty indices are high in Dire Dawa, SNNP, and Benishangul Gumuz over time though these regions showed a progressive decline in 2016. The intensity of multidimensional poverty is very severe in Benishangul Gumuz. The relative contribution of SNNP, Oromia and Amhara almost constituted about 67 percent of the relative contribution of the country's total population.

Female-headed households relatively had low consumption-based poverty and high multidimensional poverty indices compared with male-headed ones, the relative contribution for both consumption-based and multidimensional poverty indices is significantly low, but the contribution has increased over time. Furthermore, poverty in rural areas and small-towns decreased moderately, but the poverty reduction was particularly strong in small-town areas. It implies the poverty reduction was particularly strong in small-town areas. The relative contribution of poverty in rural areas was very high compared with the small town over time. Nevertheless, a steady pattern has been observed in the relative contribution of consumption-based poverty indices in rural and small town’s areas but not consistently decline multidimensional poverty indices. The relative contribution of small towns for total multidimensional poverty indices was low compared to rural areas.

The result vividly shows the importance of including long-term welfare indicators when analyzing poverty to complement money metric poverty measures to understand poverty status and its triggers better. Perhaps more interesting from a policy perspective is the different results observed between these two types of poverty measurement dynamics. Therefore, the consumption-based and multidimensional poverty measurement could provide information that can help to initiate in-depth studies at regional levels with different social groups for evidence-based, effective policy and program planning. Policymakers should consider both money metric and multidimensional poverty measurements to see the important changes in the wellbeing of households. Generally, at a national level, setting the ultimate goal of poverty eradication, narrowing the gap between regions, location, social group, the incidence of climate-related shocks, promoting the fairness of distribution of services and facilities, and reducing multidimensional deprivation of poor population are necessary. Therefore, Ethiopia and its different government stakeholders need additional efforts to improve the citizens living standards dimensions, particularly access to electricity, improved sanitation, improved water services and housing, and hence, to bring a significant difference in fighting against multidimensional poverty.

References

Adepoju, A. (2018). Determinants of Multidimensional Poverty Transitions among Rural Households in Nigeria (No. 2058-2018-5335).

Adetola, A. (2014). Trend and Determinants of Multidimensional Poverty in Rural Nigeria. *Journal of Development and Agricultural Economics* 6 (5): 220–231.

Alemayehu Ambel, Parendi, M., and Biratu, Y. (2015). Global Multidimensional Poverty Index 2018: The most detailed picture to date of the world's poorest people.

Alemayehu Geda, and Yimer Addis. (2014). May. Growth, Poverty and Inequality in Ethiopia, 2000–2013: A macroeconomic Appraisal. In a Chapter in Book to be Published by The Forum for Social Studies (FSS).

Alkire Sabina. (2018). The Research Agenda on Multidimensional Poverty Measurement Important and As-yet Unanswered Questions. OPHI Working Paper No. 119

_______. (2013). *Choosing dimensions: The capability approach and multidimensional poverty. In The many dimensions of poverty* (pp. 89-119). Palgrave Macmillan, London.

Alkire, S., and Foster, J. (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *The Journal of Economic Inequality*, 9(2), 289–314. doi:10.1007/s10888-011-9181-4

________. (2011a). Counting and Multidimensional Poverty Measurement. *Journal of public economics*, 95(7-8), pp.476-487.

________. (2007). Choosing Dimensions: *The Capability Approach and Multidimensional poverty*. *SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1646411.*

Alkire, S., Apablaza, M., Chakravarty, S. and Yalonetzky, G. (2017). Measuring Chronic Multidimensional Poverty. *Journal of Policy Modeling*, 39(6), pp.983-1006.

Alkire, S., Foster, J. E., Seth, S., Santos, M. E., Roche, J. M., and Ballon, P. (2015). Multidimensional Poverty Measurement and Analysis. Oxford: Oxford University Press. https://ophi.org.uk/wp- content/uploads/OPHIWP086_Ch5.pdf

Alkire, S., and Santos, M. E. (2010). Acute Multidimensional Poverty: A new Index for Developing Countries, OPHI working paper no. 38. Oxford Poverty and Human Development Initiative (OPHI), Queen Elizabeth House (QEH), University of Oxford.

Amao, J. O., Ayantoye, K. and Fanifosi, G. E. (2017). An analysis of Multidimensional Poverty and Its Determinants in Rural Nigeria. *Journal of Development and Agricultural Economics*, 9(11), pp.303-311.

Apablaza, M. and Yalonetzky, G. (2013). Decomposing Multidimensional Poverty Dynamics. Young Lives.

Araar, A. (2009). The Hybrid Multidimensional Index of Inequality. *SSRN Journal. https ://doi.org/10.2139/ ssrn.14965 05.*

Araar, A. and Duclos, J. Y. (2013). User Manual DASP Version 2.3. DASP: Distributive Analysis Stata Package, Université Laval, PEP, CIRPÉE and World Bank.

Arndt, C., Distante, R., Hussain, M. A., Østerdal, L.P., Huong, P. L. and Ibraimo, M. (2012). Ordinal Welfare Comparisons with Multiple Discrete Indicators: A first Order Dominance Approach and Application to Child Poverty. *World Development*, 40(11), pp.2290-2301.

Bachewe, F. N., Yimer, F. and Minten, B. (2017). Agricultural Price Evolution in Drought Versus Non-drought Affected Areas in Ethiopia (Vol. 106). International Food Policy Research Institute.

Bersisa, M. (2015). Multidimensional Measure of Household Energy Poverty and Its Determinants in Ethiopia. Economic Transformation for Poverty Reduction in Africa: *A Multidimensional Approach*, 58–83. https://doi.org/10.4324/9781315206516

Birhan Demissie Sisay and Tesfahun Asmamaw Kasie. (2017). Rural Households Vulnerability to Poverty in Ethiopia. *Journal of Poverty*, 21(6), pp.528-542.

Bourguignon, F. and Chakravarty, S. R. (2019). The Measurement of Multidimensional Poverty. In Poverty, Social Exclusion and Stochastic Dominance (pp. 83-107). Springer, Singapore.

Brück, T., and Sindu Worku. (2013). Dynamics and Drivers of Consumption and Multidimensional Poverty: Evidence from Rural Ethiopia. *SSRN Electronic Journal. https://doi.org/10.2139/ssrn.22486 70.*

Chakravarty, S. R. and Lugo, M. A. (2019). Multidimensional Indicators of Inequality and Poverty. Poverty, Social Exclusion and Stochastic Dominance, pp.223-259.

Decancq, K. and Lugo, A. M. (2013). Weights in Multidimensional Indices of Wellbeing: An Overview. *Econometric Reviews*, 32(1): 7-34. doi: 10.1080/07474938.2012.690641.

Decancq, K., M. Fleurbaey, and F. Maniquet. (2014). *Multidimensional Poverty Measurement with Individual Preferences*. Princeton: Princeton University Williams, Economic Theory Center Research Paper.

Degye Goshu. (2020). Adapting Multidimensional Poverty and Inequality Measures to National and Regional Contexts: Evidence from Ethiopia. *Tanzania Journal of Development Studies*, 17(2).

Dercon, S. and Krishnan, P. (2000). Vulnerability, Seasonality and Poverty in Ethiopia. *The Journal of Development Studies*, 36(6), pp.25-53.

Desawi Kiros Gebrekidan, Abate Mekuriaw Bizuneh, and Cameron, J. (2021). Determinants of Multidimensional Poverty among Rural Households in Northern Ethiopia. *Journal of Rural and Community Development*, 16(1).

Dotter, C. and Klasen, S. (2017). The Multidimensional Poverty Index: achievements, Conceptual and Empirical Issues No. 233. Courant Research Centre: Poverty, Equity and Growth-Discussion Papers.

Duclos, J., Araar, A., Giles, J. (2010). Chronic and Transient Poverty: Measurement and Estimation with Evidence from China. *Journal of Development Economics,* 91, 266–277.

Duclos, J. Y. and Tiberti, L. (2016). Multidimensional Poverty Indices. In the Oxford Handbook of Well-Being and Public Policy. ed. S. Rosen, 91–140. Chicago: University of Chicago Press ed. S. Rosen, 91–140. Chicago: University of Chicago Press.

Ethiopia, UNDP. (2018). Ethiopia's Progress Towards Eradicating Poverty. Implementation of the Third United Nations Decade for the Eradication of Poverty (2018–2027) Discussion Paper.

Feeny, S., and McDonald, L. (2016). Vulnerability to Multidimensional Poverty: Findings from Households in Melanesia. *The Journal of Development Studies*, 52(3), 447–464. doi:10.1080/00220388.2015.1075974

Fentaw, A., and A. Rao. (2016). Determinants of Income Inequality in Urban Ethiopia: A study of South Wollo Administrative Zone, Amhara National Regional State. *International Journal of Applied Research*, 2(1): 550–563.

Foster, J., Greer, J. and Thorbecke, E. (2010). The Foster–Greer–Thorbecke (FGT) Poverty Measures: 25 years later. *The Journal of Economic Inequality*, 8(4), pp.491-524.

Foster, J., Seth, S., Lokshin, M., and Sajaia, Z. (2013). A unified Approach to Measuring Poverty and Inequality: Theory and Practice. Washington, DC: The World Bank.

Galgalo Dinka, Degefa Tolossa, and Shiferaw Muleta Eyana. (2021). Multidimensional Poverty of Pastoralists and Implications for Policy in Boorana Rangeland System, Southern Ethiopia. *World Development Perspectives*, 21, p.100293.

Gebretsadik Gebreslassie Hishe. (2015). Multidimensional Measurements of Poverty Analysis in Urban areas of Afar Regional State. *International Journal of Science and Research*, 4(7), pp.2627-2635.

GTP II. (2016). Growth and Transformation Plan II (GTPII) (2015/16–2019/20) (vol. 1). Addis Ababa: Federal Democratic Republic of Ethiopia, National Planning Commission, Main Text.

Haughton, J. and Khandker, S. R. (2009). Handbook on Poverty+ Inequality. World Bank Publications.

Heshmati, A. and Kim, J. (2014). A survey of The Role of Fiscal Policy in Addressing Income Inequality, Poverty Reduction and Inclusive Growth.

Hirvonen, K., Sohnesen, T. P. and Bundervoet, T. (2020). Impact of Ethiopia's 2015 Drought on Child Undernutrition. *World Development*, 131, p.104964.

Huynh, P. T. and Resurreccion, B. P. (2014). Womens' Differentiated Vulnerability and

Adaptations to Climate-Related Agricultural Water Scarcity in Rural Central Vietnam. *Climate and Development*, 6(3), pp.226-237.

Kashi Kafle, Kevin McGee, Alemayehu Ambel, and Ilana Seff. (2016). Once Poor Always Poor? Exploring Consumption-and Asset-based Poverty Dynamics in Ethiopia. *Ethiopian Journal of Economics*, 25(2), pp.37-76.

Kedir, A., and A. Oterova. (2014). Parental Investments on Girls, Post-marital Residence and Motives for Private Transfers, Econometric Evidence from Ethiopia, mimeo.

Khan, A. U., Saboor, A., Ali, I., Malik, W. S. and Mahmood, K. (2016). Urbanization of Multidimensional Poverty: Empirical Evidences from Pakistan. *Quality and Quantity,* 50(1), pp.439-469.

Kim, N. S. and Heshmati, A. (2019). The relationship between Economic Growth and Democracy: Alternative Representations of Technological Change. In Panel Data Econometrics (pp. 885-929). Academic Press.

Kim, T. Y. and Heshmati, A. (2013). Economic Growth: The new Perspectives for Theory and Policy. Springer Science and Business Media.

Kuschminder, K., Andersson, L. and Seigel, M. (2018). Migration and Multidimensional Wellbeing in Ethiopia: Investigating the Role of Migrants Destinations. *Migration and Development*, 7(3), pp.321-340.

Longobardi, Sergio, Napoli Parthenope, Felice Russo, and Università Salento. (2018). Multidimensional Poverty Measures for Analysing Educational Poverty Tommaso Agasisti, Politecnico Di Milano School of Management Multidimensional Poverty Measures for Analysing Educational Poverty in European Countries. no. 739.

Lugo, M. A. (2007). Comparing Multidimensional Indices of Inequality: Methods and Application. *In Inequality and Poverty*. Emerald Group Publishing Limited.

Maasoumi, E., and T. Xu. (2015). Weights and Substitution Degree in Multidimensional Wellbeing in China. *Journal of Economic Studies* 42 (1): 4–19.

Mekonnen, A. G. (2015). Multidimensional Poverty: Theory and Empirics. Lombardy Advanced School of Economics Research, 2015.

Mekonnen Bersisa and Almas Heshmati. (2021). A Distributional Analysis of Uni-and Multidimensional Poverty and Inequalities in Ethiopia. *Social Indicators Research*, pp.1-31.

Michler, J. D., Baylis, K., Arends-Kuenning, M. and Mazvimavi, K. (2019). Conservation Agriculture and Climate resilience. *Journal of environmental economics and management*, 93, pp.148-169.

Migbaru Alamirew Workneh. (2020). Nonmonetary poverty in Ethiopia: Multidimensional approach. *Poverty and Public Policy*, 12(4), pp.326-356.

Migbaru Alamirew Workneh and Zerayehu Sime Eshete. (2021). Household Level Non-Monetary Poverty in Ethiopia and its Driving Factors: A Multidimensional

Approach with Panel Estimation. *Social Indicators Research*, 154(1), pp.145-168.

Ministry of Finance and Economic Development (MoFED). (2016). Growth and Transformation Plan II (GTP II, 2015/16-2019/20). Addis Ababa, Ethiopia: Author.

_______. (2014). Development and Poverty in Ethiopia—1995/96–2010/11. Addis Ababa: Ministry of Finance and Economic Development.

Misganaw Teshager Abeje, Atsushi Tsunekawa, Nigussie Haregeweyn, Zemen Ayalew, Zerihun Nigussie, Daregot Berihun, Enyew Adgo, and Asres Elias. (2020). Multidimensional Poverty and Inequality: Insights from the Upper Blue Nile Basin, Ethiopia. *Social Indicators Research*, 149(2), pp.585-611.

Mohammed, S. (2020). Assessment of Poverty Situation in Ethiopia. *International Journal*, 5(2), pp.109-117.

Mulugeta Yitayh, Girma Birhanu Ambaw, and Yohannis Mulu. (2017). Dynamics of Multidimensional Child Poverty and Its Triggers: Evidence from Ethiopia using Multilevel Mixed Effect Model. (2017): 1-32.

Mwanakatwe, P. and Barrow, L. (2010). Ethiopia's Economic Growth Performance: Current Situation and Challenges. *Economic Brief*, 1(5), pp.1-4.

Nawaz, S. and Iqbal, N. (2021). How cash Transfers Program Affects Environmental Poverty among Ultra-poor? Insights from the BISP in Pakistan. *Energy Policy*, 148, p.111978.

_______. (2016). Education Poverty in Pakistan: A spatial Analysis at District Level. *Indian Journal of Human Development*, 10(2), pp.270-287.

Oxford Poverty and Human Development Initiative (OPHI). (2018). Global MPI Country Briefing 2018: Ethiopia (Sub-Saharan Africa) The. (2018), 1–11.

Osabohien, R., Matthew, O., Ohalete, P. and Osabuohien, E. (2020). Population–Poverty–Inequality Nexus and Social Protection in Africa. *Social Indicators Research*, 151, pp.575-598.

Oumer Berisso. (2016). *Determinants of Consumption Expenditure and Poverty Dynamics in Urban Ethiopia: Evidence from Panel Data*, Springer International Publishing Switzerland 2016

Peterson, P., Funk, C. C., Husak, G. J., Pedreros, D. H., Landsfeld, M., Verdin, J. P. and Shukla, S. (2013). The Climate Hazards Group InfraRed Precipitation with Stations: Development and Validation. In AGU Fall Meeting Abstracts (Vol. 2013, pp. H33E-1417)

Ravallion, M. (2017). *Poverty Comparisons. Routledge.*

Saboor, A., Khan, A. U., Hussain, A., Ali, I. and Mahmood, K. (2015). Multidimensional Deprivations in Pakistan: Regional Variations and Temporal Shifts. *The Quarterly Review of Economics and Finance*, 56, pp.57-67.

Salazar, R., B. Duaz, and R. Pinzon. (2013). Multidimensional poverty in Colombia, 1997–

2013. *Institute for Social and Economic Research*, ISER working paper series.

Samuel, K., Alkire, S., Zavaleta, D., Mills, C. and Hammock, J. (2018). Social Isolation and Its Relationship to Multidimensional Poverty. *Oxford Development Studies*, 46(1), pp.83-97.

Santos, M. E. and Villatoro, P. (2020). The Importance of Reliability in the Multidimensional Poverty Index for Latin America (MPI-LA). *The Journal of Development Studies*, 56(9), pp.1784-1789.

_______. (2018). A multidimensional Poverty Index for Latin America. *Review of Income and Wealth*, 64(1), pp.52-82.

Sen, A. (2009). *The idea of justice.* London: Allen Lane.

_______. (1990). *Development as capability Expansion*. Cambridge: Harvard University.

_______. (1984). The living standard author(s): Amartya Sen Reviewed work (s): Source: Oxford Economic Papers, New Series, Vol. 36, Supplement: Economic Theory and Hicksian Themes (Nov. 1984) (pp. 74–90). Oxford University Press. *Economic Theory*, 36(May), 74–90.

Sen, B. (1992). Rural poverty in Bangladesh: Trends and Determinants. *Asian Development Review*, 10(1)

Sevinc, D. (2020). How Poor is Poor? A novel look at Multidimensional poverty in the UK. *Social Indicators Research*, 149(3), pp.833-859.

Sohnesen, T. P. (2019). Two sides to Same Drought: Measurement and Impact of Ethiopia’s 2015 Historical Drought. *Economics of Disasters and Climate Change*, pp.1-19.

Takeuchi, L. R. (2014). Incorporating People’s Value in Development: Weighting Alternatives. Development progress, World Bank Photo Collection.

Tang, L. (2019). Multidimensional Poverty and Anti-poverty Policy. In The Evolution of China's Poverty Alleviation and Development Policy (2001-2015) (pp. 155-181). Springer, Singapore.

Tasic, H., Akseer, N., Gebreyesus, S. H., Ataullahjan, A., Brar, S., Confreda, E., Conway, K., Endris, B.S., Islam, M., Keats, E. and Mohammedsanni, A. (2020). Drivers of Stunting Reduction in Ethiopia: A country Case Study. *The American Journal of Clinical Nutrition*, 112(Supplement_2), pp.875S-893S.

Tassew Woldehanna and Adam Hagos. (2013). Dynamics of Welfare and Poverty in poor rural and Urban Communities of Ethiopia. Young Lives: Oxford Department of International Development (ODID), University of Oxford, Oxford.

Tausch, A. and Heshmati, A. (2012). The Effects of Multinational Corporation Penetration on The Global Political Economy. A Re-analysis of a Recurrent Sociological Proposition with Contemporary Data. *Sociologia*, 44(3), pp.314-347.

_______. (2020). Multidimensional Inequality in Ethiopia. In A Multidimensional Economic Assessment of Africa (pp. 87-113). *Springer, Singapore*.

Tigre Getu. (2018). Economic Growth and Development in Ethiopia. *Springer Singapore*. https ://doi. org/10.1007/978-981-10-8126-2.

United Nations Development Programme (UNDP). (2018). Statistical update: Human development indices and indicators. New York. Retrieved January 29, 2021, from http://hdr.undp.org/en/content/human-development-indices- indicators-2018-statistical-update

________. (2015). Human Development Report 2015. Work for Human Development. United Nations Development Programme (UNDP), 288. https://doi.org/ISBN: 978-92-1-126398-5

_________. (2014). National human development report 2014 Ethiopia. Undp. Retrieved from http://hdr.undp. org/sites /defau lt/files /nhdr2 015-ethio pia-en.pdf. Accessed 17 March 2021.

Ward, P. S. and Shively, G. E. (2015). Migration and Land Rental as Responses to Income Shocks in Rural China. *Pacific Economic Review*, 20(4), pp.511-543.

Word Bank. (2020b). Ethiopia has Made Major Strides in Poverty Reduction but Disparities, Inequality Remain

_________. (2020a). Ethiopia Poverty Assessment: Poverty Rate Declines, Despite Challenges

_________. (2017). World Development indicators 2017.World Bank. https:// openknowledge.worldbank.org/handle/10986/26447 (accessed on 29 January 2018).

_________. (2016). Poverty and Shared Prosperity 2016: Taking on Inequality. Washington, DC.

World Bank Group. (2015). Ethiopia Poverty Assessment 2014. Washington, DC. https://openknowledge.worldbank.org/handle/10986/21323

Appendices

Appendix Table 1: Contribution of each indicator (percentage) for M0

Indicators	2012 M0	2014 M0	2016 M0	Pooled M0
Education	0.421	0.473	0.391	0.426
Years of schooling	0.168	0.18	0.138	0.161
School attendance	0.253	0.293	0.253	0.265
Health	0.157	0.07	0.271	0.14
Child mortality	0.045	0.055	0.171	0.093
Nutrition	0.112	0.015	0.1	0.047
Living standard	0.58	0.527	0.699	0.575
Electricity	0.105	0.11	0.1	0.105
Improved sanitation	0.118	0.125	0.123	0.122
Improved drinking water	0.014	0.01	0.008	0.01
Quality of floor	0.004	0.005	0.007	0.006
Cooking fuel	0.121	0.13	0.121	0.124
Assets ownership	0.061	0.077	0.069	0.068

* Observations weighted to make results representative of all individuals in Ethiopia.
Source: Computation based on ESS (2012, 2014, and 2016)

Appendix Table 2: Transition probabilities of indicators, multidimensional poverty and consumption poverty

Dimensions	Indicators		2012-2016		2014-2016		2012-2014	
			Not deprived	Deprived	Not deprived	Deprived	Not deprived	Deprived
Education	Years of schooling	Not deprived	80.28	19.72	83.99	16.01	84.3	15.7
		Deprived	52.87	47.13	42.98	57.02	36.43	63.57
	School attendance	Not deprived	68.66	31.34	71.46	28.34	75.2	24.8
		Deprived	26.13	73.87	23.45	76.26	22.0	78.0
Health	Child mortality	Not deprived	63.73	36.27	63.7	36.3	91.15	8.85
		Deprived	54.64	45.36	55.69	44.31	77.81	22.19
	Malnutrition	Not deprived	98.42	1.58	97.99	2.01	97.9	2.1
		Deprived	96.11	3.89	94.12	5.88	95.57	4.43
Living standard	Electricity access	Not deprived	7.74	92.26	87.67	12.33	88.07	11.93
		Deprived	86.14	13.86	4.16	95.84	6.46	93.54
	Improved sanitation	Not deprived	1.61	98.39	2.63	97.37	27.96	72.04
		Deprived	0.33	99.67	0.23	99.77	5.8	94.2
	Improved water source	Not deprived	94.81	5.19	94.57	5.43	94.53	5.47
		Deprived	87.36	12.64	86.86	13.14	77.3	22.7
	Housing quality of	Not deprived	96.22	3.78	97.26	2.74	97.38	2.62
		Deprived	36.72	63.28	25.97	74.03	42.97	57.03
	Cooking fuel	Not deprived	14.55	85.45	24.14	75.86	30.91	69.09
		Deprived	2.47	97.53	2.29	97.71	1.3	98.7
	Asset ownership	Not deprived	67.68	32.32	74.56	25.44	64.46	35.54
		Deprived	24.22	75.78	26.03	73.97	20.33	79.67

Source: Computation based on ESS (2012, 2014, and 2016)

Technical, Allocative and Economic Efficiency of Soya bean Production: The Case of Smallholder Farmers in Pawe District, Ethiopia[1]

Birhanu Argaw[2]*, Jema Haji[2], Mohammed Aman[2] and Gebreegziabehr Fentahun[3]

Abstract

This study was undertaken with the objective of assessing technical, allocative and economic efficiency of soya bean production and to identify factors affecting them in Pawe district. The data were collected from 203 randomly selected sampled households in Pawe district Northwestern Ethiopia. Both descriptive and econometrics model were employed to analyze the collected data. A stochastic frontier approach was applied to measure technical, allocative and economic efficiency of soya bean production. The estimated SPF model showed that amount of land, labor and DAP were found to explain the frontier function. The result found that the mean technical, allocative and economic efficiency was 72.72%, 35.378% and 25.05%, respectively. The estimated value of gamma was 0.7384 which indicates that 73.84% of the variation in soya bean output was due to technical inefficiency. This indicates there is a big opportunity to increase soya bean production in the study area through improving efficiency. For example, given fixed level of input and technology, there is opportunity to increase soybean yield by 27.28% in Pawe district. In addition, the Tobit model result showed that age, level of education, extension service, access for credit, farming experience, off/nonfarm income participation and training affected technical, allocative and economic efficiency of soya bean producer farmers in the study area. Depending on the findings the following recommendations are forwarded. Government or any stakeholder should facilitate timely access to DAP with reasonable price,

---

[1] Manuscript received: 22 August 2021
Accepted: 11 October 2021
[2] School of Agricultural Economics and Agribusiness, Haramaya University
P.O.Box 138, Dire Dawa, Ethiopia
* Corresponding author. E-mail: bireargaw2011@gmail.com
[3] Department of Agricultural Economics, Bahir Dar University

reduction in interest rate of the lending institutions and increase training to farmers using farmer training centers.

Key words: Pawe district, soya bean, efficiency, Cobb-Douglas, Tobit
JEL Code: Q01

1. Introduction

The economic development of Africa, more than any other continents, depends on the improvement of the agricultural and agro-industry sectors, which are mainly affected by the productivity of resources so that the inappropriate use of resources in these nations matter significantly. This is in particular true for Sub-Saharan Africa where agriculture is the fundamental contributor to the majority of their gross domestic product (GDP) and it is the major source of earnings and employment (Henao and Baanante, 2006). Consequently, one of the foremost policy concerns of the governments in these countries nowadays is to reap sustainable development that fulfill economic objective (Girmay, 2006).

Like to most of African countries, agriculture plays a central role to achieve economic growth in Ethiopia. The sector contributes 36.3% of the country Gross Domestic Product (GDP) and it additionally function a source of employment opportunities to more than 73% of total population that is involved in agriculture, generates about 70% of the foreign exchange earning of the country and 70% raw materials for the industry in the country (UNDP, 2018). This indicates that the overall economy of the country and the food security of the majority of the population rely on agriculture. However, the sector is explained by low performance, caused by a combination of natural calamities, demographic factors, socio-economic factors, backward and poor technologies and lack of knowledge on the efficient utilization of limited resources particularly on land and capital (WFP, 2012). Hence, being agriculture dependent country with a food deficit gap, increasing crop production and productivity is not a matter of choice rather a must to attain food self-sufficiency.

Soya bean is gaining ground globally due to its multipurpose use as human food, livestock feed, industrial purposes, and more recently, as a supply of bio energy (Myaka et al., 2005). Producing and consuming more soya bean would enhance the circumstance (Food Security) as soy gives a nutritious mix of each calorie and protein consumption. In addition, this crop is the most nutritionally wealthy crop, it contains 40% of protein compared to 18% from meat and 11% from eggs (Chianu et al., 2008).

In Ethiopia, the volume of soya bean production during the last sixteen years has been increased (CSA, 2001-2017). Despite the increased volume of soya bean production, its national average yield (22.71quintal per ha) remains low as compared to the world average yield (27.6 quintal per ha) (CSA, 2018). Besides, spatial variability in soya bean productivity is another concern for soybean productivity enhancement in Ethiopia. For instance, in 2018/19, the average soya bean productivity in Ethiopia varied from 23.20 quintals per ha (Oromiya region) to 21.38 quintals per hectare (Benishangul-Gumuz region). Similarly, the average soya bean productivity varied in other regions too (CSA, 2018). Therefore, increasing production levels and reducing its variability are both essential aspects to improved food security and well-being of the people of Ethiopia.

On the other hand, Ethiopia recorded a huge trade volume deficit in soya bean in recent years. The trade deficit which is the difference between the imported and exported volume of soya bean is about 138 million Kg on average (CSA, 2001-2017), which indicates there is a higher demand in the domestic market for soybean. However, there are many factors hindering soya bean production in Ethiopia. The problems are not only limited to market access but also to low productivity and production, lack of processing facilities, lack of capital to increase production and limited market information system for effective agricultural marketing (Bezabih, 2010).

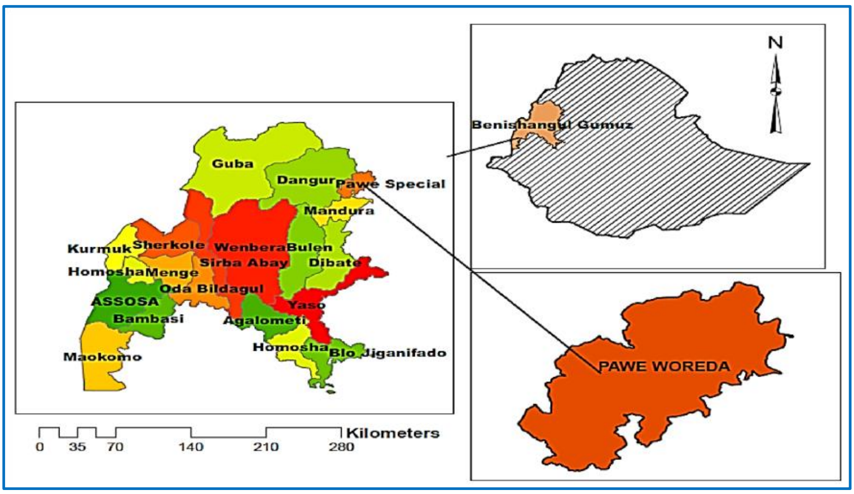
The future demand for soya bean can be met by increasing farm productivity (Masuda and Goldsmith, 2009). Basically, production and productivity can be boosted using two ways. The first method is through increased use of inputs or improvement in technology given some level of input. The second option of increasing productivity is through improving the efficiency of smallholder farmers, given fixed level of inputs and technology. However, rather than just evaluating the technical potential of the crop, it is advantageous to take a serious look at the economic considerations in terms of farmers‟ ability in the efficient allocation of a given inputs and at the same time the chance they stand in improving their livelihoods through soybean production. As a result, this study is mainly concerned about assessing economic efficiency of smallholder farmers on soya bean production.

There are many of researchers in Ethiopia who have done efficiency analysis on various crop production (for example, Kinde, 2005; Assefa, 2016; Hassen, 2016 and Moges, 2017). However, soya bean which have a great contribution for the country export in Ethiopia are scanty in this regard. There is only one study related to measuring efficiency of soya bean production in Ethiopia (Regasa et al., 2019) with some methodological problems. In this study, the method used to measure efficiency are to some extent vague and some very important variables (for instance age, offarm income, membership to cooperative and slope) are omitted from the tobit model. In addition, empirical study on measuring farm efficiency of soya bean production in Pawe district are untouched. Consequently, technical, allocative and efficiency of soya bean production under smallholder farmers and the factors that might be cause to farm inefficiency remain unidentified in the study area. Therefore, this study aimed to fill the existing knowledge gap in measuring technical, allocative and economic efficiency of soya bean production and identifying determinant factors that causes to farmers' technical, allocative and economic efficiency in soya bean production.

2. Methodology

2.1 Study Area

Figure 1: Geographical location of Pawe district



Source: Fitsum (2016)

Pawe is one of the 20 districts in the Benishangul-Gumuz regional state of Ethiopia Located at the Northwestern of Ethiopia. It is located about 570 km away from the capital city, Addis Ababa. Pawe is bordered on the south by Mandura district, on the west by Dangur district and on the northeast by Jawi district. The administrative center of this district is Almu. This district has a total of 20 kebele administration. The total population is estimated at 45,552 of whom 23,265 were men and 22,287 were women. From this 22.1% of population are urban inhabitants. The majority of the inhabitants (63.49%) practiced Ethiopian Orthodox Christianity (CSA, 2007). The farming system of the district is characterized as mixed crop-livestock farming system dominated by cereal and pulses crops. From the pulses, soya bean takes a big share in terms of production and area coverage. Despite the fact that the area is potential for crop production, agricultural productivity is generally low and it is subsistence oriented.

2.2 Sampling Techniques and Sample Size

This study employed combinations of multi-stage, purposive and random sampling techniques to draw the appropriate sample households. In the first stage, from the total seven districts in Metekel Zone, Pawe district is selected purposively for its long year experience in soya bean production. In the second stage, from the total of 20 soya bean producer kebeles in the district, three kebeles were selected by using simple random sampling method. Consequently, the three selected kebeles are village 26, village 24, and village 23/45. Finally, sample size was determined by using a formula developed by Yamane (1967).

$$\mathrm{n} = \frac{N}{1+N\,(e)^2} = \frac{49{,}578}{1+49{,}578\,(0.07)^2} = 203 \tag{1}$$

Where n = required sample size N= size of population e = desired level of precision (7%).

2.3 Data Type and Method of Collection

Both primary and secondary data were used for this study. The primary data were obtained from sample households using structured questionnaire via face-to-face interview with the heads of the households. Degree holder enumerators from the Pawe woreda were recruited and one day training was given to them by the researcher. Secondary data were obtained from Pawe district agricultural office (PDAO) report.

2.4 Analytical Methods

The analysis of production efficiency was carried out following the Aigner et al. (1977) method of the estimating the Stochastic Frontier Production Functions (SFPF). The study specified the SFPF using a Cobb-Douglas and Translog production function for smallholder soya bean producing farmers in the Pawe district, Metekel zone, Benishangul – Gumuz Regional state, Ethiopia. The linear form of Cobb-Douglas production function is represented in Equation 2.

$$lnY_i = \beta_0 + ln\sum\beta_j X_{ij} + \mathcal{E}_i \qquad \textbf{(2)}$$
$$\mathcal{E}_i = v_i + u_i$$

Where ln denotes the natural logarithm; j represents the number of inputs used; i represents the ith farmer in the sample; Y represents the observed soya bean production of the ith farmer; Xij denotes jth farmer input variables used in soya bean production of the ith farmer; β stands for the vector of unknown parameters to be estimated; εi is a composed disturbance term made up of two elements (v_i and u_i); νi accounts for the stochastic effects beyond the farmer's control, measurement errors as well as other statistical noises and ui captures the technical inefficiency.

The Trans log stochastic frontier production function initially developed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) specified as:

$$lnY_i = \sum_{k=1}^{7}\beta_k \; lnX_{ik} + \frac{1}{2}\sum_{k=0}^{7}\sum_{j=0}^{7}\beta_{jk} \; lnX_{ij}lnX_{ij} + v_i - u_i \qquad \textbf{(3)}$$

Here ln denotes the natural logarithm, Y_i represents output of the ith producer, k represents the number of inputs used, X_{ij}represents a set of 7 input variables (land, labor, seed, oxen power, chemicals, dap, and urea) used by the ith farmer, and β is a vector that collects unknown parameters to be estimated.

The random error v_i accounts for the stochastic effects beyond the farmers control, measurement errors as well as other statistical noise, and u_i captures production inefficiency due to factors that are in the control of the farmer. Both of the Cobb-Douglas and Trans log production function have their own advantage and limitation. However, in this study, the appropriate functional form which best fit the data was selected by using likelihood ratio test.

The solution to the cost minimization problem is the basis for deriving the dual cost frontier, given the input price (ω_j), parameter estimates of the stochastic frontier production function ($\hat{\beta}$) and adjusted output level Y_k^{i*}.

$$MinC = \sum_n \omega_n \, x_n$$

Subject to 1RE

$$Y_k^{i*} = \hat{A} \prod_n x_n \, \hat{\beta}_n \tag{4}$$

Where $\hat{A} = \exp\left(\hat{\beta}_0\right)$, ω_n = input price, $\hat{\beta}$= parameter estimates of the stochastic production function and $Y\,{}_k^i*$ = input oriented adjusted output level from Equation 4.

The following dual cost function will be found by substituting the cost minimizing input quantities into Equation 5.

$$C(Y_k^{i*}, w) = HY_k^{i*\mu} \prod_n \omega_n \, \alpha_n \tag{5}$$

Where $\alpha_n = \mu\hat{\beta}_n,\ \mu = \left(\sum_n \hat{\beta}_n\right)-^1 \ and\ H = \frac{1}{\mu}(\hat{A} \prod_n \hat{\beta}_n \, \hat{\beta}_n)-^{\mu}$

Therefore, the efficiency indices of the given farmer can be calculated as follows:

$$\mathrm{TE} = \frac{\mathrm{Y}}{\mathrm{Y}*} \tag{6}$$

Where Y* represents frontier output, Y represents actual yield

$$EE = \frac{C}{C*} \tag{7}$$

Where, C* represents minimum (efficient) cost, C represents actual cost. Following Farrell (1957), allocative efficiency index of the ith farmer can be derived from Equations 6 and 7 as follows;

$$AE = \frac{EE}{TE} \quad \textbf{(8)}$$

After measuring the level of efficiency, a Tobit model employed to identify the hypothesized socioeconomic and institutional factors that affect performance of farmers. This model is best suited for such analysis because of the nature of the dependent variable (efficiency scores), which takes values between 0 and 1 and yield the consistent estimates for unknown parameter vector (Maddala, 1999).

Following Maddala (1999) the Tobit model can be specified as:

$$Y_i^* = \beta_0 + \sum \beta_{Xim} + \mu_i \quad \textbf{(9)}$$

Where Y_i^* represents latent variable representing the efficiency scores of farmers i; β represents a vector of unknown parameters; Xim represents a vector of explanatory variables m (m = 1, 2... k) for farm i and µi represents an error term that is independently and normally distributed with mean zero and variance σ2.

Denoting y_i as the observed variables, $y_i = y \begin{cases} 1 & if\ y_i^* \geq 1 \\ y_i^* & if\ 0 < y_i^* < 1 \\ 0 & if\ y_i^* \leq 0 \end{cases}$ **(10)**

3. Results and Discussion

This section presents the demographic, socioeconomic and institutional characteristics of the sampled respondents. Understanding the characteristics of respondents is important in order to identify variables that can hinder or increase the production efficiency of sampled soya bean producers. The characteristics of sample households were summarized under each sub-section by descriptive (mean, minimum, maximum, percentage and charts). For this study, data were collected from 203 randomly selected households.

3.1 Descriptive Statistics for Characteristics of Sampled Households

The mean age of sampled respondents was 50.40years with minimum and maximum age of 25 and 88 years, respectively. The average formal years of schooling attend by sampled respondent is approximately three years with a maximum of 12 years (Table 1).

Table 1: Descriptive statistics for characteristics of sampled households

Variables	Mean	Std. Deviation	Minimum	Maximum
AGE	50.40	14.01	25	88
EDUCATION	2.90	2.07	0	12
FRMEXP	27.98	12.21	2	78
FAMSIZ	8.54	2.12	1	12
FARMSIZ	0.625	0.282	.25	1
FQECT	8.97	4.60	4	22
DISTMK	4.98	2.35	1	9
TLU	4.34	1.80	0.065	9.245
HTFDST	4.88	2.42	1	9

Source: Own survey result, 2020

3.2 Soya Bean Production Constraints

The problems faced by smallholder soya bean producers in the study area can disturb their performance and productivity. If the problems need to be identified, programs that might help improve the productivity must be put in place. Respondents were asked to identify major constraints faced regarding to soya bean production. Various constraints were identified and discussed as follow.

From soya bean production constraints, weed infestation was a serious problem that farmers were facing in the study area followed by crop diseases and pest infestation. From the total 203 sampled respondents about 87 (42.86%), 71

(34.98%) and 36 (17.73%) respondents reported that they were facing weed infestation, crop disease and pest infestation, respectively. Moreover, there was also labor shortage in the study area. Sample households also reported that there were animal and seed shortages during peak agricultural production seasons (Table 2).

Table 2: Soya bean production constraints faced by the respondents

Soybean production problems	Numbers of farmers	Percent
Animal Shortage		
Yes	18	8.87
No	185	91.13
Crop Disease		
Yes	71	34.98
No	132	65.02
Labor Shortage		
Yes	27	13.30
No	173	86.70
Pest		
Yes	36	17.73
No	167	82.27
Seed Shortage		
Yes	4	1.97
No	199	98.03
Weed Infestation		
Yes	87	42.86
No	116	57.14

Source: Own survey result, 2020

3.3 Summary of Production Function Variables

The production function in this study was estimated using seven input variables. The input variables used in production function of soya bean were land, labor, DAP, Urea, oxen power, seed and chemical whereas the dependent variable was soybean production. To draw some picture about input and output variables, the minimum, maximum, mean of input and output variables are presented. The sampled households had achieved a mean yield of 13.35quintal per hectare. However, due to unknown reasons too small farmers obtained less than 3 qt of soybean per hectare (Table 3).

Table 3: Descriptive statistics of output and input variables

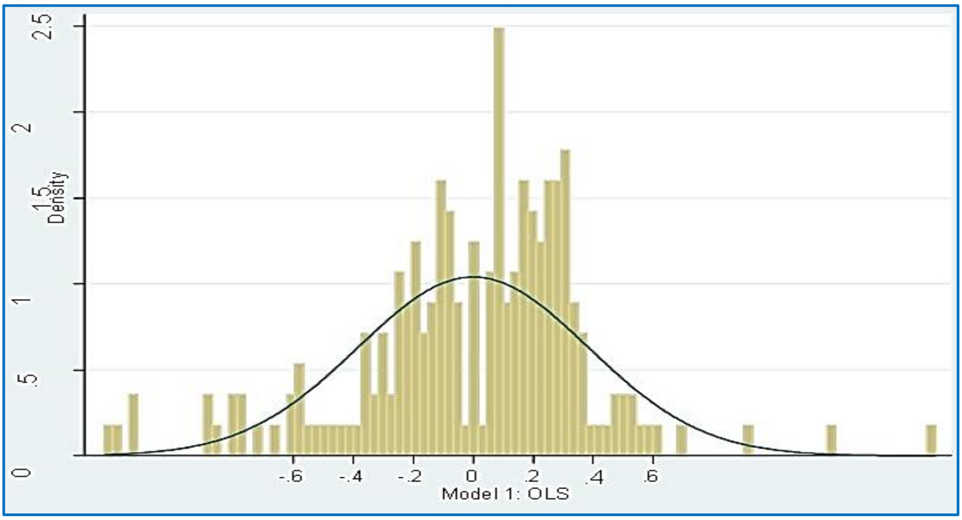
Variable	Mean	Std. Deviation	Minimum	Maximum
Output (quintal/ha)	13.35	6.67	2	37
DAP (kg)	60.53	28.56	0	100
Urea (kg)	64.90	31.02	0	100
Oxen (oxen day)	9.51	5.18	3	24
Seed (kg)	77.56	18.21	43	100
Land (ha)	0.539	0.288	0.25	1.5
Labor (MD)	41.01	19.93	10	101
Chemical (L)	7.83	5.27	1.5	24

Source: Own survey result, 2020

4. Econometrics Results

Before going to the econometric analysis, the collected data from 203 sample households was tested related to stochastic frontier model. In this study, three hypotheses were tested. The likelihood function of a stochastic frontier model is highly nonlinear and estimation can be difficult. Given this potential difficulty, it is desirable to have a simple test on the validity of the stochastic frontier specification prior to undertaking the more expensive maximum likelihood estimation. Schmidt and Lin (1984) proposed an OLS residual test to check for the validity of the stochastic frontier model specification. As a rule of thumb, for a production-type stochastic frontier model with the composed error vi-ui, and distributed symmetrically around zero, the residuals from the corresponding OLS estimation should skew to the left (i.e., negative skewness) and if the estimated skewness has the expected sign, rejection of the null hypothesis provides support for the existence of the one-sided error. Following the OLS estimation of the production function of soya bean farm, this study plots the histogram of the residuals compared to a normal density. The result showed that there was some evidence of negative skewness (Figure 2).

Figure 2: Distribution of OLS Residuals



Source: Own survey result, 2020

To formally examine and test, the study used the skewness statistic. The statistic is labeled as skewness and it had a value equal to -0.372. The negative sign implies that the distribution of the residuals were skews to the left which is consistent with a production frontier specification. As a result, the result confirms the rejection of the null hypothesis of no skewness in the OLS residuals (Table 4). This result was further confirmed by significance of the generalized log-likelihood ratio test for γ presented in Table 6 where results of the stochastic frontier model are presented.

As indicated earlier, to further verified the existence of the inefficiency effect a likelihood ratio test were applied to test the null hypothesis that the inefficiency component of the error term is equal to zero (γ: = 0) and the alternative hypothesis that the inefficiency component different from zero (γ: ≠ 0). The result obtained from Table 5 showed that the computed likelihood ratio test statistic 7.09 is greater than x2 critical value of 2.705, which indicates there was evidence to reject no inefficiency effects in the data. Thus, the null hypothesis that the average response function (OLS specification) is an adequate representation of the data were rejected and the alternative hypothesis that stated there exists considerable inefficiency among sample farmers was accepted. This finding confirms the results of skewness test presented earlier.

Table 4: Skewness statistic

Percentiles		Smallest		
1%	-1143	-1.230		
5%	-.7603	-1.199		
10%	-0.497	-1.143	Obs	203
25%	-0.193	-1.139	Sum of Wgt.	203
50%	0.073		Mean	5.12e-10
		Largest	Std. Dev.	0.383
75%	0.241	0.704		
90%	0.346	0.930	Variance	0.147
95%	0.488	1.1901	Skewness	-0.372
99%	0.930	1.541469	Kurtosis	5.148

Source: Own survey result, 2020

The second test was to select appropriate functional form which best fits the collected data. The Cobb-Douglas and the Trans-log functional forms are the most commonly used stochastic frontier functions in the analysis of efficiency in production. As a rule of thumb, if the likelihood ratio value greater than the x2 critical value we should reject the null hypothesis. Accordingly, a likelihood ratio test was applied on the null hypothesis which states the coefficients on square and interaction terms of input variables in the translog functional forms are not statistically different from zero (H0: $\beta ij=0$) against the alternate hypothesis which states that the coefficients of all interaction terms and square specification in the translog functional forms are different from zero (H1: $\beta ij\neq 0$). The value of likelihood ratio (LR) was computed form the log likelihood value of both Cobb-Douglas and translog production functions. The result of likelihood ratio test found to be lower than the x2 critical value (Table 5), which indicates the coefficient of the interaction terms and the square specification of the production variables under the Translog specification are not different from zero. Therefore, the Cobb-Douglas functional form found to be adequately represent the data. Hence, the Cobb-Douglas functional form was used to estimate efficiency of the sample farmers in the study area.

The final hypothesis was to check whether the explanatory variables in the inefficiency model contribute significantly to the explanation of efficiency variation for the soya bean-growing farmers. This hypothesis was also tested similarly by calculating the likelihood ratio value using the value of the log likelihood function under the stochastic frontier model (without explanatory variables of inefficiency effects (H0)) and the full frontier model with variables that are supposed to determine efficiency level of each farmer (H1). The λ value 60.52obtained from Table 5 was higher than the x2 critical value 27.59 at 17 degree of freedom. As a result, the null hypothesis was rejected in favor of the alternative hypothesis that the explanatory variables associated with Tobit model are simultaneously different from zero. Hence, these variables simultaneously explain the difference in efficiency among farmers.

Table 5: Generalized likelihood ratio tests of hypothesis for the parameters of SPF

Null hypothesis	λ	Critical value (x^2, 0.05)	Decision
H0: $\gamma = 0$	7.09	2.71	Rejected
H0: $\beta ij = 0$	28.49	41.34	Accepted
H0; $\delta 1 = \delta 2 \ldots \delta n = 0$	60.52	27.59	Rejected

Source: Own survey result, 2020

4.1 Estimation of Production and Cost Functions

The regress and variable in the production function was soya bean production (Qt/ha) and the input variables used in the analysis were area under soybean (ha), labor (man days in man equivalent), quantity of seed (kg), quantity of DAP (kg), quantity of urea (kg), oxen (pair of oxen days) and chemical (litter). Out of the seven input variables estimated in the maximum likelihood estimate, land, labor and DAP were statistically significant at 1%, 5% and 5% levels, respectively.

The parametric coefficients of significant input variables were 0.5478, 0.1445, and 0.0106 for area, labor and DAP, respectively. These values indicate the relative importance of each factor in soya bean production. Thus, a one percent increase in the use of land, labor and DAP will result in 0.5478%, 0.1445%, and 0.0106% increase in the level of soybean output, respectively. Consequently, land (area) appeared as one of the major important factors of production followed by labor and DAP in the order, respectively. This indicates that other things remaining constant, a 1% increase in area will increase the output of soya bean output by 0.5478%.

The return to scale value that is obtained from the maximum likelihood estimation of the Cobb-Douglas production function was 0.948 which indicates a 1%increase in all the specified production inputs will increase output by 0.948%. Therefore, an increase in all production inputs by one percent will increase soya bean yield by less than one percent. It can be escaped from stage III of production area by using their existing resources and technology efficiently in the production process. This result was consistent with a study by Gbigbi (2011) in Nigeria found returns to scale to be 0.85. The estimated value of gamma is 0.7384 which indicates that 73.84% of the variation in soya bean output was due to technical inefficiency (Table 6).

Table 6: OLS and ML estimate for the Cobb- Douglas production function

Variables	OLS		MLE	
	Coefficient	Std.Err	Coefficient	Std.Err
Land	0.5513**	0. 0615	0.5478***	0.05799
Labor	0.1280*	0. 0684	0.1445**	0.06178
Seed	0.2954*	0.1164	0.1805	0.11210
DAP	0.0088	0.0053	0.0106**	0.00504
Urea	0.0004	0.0047	0.0001	0.004366
Oxen power	0.1020	0.0693	0.0552	0.06442
Chemical	0.0156	0.0423	0.0091	0.04015
Constant	0.8757*	0.5288	1.7694***	0.52076
Lambda			1.6797	0.08302
Sigma square			0.2725	0.04429
Gama Return to scale = 0.948			0.7383	

Note: The symbol ***, ** and * shows the level of significance at 1, 5 and 10%, respectively.

Source: Own survey result, 2020

Insufficient farm level price data coupled with little or no input price variation across farmers of Ethiopia precludes any econometric estimation of a cost or profit frontier function. Thus, the use of self-dual production function allows the cost frontier function to be derived and used to estimate economic efficiency in situations where producers face the same prices was given as follows:

$$ln\,Cm_i = 2.433 + 0.033\omega_{1i} + 0.3737\omega_{2i} + 0.0066\omega_{3i} + 0.0055\omega_{4i} + 0.0867\omega_{5i} + 0.2836\omega_{6i} + 0.0874\omega_{7i} + 0.0261\,lnY_i^* \quad \textbf{(11)}$$

Where C is cost of producing soya bean; Y_i^* refers to the index of output adjusted for any statistical noise; ω1 is the observed seasonal rent of a hectare of land; ω2 is the daily wage of labor; ω3 is the price of DAP per kg; ω4 is the price of Urea per kg; ω5 is the price of seed per kg; ω6 is the daily rent of oxen and ω7 is the price index of agro chemicals per liter.

4.2 Estimation Efficiency Scores

The mean technical efficiency of sample respondents was about 72.72% with a minimum of 30.54 and a maximum level of 94.66%. Therefore, if the average smallholder farmer of the sample could achieve the technical efficiency level of its most efficient counterpart, then average sample farmers' could increase their output by 23.17% approximately [that is, 1- (72.72/94.66)]*100. Similarly, the most technically inefficient sample farmer could increase the production by 67.73% approximately [that is, 1- (30.54/94.66)]*100 if he could increase the level of technical efficiency to his most efficient counterpart.

The average allocative efficiency of sampled households was about 35.38% with a minimum 15.44% and a maximum of 62.50%. This implies that farmers are not allocatively efficient in producing soybean and hence, a farmer with an average level of allocative efficiency would enjoy a cost saving of about 43.39% (1-0.3538/0.6250)*100 to attain the level of the most efficient farmer. The most allocative inefficient farmer would have an efficiency gain of 75.29% derived from (10.1544/0.6250)*100 to attain the level of the most efficient farmer.

The average economic efficiency of the sample farmers was also about 25.05% with a minimum 12.77% and a maximum of 40.12%. This indicates that there was a significant level of economic inefficiency in the production process. The producer with an average economic efficiency level could reduce the current average cost of production by 62.43% to achieve the potential minimum cost level without reducing output levels. It can be inferred that if farmers in the study area were to achieve 100% economic efficiency, they would experience substantial production cost saving of 62.43%. Sampled households in the study area were relatively good in technical efficiency than allocative efficiency or economic efficiency. However, none of the respondents had a technical, allocative and economic efficiency of 100 percent (Table 7).

Table 7: Summary statistics efficiency estimates

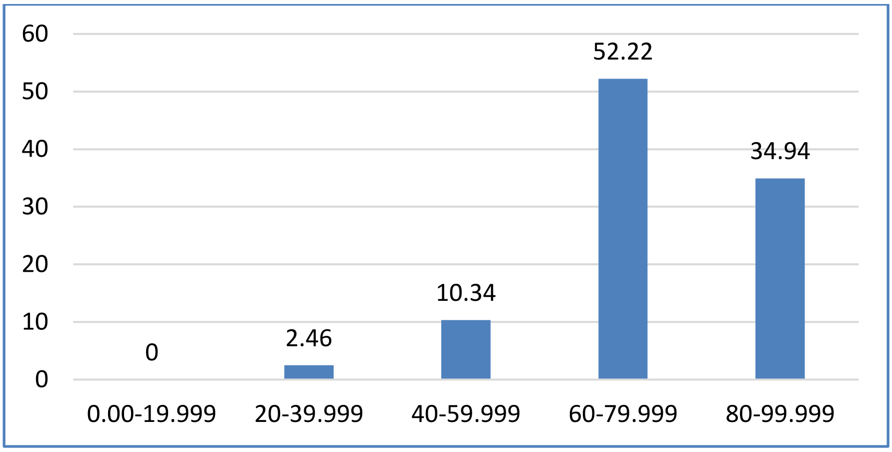
Variable	Mean	Std.Dev	Min	Max
TE	0.7272	0.1237	0.3054	0.9466
AE	0.3538	0.0818	0.1544	0.6250
EE	0.2505	0.0472	0.1277	0.4012

Source: own survey result, 2020

4.3 Frequency Distribution of Technical Efficiency

A frequency distribution presented in Figure 3 shows that most of the farmers (about 65.06 per cent) scored TE of less than 80%. The result also shows that, about 71 (34.98%) respondents in the study area were operating above the technical efficiency level of 80% while 106 (52.22%) of them were operating in the range of 60-80% of technical efficiency levels. In addition, 21 (10.34%) of the farmers were operating from 40-60% of technical efficiency level. Only 5 (2.46%) of sampled households were in the range 20-40% of technical efficiency level. However, none of sampled households were operating below 20% of the technical efficiency level (Figure 3).

Figure 3: Distribution of technical efficiency

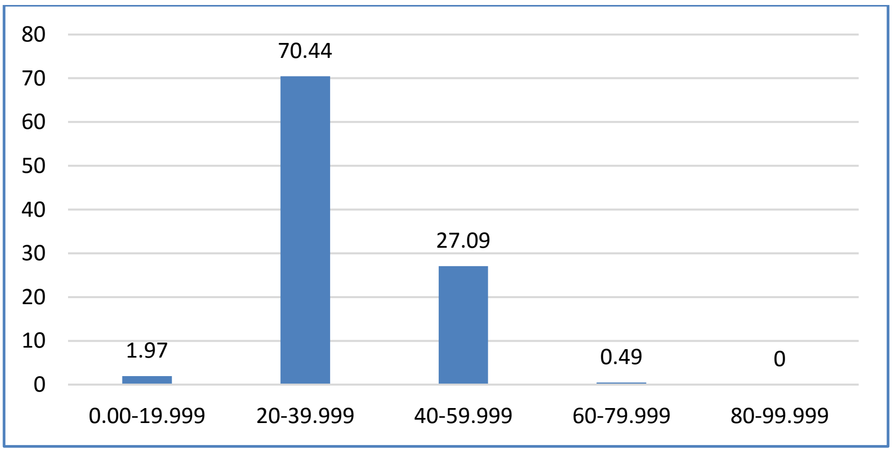


Source: own survey result, 2020

4.4 Frequency Distribution of Allocative Efficiency

The allocative efficiency presented in Figure 4 shows that the distribution is skewed to the left which indicates there are more farmers whose efficiency is far below the average allocative efficiency. This may be due to other factors that were not considered in the model. About 70.44% of the respondent was operating from 20-39.99% of allocative efficiency level while 27.09% were operating from 40-59.99%. In addition, merely 0.49% was operating 60-79.99% allocative efficiency.

Figure 4: Distribution of allocative efficiency

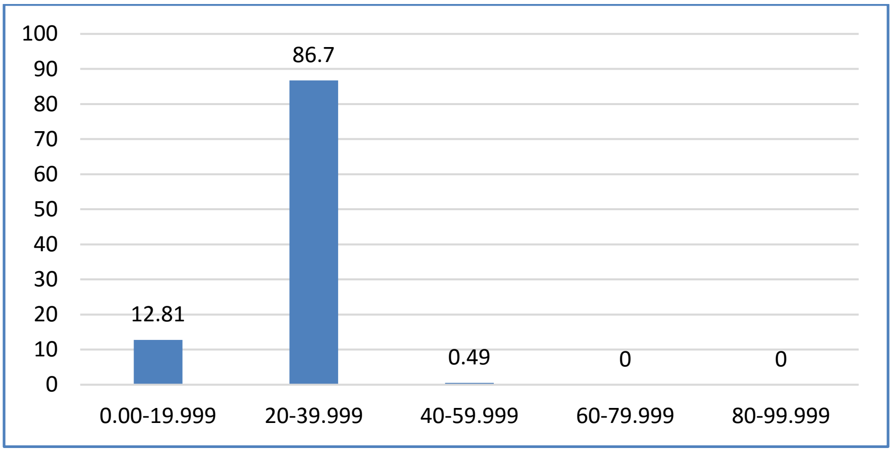


Source: own survey result, 2020

4.5 Frequency Distribution of Economic Efficiency

The result presented in Figure 5 shows that there were also considerable differences in the economic efficiency among farmers in the study area. The study found that 86.7% of the sampled producers' economic efficiency was below 40% which is an indication that more producers were economically inefficient; indicating there was greater variability in their achievement.

Figure 5: Distribution of technical efficiency



Source: own survey result, 2020

4.6 Determinants of TE, AE and EE in Soybean Production

The main interest behind measuring efficiency level is to know what factors determine the efficiency level of individual farmers. In this study, the dependent variable is efficiency not inefficiency. Therefore, technical, allocative and economic efficiency of sample respondents were estimated and regressed on socioeconomic and institutional variables that explain variations in efficiency across sampled households using Tobit regression model.

Age of farmer had a negative and significant effect on allocative and economic efficiencies of soya bean production in the study area at 5% significance levels each, indicating older farmers were allocatively and economically less efficient than younger ones. This might be due to the fact that as the farmer gets older; his ability to manage farming activities becomes decreased and resulting decrease in allocative and economic efficiency. The computed marginal effect of age of the sampled households showed that other things remain constant, a one-year increase in the age of the sampled household head decrease allocative and economic efficiency by 0.19 and 0.11%, respectively. This result is in line with the findings of some studies (Battese and Coelli, 1992; Battese and Coelli, 1995).

Access to credit has a positive and significant effect on the technical efficiency of soybean production. This variable is significant at 5% significance level. The positive sign shows that credit recipients are more technically efficient than their counterpart of non-recipient. This is due to the fact that credit permits a sample smallholder farmer to enhance technical efficiency by overcoming liquidity constraints. Hence, the use of credit access ensures timely acquisition and use of agricultural inputs such as improved seed, DAP, Urea, herbicide, education and implement farm management decisions on time and these results increased production of efficiency. This suggests that the availability of credit is an important factor for attaining a higher level of technical efficiency. Thus, credit access increases technical efficiency by 0.92%. This result is in line with the study done by Kifle (2014) and Sandip and Mohamed (2018).

The farming experience of soya bean producers significantly and positively affected allocative and economic efficiencies at 5 and 1% significance levels, respectively. This could be; because experience is a proxy for managerial aspects and improves the skill and technical capacity that enables to best match inputs and in cost saving aspect so attain higher productivity at minimum cost. The marginal effect result indicates that keeping all other variables constant, an increase in farm experience of the respondent by one year would increase allocative and economic efficiencies by 0.23 and 0.18%, respectively. The result is consistent with previous findings (Mustefa et al., 2017; Leake et al., 2018; Regasa et al., 2019).

As expected, frequency of extension contact had a positive and statistically significant effect on allocative and economic efficiency at 5% and 1% significance levels, respectively, but it was statistically insignificant for technical efficiency. This implies that households who getting more frequent extension contact increased the allocative and economic efficiency. This is due to extension service is expected to increase the farmer’s knowhow on some agronomic practices such as pest and disease control and adoption of improved seed varieties as well as soil and water conservation technologies. This puts the framer in the better position to utilize his/her limited resource to achieve higher results and hence increase their allocative and economic efficiencies. The marginal effect indicates that keeping all other variables constant, for a one-day additional extension agent contact with farmers increases the sampled households' allocative and economic efficiency by 0.3 and 0.19%, respectively. The result is in line with the previous findings done by (Desale, 2017; Mustefa et al., 2017; Osman et al., 2018; Sandip and Muhammed, 2018; Regasa et al. (2019)).

Off/non-farm participation had a positive and significant effect on farmers' technical and economic efficiency at 10% and 5% significance levels, respectively. This implies that households getting off/non-farm income were technically and economically efficient than their counter parts. This is due to the income obtained from such activities could be used for the purchase agricultural inputs and augments financing of household expenditures which would entirely dependent on agriculture. This income availability shifts cash constraint outward and helps farmers to make timely purchase of those inputs which they cannot provide from on farm income. The marginal effect indicates that holding all other variables remain constant, being households participated in off/non-farm income generating activities would increase the technical and economic efficiencies by 3.52 and 1.41%, respectively. The result of this study is found to be similar with some researchers who tried to examine the effect of off/non-farm income participation on economic efficiency (Getahun, 2014; Kifle, 2014; Milkessa et al., 2019).

The result indicated that training was positively and significantly affected technical and economic efficiencies at 1% and 5% significance levels, respectively. This implies that sampled households who have received any kind of training related to soya bean production increased technical and economic efficiency. The marginal effect indicates that holding all other variables remain constant, as farmers got training, the probabilities of sample households would increase technical and economic efficiencies 7.5% and 2.4%, respectively. Similar results were found in the work of Getahun (2014) and Moges (2018).

Table 4: Tobit model result

Dependent Variable	TE		AE		EE	
Independent Variables	**Coefficient (Robust.std.err)**	**Marginal effect**	**Coefficient (Robust.std.err)**	**Marginal effect**	**Coefficient (Robust.std.err)**	**Marginal effect**
AGEHH	0.00061 (0.0011)	0.0006	-0.00183** (0.00095)	-0.0019	-0.00105** (0.00044)	-0.0011
ACSTCDT	0.0377** (0.0176)	0.0372	-0.00963 (0.01256)	0.0096	0.00559 (0.00664)	0.0055
EDUCATION	0.00264 (0.00462)	0.0026	0.00723** (0.00286)	0.0072	0.00369** (0.00155)	0.0035
FRMEXP	-0.00020 0.00136	0.0002	0.00239** (0.00120)	0.0023	0.00182*** (0.00051)	0.0018
FQECT	-0.00034 (0.00199)	0.0003	0.00318** (0.00147)	0.0030	0.00208*** (0.00068)	0.0019
OFFARM	0.03563* (0.01695)	0.0352	-0.00714 (0.01220)	0.0071	0.01402** (0.00663)	0.0141
TRAINING	0.07648*** (0.02263)	0.0750	-0.01257 (0.01525)	0.0125	0.02368** (0.00954)	0.0237
Constant	0.65562*** (0.08086)		0.31969*** (0.04908)		0.18461*** (0.02567)	

Note: ***, ** and * shows the level of significance at 1, 5 and 10%, respectively
Source: Own survey result, 2020

5. Conclusions and Recommendations

This study was conducted to estimate technical, allocative and economic efficiencies and identify factors affecting efficiency among soya bean producer households in Pawe district, Benishangul-Gumuz Regional State, Ethiopia. The estimated SPF model showed that amount of land, labor and DAP were found to explain the frontier function. The positive coefficient of these input variables indicate that output increases as these inputs increases. Therefore, a concerned body or agricultural office of the district should focus on these input allocation. Moreover, the finding showed that soybean producers in Pawe district were technically, allocatively and economically inefficient. For example, the mean economic efficiency in the study area was 25.5%, indicating there are opportunity to increase soya bean output by 74.95% through improving farmers' economic efficiency.

The result found that age of the household heads, measured in years affect allocative and economic efficiency negatively. This might be due to the fact that as the farmer gets older; his ability to manage farming activities becomes decreased. In addition, older farmers may not easily able to adopt new technology and modern inputs. Hence, policy makers should devote a great effort to give more training to older farmers than the younger farmer regarding to adoption of new technology and modern inputs in the study area.

Access to credit was very important determining factor that has positive and significant effect to technical efficiency in the Pawe district. This could be credit enables smallholder farmers to purchases inputs that they cannot afford from their own resources, which enhance production and productivity of soybean resulting increase in technical efficiency. Thus, policy makers should devote a great effort on a reduction in the interest rate, bureaucracies and collaterals of banks on loans which will facilitate credit accessibility to smallholder farmers.

The result of the study also showed that education is positively and significantly affected allocative and economic efficiency. An increase in education level would increase farmers' allocative and economic efficiency. This might be, education helps farmers to have greater ability to understand, adopt and correlate inputs with lower cost and misuse. Thus, government should give due attention in strengthening and establishing both formal and informal type of framers' education.

Farmers who have more experience in farm increased allocative and economic efficiency than less experience farmers. This might be, as farmers get more experience, they will have more knowledge and skills that are required for prudent resource allocation and resulting increase in allocative and economic efficiency. Therefore, mechanisms should be devised to increase farmers' experience.

As expected, frequency of extension contact had positive and significant contribution to allocative and economic efficiency. This is due to extension service is expected to increase the farmer's knowhow on some agronomic practices such as pest and disease control and adoption of improved seed varieties as well as soil and water conservation technologies. This puts the framer in the better position to utilize his/her limited resource to achieve higher results and hence increase their allocative and economic efficiencies. Thus, extension services should be increase to farmers by the government agents especially District Agriculture Development Unit, and NGOs to assist these farmers to have easy access to extension so as to increase farm technical and allocative efficiencies.

Technical and economic efficiencies were significantly and positively determined by off/non-farm income activity, indicating financing timely and enough use of inputs through additional income generated by off/non-farm farm are important. Therefore, strategies that enhance the ease use of off-farm employment opportunities would help to increase technical and economic efficiency in soybean production in the study area.

It is found that training on farm affected technical and economic efficiencies positively and significantly. This is due to provision of training to farmers could improve their skills in use of improved seed and general farm management capabilities will increase their farm productivity. Therefore, efforts should be made to raise farmers training on farm.

References

Aigner, D., Lovell, C., and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics,* 6: 21-37.

Battese, G. E., and Coelli, T. J. (1995). Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Journal of Empirical Economics* 20: 325-32.

_______. J. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis*, 3(1):153-169.

Bezabih Emana. (2010). "Market Assessment and Value Chain Analysis in Benishangul Gumuz Regional State, Ethiopia", SID-Consult-Support Integrated Development. 1-84.

Birhanu Ayalew, Adam Bekele and Yalew Mazengia. (2018). Analysis of Cost and Return of Soybean Production under Small Holder Farmers in Pawe District, North Western Ethiopia. *Journal of Natural Sciences Research*: 8 (1): 2224-3186.

CSA (Central Statistical Agency). (2018). The Federal Democratic Republic of Ethiopia central statistical agency report on area and production of major crop.

_______. (2001 - 2017). Annual report.

Chianu J., Vanlauwe, B., Mahasi, J., Katungi, E., Akech, C., Mairura, F. and Sanginga, N. (2008). Soybean situation and outlook analysis: The case of Kenya. Tropical Soil Biology and Fertility Institute of International Center for Tropical Agriculture (TSBF-CIAT). African Network for Soil Biology and Fertility, Nairobi, Kenya.

Desale Gebretsadik. (2017). Technical, Allocative and Economic Efficiencies and Sources of Inefficiencies among Large-scale Sesame Producers in Kafta Humera District, Western Zone of Tigray, Ethiopia: Non-parametric approach. *International Journal of Scientific and Engineering Research*, 8(6):2229-5518.

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of Royal Statistical Society,* (120):253-281.

Fitsum Miruts. (2016). Analysis of the Factors Affecting Adoption of Soybean Production technology in Pawe District, Metekel Zone of Benishangul-Gumuz Regional State, Ethiopia. World Scientific News, 5(3):122-137.

Getahun Mengistu. (2014). Technical efficiency in onion production: the case of smallholder farmers in Dugda woreda, east Shewa zone, Ethiopia. A Thesis Submitted to the School of Agricultural Economics and Agribusiness, Haramaya University, May, 2014.

Gbigbi, M. (2011). Economic efficiency of smallholder sweet potato producers in Delta State, Nigeria: A case study of Ughelli South Local Government Area. *Research Journal of Agriculture and Biological Sciences*, 7: 163-168.

Girmay Tesfay. (2006). Agriculture, Resource Management and Institutions: A socioeconomic Analysis of Households in Tigray, Ethiopia. PhD Thesis, Wageningen University.

Henao, J., and Baanante, C. (2006). Agricultural production and Soil Nutrient Mining in Africa: Implications for Resource Conservation and Policy Development.

Kifle Degefa. (2014). Economic Efficiency of Smallholder Farmers in Maize Production in Bako Tibe District, Oromia National Regional State, Ethiopia. A Thesis Submitted School of Graduate Studies of Haramaya University.

Leake Gebresilassie, Gidey Kidu, Hareg Gebre-egzabher and Zenebe Abraha. (2018). Resources Use Efficiency of Irrigated Tomato Production of Small-scale Farmers. *International journal of Vegetable Science*, 24(1): 1-10.

Maddala, G. S. (1999). *Limited Dependent Variable in Econometrics*. Cambridge University Press, New York.

Masuda, T., and Goldsmith, P. (2009). World soybean production: area harvested, yield, and long-term projections. International Food and Agribusiness Management Review, 12(4): 143-161.

Myaka, F. A., Kirenga, G., and Malema, B. (2005). Proceeding of the First National Soybean Stakeholders Workshop, 10 - 11 November 2005, Morogoro, Tanzania.

Meeusen, W., and van den Broeck, J. (1977). Efficiency Estimation from Cobb–Douglas Production Function with Composed Error. *International Economic Review*, 18(2):435-444.

Mustefa Bati, Mulugeta Tilahun and Kumar, P. (2017). Economic Efficiency in Maize Production in Ilu Ababor zone, Ethiopia. *Research Journal of Agriculture and Forestry sciences*, 5(12): 1-8.

Moges Dessale. (2017). Measurement of Technical Efficiency and its Determinants in Wheat Production: The Case of Smallholder Farmers in Wogidi District, South Wollo Zone Ethiopia. M.Sc. Thesis presented to the School of Graduate Studies of Haramaya University.

Osman, A., Donkoh, S. A., Ayamga, M. and Ansah, I. G. K. (2018). Economic efficiency of soybean production in the Northern Region of Ghana. *Journal of Agricultural Economics and Agribusiness*, 1(1): 2637-3521.

PDAO (Pawe District Agricultural Office). (2019). Livestock population report of the woreda (unpublished).

Regasa Dibaba, Mesay Yami, and Adam Bekele. (2019). Analysis of Production Efficiency, Productivity Variances and Resource Allocation Among

Smallholder Farmers of Soybean Producers: Evidence from Benishangul-Gumuz Region Ethiopia. *International Journal of Research Studies in Agricultural Sciences*, 5(7): 18-36.

Sandip, M. and Muhammad, Y. (2018). Determinants of Tomato Farmer's Efficiency in Mymensingh district of Bangladesh: Data Envelopment Analysis approach. *Journal of Bangladesh Agricultural University*, 16(1): 93-97.

UNDP (United Nations development Programme). (2018). Ethiopia's progress to warding eradicating poverty. Paper to be presented to the inter-agency group meeting on the implementation of the third United Nations decade for the eradication of poverty (2018-2027) Addis Ababa, Ethiopia.

Welay Tesfay and Desalegn Teshale. (2019). Impact of Improved Soybean Variety on Enhancing Productivity and Gross Farm Income of Smallholder in the Case of Pawe and Jawi districts, North Western Ethiopia, *Journal of Natural Sciences Research*, 9(15): 224-3186.

WFP (World Food Programme). (2012). Crop and Food Security Assessment Mission to Ethiopia. Special Report of Food and Agriculture Organization and World Food Programme.

Yamane, T. (1967). *Statistics: An Introductory Analysis*, 2nd Ed, New York, Harper and Row.

Does Technical Efficiency Matter for Ethiopia's Sorghum Producer Farmers? A Study on its Implication for Productivity Improvement[1]

Kusse Haile[2]*, Engida Gebre[2], and Agegnehu Workye[2]

Abstract

Efficient use of the existing resources by farm households improves their productivity and thereby increases their production and achieves the goal of food security. This study examined the technical efficiency of Smallholder Sorghum Producer households and also identifies its major determinants as the case of smallholder farm households in Southwestern Ethiopia. Purposive sampling technique was employed to draw an appropriate sample of 543 sorghum producer farm households for this cross-sectional survey study. Data analysis tools such as descriptive statistics and econometrics model (stochastic frontier model) were used in combination in this study. The stochastic frontier model shows inorganic fertilizer, labor, seed amount, and oxen power were found to be an important input variable that positively affects the production of sorghum. The results show the mean technical efficiency estimate for sorghum producers was 70 percent. This indicates that there exists a room for improving the existing level of sorghum production through enhancing the level of farm household's efficiency. The stochastic frontier model results from inefficiency estimates shows that education level, of-f-farm income, frequency of extension contact, credit amount, livestock holding, proximity to farm, and total cultivated land were significantly determined the level of technical inefficiency of sorghum production. Hence, to improve the production efficiency, level extension package efforts should give focus to those less efficient farm households. As policy implications, agricultural policy packages should direct towards those important socio- economic factors to improve the productivity of smallholder farmers.

Keywords: Efficiency, MLE, Stochastic frontier, Productivity, Smallholder, Sorghum
JEL Code: Q12

---

[1] Manuscript received: 25 August 2021
Accepted: 1 October 2021
ORCID ID: https://orcid.org/0000-0002-4726-3567
[2] Lecturer, Department of Agricultural Economics, Mizan- Tepi University, P.O Box: 260, Mizan Aman, Ethiopia
*Corresponding author's E-mail: kussehaile@mtu.edu.et/ kussehaile@gmail.com
Acknowledgements
We would like to thank Mizan-Tepi University for funding this research Project. We would also like to extend our profound appreciation to all other organizations and individuals contributed to this research project.

Abbreviations

BSZAO: Bench Sheko Zone Agricultural Off-farm-income;
CSA: Central Statistical Agency;
GDP: Gross Domestic Production;
KZAO: Kaffa Zone Agricultural Off-farm-income;
LR: likelihood ratio;
ML: Maximum Likelihood;
FDRE: Federal Democratic Republic of Ethiopia;
SRS: Simple Random Sampling;
TE: Technical Efficiency;
UN: United Nations;
TLU: Tropical Livestock Unit;
MoARD: Ministry of Agriculture and Rural Development;
PPS: Probability Proportion to Size;
WFP: World Food Program.

1. Introduction

Sustainable Development Goal-2 (Target-2.3), states that by 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists, and fishers (UN, 2015). In Sub-Saharan Africa (SSA), agriculture-based economies are predominant and economic development planning is often tied to agricultural productivity growth. (World Bank 2007; Dejanvry and Sadoulet 2020). According to World Bank, (2014), poverty reduction and income growth can generally be achieved through agricultural growth that creates spillover effects to the remaining sectors.

However, production and productivity of the agricultural sector in SSA is low due to low technological adoption and techniques among others (Abraham et al., 2014; Gashaw *et al*., 2014 and Lulit *et al*., 2012). Smallholder farmers in low-income countries are characterized by low production and productivity (Azam *et al.*, 2012). Agriculture is the livelihood of the majority Ethiopian population that contributes 43% of Gross Domestic Product (GDP), 90% of export earnings, 96% of rural employment, and 70% provides raw materials for industries in the country (Biru *et al*., 2020). It is the primary activity in Ethiopian economy, where about 84% of the country's population engages in various agricultural activities and generates its income from household consumption to sustain its livelihood. Total agricultural output produced by smallholder farmers was about 94% and the farm land being cultivated by them was 95% (Gebre Selassie and Bekele, 2012; CSA, 2017). The demand for food has been increasing while the availability of land has been diminishing due to the rising of population pressure. Thus, the only way to raise agricultural production is to increase yield per unit area (Khan *et al.* 2014). More than 80% of Ethiopians live in rural areas, depending on rain-fed, small-scale farming in the highlands and pastoral livelihoods in lowland areas. With population growth, farm sizes become smaller and explained by low productivity (USAID, 2018; Alemayehu *et al*., 2012; WFP, 2010).

Smallholder agricultural will continue to be the base for agriculture sector development and increasing the production and productivity of major crops will continue to be priority as a source of growth and poverty reduction (FDRE, 2015). Cereals are the major food crops both in terms of volume of production obtained and area coverage which are predominantly produced by smallholders in Ethiopia (Abu, 2013). Out of the total grain crop area, 81.46% (10,478,218.03 hectares) was under cereals and contributed 88.52% (about 296,726,476.94 quintals) of the grain production. Sorghum accounts 14.21% (1,828,182.49 hectares) of the grain crop area and contributed 15.71% (52,655,800.59 quintals) of the grain production that makes it the third largest share of total cereal production (CSA, 2020). In the southern region, from the total land size of 1,148,320.13 hectares covered under grain crops, cereals accounted an area of 916,197.26 hectares with production of 27,057,812.44 quintals (CSA, 2020).

Sorghum is the major grain produced globally after maize, wheat, rice, and barley and Africa's second most important cereal (Naik *et al*., 2016; Omoro, 2013). Sorghum is a multipurpose crop mainly grown for food consumption and the rest for animal feed, and processed into various industrial products such as starch, malt and alcoholic beverages, biofuels (alcohol), sweeteners, edible oils, and other forms of traditional foods (Adebo, 2020; Nangobi and Mugonola, 2018; FAO, 2014; Hager *et al*., 2014). In the southern region of Ethiopia, from the total area covered by cereal crops, the area allotted for sorghum is 105,255.96 hectares with a production level of 2,849,141.51 quintals (CSA, 2020). In densely populated areas of south western Ethiopia, major cereal crops like sorghum are the most predominate crop but the population is growing rapidly and the pressure on land is increasing, resulting in marginal lands to be taken into production problems.

In Ethiopia today, there has been an increasing focus by policy makers on adoption of modern technologies rather than efforts targeted at improving the efficiency of inefficient farmers. It is obvious that, introducing modern technologies can increase agricultural productivity and production. Trying to introduce new technologies may not have the expected results or will not be cost effective in areas where there is inefficiency in which the existing inputs and technologies are not efficiently utilized (Asefa, 2012). As a result, the use of the existing technologies is more cost-effective than applying new technologies. It is known that, the level of farmers' technical efficiency has paramount implications for country's choice of development strategy (Zenebe *et al*., 2004; Rashid and Negassa, 2012). Thus, a technical efficiency analysis is crucial to find out if farmers are efficient in the use of the existing resources and to decide when to introduce new technologies.

Measuring efficiency level of farmers can benefit the economies by determining the extent to which it is possible to raise productivity by improving the neglected source of growth (efficiency) with the existing resource base and available technology. In this regard, there have been various empirical studies conducted to measure technical efficiency and showed wide efficiency differences among small-scale farmers in Ethiopia (such as Seyoum et al., 1998; Mohammad et al., 2000; Temesgen and Ayalneh, 2005; Shumet, 2011; Musa et al., 2014; Berhan, 2015; Getachew and Bamlak, 2014; Hassen, 2016; Tekleyohannes *et al*., 2018). Nonetheless, findings of these studies might not be applicable to the case of sorghum production in southwestern Ethiopia and such results need to be looked at within the production contexts that may be unique and more localized due to the diverse agro-ecological zone, differences in the know-how of the farmers, differences in the output produced, and differences in technology and means of production. Per knowledge of authors', there are no studies undertaken on productivity and technical efficiency of cereal crops in general, specifically on sorghum producing farmers in the study area.

Additionally, it is imperative to update the information based on the current productivity of farmers. Studies on technical efficiency of smallholder agriculture are not extensive, and the findings or conclusions of some of them are not consistent with one another. Thus, policy implications drawn from some of the above empirical works may not allow in designing area specific policies to be compatible with its socio-economic as well as agro-ecologic conditions. Although a study that targeted production systems of smallholder farmers would provide relevant information to policymakers and key stakeholders considering the time when productivity growth level significantly in critical policy targets, there is a great demand for analysis from diverse stakeholders to develop future strategies. Thus, increasing agricultural productivity is the major step towards transforming the rural economy and ensuring food security. Additionally, considering the production potentials and its factors vary across different agro-ecologies in the country, the very low productivity of agricultural system in the study area, lacks in empirical studies on productivity, and how much farmers are efficient in sorghum production in the study area. Therefore, this study tries to measure the technical efficiency of sorghum production and aims to bridge the prevailing information gap by providing empirical evidence on smallholder resource use efficiency in southwestern Ethiopia.

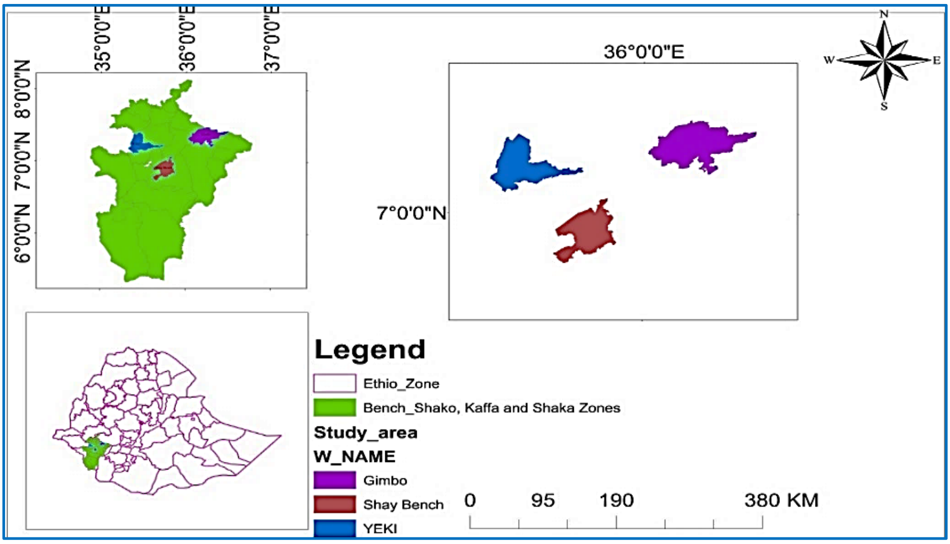
2. Materials and Methods

2.1 Study Area Description

The study was conducted in Kaffa, Sheka and Bench Sheko zones of Southern Nations Nationalities and People's Region. Kaffa Zone lies within 07°00'- 7°25'North latitude and 35°55'-36°37'East longitude. The altitude of the study sites ranges from 1600 to 1900 meters above sea level. The topography is characterized by sloping and rugged areas with very little plain land (KZAO, 2018). According to Central Statistical Agency report on population projection the total population of the zone in the year 2017 was estimated to reach 1,102,278. Out of which the total population 49.14% and 50.86% are male and female respectively (CSA, 2013).

Sheka zone lies between 7°24‟ to 7°52‟ N, 35°13‟ to 35°35‟ E, and 900 to 2700 meters above sea level. Its area coverage is 2175.25 kilometers square, out of which 47% is forest, and 56, 24, and 20% is highland, amid altitude, and lowland, respectively. The total population of the zone in the year 2017 was estimated to reach 269,243 out of which 50.30% and 49.70% are male and female respectively (CSA, 2013). Major crops that cultivated in the zone include off-farm-income, maize, sorghum, millet, beans, ginger, turmeric, ''enset'', wheat and pea (Mohammed, 2010).

Figure 1: Location of study areas



Source: ARCGIS, 2019

The total population of Bench Sheko zone in the year 2017 was estimated to reach 847,168. Out of the total population 49.31% and 50.69% are male and female respectively (CSA, 2013). The main food crops in this zone include Maize, Sorghum, Off-farm-income, Taro, and Enset. Cash crops, fruits, Spices, etc. According to report of Zones, agricultural Off-farm-income, 243522 quintals of sorghum produced from area allocated, 13529 hectare with productivity of 18 qt/ha (BSZAO, 2018).

2.2 Data Types, Sources and Data Collection Methods

For the study, relevant data were collected by two phase primary survey. First, preliminary survey was conducted to broadly understand the farming systems and the major types of crops grown in the study area. During this exploratory survey, formal and informal discussions were held with different stakeholders including farmers, DAs, farmers' association leaders, and agricultural experts/off-farm-incomers. The purpose of the survey is to facilitate characterization of the existing farming systems and livelihood strategies of the farm households in the context of their specific socio-economic and biophysical settings. It also tries to refine the study objectives, sampling methods, and the survey instrument. Once having the basic information using need assessment survey, the main survey was carried out using structured survey instrument. An interview was carried out with the selected farm households. The enumerators, who can speak the local languages and are familiar with the culture of the local people were selected. They were given training on data collection procedures and interview techniques to simplify the complexity of data collection. Thus, primary data analysis results were supported and traingulated by secondary sources like reports, books and empirical findings of different relevant published and unpublished materials.

2.3 Sampling Procedure and Sample Size Determination

The target population for this study was smallholder sorghum producer farm households. A combination of both purposive and random sampling techniques was employed to draw an appropriate sample. The data were collected from purposively selected three zones, Kaffa, Sheka and Bench Sheko. These three zones were among sorghum growing zones in southwestern Ethiopia. From these three zones, according to information obtained from the zones agricultural off-farm-income, Gimbo district (from Kaffa zone), Shay Bench district (from Bench Sheko zone) and Yeki district (from Sheka zone) have a relatively higher potential of sorghum growing than other districts have in these zones. Thus, the districts were selected purposively. First, *Kebeles*[3] in the three districts were stratified into sorghum producers and non-producers. Then, among the sorghum growing *Kebeles*, 15 (fifteen) *Kebeles* (7 *Kebeles* from Gimbo district, 5 *Kebeles* from Shay Bench district and 3 *Kebeles* form Yeki district) *were* randomly selected in order to obtain representative sample household heads**.** Finally, from the total list sorghum producer farm households of 15 *Kebels*, 543 sample farm households were selected by using a simple random sampling (SRS) technique based on probability proportional to size (PPS).

Table 1: Zone, Districts, and sample size selected from sample *Kebeles*

Zone	District	Target population	Sample size proportion	Percentage
Kaffa	Gimbo	10,522	203	37.38
Bench Sheko	Shay Bench	9,226	178	32.78
Sheka	Yeki	8,397	162	29.83
	Total	28,146	543	100.00

Source: Own sampling design

[3] *Kebele* is the lowest administrative unit of a region

2.4 Analytical Framework

Descriptive statistics like mean, percentages, frequency charts, and standard deviations were used. Inferential statistical tests like chi-square test for potential discrete (dummy) variables and t-test was used to test the significance of the mean difference of continuous variables for the sample households. Descriptive statistics often fails to predict the combined effect of explanatory variables on the dependent variable (Aldrich and Nelson, 1984). Thus, this gap is to be filled by running appropriate econometric models/ linear programming techniques. There are two analytical approaches that can be used to estimate efficiency or inefficiency level in production; the non-parametric approach and parametric approaches. A non-parametric approach is represented by Data Envelopment Analysis (DEA) while parametric approach by deterministic and stochastic frontier models. The non-parametric approach called (DEA) first developed by Charnes, Cooper and Rhodes (1978), has the power of accommodating multiple outputs and inputs in technical efficiency analysis. It is non-parametric, as it does not require an explicit functional form and constructs the frontier from the observed input-output ratios by linear programming techniques. Nonetheless, DEA fails to take into consideration the possible impact of random shock like measurement error and other types of noise in the data. Additionally, it lacks the statistical procedure for hypothesis testing (Coelli, 1995). On the other hand, the stochastic frontier does not accommodate multiple inputs and outputs and is more likely to be influenced by mis-specification issues. However, the fact that the latter incorporates stochastic components into the model increased its applicability in the analysis of technical efficiency of agricultural productions. Thus, for the study stochastic frontier production function was employed.

2.4.1 Specification of Stochastic Frontier Model

As indicated above, non-parametric approach (DEA) assumes the absence of random shocks while farmers always operate under uncertainty. Because of which, the study employed the stochastic frontier approach. The stochastic frontier model can be specified as:

$$y_i = f(x_i;\beta_j) + v_i - u_i \qquad \textbf{(1)}$$

Where: i – is the number of sorghum producing farm households, y_i – is the sorghum output measured in kilograms, x_i – is a vector of input quantities used by the i^th sample farm households, β_j – is a vector of unknown parameters to be estimated, $f(.)$ – is Cobb-Douglas or Translog production function, v_i – is the random error term, independently and identically distributed as $v_i \sim N(0, \delta_v{}^2)$ is intended to capture events beyond the control of farmers, u_i – it is a non-negative random variable as $u_i \sim N(\mu, \delta_u{}^2)$ is intended to capture technical inefficiency of the i^th farm households.

The various null hypotheses for the parameters in the frontier production function and inefficiency model were tested by using the likelihood ratio test (LR).

The first likelihood ratio (LR) test was computed from the log likelihood value obtained from the estimation of Cobb-Douglas and Translog production specifications. Thus, the computed value of likelihood ratio (LR) = 22.24 is less than the upper 5 percent critical value of 41.34. Thus, the Ho that states all square and interaction terms coefficients in Translog specification are equal to null was not rejected. Based on that, the Cobb-Douglas stochastic frontier model adequately represents the survey data and specified as;

$$LnSOUTPUT = \beta_0 + \beta_1 \ln LAND + \beta_2 \ln UREA + \beta_3 \ln DAP + \beta_4 \ln OXEN + \beta_5 \ln LABOR + \beta_6 \ln SEED + \beta_7 \ln HIP + v_i - u_i \quad \textbf{(2)}$$

Where Ln is the natural logarithm**,** i- represents the i^th farm household in the sample.

The model parameters in stochastic production function were analyzed by employing a single stage estimation procedure. In using the two-stage estimation procedure of efficiency level and factors determining, the efficiency index is estimated by the stochastic production function in the first stage and then regressed against a number of other farm specific and socioeconomic variables in the second stage. The one-stage estimation procedure of the inefficiency effects model together with the production frontier function would be used in the study. The two-stage procedure produces inconsistency in the assumption (Coelli *et al.*, 1998). Moreover one-stage procedure is the most commonly used method in the analysis of technical efficiency. Thus one-stage procedure is selected for this study. Additionally, the null hypothesis that the explanatory variables associated with inefficiency effects which are all zero (H_0: $\delta_1=\delta_2,\ldots=\delta_{13}=0$) was also tested. The calculated value $\lambda_{LR}=59.24$ is greater than the critical value of 22.36 at 13 df. Thus, the null hypothesis (H_0) that the explanatory variables are simultaneously equal to zero was rejected at 5 percent significance level.

The technical efficiency model by Battese and Coelli (1995), in which both the stochastic frontier and factors affecting inefficiency (inefficiency effect model) are estimated simultaneously as the joint estimation of a stochastic frontier production function is specified as:

$$LnSOUTPUT = \beta_0 + \beta_1 \ln LAND + \beta_2 \ln UREA + \beta_3 \ln DAP + \beta_4 \ln OXEN + \beta_5 \ln LABOR + \beta_6 \ln SEED + \beta_7 \ln HIP + v_i - (\delta_0 + \delta_1 FARMEXP + \delta_2 SEX + \delta_3 EDUCLHH + \delta_4 FAMSIZE + \delta_5 COOPMEM + \delta_6 TLU + \delta_7 CULTLAND + \delta_8 OFINCOME + \delta_9 FRQEXTC + \delta_{10} DFARM + \delta_{11} CRETAM + \delta_{12} ACCTR + \delta_{13} FRGMNT + w_i) \quad \textbf{(3)}$$

Where δ_i = parameter vector associated with the estimated inefficiency effect and w_i = stochastic is error term.

The maximum likelihood (ML) estimates were used which require distributional assumptions for the composed error term. We considered the (Battese and Coelli, 1995) parameterization. The maximum likelihood (ML) estimates of the production function were obtained from the following log-likelihood function using one-stage estimation procedure:

$$Ln(Y_i) = \frac{-N}{2}\ln\left(\frac{\pi\delta_s^{\,2}}{2}\right) + \sum_{i=1}^{N} \ln \Phi\left(\frac{-\varepsilon_i\lambda}{\delta_s}\right) - \frac{1}{2}\delta_s^{\,2}\sum_{i=1}^{N}\varepsilon_i^{\,2} \quad \textbf{(4)}$$

Where, $\varepsilon_i = v_i - u_i = \ln y_i - x'_i\ \beta$ and $\lambda = \sqrt{\delta^2_u / \delta^2_v}$

$\Phi(.)$= Is the distribution function of the standard normal random variable; $Ln(Y_i)$ = a logged output level for the i^{th} farm households; X'_i = logarithm of the level of input for the i^{th} farm households; β = regression coefficient; λ = a discrepancy parameter as defined above; $\sigma_s^{\ 2}$ = a variance of standard error of the composed error term and N = number of observations.

The technical efficiency of an individual farm household is defined in terms of the observed to the corresponding frontier output given the level of input. From Equation (1), Technical efficiency of the farm households can be specified as:

$$TE_i = \frac{y_i}{\exp(x'_i\beta + v_i)} = \frac{\exp(x'_i\beta + v_i - u_i)}{\exp(x'_i\beta + v_i)} = \exp(-u_i) \qquad \textbf{(5)}$$

Where y_i = denotes output of sorghum produced by the i^{th} farm household,
x'_i = is a (1×k) row vector with the first element equal to 1, of the input quantity used by the i^{th} farm household for the production of sorghum,
$\beta = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \ ... \ \beta_k)$ is a (1×k) column vector of unknown parameters to be estimated,
u_i = is a nonnegative random variable associated with technical inefficiency of the i^{th} farm household for sorghum production,
v_i = is the random error term of the model which captures the random error of the production of sorghum in the i^{th} farm household and i = 1, 2, …, n is the number of samples in a population.

As defined by Equation (4), the null hypothesis is that there are no technical inefficiency effects in the model is conducted by testing the null and alternative hypothesis H_0: $\gamma = 0$ versus H_1: $\gamma > 0$.

The Generalized likelihood ratio (LR) test statistic is calculated as:

$$LR = \lambda = -2\{Ln[L(H_0)/L(H_1)]\} = -2\{Ln[L(H_0) - L(H_1)]\} \quad \textbf{(6)}$$

Where: $L(H_0)$ = the log- likelihood value of the null hypothesis;
$L(H_1)$ = the log- likelihood value of the alternative hypothesis; *Ln* is the natural logarithm

Important factors need to be identified to define the problem of inefficiency by investigating for remedial measures to solve the problem if those farmers do not achieve the maximum output level with a given technology. Some of the empirical literatures that are conducted are presented hereunder in brief to support the hypothesis specified inefficiency variables. Hence the specified dependent and explanatory variables based on theoretical suggestions and previous studies are presented in (Table 2 and 3) as follows.

Table 2: Definition of variables incorporated in the stochastic production function

Variable Notation	Type	Description and measurement	Expected sign
Ln (SOUTPUT)	Continuous	Natural log of the total output of sorghum obtained from the i^{th} farm in kilogram	
Ln (LAND)	Continuous	Natural log of the total amount of land allocated for sorghum crop in hectares by the i^{th} farm household	+
Ln (UREA, DAP)	Continuous	Natural log of the total amount of Inorganic fertilizer (Urea and DAP) in kilogram applied by the i^{th} farm household	+
Ln(OXEN)	Continuous	Natural log of the total number of oxen days used by the i^{th} farm household	+
Ln (LABOR)	Continuous	Natural log of the labor force (family and hired) which is all measured in terms of man-days	+
Ln (SEED)	Continuous	Natural log of the quantity of sorghum seed used by the i^{th} household measured in terms of kilograms	+
Ln (HIP)	Continuous	Natural log of the quantity of chemicals such as herbicides, insecticides/ pesticides used as an input by the i^{th} farm household measured in Ethiopian Birr	+

Source: Own elaboration

Table 3: Definitions of the variables used in the inefficiency effect model

Variable Notation	Description and measurement	Expected sign (Hypothesis)	Theoretical suggestions and empirical literatures to support hypothesis
FARMEXP	Farming experience of the household head in sorghum production is measured in terms of years	+	Khanal and Maharjan,2013; Tadesse et al., 2017
SEX	This variable assuming a value of 1 if male headed and 0 for female household head.	+	Zenebe et al. (2005); Aynalem (2006)
EDUCLHH	Level of education attained by household heads measured in terms of years	+	Aynalem (2006); Abba, (2012); Chepng'etich *et al*., 2015; Sisay et al., 2016; Mustefa et al., 2017 and Tekleyohannes *et al*., 2018
FAMSIZE	Number of family size in terms of count	+	Aynalem (2006); Orewa and Izekor (2012)
COOPMEM	It is a dummy variable and measured as 1 if the household is involved as a member of the cooperative and, 0 otherwise	+	Abdulai et al.,2018; Khanal et al. (2018b); Wongnaa and Awunyo-Vitor, 2018
TLU	The total number of livestock owned by the household measured in terms of Tropical livestock unit (TLU)	+/-	Fekadu (2004 +[17]); Aynalem (2006+); Hassen and Wondimu, (2014-[18]); Hassen (2016-)
CULTLAND	It is the cultivated land other than sorghum that the house hold managed measured in terms of hectare.	+/-	Endrias et al. (2012+); Hailemaraim (2015-); Beyan *et al*., 2013+)

[17] "+" Indicates studies found positive relationships
[18] "-" Indicates Studies found negative relationships

Variable Notation	Description and measurement	Expected sign (Hypothesis)	Theoretical suggestions and empirical literatures to support hypothesis
OFINCOME	It is the amount of income obtained from offarm to none farm activities measured in Ethiopian Birr.	+/-	Haileselassie (2005-); Elibariki et al. (2008 +), Hassen and Wondimu, (2014-); Hailemaraim (2015+);
FRQEXTC	Frequency of the extension contact of the farm households measured in terms of frequency	+	Fekadu (2004); Haileselassie (2005); Hailemaraim (2015);
CREDITAM	It is the amount of money that the farm household head borrowed measured in terms of Ethiopian birr.	+	Bamlaku et al. (2007); Hailemaraim (2015); Hassen (2016); Kaleb and Workneh, 2016
DFARM	It is the average distance between the home of the farm household and the farm in walking minutes.	-	Kinde (2005); Alemayehu (2010); Kusse et al., 2018
ACCTR	It takes a value of 1 if the farm household head participated in the training and 0 otherwise.	+	Fekadu (2004); Tadesse et al., 2017
FRGMNT	It refers to the total number of farm plots that the farm household had managed during the survey period	-	Fekadu (2004); Elibariki et al. (2008); Hailemaraim (2015)

Source: Own elaboration

3. Results and Discussion

3.1 Descriptive Statistics Results

Under this section, the descriptive results of the socio-economic characteristics of sorghum producer farm households and variables used in stochastic production are presented and discussed.

3.1.1 Descriptive results on socio-economic characteristics

As presented in (Table 4), the mean age of sorghum producers was 42.081 years with minimum of 22 and maximum of 80 ages, respectively. As indicated in (Table 4), on average a household head has about 3.379 years of education level. The average family size of sorghum producers was 5.823 with the minimum of 2 and the maximum of 13. Males who headed households represented 80.8 percent of the total number of households under study. This shows proportion of household head in the sample is much lower than the one at national level (i.e. one fourth of the total rural household head is female). Thus, the gender distribution in the study area can be characterized as male dominated research. On the other hand, the average frequency extension contact for sorghum producers was 10.631 while 67.2 percent have participated in sorghum output improvement trainings. As depicted in (Table 4), 55.4 percent of sorghum producers are member of multipurpose cooperatives. Farm households own an average of 5.2 TLU with standard deviation of 2.77 as depicted in Table 4. On average, sorghum producer households' farmers earned 1023.252 Ethiopian Birr from off-farm activities as indicated in (Table 4).

Table 4: Summary statistics of the socio-economic variables

Variable description	Mean	Std.dev.	Minimum	Maximum
Age of household head (in Years)	42.081	11.438	22	80
Education Level (in Years)	3.379	2.746	0	11
Family size (Counts)	5.823	2.457	2	13
Farming Experience (in Years)	20.365	10.078	3	50
Credit Amount (in Ethiopian Birr)	1850.967	1978.775	0	6570
Livestock ownership (in TLU)	5.208	2.771	0	12.03
Extension contact (Frequency)	10.631	12.108	0	46
Off-farm-income (Ethiopian Birr)	1023.252	1849.414	340	9850
Cultivated Land under other crops (Hectare)	0.784	0.418	0.023	2.1
Proximity to farm (in walking minutes)	51.202	24.955	7	135
Number of plots (Fragmentation of land)	3.282	1.325	1	6
Gender of household head	0.808	0.394	0	1
Membership in cooperative	0.554	0.497	0	1
Access to training	0.672	0.470	0	1

Source: Survey result, 2018/19

3.1.2 Descriptive results of production function variables

In this study, seven input variables are used to estimate the stochastic production function. On average, sample farm households produced 1328.545 kilograms of sorghum with a standard deviation of 766.061 (Table 5). The productivity varied between a minimum of 400 kilograms and a maximum of 3800 kilograms per hectare, indicating a considerable scope for improving sorghum yields in the study area. In the study area, farm households used inorganic fertilizer (DAP and urea) for sorghum production during the survey period. The average amount of DAP and urea fertilizers applied for sorghum production by sample farm households were 51.243 kilogram per hectare and 45.759 kilograms per hectare, respectively during the production season.

Table 5: Summary of the variables used to estimate the stochastic production function

Variable description	Mean	St. deviation	Maximum	Minimum
Sorghum output (Kg/Ha)	1328.545	766.061	3800	400
DAP (Kg/Ha)	51.243	42.372	98	46
Urea (Kg/Ha)	45.759	42.082	95	25
Land (Ha)	0.805	0.398	2.35	0.235
Human labor (MDs/Ha)	36.761	9.604	59	17
HIP Chemicals (Eth. Birr/Ha)	42.679	51.154	250	45
Seed (Kg/Ha)	20.576	7.235	32	7
Oxen power (ODs/Ha)	12.112	4.980	30	5

Source: Survey Result, 2018/19

As presented in Table 5, the average land allocated for sorghum crop by sample farm households was 0.805 hectares. This is greater than the national average land allocated for sorghum (0.485 hectare) and less than regional size of 1.069 hectare by farm households. On average, the labor force used in the production of sorghum was 36.761 man-days per hectare with a standard deviation of 9.604. In addition, the average oxen power used by sample farm households was 12.112 oxen days per hectare with standard deviation of 4.980 (Table 5). And the amount of seed sample farm households' used was 20.576 kilograms, with a standard deviation of 7.235 in the study area. This indicates the average seed rate was 20.576 kilogram per hectare that is greater than the recommended rate of 12 kilograms per hectare. Moreover, another essential input was chemicals, on average; sample farm households applied 42.679 Ethiopian Birr (Table 5) for chemicals like weedicides, herbicides, or pesticides per hectare in the study area for the protection of sorghum farms during the production season.

3.2 Econometric Model Results

In this section, the econometric model results of the stochastic production function, individual efficiency scores of smallholder producers, and sources of differences in technical inefficiency of sorghum producer farm households are presented and discussed.

3.2.1 Stochastic frontier model estimation results

The result of the stochastic production function showed that inorganic fertilizer (UREA and DAP), oxen power (OXEN), labour force (LABOR), and the amount of seed (SEED) were positive and significant effect on the level of sorghum output at 1 percent significance level except for amount of seed that is at 5 percent level of significance (Table 6). That means these input variables are important in shifting the frontier output to the right (i.e., for each unit of these variables there is a possibility to increase the level of output). However, the land allocated for sorghum (LAND) and chemicals (HIP) such as herbicides or pesticides were insignificant. Thus, the insignificant value of land allocated for sorghum indicates sorghum output depends more on how well available land is used rather than land size allocated. Thus, the Cobb-Douglas production function revealed that the input variables labor force, oxen power, and amount of seed were the main inputs in determining the level of sorghum output in the study area. Whereas, the partial elasticity of inorganic fertilizers (UREA and DAP) was very low, implying that these have less effect in determining the output level for the best practice. The positive coefficients of input variables indicate that a 1 percent increase in inorganic fertilizer (Urea, DAP), labor force, amount of seed and oxen power yields 0.009%, 0.079%, 0.254%, 0.067%, and 0.203% increase in sorghum output, respectively. In other words, if all inputs are increased by 1 percent, the sorghum output would increase by 0.62 percent (Table 6).

The value estimated sigma square (δ^2) for frontier of sorghum output was 0.293, implying that significantly different from zero and significant at 1% level of significance. The significant value indicates the goodness of fit of the specified assumption of the composite error terms distribution. Stochastic production function result shows that the value of the important parameters of log- likelihood in the half- normal model $\lambda = \sigma u/\sigma v = 2.32$, this indicates that the estimated value is significantly different from zero. The null hypothesis that there is no inefficiency effect ($\lambda = 0$) was rejected at the 1percent level of significance, suggesting the existence of inefficiency effects. Additionally, the variance ratio parameter γ which found to be significant at 1percent level expressed that about 84.3% of sorghum output deviations are caused by differences in farm level TE as opposed to the random variability that are outside their control of the farm households. This also makes the stochastic frontier model appropriate for the study. Furthermore, the returns to scale analysis coefficients were calculated to be 0.62 percent indicating decreasing returns to scale. As a percent increase in all inputs proportionally would increase the total production by less than 1 percent (Table 6).

Table 6: Stochastic production frontier model results

Variable description	Parameters	Coefficients	Std. Err.	P>|z| value
Ln UREA	β_1	0.009***	0.002	0.000
Ln DAP	β_5	0.079***	0.028	0.004
Ln LAND	β_3	-0.006	0.004	0.172
Ln LABOR	β_4	0.254***	0.053	0.000
Ln HIP	β_2	0.002	0.002	0.529
Ln SEED	β_6	0.067**	0.032	0.037
Ln OXEN	β_7	0.203***	0.035	0.000
_cons	β_0	7.240***	0.211	0.000
Diagnostic statistics				
Sigma- square	δ^2	0.293 ***	0.033	
Lambda	λ	2.318 ***	0.063	
Gamma	γ	0.843***		
Log likelihood function		-214.457		
Returns to scale	$\sum\beta_{1-7}$	0.620		

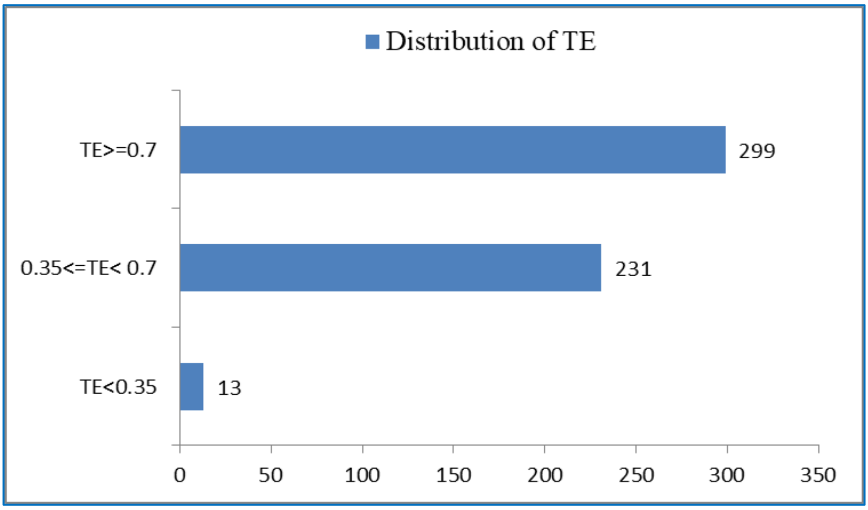
Note: "*", "**" and "***" represent the statistical significance of factors at 10, 5, and 1% levels

Source: Survey Result, 2018/19

3.2.2 Efficiency scores of sample farm households

The results of the model (Table 7) indicated that there was wide range of differences in technical efficiency scores among sorghum grower farm households in the study area. The mean technical efficiency of sample farm households during the survey period was 70.1%. The technical efficiency among households ranged from 22.3 to 93.2% (Table 7). This wide variation in household specific technical efficiency levels is consistent with the study results reported by (Ike and Inoni, 2006; Dhehibi *et al*., 2014; Wudineh and Endrias, 2016; Wongnaa and Awunyo-Vitor, 2018); Belete, 2020). This shows the existence of room for improving the existing level of sorghum production through enhancing the farm household's technical efficiency. The distribution of efficiency (TE) indexes among smallholder sorghum producers is depicted in (Figure 2).

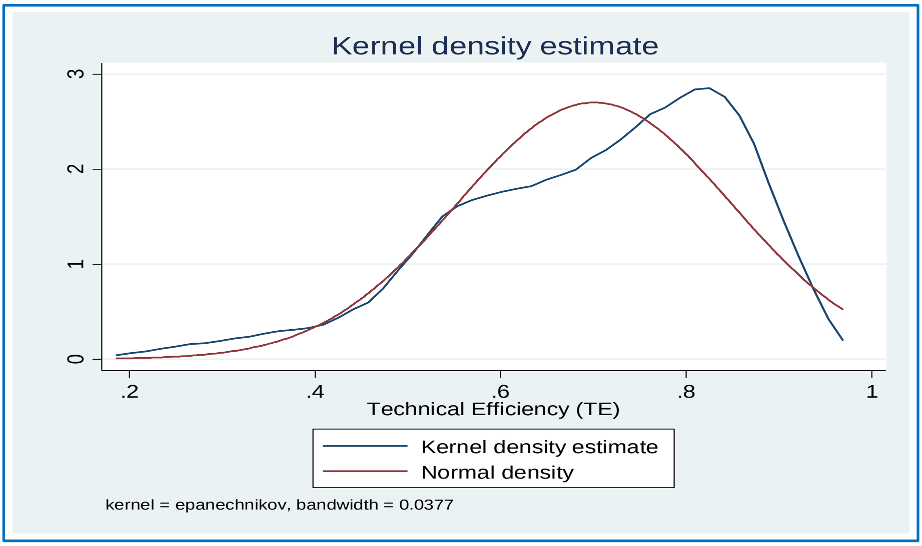
Figure 2: The distribution of efficiency (TE) indexes among smallholder sorghum producers



Source: Survey Result, 2018/19

Average level of TE further shows the level of sorghum output of the sample farm households can be increased by about 30% if appropriate measures are taken to improve the efficiency level of sorghum grower farm households. In other words, there is a possibility to increase the yield of sorghum by about 30% using the resources at their disposal in an efficient manner without introducing any other improved (external) inputs and practices. It is observed that 244 (44.93%) of the sample farm households are operating below the overall mean level of TE while 299 (55.06%) of the farm households are operating at the TE level of more than 70.12% (Figure 2). Thus, the majority (55.06%) of the sorghum growing farm households were able to attain the overall mean level of technical efficiency. In addition, a kernel density function is plotted (Figure 3) to make sure whether or not the half-normal distributional assumption is met, such as the post-estimation of stochastic frontier normal or truncated-normal model. Density function distribution closely resembles the standard half-normal inefficiency typically assumed in frontier estimation. This proves the assumption that the inefficiency effect error term u_i is nonnegatively distributed with half-normal distribution and significant at 5 percent level of significance.

Figure 3: Kernel density estimate for efficiency scores by full sample farm households



Source: Survey Result, 2018/19

3.2.3 Comparison of actual and potential output

The individual farm households' efficiency levels and their corresponding actual output enable us to determine how much yield is lost because of the inefficient use of existing resources. From the current production practice of the existing resources, it is possible to determine the potential attainable level of sorghum output. Either the farm households had used the available resources in an efficient way was calculated using the actual observed individual level sorghum output and predicted individual technical efficiency from the frontier model. Empirical literatures of (Tigabu, 2016; Abate et al., 2019; Hunde and Abera, 2019) adopted for the potential sorghum production of each individual farm household presented as follows in (Table 7).

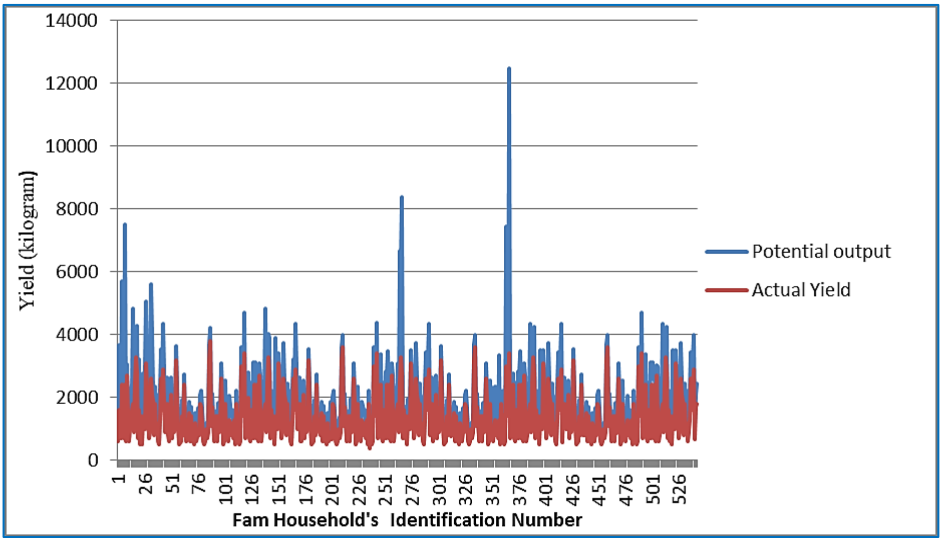
Table 7: Comparison of actual and potential output levels of the farm households

Variable description	Mean	St. deviation	Minimum	Maximum
Actual output (kilogram)	1328.545	766.061	400	3800
Mean TE	0.701	0.148	0.223	0.932
Potential output (kilogram)	1946.163	1203.204	526.890	12462.66

Source: Survey Result, 2018/19

The average level of actual and potential output during the production season was 1328.55 kilograms per hectare and 1946.16 kilograms per hectare with a standard deviation of 766.061 and 1203.204 respectively. This shows the existence of inefficiency and, if farmers use the existing agricultural inputs at the optimal proportion level, a maximum of 12462.66 kilograms of sorghum can be obtained per hectare. There is a statistical difference of the actual and potential output values at P≤0.001 significance level (Table 7).

Figure 4: Comparison of the actual and the potential level of yield



Own survey result, 2018/19

3.2.3 Determinants of technical inefficiency

The driving force behind measuring farm households' efficiency is to identify important determinants as a basis for informing agricultural policy on what needs to be done to improve smallholder agricultural productivity. Result in (Table 8) is presented in terms of inefficiency model estimates and the negative sign shows the variable negatively contributes to the inefficiency level or conversely it contributes positively to efficiency levels. One important point to be considered is that the dependent variable is the inefficiency component of the total error term estimated in combination with the production frontier.

Table 8: MLE of the stochastic frontier model with inefficiency effect

Variables	Coefficient	Std. Err	P>|z| value
FARMEXP	0.011	0.011	0.283
EDUCLHH	-0.071*	0.038	0.066
SEX	0.043	0.278	0.878
FAMSIZE	-0.042	0.046	0.360
COOPMEM	0.330	0.215	0.126
OFINCOME	-0.151***	0.029	0.000
FRQEXTC	-0.684***	0.221	0.002
DFARM	0.192*	0.110	0.082
CREDITAM	-0.101***	0.029	0.001
TLU	0.083**	0.038	0.030
TCULLAND	-0.706***	0.174	0.000
FRGMNT	0.033	0.070	0.641
ACCTR	0.064	0.114	0.577
_cons	-1.436**	0.616	0.020

"*", "**" and "***" are statistically significant at 10, 5 and 1% levels

Source: Survey Result, 2018/19

The results of the inefficiency model showed that education level, family size, non-farm income, frequency of extension contact, proximity to household's residence, Credit Amount, livestock holding and total farm land were significantly contributing to the technical inefficiency of sorghum producer farm households (Table 8). The detailed discussions on the implications of significant variables contributing to technical inefficiency were presented as follows:

Educational level (EDUCLHH)**:** The results of the model show that education level negatively and significantly affecting inefficiency at 10% level of significance. This indicates that education is improving the production efficiency of farm households. Thus, the level of education can enhance the skills of households in the allocation of homemade and purchased inputs, select the appropriate quantities of purchased inputs, utilize existing technologies, and attain higher efficiency level and choose among available techniques of production systems and hence higher efficiency level. This result is consistent with findings of (Assefa, 2012; Beyan *et al*., 2013; Zalkuwi *et al*., 2014; Hassen and Wondimu, 2014; Solomon, 2014; Chepng'etich *et al*., 2015; Sisay *et al.*, 2016; Mustefa *et al*., 2017; Kusse *et al*., 2018; Wongnaa and Awunyo-Vitor, 2018).

Off-farm-income (OFINCOME)**:** Income from of-farm non-farm activities was hypothesized that there is an efficiency differential among farm households who earn more income through engaging in off-farm-income activities and those who earn less. The study result shows that the coefficients of the variable entered into the technical inefficiency effect model indicated that the variable affects the level of technical inefficiency negatively and significantly at 1% level of significance level (Table 8). This suggests that an increase or the more income farm households obtained from off-farm-income activities the more technically efficient he/she became. Thus, income obtained from such off-farm-income activities compensate farm households' expenditures and reduce the pressure on on-farm income otherwise. The result obtained is in line with studies of (Arega and Rashid, 2005; Jema, 2008; Hassen, 2011; Ahmed and Melesse, 2018; Kusse *et al*., 2018). Contrary to this, studies of (Hassen and Wondimu, 2014) found positive relationship between level of inefficiency and income from off-farm-income activities.

Frequency of extension contact (FRQEXTC)**:** The result of inefficiency model revealed that frequency of extension contact has negative and significant influence on technical inefficiency at 1% significance level (Table 8). This indicates that the more the household had extension contact, the less he/she will become inefficient. Thus, this result shows that consultation of extension agents improves the productivity of farm households by decreasing the level of technical inefficiency. Additionally, extension advisories provided to the farm households help them to improve their farming operation and household's knowledge regarding the use of improved agricultural inputs. This result is consistent with the results of (Ahmad *et al*., 2002; Amos, 2007; Beyan *et al.,* 2013; Sienso *et al*., 2013; Sisay *et al*., 2016; Tadesse *et al*., 2017; Wongnaa and Awunyo-Vitor, 2018; Kusse *et al*., 2018).

*Proximity to farm (*DFARM)**:** The results showed that the variable had a positive signs and significant effect on technical inefficiency at 10% level as expected. This implied that there is a significant relationship between farm proximity to a household's residence and technical inefficiency (i.e., as the distance increases, technical inefficiency increases). Thus, households whose farm plot is far from residence are more inefficient than those located at relatively near to the farm plot. This could be attributed to the fact that the farther the farm land or farm plot from the farm household's residence, the greater would be the cost of transport management, supervision and opportunity costs. This in turn may hinder the optimal application of farm inputs and lead to technical inefficiency. The result is consistent with findings of (Kinde, 2005; Alemayehu, 2010; Kusse *et al*., 2018).

Credit Amount (CREDIAM): The coefficient of amount of credit had a significant effect on technical inefficiency at 1% significance level. Thus, the result shows that the coefficient of credit amount is negative, which is similar to the expected sign. Sometimes farmers need adequate and timely credit to finance their farm's various input requirements. This implies that adequate credit amount is essential element in agricultural production systems to satisfy farm households' cash needs induced by the production cycle (i.e., as amount borrowed increase, farm households became more efficient). Adequate credit amount may help farm households to purchase farm inputs that they constrained by own cash. This finding is consistent with (Mussa *et al*., 2012; Beyan *et al.*, 2013; Bempomaa and Acquah, 2014; Kaleb and Workneh, 2016; Belete, 2020).

Livestock holding (TLU): livestock holding in terms of tropical livestock units was hypothesized to have an indifferent influence on inefficiency of sorghum production. It is positively and significantly affected technical inefficiency in sorghum production at 5% level of significance. This indicates that farmers who owned large livestock might be less technical efficient compared to those who owned small livestock. This might be due to the fact that farm households who have a large numbers of livestock allocated much of their time in managing livestock and hence less time devoted for crop management. This result is in line with study of (Fekadu, 2004; Shumet, 2011; Assefa, 2012; Hassen and Wondimu, 2014; Hassen, 2016) who found that the coefficient of livestock is found to be significant and positive for technical inefficiency. However, in contrast with studies of (Tchale, 2009; Mussa *et al*., 2012; Beyan *et al*., 2013; Wudineh and Endrias, 2016; Belete, 2020).

Total cultivated land (TCULLAND)**:** The coefficient of total cultivated land other than sorghum had a negative and significant effect on technical inefficiency at 1% significance level**.** This indicated that there was a positive relationship between cultivated land and technical efficiency. This variable is mainly justified on the ground that those farmers with big cultivated land can better diversify their crops. It is not unlikely that large farms can quickly utilize existing resources and might have a greater ability to access modern inputs on time. Therefore, the justification is that large farms use modern agricultural technologies and can be less inefficient due to the economics of scale. This result is consistent with findings of (Amos, 2007; Barnes, 2008; Raghbendra *et al*., 2005; Beyan *et al*., 2013).

5. Conclusions and Policy Implications

Given the limited resources in the study area, efforts to improve the efficiency of smallholder farm households who are key actors in Ethiopia's agrarian economy are indispensable. Stochastic production frontier model results indicated that inorganic fertilizer (Urea and DAP), labour force, oxen power, and amount of seed were significantly determinants of sorghum production. The significant coefficients of these parameters indicate that the increased use of these inputs can increase the output of sorghum to a higher extent using the existing technology in the study area. Therefore, the amount and on time availability of these inputs is crucial.

Existence of inefficiency shows that there is a room to increase the output of sorghum by improving the use of existing technologies by all farm households. Therefore, there is an allowance of efficiency improvement by addressing some important policy variables that influenced households' the level of technical inefficiency in the study area. The estimated stochastic frontier model together with the inefficiency parameters show that educational level, off-farm-income, frequency of extension contacts, proximity to farm, credit amount, livestock holding, and total cultivated land were found to be the major significant determinants of technical inefficiency level of farm households in sorghum production. Thus, the significant inefficiency effect explanatory variables have important policy and development implications in an effort towards improving the efficiency of sorghum production in the study area. It is concluded that decreasing the existing level of inefficiency will have vital importance in improving the productivity in the study area. Thus, the following policy implications forwarded from the study result.

- Attention should be given to farm households through establishing and strengthening education, especially adult education by using the available human and infrastructural facilities like Farmers Training Centers in order to increase the efficiency and agricultural productivity of the country in the long run through utilization of available inputs more efficiently under the existing technology so that farmers could be benefited from the accelerated increase in productivity.
- Study results suggest that an extension contact has to keep on providing information and practical farming knowledge for all households to improve resource utilization in agricultural production.

- Study suggests that there is a need to introduce activities that could enhance the off-farm-income of farm households without affecting their farm time allocation so that the households would be in a position to invest the required amount of resources in sorghum production.
- Development programs should strength their support for farmers to improve land allocation and maintain the fertility of land through awareness creation and introduction of technology that maintain fertility for efficient production.
- Furthermore, attention should be given by the local government and supporting institutions through developing crop-specific extension packages and financial accessibility which encourages the farmers to produce efficiently.
- Therefore, a key factor in narrowing productivity gap is the development and implementation of targeted agronomic training for smallholders through encouraging the adoption of productivity enhancing practices and interventions towards important socio- economic factors. Sorghum a promising crop with the potential to enhance the productivity of smallholder farmers, while providing essential nutrients to food-insecure households. It is fund that the potential for agricultural productivity gains among smallholder sorghum producer farm households in Ethiopia is substantial.

References

Abba, W. (2012). Technical Efficiency of Sorghum Production in Hong Local Government Area of Adamawa State, *Nigeria. Russian Journal of Agricultural and Socio-Economic Sciences*, 6 (6): 10-15.

Abdulai, S., Zakariah, A., Donkoh, S. (2018). Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. Cogent Food Agriculture, 4 (1), 1–6.

Abraham B, Araya H, Berhe T, Edwards S, Gujja B, Khadka R, Sen D, Koma Y, Sharif A, and Styger E. (2014). The system of crop intensification: Reports from the field on Improving agricultural production, food security, and resilience to climate change for multiple crops. Addis Ababa, Ethiopia.

Adebo, A. (2020). African Sorghum-Based Fermented Foods: Past, Current and Future Prospects. *Nutrients* 12 (4), 1111–1116.

Ahmad M. C., Ghulam M, Igbal M. (2002). Wheat productivity, efficiency, and sustainability: a stochastic production frontier analysis. Pakistan Dev Rev., 41:4.

Ahmed, M. H. and Kumilachew Alamerie Melesse, K. A. (2018). Impact of off-farm activities on technical efficiency: evidence from maize producers of eastern Ethiopia. Agricultural and Food Economics, 6:3, 1-15, DOI 10.1186/s40100-018-0098-0

Aldrich, J. H. and F. D. Nelson. (1984). *Linear probability, logit and probit model: Quantitative application in the social science-Sera Miller McCun*. London: Sage Pub. Inc, University of Minnesota and Lola.

Alemayehu Ethiopia. (2010). Analysis of factors affecting the technical efficiency of off-farm-income producers in Jimma zone: A stochastic frontier analysis. MSc Thesis (Unpublished), Addis Ababa University, Addis Ababa, Ethiopia.

Alemayehu S, Dorosh P, Sinafikeh A. (2012). Crop production in Ethiopia: Regional Patterns and Trends Ethiopia in Food and Agriculture in Ethiopia: Progress and Policy challenges edited by Dorosh, P. and Rashid, S. University of Pennsylvania: Philadelphia.

Amos, T. T. (2007). An analysis of productivity and technical efficiency of smallholder cocoa farmers in *Nigeria. Journal of Social Sciences*, 15(2), 127-133.

Alene, A. D., & Hassan, R. M. (2006). The efficiency of traditional and hybrid maize production in eastern Ethiopia: An extended efficiency decomposition approach. *Journal of African Economies*, 15(1), 91-116.

Asefa Shumet. (2012). Analysis of Technical Efficiency of Crop Producing Smallholder Farmers in Tigray, Ethiopia. Stochastic Frontier Approach. *Global Advanced Research Journal of Agricultural Science*, 1(7): 191-200.

Aynalem Gezahegn. (2006). Technical Efficiency in Maize Production: The Case of Mecha Woreda of West Gojjam Zone of Amhara Regional State. MSc Thesis (Unpublished), Haramaya University, Haramaya, Ethiopia.

Azam, M, Imai, K. and Gaiha, R. (2012). Agricultural supply response and smallholders market participation- the case of Cambodia. Kobe University. Discussion Paper Series. DP2012-09.

Barnes A. (2008). Technical efficiency estimation of Scottish agriculture: a note. *Journal of Agricultural Economics*, 59:370–6.

Battese, G. E. and Coelli, T. J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data. *Empirical Economics*, 20: 325 - 332.

Battese, G. E. and Cora, G. S. (1977). Estimation of a Production Frontier Model: With Application to the Pastoral Zone of Eastern Australia. *Australian Journal of Agricultural Economics,* 21: 169-179.

Belete A. S. (2020). Analysis of technical efficiency in maize production in Guji Zone: stochastic frontier model. Agriculture & Food Security, 9:15, 1-15, https://doi.org/10.1186/s40066-020-00270-w

Bempomaa B, Acquah H. D. (2014). Technical efficiency analysis of maize production: Evidence from Ghana. Appl Stud Agribus Comm, 8(2–3):73–9.

Beyan A., Jema H., Endrias G. (2013). Analysis of farm households' technical efficiency in production of smallholder farmers: The case of Girawa District, Ethiopia. *Journal of Agriculture and Environmental Sciences*, 13(12):1615–21.

Biru W. D., Zeller M., Loos T. K. The impact of agricultural technologies on poverty and vulnerability of smallholders in Ethiopia: a panel data analysis. Social Indicators Res. 2020;147:517–44. https://doi.org/10.1007/s1120 5-019-02166-0.

BSZAO. (2018). Bench Sheko Zone Agricultural Off-farm-income Area Description Annual Report 2018.

Charnes, A., Cooper, W. W. and Rhodes, E. (1978). Measuring the Efficiency of Decision-Making Units. *European Journal of Operational Research*, 2: 429-444.

Chepng'etich E., Nyamwaro, S. O., Bett, E. K and Kizito. K. (2015). Factors that Influence Technical Efficiency of Sorghum Production: A Case of Small Holder Sorghum Producers in Lower Eastern Kenya. *Advances in Agriculture*, Volume 2015, http://dx.doi.org/10.1155/2015/861919

Coelli, T. J. (1998). A Multi-stage Methodology for the Solution of Oriented DEA Models, *Operations Research Letters*, 23: 143-149.

CSA (Central Statistical Agency). (2013). Population projection of Ethiopia for all regions at woreda level from 2014- 2017. Federal Democratic Republic of Ethiopia, Addis Ababa.

CSA (Central Statistical Agency). (2017). Agricultural sample survey report on crop and livestock product utilization (Private Peasant Holdings, Meher season). Statistical Bulletin Vol. VII, Addis Ababa, Ethiopia.

CSA (Central Statistical Agency). (2020). Agricultural sample survey report on area and production of major crops (Meher season). Statistical Bulletin, Vol. I, Addis Ababa, Ethiopia.

Dejanvry A., and Sadoulet E. (2020). Using agriculture for development: Supply- and demand-side approaches. World Development 133: 105003.

Dhehibi, B., Alimari, A., Haddad, N., and Aw-Hassan, A. (2014). Technical Efficiency and Its Determinants in Food Crop Production: A Case Study of Farms in West Bank, *Palestine Journal of Agricultural Sciences and Technology*, Vol. 16: 717-730.

Elibariki, E., M. Shuji and Nariu, T. (2008). Explaining Productivity Variation among Smallholder Maize Farmers in Tanzania. M.Sc. Thesis, Koyoto University, Tanzania.

FAO (Food and Agricultural Organization). (2014). Crop and Food Security Assessment Mission to Ethiopia. Special Report of Food and Agriculture Organization.

FDRE (The federal Democratic Republic of Ethiopia). (2015). Second Growth and Transformation Plan (GTP-II), National Planning Commission, Addis Ababa, Ethiopia.

Fekadu Gelaw. (2004). Analysis of Technical Efficiency of Wheat Production: A study in Machakel Woreda. MSc Thesis, Haramaya University, Haramaya, Ethiopia.

Gashaw T., Alan B., Nicholas M., and Tanguy B. (2014). The impact of the use of new technologies on farmers wheat yield in Ethiopia. International Food Policy Research Institute (IFPRI). Washington.

Gebre-Selassie A., Bekele T. (2012). A review of Ethiopian agriculture: Roles, policy and small-scale farming systems. In Eder, C., Kyd-Rebenburg, D. and Prammer, J., editors. Global Growing Casebook - Insights into African Agriculture (Global Growing Campaign). Retrieved from http://global-growing.org/.

Hager, Anna-Sophie, Taylor, Josh P., Waters, Deborah M., Arendt, Elke K. (2014). Gluten free beer–A review. *Trends in Food Science and Technology*. 36 (no. 1), 44–54.

Hailemaraim Leggesse. (2015). Technical Efficiency in Teff Production: The Case of Bereh District, Oromia National Regional State. MSc Thesis, Haramaya University, Haramaya, Ethiopia.

Haileselassie Amare. (2005). Analysis of Technical Efficiency in Sorghum Production: The Case of Smallholder Farmers in Raya-Azebo District, Southern Tigray. MSc Thesis (Unpublished), Haramaya University, Haramaya, Ethiopia.

Hassen B. (2011). Performance of mixed crop-livestock production system: The data envelopment approach. Livestock Research for Rural Development. Volume 23, Article #200. Retrieved July 1, 2012, from http://www.lrrd.org/lrrd23/9/besh23200.htm.

Hassen Beshir. (2016). Technical Efficiency Measurement and Their Differential in Wheat Production: The Case of Smallholder Farmers in South Wollo Zone, Ethiopia. *International Journal of Economics, Business and Finance,* 4(1): 1-16.

Hassen, B. and Wondimu, T. (2014). Determinants of Technical Efficiency in Maize Production: The Case of Smallholder Farmers in Dhidhessa District of Illuababora Zone, Ethiopia. *Journal of Economics and Sustainable Development*, 5(15): 274-284.

Hunde K. and Abera N. (2019). Technical Efficiency of Smallholder Farmers Wheat Production: The Case of Debra Libanos District, Oromia National Regional State, Ethiopia. *Journal of Agricultural Resource,* 4(5): 000232.

Ike, P. C. and Inoni, O. (2006). Determinants of Yam Production and Economic Efficiency Among Smallholder Farmers in South Eastern Nigeria. *Journal of Central European Agriculture*, 7(2): 337-342.

Jema, H. (2008). Economic Efficiency and Marketing Performance of Vegetable Production in Eastern and Central Parts of Ethiopia (unpublished doctoral dissertation). Acta Universitatis Agriculture Sueciae (SLU) Uppsala, Sweden.

Kaleb Kelemu and Workneh Negatu. (2016). Analysis of levels and determinants of technical efficiency of wheat producing farmers in Ethiopia. *African Journal of Agricultural Research*, 11(36): 3391-3403.

Khan M. A., J. Chen, Q. Li, W. Zhang, L. Wu, Z. Li, and W. Lin. (2014). Effect of interspecific root interaction on soil nutrition, enzymatic activity and rhizosphere biology in maize/peanut intercropping system. *Pakistan Journal of Agricultural Sciences*. 51(2).

Khanal, U., Wilson, C., Lee, B., et al. (2018b). 'Do climate change adaptation practices improve technical efficiency of smallholder farmers? Evidence from Nepal', Climate Change. Climatic Change, 147, pp. 507–521. doi: https://doi.org/https://doi.org/10.1007/s10584-018-2168-4.

Kinde Teshome. (2005). Technical efficiency of maize production: A case of smallholder farmers in Asosa wereda, Ethiopia. MSc Thesis (Unpublished), Haramaya University, Haramaya, Ethiopia.

Kusse H., Jema H., Bosena T. (2018). Technical Efficiency of Sorghum Production: The Case of Smallholder Farmers in Konso District, Southern Ethiopia. *Agricultural Development*, 3(1): 1-15*, DOI: 10.20448/journal.523.2018.31.1.15*

KZAO. (2018). Kaffa Zone Administrative Off-farm-income Geographical Location Profile Data of the Kaffa Zone.

Lulit M., Ermias E., and Zelalem H. (2012). Public investment in irrigation and training for agriculture-Led development: a CGE approach for Ethiopia. Addis Ababa, Ethiopia.

MoARD (Ministry of Agriculture and Rural Development). (2010). Ethiopia's Agricultural and Sector Policy and Investment Framework (PIF): 2010-2020, Addis Ababa, Ethiopia, 2010.

Mohammed W. (2010). Prevalence and distribution survey of an invasive alien weed (Parthenium hysterophorus L.) in Sheka zone, Southwestern Ethiopia. *African Journal of Agricultural Research*, Vol. 5(9), pp. 922-927 (2010). DOI: 10.5897/AJAR09.048.

Mussa, E. C., Gideon, A. O., Ayalneh Bogale, Franklin, P. S. (2012). Analysis of resource use efficiency in smallholder mixed crop-livestock agricultural systems: Empirical evidence from the central highlands of Ethiopia. Developing Country Studies, 2(9), pp.30–40. https://www.iiste.org/Journals/index.php/DCS/article/view/2964, date: 02.03. 2017.

Mussa, E. C., Gideon, A. O., Ayalneh Bogale, Franklin, P. S. (2012). Analysis of resource use efficiency in smallholder mixed crop-livestock agricultural systems: Empirical evidence from the central highlands of Ethiopia. Developing Country Studies, 2(9), pp.30–40. https://www.iiste.org/Journals/index.php/DCS/article/view/2964, date: 02.03. 2017.

Mustefa Bati, Mulugeta Tilahun, Raja Kumar Parabathina. (2017). Economic efficiency in maize production in Ilu Ababor zone, Ethiopia. *Research Journal of Agriculture and Forestry Sciences*, Vol. 5(12), 1-8.

N. Khanal and K. L. Maharjan. (2013). "Technical efficiency of rice seed growers in the Tarai region of Nepal," *Journal of Rural Problems*, vol. 49, no. 1, pp. 27–31.

Naik, A., Teggelli, R. G., Ahamed, Z., Patil, D. H. (2016). Yield gap analysis of sorghum through front line demonstrations in Kalaburagi region of northern Karnataka. Res. Environ. Life Sci. 9 (5), 597–598.

Nangobi, R., Mugonola, B. (2018). Determinants of collective marketing and marketable surplus for smallholder Sorghum producers in Oyam district, Uganda. *Journal of Development and Agricultural Economics*, 10, 213–224.

NPC (National Planning Commission). (2016). Federal Democratic Republic of Ethiopia Growth and Transformation Plan II (GTP II) (2015/16-2019/20). Volume I: NPC May, 2016, Addis Ababa.

Omoro, W. (2013). Factors for low sorghum production: A case study of small-scale farmers in East Kano sub location, Nyando District, Kenya. Master Thesis, Rural Development and Food Security, Specialization.

Orewa, S. I. and Izekor, O. B. (2012). Technical Efficiency Analysis of Yam Production in Edo State: A Stochastic Frontier Approach. *International Journal of Development and Sustainability*, 1(2): 516–526.

Raghbendra J., Hari K. N., Subbarayan D. P. (2005). Land fragmentation and its implications for productivity: evidence from Southern India. Australia South Asia Research Centre (ASARC) working paper 2005/01.

Rashid, S. and Negassa, A. (2012). “Policies and Performance of Ethiopian Cereal Markets”, Food and Agriculture in Ethiopia: Progress and Policy Challenges. P. A. Dorosh and S. Rashid, eds. Pennsylvania, University of Pennsylvania Press, US, 123–128.

SDG (Sustainable Development Goals). (2015). Transforming our world: the 2030 Agenda for Sustainable Development. *The General Assembly,* United Nations.

Shumet Asefa. (2011). Analysis of technical efficiency of crop producing smallholder farmers in Tigray, Ethiopia. MPRA Paper No. 40461. Available online at http://mpra.ub.unimuenchen.de/40461 and accessed on December 2015.

Sienso G., Asuming-Brempong S., Amegashie D. P. K. (2013). Estimating the efficiency of maize farmers in Ghana. In: Contributed paper prepared for presentation at the 4th international conference of the AAAE, Cape Town, Hammamet, Tunisia, 22–25 September, 2013.

Sisay, D., Jema, H., Degye, G., Abdi-Khalil, E. (2016). Technical, allocative, and economic efficiency among smallholder maize farmers in Southwestern Ethiopia. *Journal of Development and Agricultural Economic*, 7(8), pp. 282–291. doi:10.5897/JDAE2015.0652.

Solomon Bizuayehu. (2014). Technical efficiency of major crops in Ethiopia: Stochastic frontier model. *Academia Journal of Agricultural Research*, 2(6): 147-153.

Tadesse Zenebe Lema, Solomon Amare Tessema and Fentahun Addis Abebe. (2017). Analysis of the Technical Efficiency of Rice Production in Fogera District of Ethiopia: A Stochastic Frontier Approach. *Ethiopian Journal of Economics*, Vol. XXVI No 2:89-108.

Tchale, H. (2009). The efficiency of smallholder agriculture in Malawi. African *Journal of Agricultural and Resource Economics*, 3 (2), 101-121.

Tekleyohannes Hailekiros Berhanu Gebremedhin and Tewodros Tadesse. (2018). Technical Inefficiency of Smallholder Wheat Production System: Empirical Study from Northern Ethiopia. *Ethiopian Journal of Economics* Vol. XXVII No 2: 151-171.

UNDP. (2015). Ethiopia: Key economic and social indicators. UNDP Ethiopia’s policy advisory unit, 2015, No. 2.

United Nations (UN). (2015). Transforming our world: The 2030 Agenda for Sustainable Development, General Assembly, 70th session, Resolution adopted by the General Assembly on A/RES/70/1 (New York).

WFP (World Food Program). (2010). Summary of Food Security and Vulnerability in Selected Cities of Ethiopia, Addis Ababa, Ethiopia.

Wongnaa, C. A. and Awunyo-Vitor, D. (2018). Achieving sustainable development goals on no poverty and zero hunger: Does technical efficiency of Ghana's maize farmers matter? *Agriculture & Food Security (2018) 7:71*, https://doi.org/10.1186/s40066-018-0223-z

World Bank. (2014). Ethiopia poverty Assessment. Document of the WB for off-farm-income use only.

_______. (2007). World Development Report 2008: Agriculture for Development. Washington DC: The World Bank.

Wudineh Getahun and Endrias Geta. (2016). Technical efficiency of smallholder wheat farmers the case of Welmera District, Central Oromia, Ethiopia. *Journal of Development and Agricultural Economics*, 8 (2): 39-51.

Zalkuwi, J., Rakesh Singh, and Singh, O. P. (2014). Assessment of Technical Efficiency of Sorghum Production in Adamawa State, Nigeria. *Asian Journal of Agriculture and Food Sciences*, 2(6): 542-547.

Zenebe, G., O. A. and Tassew W. (2005). Technical Efficiency of Peasant Farmers in Northern Ethiopia: A Stochastic Frontier Approach. pp 103-123. In: Alemayehu, S., Assefa, A., B. D., Berehanu, N., Mulat D., T. B. and Wolday, A. (eds.), Proceeding of the Second International Conference on the Ethiopian Economy. Ethiopian Economic Association. Addis Ababa, Ethiopia.

Labor allocation to Non-agricultural Activities in Rural Ethiopia: A Gender Perspective[1]

Martha Kibru[2]

Abstract

The aim of this paper is to identify factors influencing labor allocation decisions of adult members of farm households in rural Ethiopia. The analysis is done using a Two Part Model (TPM) based on data pooled from the first three waves of the Ethiopian Rural Socio-economic Surveys (ERSS). The results show that labor allocation is influenced by both incentive (pull/push factors) and capacity factors such as education, land size, livestock possession and non-labor income. Besides, the results suggest that there is a gender disparity in the allocation of labor to nonagricultural activities in rural Ethiopia. That is, female members of farm households are more likely to participate in nonagricultural works, and when they do, they also work more hours than the male members. Furthermore, gender differences are observed in some factors such as education, number of infants in a household, and non-labor income that affect labor allocation decisions. Therefore, policies that aim at improving efficiency of labor allocation in rural areas should take into consideration differences in responses to various factors that affect decisions of male and female members of farm households.

Keywords: Time allocation, Nonagricultural activities, Two Part Model, Rural Ethiopia
JEL Codes: D13, J22, Q12

[1] Manuscript received: 8 July 2021
Accepted: 27 August 2021
[2] Lecturer, Department of Economics, Addis Ababa University, Addis Ababa, Ethiopia. martha.kibru@gmail.com

1. Introduction

As is common in most developing countries, a significant number of the Ethiopian population lives in the rural areas depending mainly on agriculture for their livelihoods. About three quarters of the population is engaged in agricultural activities such as crop production, livestock rearing and fishery (Schmidt and Woldeyes, 2019). However, the agricultural sector has failed to offer a sufficient means of livelihood. The sector is unable to retain the existing disguised labor force or to productively absorb additional workforce (Van Den Berg and Kumbi, 2006; Bezu and Holden, 2014). The problem of the sector is because of the high population growth that leads to persistently declining farm sizes and increasingly fragmented land possessions.

Agricultural activities in rural Ethiopia are highly characterized by subsistence production overwhelmingly dominated by smallholder farmers cultivating less than 0.5 ha using crude tools and traditional farming systems (Etea et al., 2020). Consequently, this has led to low agricultural productivity that results low income. Besides, agriculture in Ethiopia is primarily rain-fed and thus it has been challenged by recurrent climate shocks.

Consequently, individuals who are constrained by meager employment opportunities in the agricultural sector are often pushed to look for alternative employment opportunities outside farming. An increasing number of Ethiopian rural household members participate in different nonagricultural activities in order to supplement and sustain their livelihood. Yet, there is a lack of rigorous investigation about the multifaceted factors that influence such labor allocation decisions. Cognizant to this fact, the current study attempts to identify major factors influencing participation in, and the number of engagement hours dedicated to nonagricultural activities among adult members of farm households in rural Ethiopia. Furthermore, the study examines gender differences in their allocation of time and in the extent nonagricultural work participation and hours of work varies.

Considerable number of studies look into factors behind labor allocation decisions in developing countries. Yet, their analysis is limited to the extensive margin where they only look at determinants of the decision to participate or not to participate in a given rural activity, and hence they fail to further look into the factors that influence the extent of participation. Besides, previous studies have failed to take into account the fact that labor allocation to a specific rural activity may actually not represent a separate decision, rather it is the outcome of an optimization process in which allocation of time to different activities are jointly determined.

This study aims to contribute to the existing literature related to livelihood diversification strategies by examining factors that drive labor allocation to nonagricultural activities in the context of rural Ethiopia. The analysis is done both at the extensive as well as at the intensive margins using a Two Part Model based on nationally representative household survey data. Moreover, a Control Function Approach is used to address a potential simultaneity bias that may result from the interdependence of work decisions across alternative rural activities.

A thorough understanding of determinant factors that influence employment choices of adult members of farm households is of great importance to policy makers. Of particular importance is a consideration of whether there is gender inequality in labor allocation across different rural activities. The information that comes from such a study helps concerned stakeholders to come up with development programs, policies and strategies that could help them improve livelihoods in the study area.

The paper is organized as follows. The next section presents a brief review of the empirical literature from Ethiopia and identifies the existing knowledge gap. Section three sets the theoretical framework which serves as a foundation for the empirical analysis relating to time allocation decisions. Section four discusses the data and specifies the empirical strategy for the analysis. Section five presents the descriptive and econometric results followed by some discussion. The last section concludes with a discussion of results and attempts to outline possible policy implications.

2. Empirical Literature Review

There are a few studies from Ethiopia that look into labor allocation decisions in rural areas. Woldenhanna and Oskam (2001) have examined households' labor supply to nonfarm employment and they found upward sloping labor supply curves for both wage and self-employment. According to their findings, households are engaging in wage employment due to push factors while they are pulled to self-employment to gain attractive returns. Also, Lemi (2010) have studied labor allocation between on-farm tasks and off-farm employment in rural Ethiopia. The results have shown that labor allocation is heavily determined by individual, household, and their farm characteristics. Female headed households with high dependency ratio, high livestock value, and poor quality of land were found to participate less in off farm activities. The results have also shown that the intensity of off farm employment increases with land size and decreases with livestock holding.

Likewise, Bezu et al. (2014) have analyzed rural nonfarm employment choices of individuals in Ethiopia. The findings suggest that factors that influence individuals' decision to participate in nonfarm employment differ for the different types of activities. Determinants of participation in high return activities are dominated by capacity variables while determinants of participation in low return activities are dominated by push factors. Recently, Schmidt and Woldeyes (2019) have examined labor diversification in Ethiopia focusing on youth that have relatively greater probability of working in nonagricultural enterprises. Their analysis suggests that push factors are at play with regards to nonagricultural diversification, whereby those that live in less favorable agricultural potential areas, with fewer assets such as livestock, and less access to agricultural credit are more likely to seek off farm work.

Prior studies on nonfarm activities in Ethiopia are very limited to inform policy makers. Most of the studies are conducted based on household surveys with limited coverage that hardly represent the whole country (Woldenhanna and Oskam, 2001). Besides, most studies consider the household as their unit of analysis and fail to look into intra household differences in labor allocation; thus, they are not able to differentiate which family member involves in nonfarm activities. Few studies analyze gender effects by considering gender of the household head and fail to recognize the inherent differences between male and female headed households (Lemi, 2010; Bezu et al., 2014).

3. Theoretical Framework

The analytical framework for the current study is based on a modified agricultural household model suggested by Singh, Squire, and Strauss (1986). A non-separable model is used where, production, consumption, and work-related decisions are brought together into a single framework. This is suitable in the context of rural areas of developing economies where there are multiple market imperfections leading to non-separable decision (Sadoulet, De Janvry, and Benjamin, 1998).

Under the assumption of perfect labour markets, individuals choose to engage in nonagricultural activities as long as the marginal value of agricultural labor (reservation wage) is less than the income offered in the nonagricultural sector. However, in case of imperfections, the decisions to participate in non-agricultural activities are much influenced by a host of socio demographic, economic, and institutional factors.

Conceptually, the decision for allocating labor to nonagricultural activities may be influenced by incentives offered (that is, demand pull and distress push factors) and capacity factors. Employment diversification due to demand pull factors occurs as a deliberate strategy taking into account the earning difference between sectors and associated riskiness (Ellis, 1998). Individuals are motivated to participate in nonagricultural activities with the desire to accumulate wealth through the extra income generated from such activities and/or to take advantage of market and nonmarket opportunities in the nonfarm economy (Reardon, 1997; Ellis, 2000; Barrett et al., 2001).

Another set of motives comprise distress push factors, where nonagricultural employment serves as an involuntarily strategy for survival in the struggle to overcome livelihood distress under deteriorating conditions (Lanjouw and Lanjouw, 2001; Barrett et al., 2001). Employment diversification for the push reasons is generally carried out as ex ante risk management strategy and/or ex post coping mechanism against shocks that may cause transitory drops in farm income (Alobo Loison, 2015; Reardon, 1997). Farm households in rural areas of most developing countries are constrained by market imperfections such as missing or incomplete markets for factors and/or lack of formal risk management instruments. Hence, they are often pushed to engage in rural nonagricultural activities in order to self-insure themselves against the possible risks (Barrett et al., 2001).

In addition to the push and pull factors, whether and to what extent farm households are engage in nonagricultural activities also depends on capacity factors such as human and financial capital, as well as availability of infrastructure (Reardon, Berdegue, and Escobar, 2001; Bezu et al., 2014). Resource constraints related to such capacity factors become binding only where markets do not operate in a competitive way (Reardon, 1997).

The main explanatory variables to be considered for this study are chosen in order to capture main incentives and capacity factors that could influence the relative marginal values of investing labor in various activities. The focus on individual and household characteristics such as indicators of gender, age and education status; household composition (number of children in a household); wealth indicators (land and livestock holding); and exposure to covariate shocks such as drought, flood and landslides) undoubtedly play an important and direct role in determining the way people allocate their time. Furthermore, gender interaction is included for some of the variables which are presumed to have differential impacts on the labor allocation decisions of male and female members of a household. Specifically, education status, number of infants and non-labor income are made to interact with gender. The region and year effects are controlled. The list of variables and summary statistics is presented in Table A1 in the Appendix.

All the aforementioned variables may affect both the reservation and non-farm wage. Hence, the direction of the influence on non-farm employment is indeterminate. Variables that raise the reservation wage reduce the probability and level of participation in non-farm work. By the same token, the variables that raise the value of marginal product of labour in non-farm employment have the opposite effect.

4. Methodology

4.1 The Data

This paper uses pooled data from Ethiopian Rural Socio economic Surveys (ERSS) of the World Bank's Living Standards Measurement Study - Integrated

Surveys on Agriculture (LSMS-ISA) database. It is the result of nationally representative, household level panel data surveys covering three rounds over a time span of five years, from 2010/11 to 2014/15. The data have a section for time use data collected during the post-harvest season for the major agricultural season in many parts of the country (January-May). This section has details on how individuals spend their time on different rural activities (collecting fuel wood, fetching water, working on agricultural activities, nonagricultural activities, temporary/casual work or salaried job, and unpaid apprentice). Thus, the data are helpful to make precise analysis of the labor allocation decisions.

A restricted sample was used for analysis considering only adult members of households (between 15 and 65 years) that consists of 3450 individuals observed in three waves, resulting in a pooled sample of 10350 adults.

4.2 Empirical Strategy

In this paper, a Two Part Model (TPM) is used to analyze labor allocation decisions of adult members of farm households. TPM is a more flexible alternative than the Tobit model (Tobin, 1985) or Heckman selection model (Heckman, 1979). TPM is suitable to sequentially model the participation decision (whether or not to participate in the nonagricultural work) and the intensity of participation (amount of time allocated by participants). TPM allows including different covariates in the two decisions and does not assume the determinants of the binary participation decision to similarly explain the intensity of participation decisions (Cragg, 1971; Duan et al., 1984). This is in contrast to Tobit model, which is restrictive assuming a single decision process whereby both decisions are determined by the same underlying process (Tobin, 1985).

Furthermore, TPM allows the possibility of zero observations in the first and second hurdles. Unlike the Tobit model, which is restrictive in interpreting the zero values for nonparticipation as corner solutions in utility maximization (Amemiya, 1984), TPM considers the fact that zero observations may arise due to behavior of respondents, deliberate choices, sampling errors, absenteeism or random circumstances. Zeros may arise due to the short reference period of the survey time relative to the period over which participation decisions are made (Stewart, 2013).

Heckman's sample selection model is a candidate in such a context but it is restrictive assuming that the zeros denote censored values of the positive outcome and none of the zero observations may be due to a corner solution (Heckman, 1979; Belotti et al., 2015). Furthermore, Heckman's model only considers those who chose positive hours of work, and does not observe anything about the people who do not participate in a given work (Heckman, 1979). On the other hand, TPM allows the inclusion of all observations in the sample; where it is still possible to observe those who do not work, but record zero hours of work.

TPM has been used to model labor supply decisions in developing countries. For instance, Matshe and Young (2004) has applied TPM to model off farm labor allocation Zimbabwe. Similarly, Ibrahim and Srinivasan (2011) has used the double hurdle model to examine the off farm labor supply decisions of rural households in Nigeria. Recently, Salmon and Tanguy (2016) has employed the hurdle model to investigate the impact of electrification on male and female labor supply decisions within rural households in Nigeria.

The Two Part Model (TPM) used in this paper can be written as follows:

$$p_i^* = z_i'\gamma + \varepsilon_i\ , \quad p_i = \begin{cases} 1 \text{ if } \quad p_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \qquad \textbf{(1)}$$

$$h_i^* = x_i'\beta + u_i, \qquad h_i = \begin{cases} h_i^* \text{ if } \quad h_i^* > 0 \text{ and } p_i^* > 0 \\ \quad 0 \text{ otherwise} \end{cases} \qquad \textbf{(2)}$$

The first part, Equation 1, is a binary model which captures the likelihood of participation with a dummy variable that takes a value of one if individual i participates in any nonagricultural work during the reference period, and a value zero if no participation is recorded. p_i^* is a latent variable associated with nonagricultural work participation and it represents the binary censoring, while p_i is the corresponding observed value.

Equation 2 presents the second part which is a continuous model for the decision on the intensity of participation conditional on the participation decision, explicitly considering that the observed hours of nonagricultural work (h_i) is censored at zero. The actual observed hours of work (h_i) equals the unobserved latent value associated with potential hours of nonagricultural work (h_i^*) only when a positive hour of work is reported; otherwise, it takes the value of zero. In this model, a two stage process must have been completed before a positive hours of work is observed: first, the individual has decided to participate in nonagricultural work; and second, this individual has allocated some amount of time to nonagricultural work (Cragg, 1971).

z_i' *and* x_i' represent vectors of variables that explain the participation and hours of work decisions, whereas γ and β are the corresponding vectors of parameters.

ε_i and u_i are the error terms. In the model originally proposed by Cragg (1971), error terms of the two hurdles are assumed to be uncorrelated and normally distributed. But, the TPM used in this paper does not make any assumptions about correlation between the errors. The errors are assumed to follow a bi-variant normal distribution. That is,

$$\begin{pmatrix}\varepsilon_i \\ u_i\end{pmatrix} \sim BVN\left[\begin{pmatrix}0 \\ 0\end{pmatrix} \quad \begin{pmatrix}1 & \rho^{\sigma} \\ \rho^{\sigma} & \delta^2\end{pmatrix}\right].$$

This study follows the formulation presented by Jones (1992) in which hurdles are not independent. If information on censoring is available, the likelihood function can be written as:

$$L = \prod_{h=0}\left\{1 - \Phi_2\left(z_i'\gamma\,, \frac{x_i'\beta}{\sigma_h}, \rho\right)\right\} \prod_{h>0}\left\{\Phi_1\left\{\frac{z_i'\gamma + \frac{\rho}{\sigma_h}(h_i - x_i'\beta)}{\sqrt{1-\rho^2}}\right\}\frac{1}{\sigma_h}\emptyset\left(\frac{h_i - x_i'\beta}{\sigma_h}\right)\right\} \quad \textbf{(3)}$$

where Φ_1 is the normal cumulative distribution function, Φ_2 is the bivariate normal cumulative density, and and $\emptyset$ is the density function of the normal distribution.

5. Results and Discussion

5.1 Descriptive Results

Table A1 in the Appendix reports the summary statistics for the variables included in the analysis on the restricted sample of adult members of households (between 15 and 65 years). For the sake of parsimony, in what follows details are provide only for the outcome variables of our analysis that indicate participation and level of participation in rural nonagricultural activities. The data have information on hours of nonagricultural work recorded for each individual during the seven days preceding the survey. Nonagricultural activities include all economic activities in rural areas except primary agriculture, livestock, fishing and hunting. They include all secondary and tertiary sector employment of both permanent and casual nature, and they can be categorized into nonagricultural self-employment, wage employment and unpaid work.

More than one-third of the adults in the sample have reported zero hours of work, may be because they were unable to work in the reference week or they may choose not to work with the given amount of economic incentives. On one hand, agriculture remains by far the primary source of employment in rural Ethiopia (61 percent of the adults in the sample reported to have allocated some time to agricultural activities in the reference week). On the other hand, working in nonagricultural work is still rare (only 12 percent of the adults report to have spent positive hours in nonagricultural activities in the reference week). Conditional on working, an individual in rural Ethiopia allocates, on average, 24 and 22 hours a week for agriculture and nonagricultural activities respectively.

Table 1: Labor allocation across rural activities in Ethiopia
(Summary statistics on pooled sample disaggregated by gender)

	Pooled-Sample (N=10530)	Sub-Sample	
		Male (N=5034)	Female (N=5316)
Incidence of Work (Weighted Percentage of Individuals that Report Positive Hours of Work)			
Agricultural Activities	0.61	0.72	0.51
Nonagricultural Activities	0.12	0.11	0.14
Any Rural Activity (Agri/Non-Agri/Temporary/Paid/Unpaid)	0.68	0.78	0.59
Intensity of Work (Weighted Mean Weekly Hours Allocated, Conditional on Working)			
Hours Spent on Agricultural Activities	23.96	26.32	20.61
	(16.69)	(16.56)	(16.27)
Hours Spent on Nonagricultural Activities	22.4	19.49	25.06
	(16.7)	(15.18)	(17.63)
Hours Spent on Any Rural Activity	28.68	31.03	25.51
	(21.23)	(20.79)	(21.39)

Note: Statistics based on the restricted sample adult members of households (15-65 years) in rural Ethiopia.
Standard deviations are reported in brackets.

The statistics reported in Table 1 clearly indicate that time use patterns vary by gender. Agricultural activities are more commonly carried out by male than female household members. Approximately 72 percent of male members are engaged in agricultural activities as compared to 51 percent of female members. Adult male members of rural households allocate, on average, 26 hours per week to agricultural activities while female members allocate only about 21 hours per week to agricultural activities. On the other hand, slightly higher percentage of female (14%) as compared to men (11%) reported to have allocated positive labor hours to nonagricultural activities in the reference week. Besides, the reported weekly average hours spent on such activities is higher for female (25 hours) than male (20 hours).

The total workload of men seems to exceed that of women in rural Ethiopia. Approximately 78 percent of adult male (relative to 59 percent of the female) have reported positive hours of work in the reference week. On average, men spend five more hours in different agricultural and nonagricultural activities as compared to their women counterparts.

when analyzing labor allocation, it is important to consider household activities in rural areas where access to basic infrastructure is usually limited and traditional gender roles are deeply rooted. However, the analysis in this paper does not cover such activities due to data paucity. Yet, it is well established that women in rural Ethiopia are predominantly engaged in time consuming household activities, which ultimately limit their time available to other works. Hence, once such household works are considered, the total workload on women is expected to far exceed those of men.

5.2 Econometric Regression Results

These papers conduct extensive analysis on nonagricultural labor market participation and amount of time allocated using Two Part Model (TPM) regression technique. Parameter estimates have been obtained using the Stata user written command twopm. The regression adjusts for the complex sample design of the ERSS data in computing the parameter estimates and the standard errors of those estimates.

It is important to check whether the model fits the data by exploring the assumptions of the model specification. The distribution of the dependent variable tested by plotting a histogram for the nonagricultural work participants (see Figure A1). As expected, the distribution is skewed to the right which has direct implications on normality of the error terms. TPM assumes that unobserved errors are normally distributed in the positive part. The maximum likelihood estimator may be inconsistent when the normality assumption fails. Beyond the graphical examination of the data, the normality assumption is also checked with Shapiro-Wilk W test using residual estimates from a truncated regression model. The normality assumption is rejected as the test yields very small p-value which is confirmed with the kernel density plot of residuals, which supports non-normality in residuals (see Figure A4). One way to relax the normality assumption is to use non-normal distributions, such as the log-normal or the gamma distribution.

The first part of the TPM is analyzed with a Probit model. The results are not sensitive to the model used in the first part; running a Logit model gives identical results. The second part is analyzed with generalized linear model (GLM) employing the log-link (as well as square root-link) between the expected value of the dependent variable (hours of nonagricultural work) and the linear index of covariates, assuming the random component of the outcome follows gamma distribution. Gamma distribution has a variance function that is proportional to the square of the mean function. It is usually more appropriate than the normal distribution when data are skewed, especially a positively skewed. Appropriate tests are done to check the extent to which the presumed structure of the model fits the data in terms of the link and distribution assumptions. The specification tests for the positive hours of nonagricultural work are reported in Table 2.

Table 2: GLM specification tests: link and distribution

Link: Log **Family: Gamma**	
Test for link function Pregibon link test	-0.0705 (0.055)
Modified Park test: $\lambda 2$(p-value) ν coefficient	1.5091
ν = 0 : Gaussian	59.15 (0.0000)
ν = 1 : Poisson	6.73 (0.0095)
ν = 2 : Gamma	6.26 (0.0124)
ν = 3 : Inverse Gaussian	57.72 (0.0000)

Source: Author's own computation

5.2.1 Specification tests for Generalized Linear Model (GLM)

The GLM specification requires to define the link function that characterizes how the conditional mean is related to the set of covariates. In order to assess which GLM link makes the dependent variable (hours of nonagricultural work) symmetric, the dependent variable is transformed and the histogram is checked. The untransformed dependent variable has a distribution that is skewed to the right, the log-transformation is skewed to the left while the square root transformation yields fairly symmetric distribution (see Figures A1, A2 and A3).

The log-linear model transformation is preferred over linear in the estimations. First, the link test is performed (Pregibon, 1980) in examining the GLM specification. The link test refits the model using the predicted linear index and its square as covariates. The parameter estimate is found to be very small and insignificant (see Table 2). As a result, misspecification is rejected at any level of significance, suggesting that the link is correctly specified and so there is no need to include the square term as additional explanatory variable.

Finally, a modified park test is used to assess how variance is related to the mean. The test is done by regressing logarithm of the untransformed square errors from the GLM model on the logarithm of the predicted outcomes. The test constitutes evaluating the value of the resulting parameter estimates which could be close to 0, 1, 2 or 3 implying the use of Gaussian, Poisson, Gamma or Inverse Gaussian distribution, respectively. According to the modified park test, where the coefficient (1.5091) is found to be close to 2, Gamma proves to be the most appropriate distributional family to model positive hours of nonagricultural work (see Table 2).

5.2.2 Results from Two Part Model (TPM)

Results from the two-part model (TPM) with log-link and gamma distribution are presented in two parts. The first part presents coefficient estimates of the Probit version of TPM (for the analysis at the extensive margin: the probability of participation in nonagricultural activity); the second part presents coefficient estimates of the GLM version of TPM (for the analysis at the intensive margin: weekly hours allocated to nonagricultural work by the participants)1. The marginal effects based on the combined results are presented in Table 3 herein below.

Model 1 presents results for covariates where the effect of hours of agricultural work is not controlled for while it is controlled for in Model 2. The former will be discussed herein below while the latter will be discussed under section 5.2.3.

[1] The complete results for the first and second part are not presented in this paper. But they can be presented upon request.

Table 3: Results from two-part model with log-link and gamma distribution (Marginal effects based on the combined results from the first and second part of TPM)

	MODEL 1	MODEL 2
Female	1.99***	-0.27
	(0.34)	(1.09)
Age	0.24***	0.37***
	(0.07)	(0.09)
Age Squared	-0.00***	-0.01***
	(0.00)	(0.00)
Educ_Status	1.61***	0.96**
	(0.24)	(0.38)
No of Child(<6yrs)	0.61***	0.57**
	(0.21)	(0.23)
No of Child(6-15yrs)	-0.02	-0.15
	(0.13)	(0.17)
Land Holding (Relative to Marginal < 0.5 Ha)		
Smallholder (0.5-2 Ha)	-0.73***	-0.57*
	(0.27)	(0.29)
Largeholder (> 2 Ha)	-0.71	-0.58
	(1.13)	(1.13)
Livestock_Holding	-0.21*	-0.10
	(0.10)	(0.10)
Ln_Nonlabor_Income	0.01	0.01
	(0.05)	(0.06)
Covariate_Shock	-0.25	-0.41
	(0.29)	(0.37)
Region Dummy		
Tigray	-0.13	-0.14
	(0.92)	(0.93)
Amhara	-1.12	-0.42
	(0.79)	(0.63)
Oromia	-1.09	-0.77
	(0.73)	(0.66)
SNNP	-1.52**	-1.20*
	(0.72)	(0.65)

	MODEL 1	MODEL 2
Year Dummy (Relative To 2011)		
Yr_2013	-3.53***	-3.62***
	(0.59)	(0.60)
Yr_2015	-4.14***	-4.52***
	(0.44)	(0.48)
Gender Interaction Terms		
Female*Educ_Status	-0.94***	-0.64*
	(0.34)	(0.35)
Female*Child(<6yrs)	-0.97***	-0.89***
	(0.21)	(0.21)
Female*Ln_Nonlabor_Income	0.20**	0.20**
	(0.08)	(0.08)
Control For Interdependence in Work Decisions		
Agr_Hours		-0.03***
		(0.01)
Predicted Residual		-0.19**
		(0.09)
Observations	10350	10350

Gender is the major variable of interest for the analysis indicated by a dummy variable which takes a value of one for female members of a household, and zero otherwise. According to the result, female are more likely to participate in nonagricultural activities and conditional on participation, than their male counterparts. Similarly, females work longer hours in nonagricultural activities than their male counterparts. The marginal effects for the gender dummy implies that adult female involve in nonagricultural activities significantly more than male by about 1.99 hours (see Table 3). Although female are found to work more than male at all ages, the difference is much greater for elderly than young perhaps due to the assumed log-link (see Figure A5).

Nevertheless, the response is tempered with when there are infants in the household, as implied by the negative significant coefficient of the interaction term for gender and number of infants in the household. That is to say, adult female from households with many infants are less likely to engage in nonagricultural work as compared to their male counterparts, probably because taking care of infants is mainly in the female's domain of work and it is time consuming. In contrast to findings of studies, raising children and nonagricultural work are not necessarily competing activities in rural areas of developing countries, where there is an extended family that support in taking care of children (Salmon and Tanguye, 2015).

Most of the control variables have the expected signs. Age captures the effect of experience which is believed to affect an individual's potential productivity. According to the results reported in Table 2, age is statistically significant and it has the expected positive sign while age squared has a negative sign, implying that an increase in age is translated to higher expected hours of nonagricultural work until 37 years (see Figure A6). Naturally a person would gradually start losing job opportunities after reaching a certain age, or it may be due to rigidity in shifting of activities for the elder persons, or because the demand for leisure increases at older ages (as suggested by Ibrahim and Srinivasan, 2011). The finding is consistent with the findings of Abdulai and CroleRees (2001) in their study of households in Mali. According to their findings, the likelihood of participation in nonagricultural activities first rises with age and then declines after reaching peak age. Similar results are reported by Nagler and Naudé (2017) based on their analysis of World Bank data from Ethiopia, Malawi, Niger, Nigeria and Uganda. They found older cohorts to be more likely to engage in nonfarm activities, reflecting the fact that many of who are less than 25 years old are still attending school.

Education is expected to increase the marginal value of time and reservation wage as it enhances the range of work related skills, the ability to acquire new skills and makes individuals more employable (Reardon, 1997). The result in this paper confirms the positive effect of education. Literacy increases the likelihood of participation in nonagricultural work, as well as the hours of nonagricultural work conditional on participation. The negative coefficient for the interaction term of gender and education implies that the magnitude of the effect of education is relatively lower for female compared to male members of farm households (see Model 1 in Table 3).

The existing discourse evidenced in rural Africa shows that education enhances nonagricultural work participation, especially in more remunerative salaried and skilled employment (Barrett et al., 2001; Lanjouw and Shariff, 2004;

Van Den Berg and Kumbi, 2006). Salmon and Tanguy (2016) have shown that educated individuals in Nigeria are likely to prefer to work outside agriculture. Also, Bezu et al. (2014) have identified education to be the most important factor that positively influences participation in all types of nonagricultural employment in Ethiopia.

Land and livestock possessions are important resources for agriculture and they are the main indicators of wealth in rural Ethiopia. According to the results, conditional on participation, and an increase in land size are associated with a reduction in hours of nonagricultural work for members of households with better agricultural resources (such as large land size of 0.5-2 ha) relative to less endowed households (such as those with small land size of less than 0.5 ha). The study result suggests that land constraint, which is one of the push factors to engage in nonagricultural activities, is relatively relaxed for members of households with better land holdings. On the other hand, households with large land size may choose to specialize in agricultural production, which is labor intensive in case of Ethiopia; thus, may face more binding labor constraints than those households with smaller landholdings. The finding is of course in contrast to some of the earlier findings such as Abdulai and CroleRees (2001) for Mali, Ellis (2000) for developing countries, while it is consonant to the findings of Woldenhanna and Oskam (2001) for Ethiopia.

Income is an important determinant of labor allocation decision. In the analysis, the non-labor income is controlled as other incomes as it may give rise to endogeneity problems. Furthermore, non-labor income is more relevant given the increasing flows of remittances and other transfers in the context of Ethiopia. Non-labor income may help recipient households by relaxing liquidity constraints or it may raise reservation wages and discourage participation in nonagricultural activities. The result from TPM also show that an increase in non-labor income of a household is translated to higher expected hours of nonagricultural work but it is due to higher likelihood of participation, rather than how much actual participants worked. The result is observed only for female members of farm households as indicated by a statistically significant positive coefficient of the interaction term of gender and non-labor income (see Table 3). The result, however, is in contrast to the findings of studies in many rural areas of developing countries with noncompetitive labor markets with high unemployment (Azizi, 2018).

5.2.3 The Control Function Approach (CFA) to addressing simultaneity bias in labor allocation

Hours spent in each rural activity may actually not represent a separate decision, rather are outcomes of an optimization process in which allocation of time to different activities are jointly determined. So, it is important to assess the impact of each type of work on the other to know to what extent the decisions are interrelated. Thus, in this paper, hours of agricultural work are included as an explanatory variable for the hours of nonagricultural work decision in order to account for potential interrelatedness of work decisions. However, this may result in a simultaneity bias since hours of agricultural work may relate with unobservables. Such biases are corrected by using the Control Function Approach (CFA), which entails estimation in two stages (Wooldridge, 2012). First, the reduced form equation for potentially endogenous variable (hours of agricultural work) is estimated. Then, hours of nonagricultural work are analyzed with hours of agricultural work and the residual from reduced form model as additional covariates in the structural model.

Control Function Approach (CFA) requires an exclusion restriction. That is, some strictly exogenous covariates need to be excluded from the structural model of hours of nonagricultural work to be used as instruments with other covariates in the reduced form model. A measure of temperature (weather indicator) and access to extension program are used as instruments as they are exogenous and unobservable ability is presumably independent of such variables. They affect nonagricultural activities only through their effect on agricultural activities.

In the analysis, the predicted residual from the reduced form equation is found to be significant, indicating that the variable for hours of agricultural work is actually endogenous. Thus, the predicted residual is kept as extra regressor so that remaining variation in the endogenous variable would not be correlated with unobservables.

The statistically significant negative coefficient for hours of agricultural work suggests trade-off in time allocation decisions in rural Ethiopia. Though, this coefficient is statistically significant, its impact in magnitude is very small. An hour increase in agricultural work translates to only 0.03 (less than two minutes) lower expected hours of nonagricultural work. The amount of hours devoted to nonagricultural activities seem to be constrained very marginally by the amount of hours allocated to agricultural activities (see Model 2 in Table 3).

Even after properly controlling for simultaneity bias related with the interrelatedness of agricultural and nonagricultural work decisions, the effects of most of the incentive and capacity factors still hold, with slight declines in magnitudes. Although gender is no more significant, there is still difference in response to the various factors that affect the labor allocation decisions of male and female members of farm households in rural Ethiopia.

6. Conclusion

The study examines the labor allocation decisions of adult members of farm households in rural Ethiopia using data pooled from the first three rounds of Ethiopian Rural Socio-economic Surveys (ERSS). The analysis is done using Two Part Model (TPM), which provides a more realistic model of the labor market by distinguishing between the participation and intensity of participation.

The descriptive analysis displays gender disparity in the allocation of labor time between agriculture and nonagricultural activities in rural Ethiopia. Agricultural activities are more commonly carried out by male members of farm households. On the other hand, female members of farm households participate more and spend longer hours in nonagricultural activities than their male counterparts. The econometrics analysis confirms that gender is, indeed, one of the important individual characteristics associated with labor allocation decisions in rural Ethiopia. Female members of farm households are more likely to participate in nonagricultural activities; and conditional on participation, they spend more hours than their male counterparts. However, female members of households with many infants are less likely to participate in nonagricultural activities and allocate relatively shorter hours than male members do, on conditional participation.

Besides, labor allocation is affected by both incentive (pull/push factors) and capacity factors such as education, land size, livestock holdings and non-labor income. Gender disaggregated analysis shows difference in response to the various factors that affect the labor allocation decisions of male and female members of farm households in rural Ethiopia. For instance, education is found to increase the likelihood of participation in nonagricultural activities as well as the hours of work for both male and female members, with relatively higher increase for male than female members of farm households. Similarly, non-labor income is found to increase the probability of participation in nonagricultural activities only for female members of rural farm households.

There are some caveats which should be kept in mind when considering the results discussed above. First, wage is not included in the model because of limited records in the data as most of the nonagricultural works in rural areas are informal and non-monetary payments for labor is common. It is difficult to calculate shadow wage rate for those who do not work during the survey period based on the limited records for the very few who worked. Instead, exogenous variables that affect individual's shadow price of time and the reservation wage rate are included.

Second, the analysis in this paper does not cover time allocated to household chores due to data paucity. ERSS data does not provide sufficient information on such activities on which rural women spend long hours working and is likely to limit their time available to other works. Third, our analysis considers attributes of only the decision maker. However, there are theories that suggest individuals' labor decision also depends on attributes of other household members. It is difficult to control for in case of rural Ethiopia where there are variety of household types (such as monogamous/polygamous households, households with children and several adults, households with absentee head or spouse). It will be very complicated to jointly model labor supply decisions of members within a household and test for interdependence.

Finally, since the analysis is done on a pooled cross-sectional data, the estimated effects should be considered as associations as opposed to causal effects. Further econometric analysis is required in order to make inferences as to the causal effects of the individual and household characteristics.

Attention should be given to the nonfarm sector given the fact that it mostly employees vulnerable groups (such as women, youth, and the land poor) that need to supplement meager production on subsistence agriculture. Besides, Ethiopia would benefit from pursuing and intensifying its efforts to ensure better access to education because, as this study and others show, better educated individuals are likely to prefer to work outside agriculture, participate more and for longer hours in nonagricultural activities. Most importantly, policies that aim at improving the efficiency of labor allocation in rural areas should take into consideration the difference in response to various factors that affect the decisions of male and female members of farm households.

References

Abdulai, A. and Crole Rees, A. (2001). Determinants of Income Diversification amongst Rural Households in Southern Mali. Food Policy, 26(4), 437–452.

Alobo Loison, S. (2015). Rural Livelihood Diversification in Sub-Saharan Africa: A Literature Review. *Journal of Development Studies*, 51(9), 1125–1138.

Amemiya, T. (1984). Tobit models: A survey. *Journal of Econometrics*, 24(1–2), 3–61.

Azizi, S. S. (2018). The Impacts of Workers' Remittances on Human Capital and Labor Supply in Developing Countries. Economic Modelling, 75(July), 377–396.

Barrett, C. B., Reardon, T., and Webb, P. (2001). Nonfarm Income Diversification and Household Livelihood Strategies in Rural Africa: Concepts, dynamics, and policy implications. Food Policy, 26(4), 315–331.

Belotti, F., Deb, P., Manning, W. G., and Norton, E. C. (2015). twopm: Two-part models. *Stata Journal*, 15(1), 3–20.

Bezu, S., Barrett, C. B., Holden, S. T., Barrett, C. B., and Holden, S. T. (2014). Activity Choice in Rural Non-farm Employment (RNFE): Survival versus accumulative strategy. Norwegian University of Life Sciences (NMBU)

Bezu, S., and Holden, S. (2014). Are Rural Youth in Ethiopia Abandoning Agriculture? World Development, 64, 259–272.

Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica*, 39(5), 829.

Duan, N., Manning, W. G., Morris, C. N., and Newhouse, J. P. (1984). Choosing between the Sample-selection Model and the Multi-part Model. *Journal of Business and Economic Statistics*, 2(3), 283–289.

Ellis, F. (1998). Household Strategies and Rural Livelihood Diversification. *Journal of Development Studies*, 35(1), 1–38.

Ellis, F. (2000). The Determinants of Rural Livelihood Diversification in Developing Countries. *Journal of Agricultural Economics*, 51(2), 289–302.

Etea, B. G., Zhou, D., Abebe, K. A., and Sedebo, D. A. (2020). Is Income Diversification a means of Survival or Accumulation? Evidence from rural and semi-urban households in Ethiopia. Environment, Development and Sustainability, 22(6), 5751–5769.

Ibrahim, M. K., and Srinivasan, C. S. (2011). Off-farm Labour Supply Decision of Households in Rural Nigeria: A Double hurdle model Approach. 1–24.

Heckman, J. (1979). Sample Selection Bias as a Specification Error.Econometrica,47(1),153–161.

Jones, A. M. (1992). A Note on Computation of the Double Hurdle Model with Dependence with an Application of Tobacco Expenditures. Bulletin of Economic Research 44: 67–74

Lanjouw, J. O., and Lanjouw, P. (2001). The Rural Non-farm Sector: Issues and evidence from developing countries. Agricultural Economics, 26(1), 1–23.

Lanjouw, P., and Shariff, A. (2004). Rural Non-Farm Employment in India: Access, Incomes and Poverty Impact. Economic and Political Weekly, 39(40), 4429–4446.

Lemi, A. (2010). Determinants of Income Diversification in Rural Ethiopia: Evidence from panel data. *Ethiopian Journal of Economics*, 18(1), 35–69.

Matshe, I., and Young, T. (2004). Off-farm Labour Allocation Decisions in Small-scale Rural Households in Zimbabwe. *Agricultural Economics*, 30(3), 175–186.

Nagler, P., and Naudé, W. (2017). Non-farm Entrepreneurship in Rural Sub-Saharan Africa: New empirical evidence. Food Policy, 67, 175–191.

Pregibon, D. (1980). Goodness of Link Tests for Generalized Linear Models. Applied Statistics, 29(1), 15.

Reardon, T. (1997). Using Evidence of Household Income Diversification to Inform Study of the Rural Nonfarm Labor Market in Africa. World Development, 25(5), 735–747.

Sadoulet, E., De Janvry, A., and Benjamin, C. (1998). Household Behavior with Imperfect Labor Markets. Industrial Relations, 37(1), 85–108.

Salmon, C., and Tanguy, J. (2016). Rural Electrification and Household Labor Supply: Evidence from Nigeria. World Development, 82, 48–68.

Schmidt, E., and Woldeyes, F. B. (2019). Rural Youth and Employment in Ethiopia. Youth and Jobs in Rural Africa, 109–136.

Singh, I., Squire, L., and Strauss, J. (1986). A survey of Agricultural Household Models: Recent findings and policy implications. World Bank Economic Review, 1(1), 149–179.

Stewart, J. (2013). Tobit or not tobit? *Journal of Economic and Social Measurement,* 38(3), 263–290

Tobin, B. Y. J. (1985). Estimation of Relationships for Limited Dependent Variables. *Econometrica*, 26(1), 24–36.

Van Den Berg, M., and Kumbi, G. E. (2006). Poverty and the rural nonfarm economy in Oromia, Ethiopia. Agricultural Economics, 35(SUPPL. 3), 469–475.

Woldenhanna, T., and Oskam, A. (2001). Income Diversification and Entry Barriers: Evidence from the Tigray region of Northern Ethiopia. Food Policy, 26(4), 351–365.

Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach*. South-Western Cengage Learning, 5th edition.

Appendix

Table A1: Summary statistics on the restricted sample of adults (N=10350)

Variable name	Definition	Mean	Std. Dev.	Min	Max
Dependent variables					
Agr_hours	Hours spent in any agricultural activity during the last seven days	14.51	17.5	0	98
Nonagr_hours	Hours spent in any nonagricultural activity during the last seven days	2.52	9.02	0	98
Total_hours	Hours spent in any rural activity during the last seven days	19.10	21.92	0	176
Explanatory Variables					
Individual characteristics					
Female	Gender of individual (=1 if female; =0 if male)	0.51	0.5	0	1
Age	Age of individual	35.54	12.14	15	65
Educ_status	Literacy (=1 if individual can read and write)	0.45	0.5	0	1
Schooling	Years of schooling of the individual	4.75	3.17	0	15
Household composition and wealth indicators					
No of child<6yrs	No of children under age 6 (infants)	0.74	0.91	0	5
No of child7-15yrs	No of children aged 6-14 (teenagers)	1.85	1.33	0	7
No of adult 15-65yrs	No of adult members aged 15-65	3.22	1.43	0	10
Household wealth indicators					
Landholding	Measured in hectares	0.51	1.09	0	15.15
Livestock holding	Measured in tropical livestock unit	1.06	2.13	0	26.6
Nonlabor_income	Non-labor income (unearned income)	2888.6	6096.4	0	42000
Shock occurrence					
Covariate_shock	(=1 if household faced covariate shocks such as flood, drought and landslides in last 12 months)	0.19	0.39	0	1
Instruments					
Avg_temp_wet_qrt	Mean temperature of the wettest quarter (°C)	177.98	30.36	103	319
Extension_program	(=1 if household has access to agricultural extension service)	0.16	0.37	0	1

- *The data source is LSMS-ISA (2010/11-2014/15) considering only adult members (15-65 years) of rural households.*
- *Survey weights are used when calculating mean and standard deviation.*
- *Weighted mean hours is computed for the whole sample, including zero hours reported.*
- *Weighted average years of schooling is computed for the literate group. Similarly, the average non-labor income is computed for the sub-sample of households that report to have received such income (8 percent).*

Figure A1: Histogram for hours of nonagricultural work for participants (untransformed)

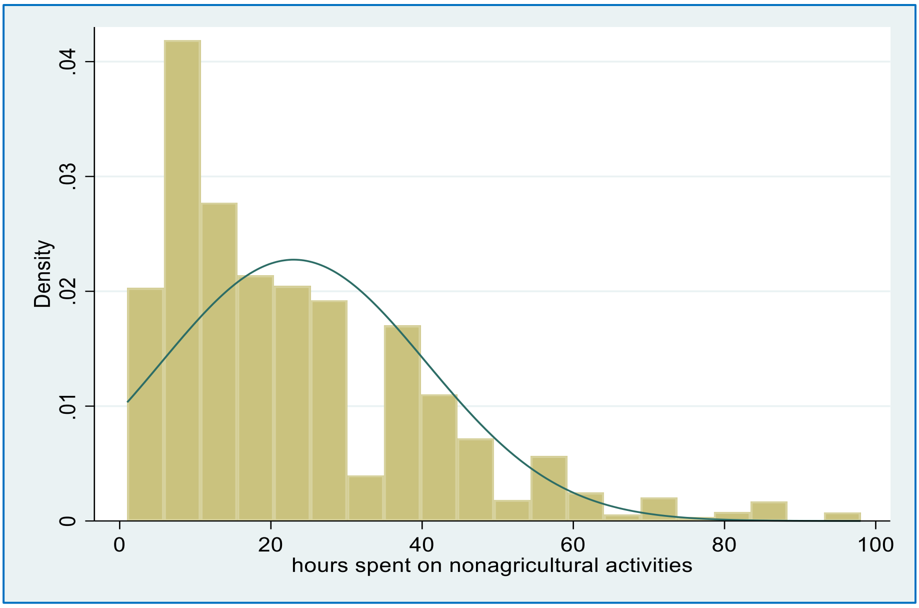


Figure A2: Histogram for logarithm hours of nonagricultural work (log transformation)

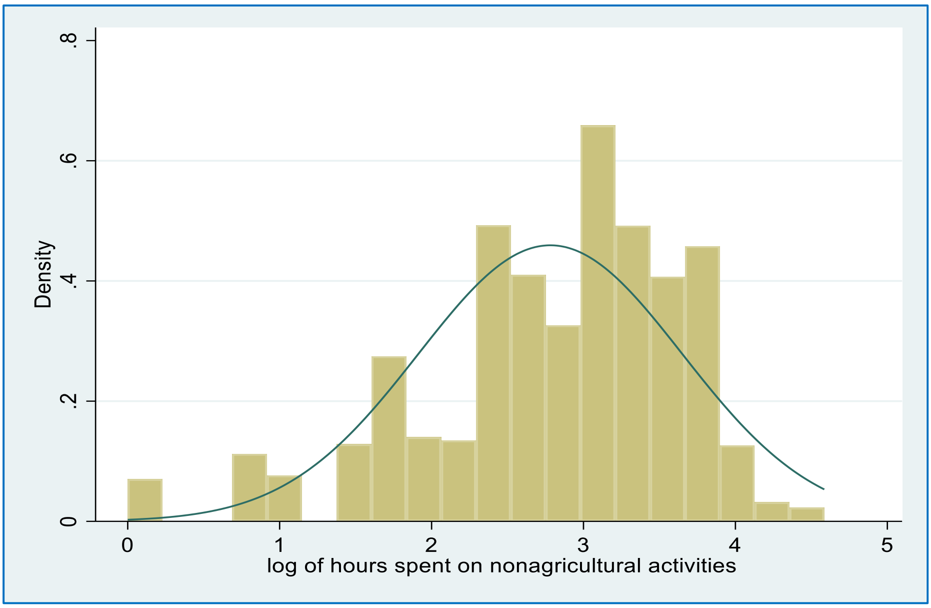


Figure A3: Histogram for square root of hours of nonagricultural work (square root transformation)

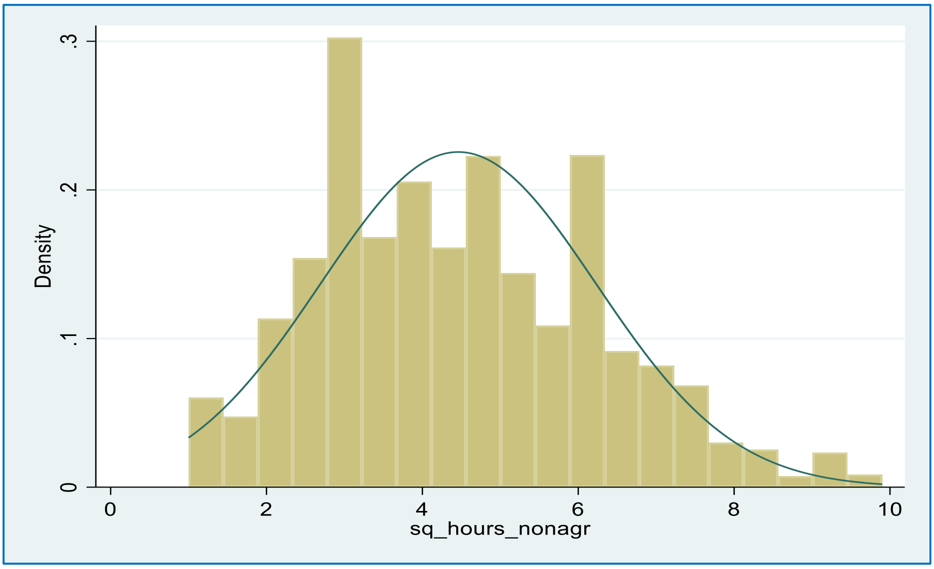


Figure A4. Kernel density plot of residual

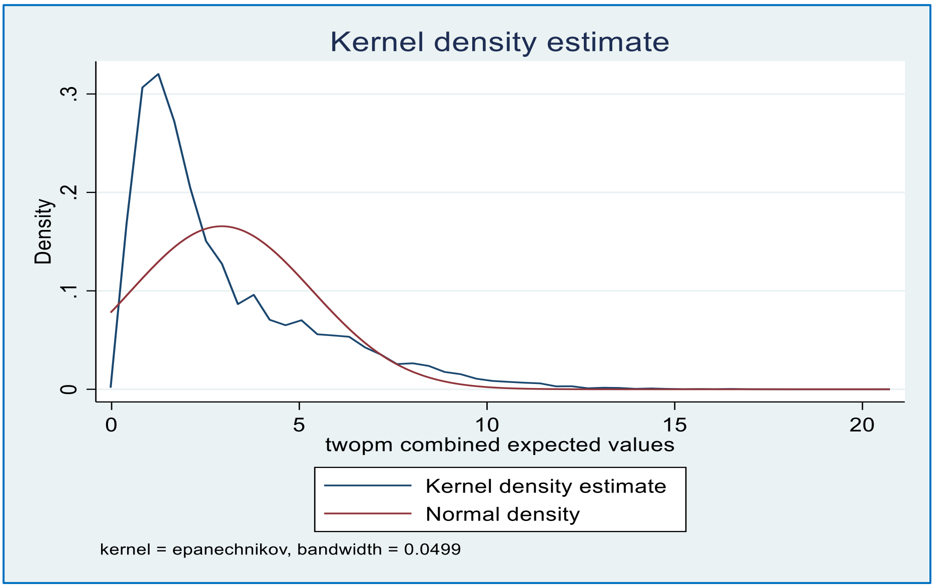


Figure A5. Gender differentials in hours of nonagricultural work

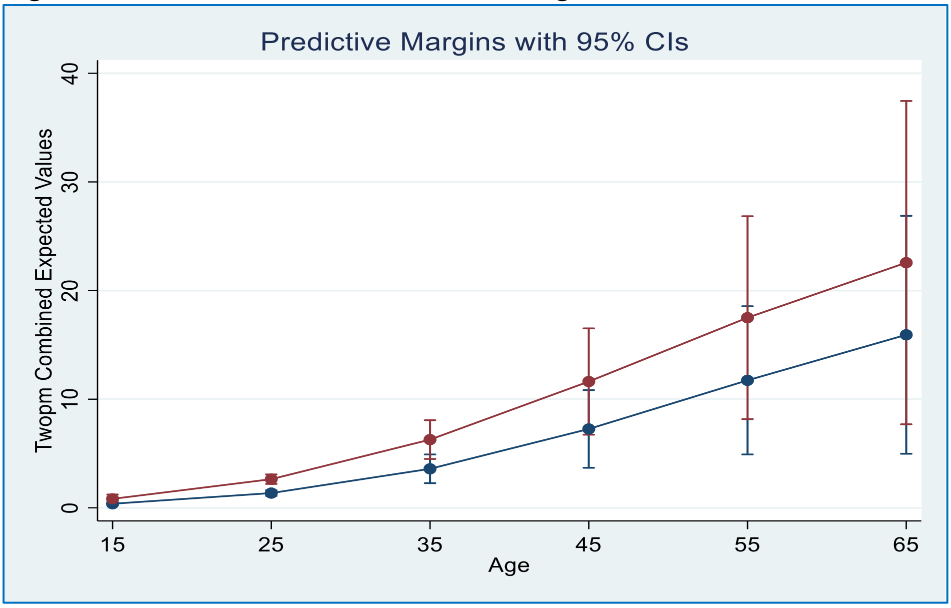
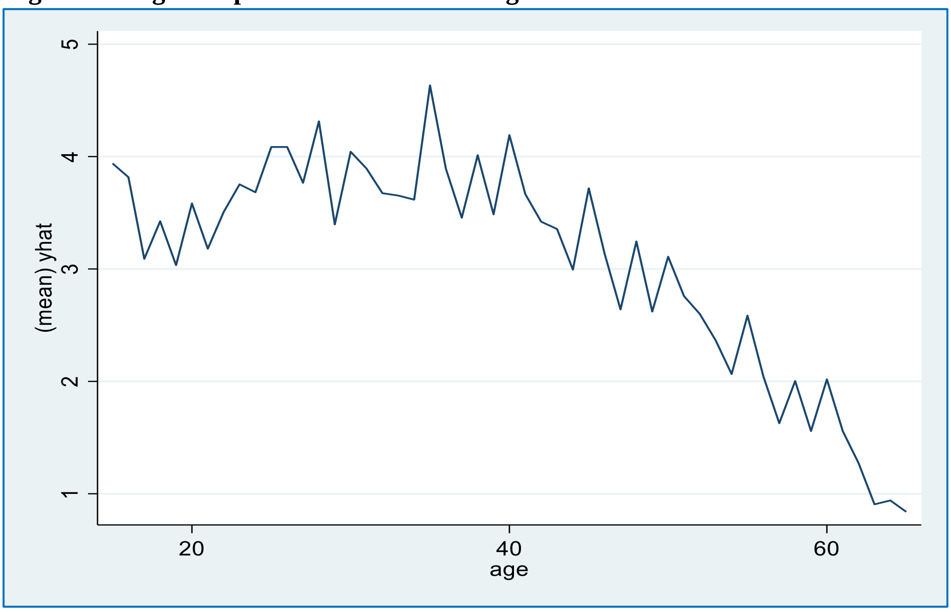


Figure A6. Age and predicted hours of nonagricultural work



Farmers Economic Valuation of Agro-biodiversity in West Gojjam Zone, Amhara Region, Ethiopia: Choice Experiment Approach[1]

Teshager Mazengia Asratie[2]* and Wassie Berhanu[3]

Abstract

The public goods nature of the resource and the absence of market prices is one of the major challenges of agro-biodiversity conservation. Therefore, the use of non-market valuation methods, which takes into account both use and non-use values of resources is very crucial. This study was designed to quantify farm household's economic values of agro-biodiversity in a selected region in the northern Ethiopian highlands. We used the choice experiment method to evaluate farm households' willingness to pay for different agro-biodiversity attributes. The study used six agro-biodiversity attributes and 16 choice sets randomly blocked into two blocks. Sample of 200 respondents each presented with 8 choice sets resulting a total of 1600 observations. The random parameter logit estimates revealed that farmers willingness to pay for landrace, organic farming, and crop species diversity were 549.58, 430 and 228.53 birr per year per household respectively. The study recommends that, to conserve agro-biodiversity effectively, the government and agricultural development agencies should motivate the production of organic farming through price premiums and quick certification of organic crops, expanding gene banks to restore lost traditional varieties, and motivate farmers to adopt the practice of modern organic farming methods.

Key words: Agro-biodiversity, Choice Experiment, Economic Valuation
JEL Codes: D1, Q12, Q51, Q57

---

[1] Manuscript received: 2 July 2021
Accepted: 28 August 2021
[2] Department of economics, Debre Berhan University, Ethiopia
*Authors to whom correspondence should be addressed;
Email: teshagerm2016@gmail.com
[3] Department of economics, Addis Ababa University, Ethiopia

1. Introduction

This paper is centrally concerned with economic valuation of agro-biodiversity based on a case study from the northern Ethiopian highlands. Agro-biodiversity is a vital subset of biodiversity which is associated with agricultural ecosystems (Brookfield and Stocking, 1999; FAO, 2007). It generally refers to a totality of various animals, plants and micro-organisms at genetic, species and ecosystem levels, which are indispensable for direct or indirect use for sustainable livelihoods and food security. Agro-biodiversity is generally the outcome of the interaction among the environment, genetic resources and the management practices of culturally diverse peoples of different livelihood systems (farming, pastoralism, etc.) that dynamically adopt various technologies over a course of time periods (FAO 2007; FAO, 2018). The importance of diversified and sustainable agriculture for the maintenance of ecosystem and viable livelihoods in the context of poor agrarian countries in Africa cannot be overemphasized. Since a great majority of rural households in these countries rely on biological resources for their livelihoods requirements (Munzara, 2007), quantifying the value of agro-biodiversity is found to be very crucial. Ethiopia is a country of diverse agro-ecological systems, and is often considered as a center for diversity of crops, which is generally a result of considerable variations in rainfalls, temperature, and diverse social and cultural conditions of the country (McGurie, 2000). Although the nature and rate of biodiversity loss and species extinction is not fully documented, agro-biodiversity in Ethiopia has been under constant threat of degradation because of the replacement of local varieties by improved seeds and concomitant limitations of farmers' contribution to the conservation of agro-biodiversity (Worede, 1991, Brown et al., 1993; FDRE, 2005).

There is a general understanding that agro-biodiversity conservation is crucial to food security of smallholder operators in agrarian countries that are exposed to adverse outcomes of global climate change (Narloch et al., 2011). While recognizing the threatening pressure of changing climatic conditions in terms of species extinction, it is quite notable that adaptation initiatives should consider the value of biodiversity conservation for food security of smallholder poor agricultural operators in less developed countries (see Narloch et al., 2011). The small farmers in less developed countries are often considered as custodians of key agro-biodiversity natural capital of the world. Nevertheless, Kontoleon et al. (2009) underline that the threat to world agro-biodiversity in the present era of growing tendency for specialized agriculture. This is then particularly considered to signify the failure of free market to compensate the custodians (small farmers) for their investment in the conservation of diverse portfolios of global agro-biodiversity natural capital resources. An important feature of traditional agriculture is the risk-averse response behavior of poor peasant operators. In the typical case of financial market failure in rural areas of less developed countries, a key strategy of traditional farmers is to grow diverse portfolios of crop species on their farms along with non-crop biodiversity management as a form of natural insurance with a goal to decrease the variance of yields and increase mean level of income (Baumgärtner & Quaas 2010). Besides this private benefit of natural insurance function, the management of traditional crop varieties is also considered to have a significant value of generating public benefits of CO_2 storage and regulating climate-induced unpredictable future agricultural problems of increased pests and plant diseases (Wale, 2012).

The estimation of both the use values and non-use values, i.e. estimating the total economic value in monetary terms, of agro-biodiversity is an important prerequisite for conservation planning (Pearce, 2001). Provided that farmers only consider the direct benefit of farming and due to the public goods nature of agro-biodiversity resources, application of an appropriate valuation method that help capture the total economic value of the resource is required in order to express it in monetary terms. Therefore, with a view to add to the existing limited literature, this paper uses the choice experiment method in order to assess household economic valuation of agro-biodiversity resources based on a household level survey in the Ethiopian highlands. We hope it will help contribute to bridging some knowledge gaps, and will also motivate a similar and insightful further research in the area. The rest of the paper is organized as follows. The next section discusses the methodological approach of the Choice Experiment method, the adopted empirical model and sources of data. Section 3 is devoted to presentation and discussion of empirical findings. Concluding remarks and recommendations are given at the end.

2. Methods

2.1 Description of attributes and assignment of its levels

In this study, based on Central Statistical Agency of Ethiopia (CSA, 2017/18) and National Assessment of Educational Progress as well as agricultural scientist's classification, 6 agro-biodiversity attributes were identified and used. The first attribute is crop species diversity defined as the number of different crop species that farm household's produce and it has four levels (5, 10, 15, and 20 different crop species produced). The four level of crop species diversity attribute is identified based on CSA (2007/8) classification in that in the study area the most frequently cultivated cereals are five crops (wheat, maize, teff, barely, and sorghum) and for combined (cereal, horticulture, and other crops) maximum of 20 crops were produced and the other are taken purposively by considering practically cultivated crops of all types in the study area. The second attribute is crop type which is identified by capturing all the seven crop types (cereal, pulses, oil-seeds, vegetables, root crops, fruits, and stimulants or coffee and chat), and classifying in to four groups/levels based on Central Statistical Agency (CSA, 2017/18) classifications. These are cereal crop, horticulture (fruits and vegetables), crops other than cereal and horticulture crops, and combined crops of all types. Organic farming is the third attribute used in this study. According to Sivaraj (2016), organic farming is a practice of cultivating land and raising crops in such a way that it keeps the soil alive by using organic inputs (animal dung, plant wastes, and crop residues). In this study, organic farming takes two levels. These are whether farm households produce crops using the practice of organic farming or not.

The fourth attribute identified as determinants of farm household's utility of farming is landrace defined by Villa et al., (2005) as a bulk of genetic diversity in domesticated species located in traditional varieties maintained by farming systems. It is severely threatened by genetic extinction because of replacement by modern genetically modified crops. Hence, the landrace attribute of crop production has two levels: whether a farm household produces landrace crops or not. The fifth attribute is yield per hectares, which is used to capture preference of households about the types of crops produced and methods of production adopted. For instance, organic farming is less productive as compared to conventional farming, but the former conserve soil fertility and other microorganisms and the latter does not. Moreover, the productivity of traditional crops is lower than modern varieties. Finally, the productivity of a cereal crop is lower than that of horticulture and other crops. Hence, including expected yield attribute will help to capture the case of whether farm households prefer biodiversity to productivity. Expected yield attribute has four levels determined depending on (CSA, 2017/18) report on the average productivity of crop groups (cereal, horticulture, others, and combined) with cereal the lowest and other types of crops including root crops exhibiting the highest productivity. This study used CSA (2017/18) report of average crop productivity by type. For instance, the average productivity of cereal crop is 15.7 approximately 16 quintal per hectare, for horticulture (vegetable= 39.6 and fruit = 73.7) the average productivity is 56 quintals, for other crops the average productivity is 83 quintals. The last attribute used in this study is net benefit, which is a monetary attribute. The price of cereal crops is different from that of horticulture. On the other hand, prices for organically produced crops are higher than conventional farming in markets where price premium for organically produced crops were formed (CSA, 2017/18). In addition, the productivity of organic farming is lower than conventional farming. Thus, the net benefit of different groups of crops using different types of farming (conventional or organic farming) is different. Hence, it captures the trade between agro-biodiversity attributes and the monetary attribute. Accordingly, the net benefit attribute has four levels. These are 15000, 18000, 20000, and 25000 per cropping season from the total crop production. Because of constraints in getting data for the average price of crops by type and the cost of production for each group of crops, the levels for net benefit attribute are determined by using 2018's average price of major crops in each crop groups (cereal, horticulture, other and combined of all groups) and taking 75% of revenue as cost of production. Summary of variables and levels used in the choice experiment exercise are reported below in Table 1.

Table: 1: Summary of agro-biodiversity attributes used in the choice experiment study

Agro-biodiversity attribute	Symbols	Levels
Crop species diversity	CSD	5 10 15 and 20
Crop type	CT	Cereal, horticulture, other, and combined of all types
Landrace	LR	Landrace vs. improved seed
Organic farming	OF	Organic vs. conventional
Expected Yield	YLD	16 35 56 83
Net benefit	NB	15000 18000 20000 25000

2.2 Choice Experiment Design

By taking into account only main effects, we used 6 agro-biodiversity attributes, and the levels of each attribute is combined using fractional factorial design, which takes into account only main effects. This is because full factorial design is difficult to handle. Moreover, Louviere et al. (2000) argues that though factorial design only considers main effects it explains 80% of total variation. To make the design 100% efficient orthogonalization[4] and balancing[5] were used; and 16 pairwise attribute combinations were randomly assigned to 2 blocks, with 8 choice sets of each block. Thus, the respondents were presented 8 choice sets with 2 alternatives, and the status quo as the third options. Incorporating the third option ensures theoretical validity of estimates of farm household's welfare. For all attributes the status quo takes zero value i.e., no improvement in the farming system. A sample of choice set is shown in Table 2.

[4] Orthogonalization is a situation where the variations of the attributes of the alternatives are uncorrelated in all choice sets
[5] Each level of each attributes has equal chance of occurrence or existence

Table 2: Sample choice set presented to respondents

Attributes	Alternative 1	Alternative 2	Status quo
crop species diversity	5 crops	20 crops	0
Landrace	Yes	No	0
Crop type	combined	horticulture	0
Yield per hectare	35 quintals	83 quintals	0
Organic farming	yes	no	0
The net benefit of crop production	25000Birr/year	18000 Birr/year	0
I prefer (please tick in the box)	☐	☐	☐

2.3 The study area and source of data

In this study cross sectional data collected from farm households for 2018 cropping season. The study employed hybrid sampling that first two weredas (Bure with 24 kebeles and Bahir Dar Zuria with 36 kebeles) from West Gojjam Zone were selected purposively. The rationale for the selection of these woredas is based on the long period experience of horticulture (fruits and vegetable) and other crop production in the area. Then using systematic sampling, the researcher selected four and three kebeles from Bahir Dar Zuria and Bure Wereda respectively. The first kebele was selected using random sampling and the remaining 3 and 2 from Bahir Dar Zuria and Bure respectively have chosen at every eighth interval. The selected kebeles are Andassa, Wenjeta, Robit and Wegelsa from Bahir Dar Zuria and Wangadam, Gulem and Wundegi are from Bure. 2nd from the total population of selected Kebeles of each wereda (Andassa, Wenjeta, Robit and Wegelsa) with a total of households of 5646 from Bahir Dar Zuryia and Wangadam, Gulem and Wundegi from Bure with a total household of 4323 a sample of 200[6] respondents were determined by using sample size determination formula developed by Carvalho (1984) cited in Zelalem (2005) and each respondent from each kebele was selected by using simple random sampling technique. Population ranges and sample size for each respective range are presented on Table 3 below.

[6] We used medium size sample determination

Table 3: Population target and required number of samples based on Carvalho (1984)

Determination Population Size	Low	Medium	High
51-90	5	13	20
91-150	8	20	32
151-280	13	32	50
281-500	20	50	80
501-1200	32	80	125
1201-3200	50	125	200
3201-10000	80	200	315
10000-35000	125	315	500
35001-150000	200	500	800

Then to determine the number of respondents from each kebele the study used proportional sampling using the formula of $\frac{HHi}{HH}$*n, where HHi= household size of kebele i, HH= total household size of the selected kebeles. Following this the number of respondents from each kebele was determined as follows reported on Table 4.

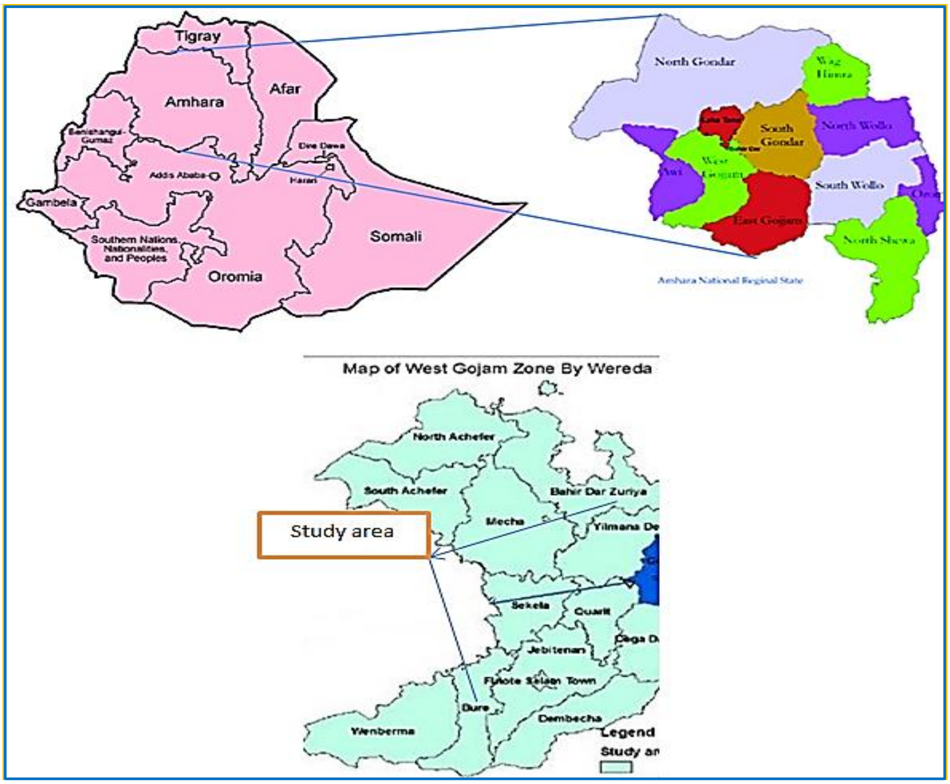
Table 4: Number of respondents from each kebele

Bahir Dar Zuria	Bure
Andassa = $\frac{1468}{9{,}969}$*200 = 29	Wangadam = $\frac{1770}{9{,}969}$*200 = 36
Wenjeta = $\frac{1481}{9{,}969}$*200 = 30	Shekwa = $\frac{1182}{9{,}969}$*200 = 24
Robit = $\frac{1917}{9{,}969}$*200 = 38	Wudegi = $\frac{1371}{9{,}969}$*200 = 27
Wagelsa = $\frac{780}{9{,}969}$*200 = 16	

Bure is the first district selected for this study. According to Bure district agricultural office report (BDAOR, 2015) the district is located $10^{o}17'$ to $10^{o}45'$N latitude and $37^{o}00'$ to $37^{o}10'$ E longitude with an average altitude of 1,500 to 2400 meter above sea level. The district has a total population of 175, 000 and 25,000 households having an average family size of 7 members per household. The population density is estimated to be 127.5 person/km^2. The second district is Bahir Dar Zuria and it has a total population of 182,730 (93,642 are men and the remaining 89,088 are female. It is located 1700 to 2300 meter above sea level altitude with average area coverage of 151,119 hectare. The district receives mean annual rainfall ranging from 820 to1250 mm. surveys in the district shows that 21% of the total district's area is cultivable and 36% are covered by water. The remaining 43% are used for pasture, forest coverage, and degraded land.

Though both districts have similar farming systems, in which farm households heavily rely on seasonal rainfall and traditional method of farming, each district has different types of soils. For instance, Bure district has three basic soil types. Namely, Humic Nitosols cover 63% of the district, and this is followed by Eutric Cambisols and Eutric Vertisols covering 20 and 17% respectively. Areas in wet Dega agro-ecology of the district receive torrential rainfall and it has relatively undulating topography, which is easily erodible. While in Bahir Dar Zuriya district, all 36 kebeles have Woina-Dega climatic zones (MoWR, 2009), the greater part of the district is covered by Luvisols. This in turn shows difference in agro-ecological conditions between the two districts and this difference makes differences in the types of crops cultivated and differential farm households' level of preferences. Moreover, unlike to the previous decades, the current agricultural development goals proposed by the government have resulted massive use of chemical fertilizers and crop protection chemicals, which is often considered to have damaging effect on the conservation of agro-biodiversity.

Figure 1: Map of the study area



2.4 Empirical Model of Discrete Choice Experiment

Here, a consumer is assumed to generate utility from both the consumption of goods themselves and pleasures derived from their attributes. Using a similar approach to Rose et. al., (2005), the model can be specified as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad \textbf{(1)}$$

Where U_{ij} is the utility that individual i derive from alternative j, which is alternative one, alternative two, and the status quo and V_{ij} is the attributes of crop diversity, and ε_{ij} is random error term that indicates unknown factors about respondent I that cannot explained by attributes in alternative j. Given the above formulation, the probability that any respondent prefers alternative (j) in the choice set to any alternative option (k) of different groups of crops is expressed as:

$$P_{ij} = prob(U_{ij} - U_{ik}) > (\varepsilon_{ik} - \varepsilon_{ij}) \quad \text{where } j \neq k \text{ and } k \in C \qquad \textbf{(2)}$$

Following Haan (2006), the conditional logit model is derived from a random utility model, which assumes that farm household's utility depends on choice set C with element x_{ij} and household characteristics (Si), which comprises all options in crop attributes. Thus, farm households were assumed to have a utility function of the form:

$$U(S_i, X_{ij}) = V(S_i, X_{ij}) + \varepsilon(S_i, X_{ij}) \qquad \textbf{(3)}$$

Where U is the utility farm household i received from alternative j. X_{ij} represents values of attribute i in alternative j and it assumes different values for each alternative. The probability that a farm household chooses alternative j over another attribute k is:

$$P_{ij} = prob(U_{ij} - U_{ik}) > (\varepsilon_{ik} - \varepsilon_{ij}) \quad \text{where } j \neq k \text{ and } k \in C \qquad \textbf{(4)}$$

Finally, the estimable model statistical specification of the conditional logit model is specified as follows:

$$P_{ij=} \frac{e^{V_{ij}}}{\sum_i^n e^{V_{ij}}} \qquad \textbf{(5)}$$

Then, based on the above formulation conditional random utility was estimated using NLOGIT 5.0 econometrics software. For the purpose of this study, conditional logit model takes the form:

$$V_{ij} = ASC + \beta_1 * CSD + \beta_2 * LR + \beta_3 * OF + \beta_4 * CT + \beta_5 YLD + \beta_6 * NB + \varepsilon_i \qquad \textbf{(6)}$$

Where V_{ij} is indirect utility function for farm household i for alternative J =1, 2, 3. The alternative specific constant (ASC) shows the average effect of any attributes not included in the utility model. The ASC takes the value 1 for either of alternatives chosen otherwise zero for the status quo. The parameter β_1 to β_6 represents coefficients of crop attributes (crop species diversity, landrace, organic farming, crop type, expected yield and net benefit). For a given household, social and economic characteristics are constant across alternatives. Thus, the study used social and economic characteristics only as interaction terms. From conditional logit model specification, the welfare that farm household generates from agro-biodiversity attribute is modeled as:

$$CS = \ln \sum_{i}^{n} e^{Vi1} - \ln \frac{\sum_{i}^{n} e^{Vi0}}{\alpha} \quad \textbf{(7)}$$

According to Hanely et al. (2001), it is possible to reduce the model of marginal values of a particular attribute if the utility index is linear. Following this, the marginal values of an attribute is reduced as:

$$CS = -1\left(\frac{\beta attribute}{\beta monitaryattribute}\right) \quad \textbf{(8)}$$

It is the marginal welfare measure of willingness to accept (WTA) or willingness to pay (WTP), which measures the amount of income deducted/given from/to a farm household to make his/her utility to be equal to the level of utility before changes when improvement/environmental damages occur, respectively.

In Equation 7, α is monetary attributes in the choice experiment (marginal utility of income), V_{i1} and V_{i0} is indirect utility after and before changes under consideration, respectively, and CS is compensating surplus. When estimating conditional Logit model, the distribution of the error term imposes independence of irrelevant alternative (IIA) assumptions[7]. If this assumption is violated, the conditional logit results are considered to be biased estimates (Bateman et. al., 2005). Hence, to rectify this with an alternative model specification, this study

[7] IIA assumption means the relative likelihood of two alternatives being chosen are independent of other alternatives.

has adopted the random parameter logit model, with interaction terms of crop diversity attribute and socio-economic characteristics, to compare the results with that of the basic conditional logit model. The random parameter logit model is given by

$$U_{ij} = V_{ij} + \varepsilon_{ij} = Z_j(\beta + \eta_i) + \varepsilon_{ij} \qquad \textbf{(9)}$$

Where U_{ij} is the level of utility that respondent i receives from attribute j, Indirect utility is assumed to be a function of the choice attributes Z (as well as of social and economic characteristics S, if included in the model) with parameters represented by β, which due to preference heterogeneity may vary across respondents by a random component η_i. By specifying the distribution of the error terms e and η_i the probability of choosing j in each of the choice sets can be derived by accounting for unobserved heterogeneity.

3. Results and Discussion

In this section conditional logit and random parameter logit model estimates are discussed. However, conditional logit model is based on the assumption of homogenous preference across districts and farm households. This assumption is tested by Mcfadden's test of independence of irrelevant alternative, which was done by excluding each alternative and running separate regressions. The test statistics is reported in Table 5 and 6 below with and without alternative specific constant, and which confirms the violation of the assumption i.e. in the study area there is preference heterogeneity across districts. This assures that the conditional logit estimates can be misleading. As a result, we employed estimation techniques which take in to account preference heterogeneity that enables us to get consistent and unbiased estimates of individual preference (Green & Rao, 1971). These are conditional logit model with interaction terms and random parameter Logit models. Estimation results of these models are discussed below.

Table 5: IIA test for the pool of two districts with ASC

Excluded alternatives	Chisqrd	df	Pr(C>c)	IIA assumption decision
Alternative1	144.3246	7	0.0000	Rejected
Alternative 2	128.33	7	0.0000	Rejected

Source: own computation using Nlogit 5.

Table: 6. IIA test for the pool of two districts without ASC

Excluded alternatives	Chisqrd	Df	Pr(C>c)	IIA assumption decision
Alternative1	49.3528	6	0.0000	Rejected
Alternative 2	90.8178	6	0.0000	rejected

Source: own computation using Nlogit 5.

3.1 Random Parametric Logit Model Estimates

The random parameter logit estimates for the pool and by district are reported in Table 7 the pooled sample estimated result shows that crop species diversity, crop type, net benefit, organic farming, expected yield and land-race attributes have positively significant effect on the utility of farm households'. The alternative specific constant (ASC) has negatively significant effect, indicating that farm household's responsiveness of choice set quality, and the attributes used in the estimation, explains variation in the utility of farm household's. Relative to other attributes, the land-race attribute has the highest effect on utility, which evidenced farm household's preference for traditional crop varieties instead of uniform but modern crop varieties. Farm household's utility is also a positive function of organic farming. This result is in line with Scialabba (2003) that indicates organic farming as a guarantee for the protection of land degradation, soil erosion and health of human being, particularly in a country or community where farm households are unable to buy chemical inputs. Despite this fact, the current system of expanding supply of chemical fertilizer and improved seed varieties appear to discourage farm household's contributions to agro-biodiversity. Moreover, farm household's utility increases with an increase in the number of different crops produced, because it is important to ensure better nutrition, resistance of crops to influences of climate variability, and keep cultural values.

The above discussion is based on the pooled sample of two different districts (Bahir Dar Zuriya and Bure). However, in these two districts there may be differences in farm land characteristics (including the type and quality of soil), socio-economic considerations, and market conditions. If this is the case, it will require different production process and conservation mechanisms (Birol, 2004). In this study, to check whether a pooled random parameter estimate are equally shared across the two districts or not, the log-likelihood ratio test introduced by Swait Louviere is employed. The test statistics[8] shows us the pooled estimate of random parameter logit model does not distribute across districts equally. Moreover, in the model there are statistically significant derived standard deviations, which is an indicator for the existence of choice specific unconditional unobserved heterogeneity. As a result, the effect of agro-biodiversity attributes on farm households' utility is discussed by running separate regressions for each of the districts.

For instance, in Bure district estimation results reported in column 3 of Table 7 show that crop species diversity, organic farming and net benefit attributes of agro-biodiversity have positive significant effect on farm household's utility. The Bahir Dar Zuria district estimates reported in column 4 of Table 7, on the other hand, show that crop species diversity, landrace, expected yield and crop types are statistically significant attributes affecting demand for agro-biodiversity positively. These indicate that the effect of agro-biodiversity attribute on utility of farm household depends on agro-ecological, economic and market characteristics of the study area under consideration.

[8] For the pool LR = -2(-1635.664-(-1552.025)= -2(-1635.664 + 1552.025) = 162.28
For Bure woreda LR = -2(-832.612-(-787.76) = -2(-832.612 +787.76) = 89.7
For Bahir Dar Zuria LR =-2(-785.54-(-722.8) = -2(-785.54 + 722.8) = 125.48
CHI2 critical value at 14 degree of freedom and 5% level of significance is 23.685. Hence, for all Likelihood ratios test statistics is greater than chi2 critical value. Reject Ho.

Table 7: Random parameter logit model estimates of the pool and by district

Attributes	Pool	Bure	Bahir Dar Zuria
	Coefficients (standard error)		
	Random parameters in utility functions		
Alternative specific constant	-.58409*	-.98453	.79049
	(.31858)	(.64036)	(.66320)
Crop species diversity	.2141***	.03236**	.08611***
	(.00634)	(.01305)	(.01626)
Crop type	.08580**	-.02297	-.30741***
	(.04367)	(.07684)	(.08945)
Land rac	.35816***	-.08453	-.090404***
	(.06366)	(.11733)	(.14232)
Expected yield	.15772***	.00749	.26952***
	(.03337)	(.06287)	(.06373)
Organic farming	.28063***	.41553***	.16786
	(.06974)	(.14459)	(.11904
Net benefit	.6517D-03***	6967D-03***	.1986D-03
	(.1114D-04)	(.2322D-04)	(2122D-04)
Derived standard deviations of parameter distribution			
NsASC	.97362***	1.17431***	1.37210***
	(.15197)	(.24902)	(.30445)
NsCSD	.00141	.01049	.00266
	(.00779)	(0.02087)	(.00898)
NsCT	.39368***	0.32318***	.54738***
	(.04262)	(0.06745)	(.08059)
NsLR	.01309	0.00717	.03039
	(.05813)	(0.10081)	(.08711)
NsYLD	.00965	0.02087	.007344434)
	(.02959)	(0.03962)	
NsOF	.41110***	0.89449***	.07632
	(.07376)	(0.13629)	(.08961)
NsNB	.82631D-06	0.42570D-05	.14113D-04
	(.6730D-05)	(0.9770D-05)	.1123D-04
Number of respondents	200	100	100
Number of observations	1600	800	800
Log-likelihood function	1552.025	-787.8	-722.8
Chi squared [14 d.f.]	411.51	182.23	312.18
Significance level	0.0000	0.0000	0.0000
McFadden Pseudo R-squared	.12	0.104	.18

Note: ***, **, * ==> Significance at 1%, 5%, and 10% level. Standard error in parenthesis
Source: own computation using NLOGIT 5.0 Econometrics software

3.1.1 The WTP values of random parameter logit estimates

Hanely et al., (2001) proposed that under standard consumer theory marginal rate of substitution between agro-biodiversity attributes can be computed by calculating the ratio of the partial derivatives of indirect utility function with respect to each attribute. Following this, under linearly additive indirect utility function the welfare, WTP value of each, attribute is obtained as the ratio of attribute's coefficient to the coefficient of monetary attribute. Hence, the marginal willingness to pay values of random parameter logit estimates for the pool and by district is reported in Table 8 below. In our case the monetary attribute is net benefit attribute of agro-biodiversity. For the total sample of the study (pooled estimation), the maximum willingness to pay is attached to landrace agro-biodiversity attribute followed by organic farming. To get one more landrace crop, farm households are willing to pay 549.58 Ethiopian birr per year. Moreover, to shift from conventional to organic farming they are willing to pay 430 Ethiopian birr. On the other hand, crop type attribute has the least effect on farm household's utility with marginal willingness to pay value of 131.66 Ethiopian birr. Since the random parameter logit estimation results of the pooled sample are not the same for separate regression estimation results of each district, the marginal willingness to accept value for each district is also computed separately. Hence, farm households in Bure district attached highest willingness to pay to the organic farming attribute with marginal WTP value of 596.43 followed by crop species diversity attribute of a willingness to pay amount of 46.45 Ethiopian birr. However, in Bahir Dar Zuria District the maximum willingness to pay is attached to the type of crops produced followed by expected yield with marginal WTP value of 1547.89 and 1357.1 ETB per year.

Table 8: WTP values for each agro-biodiversity attributes for the pooled and by district derived from random parameter logit estimates.

Attribute	Pool	Bure	Bahir Dar Zuria
Crop species diversity	328.53	46.45	433.58
Landrace	549.58	------	455.21
Organic farming	430	596.43	----
Crop type	131.66	-------	1547.89
Expected yield	242	------	1357.1

Source: own computation using NLOGIT 5.0 software

3.2 Conditional Logit Model Accounting for Preference Heterogeneity

In addition to agro-biodiversity attributes, decision maker characteristics could also affect utility that farm households can get from agro-biodiversity. To identify this effect, conditional logit model with interaction terms was estimated. Here introduction of the interaction terms is found to be important because of the often-underlined notion that social and economic characteristics on choice cannot be examined in isolation from the attributes of products of choices (Birol, 2004). But including all decision maker characteristics may create the problem of multicollinearity. To minimize the problem of multicolinearity we used auxiliary OLS regression, and decision maker characteristics with the lowest VIF were taken an interaction term. The decision maker characteristics used in the interaction terms are household size (HHSIZE), education level (EDU), age of farm household head (AGE), and income (Y). With six agro-biodiversity attributes and four decision-maker characteristics 24 interaction terms are created. The estimation result of the model for the pooled sample and separate regressions for each district are reported in Table 9. Only interaction terms with significance level of 1%, 5% and 10% precision with the two-tailed test are reported.

In the pooled sample estimates reported in column 2 of Table 9 shows that only household size, age of household head, and education are found to be statistically significant. The demand for crop species diversity and organic farming are negatively affected by household size, but positively affected by the age of household head. In addition, the demand for organic farming increases with more education. This finding is consistent with the hypothesis that household heads with more education have more chance of acquiring knowledge about the advantages of organic farming. The demand for crop type increases with the age of household head, but decreases with household size.

Table 9: Conditional logit estimates accounting preference heterogeneity for the pool and district

Attributes	Pool	Bure	Bahir Dar Zuria
		Coeff(se)	
Alternative specific constant	-2.90885*** (1.05696)	-4.97865*** (1.70669)	0.69925 (.58030)
Crop species diversity	0.04828* (0. .02595)	.04324 (.03898)	.09163 (.07290)
Land race	0.03500 (0.48922)	.12151 (.84069)	-.72905*** (.20831)
Crop type	-0.44629* (0.24994)	-.98293* (.56039)	-.24831*** (.06069)
Expected yield	0.41553* (0.24271)	.26824 (.44555)	.21446*** (.05810)
Organic farming	1.21419** (0.48947)	2.53800*** (.91762)	-.27776 (.60229)
Net benefit	0.49570D-04 (0. 4367D-04)	.00016** (.8085D-04)	.15512D-05 (.1850D-04)
Crop species diversity* household size	-0.00937** (0.00557)	----------	.00026 (.00370)
Crop species diversity*age	0.02435* (0.01345)	-----------	-.15032D-04 (.00148)
Organic farming* household size	-0.04134*** (0.01369)	07695*** (.02912)	-.00607 (.03162)
Organic farming*age	0.01476*** (.00563)	.03271*** (.01167)	.01104 (.01262)
Organic farming*education	0.01617* (0.0088)	---------------	----------
Crop type* household size	-0.02839* (0.01369)	-.09635*** (.03532)	---------
Crop type* age	0.01329** (0.00556)	.03343** (.01443)	-----------
Net benefit* education	----------	.32625D-05* (.1957D-05)	-----------
Net benefit* household size	----------	.90847D-05* (.4828D-05)	----------
Number of respondents	200	100	100
Number of observations	1600	800	800
Log likelihood function	-1629.83	-821.54	-779.654
R-sqrd (R2Adj)	.0384(.0339)	0.0308(0.0216)	0.08(0.07)
AIC(AIC/N)	3289.7(2.056)	1673.1(2.091)	1589.3(1.987)

Note: ***, **, * ==> Significance at 1%, 5%, 10% level and standard error in parenthesis
Source: own computation using NLOGIT 5.0 Econometrics software

In addition to estimation result of pooled sample conditional logit model with interaction terms, separate estimations for each district were also conducted. In Bure district household size and farm household head's age have positive significant effect on organic farming attribute, and in turn the utility of farm households. On the other hand, household size and age of the farm household head's age has negative and positive significant effect on crop type attribute, respectively. However, there is no interaction term, which has significant effect on agro-biodiversity attributes in Bahir Dar Zuria district.

4. Conclusion and Recommendation

This study employed discrete choice experiment study using 100% D-efficient experimental design in order to examine farm household valuation of agro-biodiversity, especially by identifying the biodiversity attributes to which they attach the highest value. The NLOGIT 5.0 econometrics software was used to run and analyze the choice experiment model. The test statistics of IIA assumption is violated indicating the presence of preference heterogeneity, which indicates the biasedness and inconsistency of the conditional logit model. As a result, Random Parameter Logit model (RPL) estimates were used to compute WTP value of agro-biodiversity attributes. The Parametric estimates of the RPL model for the pooled samples revealed that all attributes are statistically significant and have expected signs. It is found that the utility of farm household increases with an increase in the number of crops produced, with production of traditional crops using organic farming, and with more diversified groups of crops of higher expected yield. The result further shows that farm households attach the highest value to the production of traditional crop varieties, followed by organic farming and crop species diversity with WTP value of 549.58, 430, and 228.53 birrs per year, respectively.

In addition, to test whether RPL estimate distributed across districts, separate RPL regressions were conducted for each district. The result suggests that farm households in the two districts have different preferences for different attributes (characteristics) of agro-biodiversity. For instance, in Bure district only organic farming and crop species diversity attributes are statistically significant with WTP value of 596.43 and 46.45 birr/year, respectively. In Bahir Dar Zuria district, on the other hand, farm households' utility is significantly affected by types of crops produced, expected yield, production of landrace crops, and crop species diversity. In this district, farm households attach the highest value for types of crops produced followed by expected yield, landrace, and crop species diversity with WTP value of 1547.89, 1357.1, 455.21, and 433.58 birr year, respectively.

To show the effect of decision maker characteristics on the choice of agro-biodiversity attribute, and the utility of farm households, conditional logit model with interaction terms was regressed. To avoid multicollinearity four decision-maker characteristics with the lowest VIF were selected. These are household size, age, education, and income, which are interacted with six choice variant attributes. The result revealed that larger household size lowers the demand for crop species diversity and organic farming. On the other hand, the demand for crop species diversity and organic farming increases with older age and a higher level of education.

Generally, based on the findings this study draws the following policy implication for the conservation of agro-biodiversity.

The results of a choice experiment study show that farmer’s utility increases with the production of crops using organic inputs. However, in Ethiopia, there is little emphasis on the preparation and use of organic inputs. This is simply because of the central focus of policy makers and extension agents currently being on the promotion of use of chemical inputs by smallholder farmers with a view to boost the productivity in the agricultural sector. However, the roles of the government, agricultural research institutes, and biodiversity conservation institutes are also critical in motivating farmers towards organic farming through setting and announcing premium prices for organic crops, introducing certification process for organic crops, and creation of separate green channels of marketing organic crops. Crop species diversity is another policy variable, which increases the utility of farm households. It has also the benefit of reducing vulnerability and improving overall health, increasing productivity, stabilizing income, and enhancing well-functioning of ecosystems. The government should also increase the capacity of gene banks to restore lost crop varieties.

References

Amhara National Regional State, Bureau of Plan and Economy (ANRS-BoPE). (2007). Annual report, Bahir Dar, Ethiopia.

Bateman, I. J., Cooper, P., Georgiou, S., Navrud, S., Poe, G. L., Ready, R. C., & Vossler, C. A. (2005). Economic valuation of policies for managing acidity in remote mountain lakes: Examining validity through scope sensitivity testing. *Aquatic Sciences*, *67*(3), 274-291.

Baumgärtner, S., & Quaas, M. (2010). What is sustainability economics? *Ecological Economics*, *69*(3), 445-450.

Birol, E. (2004). Valuing agricultural biodiversity on home gardens in Hungary: An application of stated and revealed preference methods (Doctoral dissertation, University of London)

Brookfield, H., & Stocking, M. (1999). Agro-diversity: definition, description and design. *Global environmental change*, *9*(2), 77-80.

Brown, K., Pearce, D., Perrings, C., Swanson, T., & Mundial, B. (1993). Economics and the conservation of global biological diversity (No. 2). World Bank.

Burie District Agriculture Office Report (BDAOR). (2015). District annual report of livestock. Unpublished survey article.

Central Statistical Authority (CSA). (2017/18). Large and Medium Scale Commercial Farms Sample Survey 2007/2008 (2000 E.C.). Results at Country and Regional Levels: Report on Area and Production of Crops, and Farm Management Practices. Statistical Bulletin 443. Addis Ababa, Ethiopia.

________. (2011). Central Statistical Authority Abstract of Federal Democratic Republic of Ethiopia. Addis Ababa, Ethiopia

________. (2007). Large and Medium Scale Commercial Farms Sample Survey 2007/2008 (2000 E.C.). Results at Country and Regional Levels: Report on Area and Production of Crops, and Farm Management Practices. Statistical Bulletin 443. Addis Ababa, Ethiopia.

Federal Democratic Republic of Ethiopia (FDRE). (2005). National Biodiversity strategy and action plan. Institute of biodiversity conservation, Addis Ababa, Ethiopia.

Food and Agricultural Organization (FAO). (2018). Biodiversity for sustainable agriculture.

Green, P. E., & Rao, V. R. (1971). Conjoint measurement-for quantifying judgmental data. *Journal of Marketing research*, *8*(3), 355-363.

Haan, P. (2006). Much ado about nothing: Conditional logit vs. random coefficient models for estimating labour supply elasticities. *Applied Economics Letters*, *13*(4), 251-256.

Hammer, K. (2003). A paradigm shift in the discipline of plant genetic resources. Genetic Resources and Crop Evolution, 50(1), 3-10.

Joint FAO/WHO Expert Committee on Food Additives. Meeting, & World Health Organization. (2007). *Evaluation of certain food additives and contaminants:*

sixty-eighth report of the Joint FAO/WHO Expert Committee on Food Additives (Vol. 68). World Health Organization.

Kontoleon, A., Pascual, U., & Smale, M. (2009). Introduction: agrobiodiversity for economic development: what do we know? Agrobiodiversity conservation and economic development. Agrobiodiversity, Environment and Economic Development. UK: Routledge Explorations, 1-24.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). Stated choice methods: analysis and applications. Cambridge University Press.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. 105-135 in P. Zaremiibka (ed.), Frontiers in Econometrics. New York: Wiley.

Ministry of Water Resources. (2009). Ethiopian Water Resources Management Policy, unpublished survey result.

Munzara, A. (2007, October). Agro-biodiversity and Food Security. In UN/Trondheim Conference on Biodiversity and Ecosystems. October (Vol. 28).

Narloch, U., Drucker, A. G., & Pascual, U. (2011). Payments for agrobiodiversity conservation services for sustained on-farm utilization of plant and animal genetic resources. *Ecological Economics*, *70*(11), 1837-1845.

Organisation for Economic Co-operation and Development. (2004). *Handbook of market creation for biodiversity: Issues in implementation*. Organisation for Economic Co-operation and Development.

Pearce, D. (2001). Valuing biological diversity: issues and overview (pp. 27-44). OECD: Valuation of Biodiversity Benefits; Selected Studies. Paris, OECD.

Rose, J. M., Hensher, D. A., & Greene, W. H. (2005). Recovering costs through price and service differentiation: accounting for exogenous information on attribute processing strategies in airline choice. *Journal of Air Transport Management*, *11*(6), 400-407.

Scialabba, N., Grandi, C., & Henatsch, C. (2003). Organic agriculture and genetic resources for food and agriculture.

Sivaraj, P. (2016). A scale to measure attitude of farmers towards organic farming in western zone of Tamil Nadu. *International Journal of Agriculture Sciences, ISSN,* 0975-3710.

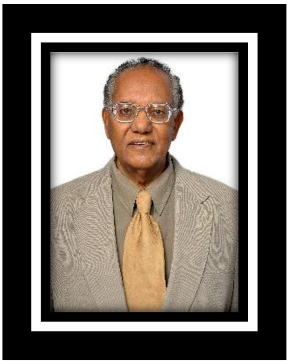
Villa, T. C. C., Maxted, N., Scholten, M., & Ford-Lloyd, B. (2005). Defining and identifying crop landraces. *Plant Genetic Resources*, *3*(3), 373-384.

Wale, E. (2012). Addressing the information problem in agriculture via agro biodiversity: Streamlining the issues, challenges and policy questions. African Journal of Agricultural Research, 7(30), 4187-4197.

Worede, M. (1991). An Ethiopian perspective on conservation and utilization of plant genetic resources. Plant genetic resources of Ethiopia. Cambridge University Press, Cambridge, 3-19.

World Health Organization, & Joint FAO/NACA/WHO Study Group on Food Safety Issues Associated with Products from Aquaculture. (1999). *Food safety issues associated with products from aquaculture: report of a joint FAO/NACA/WHO study group* (Vol. 883). World Health Organization.

Condolence message on the passing of Prof. Teshome Mulat



The Editor-in-Chief, together with the Editorial Board Members of the Ethiopian Journal of Economics (EJE), and the Executive Committee of the Ethiopian Economics Association (EEA) express their sadness over the recent passing of the Honorary Advisory Board Member, Prof. Teshome Mulat. Prof. Teshome was a founding member of EEA, an Editorial Board Member of EJE from 1992 – 1993 and an Honorary Advisory Board Member since 1994.

In 2011, the EEA awarded certificate in recognition of his considerable contribution to the teaching of economics in Ethiopian higher learning institutions.

He contributed publications on the EJE. His contributions to the journal and to the EEA in general were tremendous, and we greatly missed him.