ADDIS ABABA UNIVERSITY
COLLEGE OF BUSINESS AND ECONOMICS
DEPARTMENT OF ECONOMICS

MULTIDIMENSIONAL ENERGY POVERTY AND ITS DYNAMICS IN RURAL AND SMALL TOWNS OF ETHIOPIA:A FUZZY SET ANALYSIS

A THESIS SUBMITTED TO THE SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR DEGREE OF MASTERS OF SCIENCE IN NATURAL RESOURCE AND ENVIRONMENTAL ECONOMICS

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Declaration

I, Mahlet Getahun declared that this thesis entitled "Multidimensional Energy Poverty and Its Dynamics in Rural and Small Towns of Ethiopia: A Fuzzy Set Analysis ” prepared in the partial fulfillment of the requirement for degree for Masters of Science in Natural Resource and Environmental Economics under the guidance of my adviser, Dr. Adane Tufa is my original work and has never been presented for award of any degree in any other university. And all the materials used for the study are fully acknowledged.

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This is to certify that the thesis prepared by Mahlet Getahun entitled "Multidimensional Energy Poverty and Its Dynamics in Rural and Small Towns of Ethiopia; A Fuzzy set Analysis" which is submitted in partial fulfillment of the requirements for degree in Masters of Science in Natural Resource and Environmental Economics complies with regulation of the university and meets the accepted standards with respect to originality and quality.

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Acronyms

CSA .... Central Statistical Agency

EAs .... Enumeration Areas

EIA .... Energy Information Administration

EJ .... Exajoule

ESS .... Ethiopian Socioeconomic Survey

FMEPI .... Fuzzy Multidimensional Energy Poverty Index

GERD .... Grand Ethiopian Renaissance Dam

GTP .... Growth and Transformation Plan

LMIC .... Low and Middle Income Countries

LSMS-ISA .... Living Standard Measurement Study-Integrated Survey on Agriculture

MDGs .... Millennium Development Goals

MEPI .... Multidimensional Energy Poverty Index

MPI .... Multidimensional Poverty Index

MW .... Mega Watt

SDGs .... Sustainable Development Goals

UNDP .... United Nations Development Programme

WB .... World Bank

Abstract

Ethiopia, like many others in the sub-Saharan Africa, hosts its largest share of population in its rural areas and small towns. And among many factors, these areas of the country are characterized by having lower access to modern energy fuels. Thus, using panel data set constructed from the three rounds of Ethiopian Socio Economic Survey, this paper has attempted to investigate the level of multidimensional energy poverty and its dynamics in these areas. Unlike number of researches made on energy poverty, this paper has attempted to divert from the traditional crisp poor non poor dichotomization using a fuzzy set approach which represent each household by the degree of energy poverty it faced in values that range between zero and one through the use membership functions. Given selected dimensions which include type of cooking fuel, indoor air pollution, source of light and access to media and communication, and applying methods of average, intersection and union as techniques to aggregate degree of deprivation across each dimension selected, a fuzzy multidimensional energy poverty index for the study area was determined, and it was further decomposed to see which dimensions contribute the most for it. During the first survey, households in the study area were found to be faced with 79.98% average deprivation while experiencing a minimum degree of deprivation that reaches to 47.64% in each selected dimension. These numbers fall only slightly during the last survey where average deprivation declines to 72.41% while minimum deprivation in each selected dimension falls to 34.61%. Across each survey, households were found to be faced with a degree of deprivation that is close to 100% at least in one of the dimensions selected. These results are further supported by a fuzzy set longitudinal analysis made with the application of joint membership functions. And the rate of re-entry is found to be 98.11% and exit rate 42.24%. Further, given the fractional nature of the dependent variable, dynamic fractional regression was used to investigate the presence of state dependence, and a one percent rise in the propensity of experiencing deprivation in all dimensions in the previous period was found to cause a 3.8% rise in a given year's deprivation overlap. And among other selected determinate variables of energy poverty, number of rooms available, proportion of children aged seven and above, log of real income per adult equivalent and year of survey are found to have significant and negative effect on households energy poverty. And proportion of labour aged female household members, living in rural areas, and compared to region Tigray living in other selected regions of the country are found to cause a significant and positive influence on households energy poverty.

Keywords; Multidimensional energy poverty, fuzzy set analysis, dynamic fractional regression

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Chapter 1

Introduction

1.1 Background of the Study

Access to modern energy is found to play a major role in world's rapid transformation that includes drastic change in quality of life (EIA, 2007). And due to this, increasing access modern energy is made part of both national and international level efforts being made to tackle overall poverty. For example Lack of access to modern energy was found to be one of the major factors that held back countries from achieving better in Millennium Development Goals (MDGs)(Accorsi et al., 2010; Bank, 2010; Ha and Porcaro, 2005; Jahan, 2010). And, in the recent Sustainable Development Goals, (SDGs) achieving universal access for affordable, reliable, and sustainable energy by 2030 is included as one of the major goals, and the inevitable role it can play in the achievement of the other sixteen SDGs is boldly underlined (Griggs et al., 2013; Pradhan et al., 2017).

Energy poverty, which according to world economic form is defined as lack of access to sustainable and modern energy services and products, even though it has been on policy agendas for long, it continues to appear both as a cause and manifestation of overall poverty, and become a persistent problem especially in the rural parts of developing countries (Kaygusuz, 2011). And as Birol (2007) has indicated it, for the rural residents of the developing world, the problem associated with energy poverty is not only linked with the lack of economic affordability and reliability of modern energy sources, but even the modern energy supply is at its primal stage making question of its physical availability still an unsolved issue. And, the situation is being made even worse due to residents heavy reliance on non commercial fuels, and the fact that in most of these areas the rate of energy production and supply is being outstripped by population growth rate (Kaygusuz, 2011;

Nations, 2018).

Like the case of other developing areas, in Africa too majority of annual energy is produced from biomass fuels and most of these energy is consumed by the residential sector(Nations, 2018). According to IEA and Special (2019), in 2018 alone, 44% of the energy supply of the continent was generated from biomass fuels, and during the same year, hosting 600 million people without access to electricity and 900 million people without access to clean cooking fuel, the continent was the least electrified area in the world.

In Africa, given the residential sector is the major consumer of the overall energy and especially of energy generated from biomass fuels, it is important to investigate and come up with policies that consider the nature of households energy consumption behavior and the extent of energy poverty they face as it will have a far reaching impact that extend from the welfare of household members upto the environment they live in. In developing countries, indoor air pollution that results from the combustion of biomass fuels is the cause for over 2 million premature death and 0.4% of disability among children every year (Emmelin and Wall, 2007; Fullerton et al., 2008; Smith et al., 2000). Beside the health impacts, researches have also shown the negative consequence of time spent by children and women to collect firewood on their school performance, and economic and political empowerment respectively (Alam and Kaneko, 2019; Kes and Swaminathan, 2006; Nagbrahmam and Sambrani, 1983). And the extended dependence on biomass fuels causes environmental degradation through air pollution and deforestation (Allen and Barnes, 1985; Ravindranath et al., 1995). Thus, it will be important to investigate the extent of energy poverty and its persistence especially in rural areas where the level of physical accessibility of modern energy is limited. And, the policy attentions are much needed as the problem of energy poverty has a state dependence nature, and this can make associated negative consequences to be prolonged.

There are alternative approaches used to measure the extent of energy poverty faced by households especially for the case of developing countries. These include the uni dimensional methods like Modi et al. (2005) minimum energy requirement based approach, Barnes et al. (2011) energy demand based approach, Boardman (2013) energy expenditure based approach, and Nussbaumer et al. (2012) Multidimensional Energy Poverty Index based approach. But, according to Culver (2017) all these approaches are similar in the way they use some predetermined energy poverty line, and so far they have not addressed the fuzzy nature of energy poverty.

Ethiopia, being one of the sub Saharan African countries, I believe the extent of energy poverty faced by the households of the rural and small towns of the country must be studied using appropriate energy poverty measurement approach which can consider both its vague and multidimensional nature. And the presence of state dependence in the problem must also be estimated using appropriate model that can handle the fractional nature of the energy poverty index, and the use of the lagged dependent variable as explanatory.

1.2 Statement of the Problem

Ethiopia, which according to Poverty et al. (2020) is one of the countries with the lowest performance in Multidimensional Poverty Index(MPI), in 2016 alone scored 48.9% in MPI [1] [2]. And 50% of the poverty score was contributed by deprivation in standard of living which includes deprivation in access to electricity and modern cooking fuels.

In a country where over one hundred million people live with population growth rate of 2.56%, despite the fact that it has the potential of generating about 45 GW of electricity only from hydroelectric dams, currently only 4500 MW(4.5 GW)of electricity is being produced annually (Mengistu et al., 2015; Mondal et al., 2018). And according to Bank (2020), the estimated per capita electricity consumption of the country was only 70 kwh in 2014, and this was far below the continental average of Africa which was at 500 kwh during the same year (Mengistu et al., 2015; Mondal et al., 2018). Further, the level of access to electric grid is only at 56% with only 25% of household connectivity rate(Mondal et al., 2018).

According to Bank (2020) the per capita energy consumption of the country was 5735.103 kwh in 2014 where the primary energy source was mainly traditional fuel. In 2015, biomass

[1] An index calculated by finding percentage of multidimensional poor households adjusted for the intensity of deprivation they facedPoverty et al. (2020)

[2] Head count ratio of 83.5% and poverty intensity level of 58.5%

take about 90% of the annual final energy consumption where 99% of it was consumed by the residential sector (Yurnaidi and Kim, 2018).

According Bank (2020), in 2015, access to clean cooking fuel in the country was very low and stands only to 3.4%. During the same year, in the urban areas where the rate of electrification reached to 85%, access to clean cooking fuel was limited only to 22%. And, the situation is even worse in the rural parts of the country where the rate of electrification is limited to 15.49% and access to clean cooking fuel was only 11%.

Though it is in its early stage, growing number of researches related to energy poverty in Ethiopia are being conducted. One of the pioneering work in the area is Bekele et al. (2015) research on multidimensional energy poverty in Addis Ababa. But the research tried to investigate the extent of the problem only on a single geographical area and point of time. And, these made it impossible to conclude about the trend of the problem over time and across other major cities of the country. Later, Alem and Demeke (2020), using data from urban socio economic survey, undertook a dynamic analysis to investigate the presence of state dependence in energy poverty in major towns of Ethiopia. After measuring energy poverty using alternative approaches like Modi et al. (2005) minimum energy requirement approach, Barnes et al. (2011) energy demand based approach and multidimensional energy poverty index, with application of dynamic probit analysis, they have showed the presence of state dependence in energy poverty in the major towns of the country. But they left the extent and persistence of the problem in the rural and small towns of the country untouched. Later,Bersisa (2019) took the energy poverty analysis to the rural and small towns of the country, and showed the presence of high but slowly declining multidimensional energy poverty in the area. But confined to data made available through only two rounds of Ethiopian socioeconomic survey, his analysis lacks investigation of the presence of state dependence in the problem. Further more, even though he has addressed the multidimensional nature of energy poverty, he left fuzzy nature of energy poverty as a predicate. And, I believe the multidimensional conceptualization energy poverty need to be augmented with its fuzzy nature to get reasonable understanding of it.

The application of fuzzy set theory was first introduced in Zadeh (1965) work, and the need to conceptualize and measure poverty as a fuzzy predicate was first pioneered by (Cerioli and Zani, 1990). Ever since then number of papers have applied the method to investigate the extent of poverty for example see (Betti et al., 2006; Betti and Verma, 2008; Cheli and Lemmi, 1995; Costa and De Angelis, 2008)etc. But, even though the concept of poverty used in energy poverty is not different from the one used in overall poverty studies, the application of the fuzzy set analysis in measuring energy poverty is not well exploited yet.

Energy poverty is not a one time phenomenon and its nature over long period of time has to be investigated. Such analysis will help us to understand if the households in the study area are experiencing a persistent or transitory problem, and understand if the household which experience poverty or deprivation in one period will stay in the same situation over longer period of time or will they leave out of it (Biewen, 2014). To do so, many has conducted a persistence and dynamic analysis (for example see (Adusah-Poku and Takeuchi, 2019; Alem and Demeke, 2020; Drescher and Janzen, 2021; Munro et al., 2020; Phimister et al., 2015)). But undertaking such analysis given the level of energy poverty measured using a fuzzy set approach will require selecting methods which can manage the fractional and bounded nature of the index that represent households energy poverty.

In order to investigate if the households of the study area experience either a persistent or a transitory poverty, like the traditional crisp poor non poor approach which can enable us to determine the level of persistence of poverty through re-entry and exit rates, though its application is not exploited in the case of energy poverty, the fuzzy set approach can also be modified through the use of joint membership functions and composite operators to determine energy poverty persistence and re-entry and exit rates (Betti et al., 2006).

In investigating determinants of poverty measured applying fuzzy set approach, the available researches divert to the poor and non poor dicothomiation, and leave the very reason fuzzy set approach was applied. Instead, the investigation of determinants in general and presence of state dependence in particular requires appropriate fractional regression. Among alternative approaches which are common in dealing with fractional dependent variables, there are log odds transformation and beta regression which according to Loudermilk (2007); Papke and Wooldridge (1996, 2008); Ramalho et al. (2011) would fail once the dependent variable starts to take on values at the border, and the fractional regression of Papke and Wooldridge (2008) which though it can deal with observations at the corner, would fail once the lagged dependent variable is used as an explanatory variable. On the other hand, we have the random effect tobit regression which if substantial number of observations are going to be found at each border (zero and one) can result in consistent estimates (Loudermilk, 2007). This approach can also manage the endogenity problems that can result from the correlation of unobserved heterogeneity and lagged dependent variable through modeling the unobserved heterogeneity as stated in (Wooldridge, 2005).

Thus, i have selected the following points as a research gap to be addressed in this research.

- Though increasing number of researches are being made on the energy poverty in Ethiopia, they have not addressed its vague or fuzzy nature.
- The extent of energy poverty persistence and dynamics in the rural and small towns of the country have not been investigated so far.
- The application of dynamic fractional regression is in its early stage. And researches have not addressed how to investigate the presence of state dependence when poverty is measured through fuzzy set approach.

By taking issues raised above as a research gap, this research has tried to study multidimensional energy poverty in its vague nature in rural and small towns of the country by applying fuzzy set theory and tried to investigate the presence of state dependence in energy poverty experienced by households using dynamic fractional regression.

1.3 Objective of the Study

1.3.1 General Objective

This paper is prepared with general objective of investigating Ethiopia's rural and small town's multidimensional energy poverty; its fuzzy character, level, persistence and sate dependence during the three rounds of Ethiopian socio economic survey periods which cover years from 2010/11 up to 2015/16.

1.3.2 Specific Objectives

The study has tried to

- Examine the level of deprivation in each selected dimensions of multidimensional energy poverty, and show the progress over the three rounds of survey.
- Measure the level of fuzzy multidimensional energy poverty, and decompose the results by dimensions and indicators, and compare the results across the three rounds of survey.
- Investigate the longitudinal nature of fuzzy energy poverty.
- Investigate the presence of state dependence in household's fuzzy multidimensional energy poverty while also examining the effect of selected socioeconomic and demographic factors on household's energy poverty.

1.4 Hypothesis

According to (Verbeek, 2008), those who remain in a certain situation for long will develop a character that despite all other factors, it will be hard for them to escape from it. And such situation is called state dependence. State dependence in poverty has been studied for long, and growing number of researches are indicating its presence in the case of energy poverty too citealem2020persistence. Household members who live in households with multidimensional energy poverty in one period are exposed to number of factors that can impact their well being. One of its impacts is on their health which can influence their productivity thereby their income (Khandker et al., 2010). Households which have access to electricity can also create a small business over which they can generate an income. If the biomass fuel generated from animal dung is used as a fertilizer on farms, it can increase the farm productivity of the households (Khandker et al., 2010). Thus, I hypothesize that household's experience of energy poverty in one period can lead them to experience some positive amount of energy poverty in the next period thus create a state dependence.

1.5 Scope of the Study

This study used panel data set constructed using data from the three consecutive rounds of Ethiopian socioeconomic survey (ESS) which were conducted starting from year 2010/11 up to 2015/16. Households from large and medium towns of the country were included to the survey only after the first round. Creation of balanced panel data set for dynamic analysis using data from sampled households of rural areas, small, medium and large towns would have caused removal of data from first round of survey. And this would have reduced the time dimension of the panel data set only to two periods, and made it impossible to conduct a dynamic analysis. Rather in this paper, I remove sampled households of medium and large towns of the country and create a balanced data set having observations from sampled households of rural and small towns of the country surveyed during all three rounds of ESS. And having panel dataset with time dimension of only three periods works fine with nonlinear dynamic regressions.

Though there are alternative methods of defining and measuring energy poverty, this research is made focusing on the vague and multidimensional nature of energy poverty. And this calls for the use of fuzzy set analysis. The resulting numerical values that explain household's status of energy poverty becomes continuous values bounded between zero and one. And given the objective of investigating the persistence of energy poverty, a method of analysis that can support the fractional nature of the dependent variable while also accepting the lagged dependent variable as an explanatory was supposed to be selected for the econometric analysis. And this calls for the application of dynamic fractional analysis.

Thus, the final results of the research are forwarded based on the dimensions, indicators, weights and fuzzy set analysis methods selected for the study of multidimensional energy poverty, and the type of model used to undertake dynamics analysis of energy poverty in the rural and small towns of the Ethiopia during ESS's survey period which extends from 2010/11 up to 2015/16.

1.6 Significance of the Study

I believe this research will be helpful for policy makers in the way it can give them the exact level of multidimensional energy poverty as experienced by the rural and small towns of the country rather than providing them with just a mere count of those who are energy poor. And they will not be deluded with the traditional norm of using 30 percent deprivation as a poverty cutoff to distinguish the multidimensional energy poor households from those who are not. Those households who experience positive level of poverty but manage to be just above the poverty line will not be excluded from the policy recommendation. Further the decomposition of results will be helpful in directing on which areas and dimensions to exert their efforts more. Moreover, the dynamic analysis which shows the presence of state dependence will provide them with an evidence for the need to urge to combat energy poverty problem which if leaved unchecked will become impossible to curb by using other policy variables.

This research is an addition to the growing incline towards analyzing poverty in general and energy poverty in particular in its vague and multidimensional nature. It also adds to the increasing application of fractional analysis in economics. So I believe, this research can be used as reference for studies to be made in these and related areas in the future.

1.7 Limitation of the Study

The first Ethiopian socioeconomic survey was confined to rural areas and small towns of the country leaving medium and large towns, which later were included in the second and third one, out of the survey. Had the analysis been based on observations from sampled households from the whole country, we would have been staked with a panel data set with only two rounds of surveys. This would have made it impossible to forward conclusion about fuzzy multidimensional energy poverty level and its dynamics across the country since the dynamic nonlinear regression to be used to address such objective requires a panel data set constructed of at least three rounds of surveys. As a result, the research is confined to small town and rural areas since a panel data set with three period time dimension is available.

Further, during the conduction of this paper, the last updated data available from ESS was data from ESS4, which is the fourth round of survey undertaken during 2018/19. But this version of the data was collected so as to formulate a whole new panel series which the data provider entitled it as panel two. Thus, possible information from this round of survey is not made part of output of the analysis made in this research. As a result, the conclusions forwarded by the paper are confined to data from the three rounds of ESS, and do not consider the possible progresses or leap backs happened after the last survey made in 2015/16.

As Sokołowski et al. (2020) has clearly indicated on his paper, researches made on energy poverty in most developing countries applying multidimensional poverty index highly relay on self reported deprivations. While it is important to include factors like. And due to lack of variables that can indicate such important factors about household energy poverty, such factors are also not included in this study.

1.8 Organization of the Study

This research contains five chapters. Chapter one is the introduction part, and it contains background of the study, statement of the problem, the research's general and specific objectives and the hypothesis to be addressed in the study. It also includes the scope, significance, limitations and organization of the study. Chapter two contains a brief theoretical and empirical literature review on issues related to the study. Chapter three presents methodologies used to address specific objectives of the study. Chapter four presents analysis and findings of the research. And chapter five presents conclusion and recommendations.

Chapter 2

Literature Review

2.1 Theoretical Literature Review

2.1.1 World energy demand and supply

Human beings require energy to undertake number of tasks that extend from daily household level activities up to operation of big and complex industries that require huge amount of energy. And, through time demand for energy is increasing. In 2018, world energy demand grow by 2.3%, and it is projected to grow on average by 1.3% every year until 2040 **???**. BP's 2019 statistical review on world energy also confirm the presence of rise in energy demand and, the report estimates the growth rate to be 2.9%, which it claims to be the highest registered growth rate in energy demand ever since 2010 (Dudley, 2018).

So as to fulfill this rising energy demand, every year huge amount of energy is produced from both renewable and nonrenewable resource (Nations, 2018). And the supply of energy is showing nothing but a rise over the past decade. In 2015 alone world's total energy supply showed 60% rise from what it used to be in 1990, and 551.7 EJ of energy was supplied Nations (2018). From this total energy supply (TES), the highest share which makes up to 21.7% was produced in China followed by another big economy, USA, which produced about 16.4% of world's TES. During the same year, Africa's contribution in energy production was only 5.8%.

In Africa,like the rest of the world, both demand and supply of energy are rising. But, there are factors which make the energy sector of the continent unique. Even though as it is stated in Commission et al. (2015) Africa is thriving to achieve universal coverage of access to clean, efficient, modern, affordable and sustainable energy source by 2063 , despite the positive progress being made by countries like Ethiopia, Ghana, etc, the progress among the rest is being outpaced by the population growth rate (Nations, 2018). In the continent which makes up to only 4% of world total energy investment, the amount of energy produced from biomass fuels takes up to 44% of total energy supply (IEA and Special, 2019). And the majority of this energy is consumed by the residential sector (Nations, 2018). According to IEA and Special (2019), in 2018, 600 million people in the continent did not have access to electricity while 900 million lack accesses to clean cooking fuel. The report also claims that given the higher population growth rate of the continent, by 2040, 530 million people are expected to be without access to electricity, and this is projected to be 90% of world population without electricity at the time. Nearly one billion people of the continent are also expected to have no access for clean cooking fuel by 2040, and this number is expected to make up 50% of world population without access to clean cooking fuel at the time (IEA and Special, 2019). The continent's energy supply is projected to grow by 35% in 2030, but even by then biomass fuels will manage to be the most important fuels even though its relative share is expected to decline (Pappis et al., 2019).

2.1.2 Why Focus on Household Energy Consumption?

The residential sector is one of the major consumers of energy supplied each year. Between the year of 2000 and 2011 alone, global demand for energy in the residential sector increased by 14%, and most of this increment was contributed by households living in developing countries (Nejat et al., 2015).

Population size of the developing world is increasing, and while putting the rest of factors aside, with raised population higher investment will be required to address modern energy for residential users. Moreover, numerous efforts are being made to improve the living standard of those who live in developing countries, and this also requires increasing access modern energy source.

According to Nejat et al. (2015), about 40% of global energy demand by the residential sector is covered by energy from biomass fuels. And most of this is contributed by biomass combustion in the households of developing countries (Nejat et al., 2015). But this huge dependency of households on biomass fuels has far reaching impact that extend from household's own welfare up to their surrounding environment.

In 2016, WHO estimated that about three billion people which make about 41% of the world population used polluting fuels to cook. And using these cooking fuels with unimproved cooking stoves in poorly ventilated areas causes the emission and concentration of toxic pollutants like particulate matter (PM), carbon monoxide (CO), metals, hydrocarbons, oxygenated organic compound inside the living environment (Emmelin and Wall, 2007). And the concentration of these toxic pollutants indoor is believed to be five and six times more than level in the ambient air, and cause severe health problems like acute respiratory infections (ARIs), chronic obstructive pulmonary disease, pulmonary tuberculosis, cataracts, low birth weight, prenatal and infant mortality, nasopharyngeal and laryngeal and lung cancer, blindness, heart disease etc (Gall et al., 2013). In 2016 alone 3.8 million premature deaths and over 400,000 deaths of children under the age of five years was caused by health problems related to indoor air pollution.

The other problem related to the huge dependence of households on solid biomass fuels for cooking, heating and lighting has adverse impact on women and children. Beside the huge health burden of indoor air pollution on children, the time they are expected to spend to collect fire wood will affect their school attendance, dropout rate, school performance, and even expose them to sexual assaults (Nagbrahmam and Sambrani, 1983).

The use of solid fuels has direct impact on the environment as households become increasingly dependent on these fuels both in rural and urban areas. Those households which depend on collected firewood are usually dependent on the nearby forest, and this is one of the factors that result in accelerated level of deforestation especially in developing countries (Allen and Barnes, 1985). And the existing tradition of sticking to solid fuels even in urban areas of developing countries together with increasing urbanization rate resulted in huge demand for purchased firewood and charcoal Allen and Barnes (1985). And in some countries these fuels are used as backups in case households face price fluctuation in modern fuels Alem and Demeke (2020). This will encourage others to see the opportunity as a huge source of income and lead for the depletion of forest (Ravindranath et al., 1995). On the other hand, the attempt made by policy makers to substitute solid fuels by liquefied petroleum gas (LPG) will create a burden on the national economy for those countries like Ethiopia where the resource is not well exploited yet, and it will contribute for the intensification of the depletion of non renewable resources worldwide.

2.1.3 Focusing on Access to Modern Energy

In 2000, world leaders meet in United Nations headquarters and signed an agreement on eight goals, which are collectively known as millennium development goals (MDGs), that could speed up world countries thrive towards the eradication of extreme poverty by 2015. Even though there were no specific goals that were exclusively related to energy and energy poverty, the achievement of the each goal in MDGs was believed to be highly dependent on the improvement of access to modern, clean, renewable, reliable and affordable energy sources (Energy, 2005; IEA and Special, 2019).

During the fifteen years life span of MDGs, number of world countries had witnessed improvement in the rate of electrification and access to modern cooking fuels. But the question was do they expand the access as much as it was required for the achievement of MDGs. According to IEA and Special (2019), in 2010 alone 1.2 billion people in world were without access to electricity, and through huge efforts made during the next five years the figure drops to 1 billion. Up on the completion of the MDG period, countries achievement on each goal were carefully examined, and inability to expand access to modern energy services as much as required was found to be among many factors that held back countries from achieving better in MDG (Accorsi et al., 2010; Bank, 2010; Ha and Porcaro, 2005; Jahan, 2010).

In 2015, world leaders meet again to sign an agreement on the new set of goals, which are called sustainable development goals (SDGs), which are supposed to be used as world road map to development up to year 2030. This time goals that are directly and indirectly related to energy were incorporated (Griggs et al., 2013). Goal seven of SDG (SDG 7) is exclusively related to access to modern energy. And, its first aim is to achieve universal access for affordable, reliable, and sustainable energy by 2030, and its second aim is to increase the share of renewable energy in the energy mix, and third one is to improvement the level of energy efficiency.

Beside SDG7, the achievement of the other goals are believed to be highly dependent on the improvement of access to modern energy (Pradhan et al., 2017). For example SDG3 states the need to create access to essential health care service. Health and energy access are highly related. We know that the use of biomass fuels for cooking will result in indoor air pollution. Researches show that the concentration of pollutants indoor created by the use of solid fuels is higher than concentration of pollutants outdoor even in most air polluted countries of the world (Jahan, 2010). This will result in respiratory related health problems that could result in premature death especially among children. Thus, the use of clean energy sources for cooking will reduce diseases and death burden caused by the use of traditional fuels. The other dimension where health and energy are related is in the need to have clean, reliable and affordable energy in health centers. Unless they are provided with modern energy, health centers will just be buildings which cannot deliver services they are intended for (Babatunde et al., 2019). SDG4 states the need to deliver quality education. Education and energy are also related in many directions. Students' achievement in school is highly dependent on their access to electric light to study and do their home work; their school attendance is dependent on the time they are supposed to spend collecting firewood. Schools capacity to deliver quality education is highly dependent on schools access to clean, efficient, reliable and affordable energy. A research made in Bangladesh indicates students which live in those households with access to electricity have 42% more achievement in schools than those from households without access (Nath, 2012). Another study from Bangladesh indicates the presence of positive and significant impact of access to electricity on students' grade and negative and significant impact on non attendance rate (Alam and Kaneko, 2019). SDG11 is concerned with adaptation for and mitigation of climate change. Household's dependence on biomass fuels will create a burden on the environment in terms of air pollution, Metan gas emission, environmental degradation, deforestation etc. Thus, the move towards clean energy will not only impact households but also can save a greater deal of the environment.

The question is given that there are ten years left to 2030, is the world progressing towards achieving universal access to clean, affordable and sustainable energy on the right track. The 2020 edition of ”tracking SDG7” reports that as of 2018, 789 million people worldwide were still without access to electricity while 3 billion of them were with no access to clean cooking fuels (Müller et al., 2021).

The other attempt to address access to modern energy is seen in the inclusion of access to electricity and modern cooking fuels as one of the indicators of global multidimensional poverty index (MPI). The index which is jointly developed by United Nation Development Programme (UNDP) and Oxford Poverty and Human Development Initiative (OPHI) is the outcome of an attempt made to study poverty in its multifaceted nature. And it includes three major dimensions; health, education and standard of living. Each dimensions have their own indicators; and among the indicators of standard of living, we have households access to electricity and type of cooking fuel used. OPHI’s recent report indicates that among countries included in the study, there is a significant decline in MPI among sixty seven countries which are countries that host 98% of world population (Alkire et al., 2020). And according to Alkire et al. (2020), among the major contributors for the world MPI, lack of access to modern cooking fuel takes the lead after contributions made by indicators in education and health dimensions.

When we come to our continent, Africa, which hosts one of the least electrified places in the world, electrification rate in the area is highly influenced by adequate policy design, availability of finance, and presence of favorable political condition (Trotter et al., 2017).

2.1.4 Access to Modern Energy in Ethiopia; Potentials and Resources Exploited so far

Though it has shown improvement overtime, Ethiopia is one of the countries with very low per caita energy consumption. According to Bank (2020), in 2000, per capita energy consumption of the country was only 22.75 kwh per year and this figure rose to 69.198 kwh per year in 2014. But still it is lower than the average per capita energy consumption of Africa which is above 500 kwh per capita per year. When we come to the rate of electrification in the country, in 2019 the rate was only 45% which is far behind what the government plan to achieve in 2020 by increasing its electric power supply to 10,000 MW via its second round of growth and transformation plan (GTP). According to IEA and Special (2019), despite the efforts, Ethiopian electrification rate is being out phased by the population growth rate, and unless more effort is exerted the plan to achieve 100% electrification rate by 2025 will most likely fail (IEA and Special, 2019). Aside from being a country with low electrification rate, the country is known for being one of the countries with the highest scorer in the global multidimensional energy poverty index. Nussbaumer et al. (2012), in their pioneering paper which undertook a multidimensional energy poverty analysis, confirmed that Ethiopia was one of the countries with energy poverty index exceeding 90%. The number is an indicator for the presence energy deprivation experienced by the large majority of households in the country. Later, number of researches were undertaken regarding multidimensional energy poverty of the country, and they confirmed that though there is a progress, energy poverty is still high (Alem and Demeke, 2020).

Like the rest of countries in sub Saharan Africa, most of the energy produced each year is consumed by the residential sector. According to Trotter et al. (2017), in 2011, 93% of energy produced in the country was consumed by the residential sector while the rest 7% was shared among the transport, service and industry sectors. And 98% of energy consumption in the residential sector was dominated by the use of biomass fuels where about 87% of it was collected fire wood (Trotter et al., 2017).

Given the existing problems, Ethiopian energy sector is driven by four major strategic priorities; universal access to clean energy, improving energy efficiency, decentralizing power generation through renewable energy technologies and even exporting electricity (Bayissa, 2008). But the question is how can a country like Ethiopia can achieve these.

Though Ethiopia is characterized by its lower performance in the energy sector, it is believed that the country is one of the promising areas in Africa with huge potential to produce renewable energy. Number of researches are being made on the country's potential to produce renewable energy sources for example see ((Mondal et al., 2018, 2017; Tucho et al., 2014)). And they showed that the country has the potential of producing 45,000 MW of energy through hydroelectric power plants. And by 2020, it was planned to generate

10,000 MW assuming major electric generating hydro plants like the Grand Ethiopian Renaissance Dam (GERD) and GebeIII plant will join the energy production. Now it is 2020 and GERD only started to be filled with the required first round of water reserve, and has not start energy generation yet. The other potential of the country given its location in the equator is production of energy through solar technology. The country has the potential of generating 4-6 kwh of energy per meter square. The other potential is generating energy through wind. Projects in Ahegoda and Adama have shown successes story, but still less than one percent of the potential in the area is exploited. The country also has the potential of producing 7,000MW of energy via geothermal, and only less than one percent of it is exploited so far.

Mondal et al. (2017), after analyzing the trend in energy demand of Ethiopia and existing potentials, they have projected the following to happen in energy production of the country by 2045. They expect energy demand to rise overtime, and so as to meet this demand Ethiopian yearly power generation will rise from 3.1 GW in 2015 to 24.81 GW in 2045. Power generating capacity of large hydro power plants is expected to rise from 1.66 GW in 2015 to 6.16 GW in 2045. During the same period the cost of generating power from solar and wind technologies is expected to fall over time and they are expected to contribute significant amount for the national energy supply. At the same time it is projected that the country will increase its share of energy production from natural gas and coal (Mondal et al., 2017).

As it is explained above, access to modern energy has been given great deal of attention both at national and international level. And among the sectors that consume of energy, the residential sector is given a priority since access to modern energy by this sector can have far reaching impact that extend from improving living standard of the society up to the protection of the environment and combating resource depletion. One of the areas of concern regarding energy consumption by the household sector is to understand level of energy poverty at household level. Estimates like electrification rate, per capita energy consumption can only tell the story at national level or at a given geographical area. But when we question the problem being experienced at household level, this numbers can not tell us more than the access or no access of electricity. Thus, a more detailed micro level analysis will be more informative.

2.1.5 Measuring Energy Poverty

According to Sen(), in measuring the level of poverty, there are two basic steps that every poverty measurement approach must fulfill. The first one is identification of the poor. And the second one is the aggregation process which will give us an index that represent the extent of the problem in the given study area.

The first process in measuring poverty requires proper definition of poverty and poverty line. And we have two basic approaches of defining poverty; functioning and capability approaches. Functioning are beings and doings that a person can undertake while capabilities are freedoms and opportunities that a person requires in order to achieve functioning (Hick, 2012). For example, when the functioning approach cares about being able to perform any task during night time, capability approach will care about having access to electric light. Or when the functioning approach cares about being able to cook around an environment with no indoor air pollution, capability approach will consider about having modern kitchen outside the living environment. Based on the capability approach, poverty is defined as deprivation in some given capability which can lead an individual or household to be able to do or be something. Now once poverty is defined, the next step will be to mark the poverty line that differentiates those who are going to be considered poor from those who are not.

In the case of income poverty, we have the internationally agreed up on definition that was first proposed by World Bank in 1990. The line is estimated based on assumed expenditure on selected basket of products and services that are required for the survival of a given individual (Jolliffe and Prydz, 2016). After considering these factors $1.90 adjusted for purchasing power parity (PPP) per day per individual is taken as a poverty line. Beside the internationally agreed up on income poverty line, nations also draw their own poverty line to understand the level of income poverty in their respective context. This line is usually drawn after national level household surveys, and it is constructed so that it can be adjusted for spatial and temporal differences.

In the case of multidimensional poverty, which is one of the recent developments in the study of poverty which inclines towards analyzing poverty as a multifaceted phenomena, rather than picturing it as a one dimensional problem that can be solved by improving income of households/ individuals, in most researches done using the approach including the global MPI use 30% of aggregate deprivation in selected dimensions as a poverty line.

Here, we have to make it clear that though poverty and deprivation are used interchangeably in some cases, they are predicates which refer to though related but different issues. According to Townsend (1979), the difference between poverty and deprivation is that the earlier is more focused on general circumstances while the later one gives an explanation about specific conditions that can be metal, physical or emotional (Townsend, 1979). While deprivation can be conceptualized as continuum that extends from no deprivation to extreme deprivation, aggregation of these deprivations in some specific issues will give rise to poverty (Gordon, 2003).

There is no single internationally agreed up on definition for energy poverty and energy poverty line. As a result, we do not have unanimously agreed up on threshold that represents the minimum basket of energy services required to differentiate energy poor households form those who are not (Culver, 2017). Different institutions and researchers define energy poverty line in the way it can fit their interest and the reality of their study area. And among them we have the definition given by UN Secretary General's Advisory Group on Energy and Climate Change. And it defines thrive towards elimination energy poverty as providing basic minimum threshold of modern energy services both for consumption and productive uses. And access to these modern energy services must be reliable, affordable, sustainable and where feasible from low-GHG-emitting energy sources AGECC (2010). But the question is how can we determine those minimum threshold of modern energy services required by households and use it as energy poverty line.

As it is indicated in Samad et al. (2010), the attempts made in measuring energy poverty line can be categorized in to two, the expenditure based approaches and the physical energy requirement approaches. The first one is dependent on the proportion of households income spent on accessing modern energy services. The leading attempt in applying such approach is Boardman (2013) which makes the use of 10% of income spent on energy expenditure as an energy poverty line. Those who are found to spend more than this percent are considered as being energy poor. The approach is mainly used by researches made on energy poverty in the developed world, and later this approach has developed to low income and high cost approach which tried to incorporate not only households status but also the nature of the energy market (Kyprianou et al., 2019). The approach is prized for its ability to incorporate and become sensitive to more than one variable, which are energy demand, energy cost and households income (Hills, 2012). This approach is constructed based on the fact that European countries are experiencing stagnant income and sharply raising energy price over the last decade coupled with the climatic condition of the area which make thermal heating mandatory (Csiba et al., 2016).

There are number of attempts made in estimating the minimum requirement of energy per household. Bravo et al. (1979), which tried to investigate energy poverty by estimating the minimum required energy for households, tried to estimate required energy for households direct and indirect use of energy. The first one represents households need for energy to fulfill daily household chores while the second one represent energy embodied in the consumption of additional goods and services that are not produced at home. But, later Modi et al. (2005) tried to simplify the process by reducing the need for modern energy in rural households only for cooking and lighting. Even though it was criticized later by number of researches for its ignorance for the requirement of energy for other household activities, and its ignorance for different energy demand natures in different climate and socio economic conditions, Modi et al. (2005) used 50 kgOE as energy poverty line. The later development made on estimating energy poverty line is Barnes et al. (2011) attempt to determine energy poverty line based on household's energy demand, income and other characters.

Introduced by Nussbaumer et al. (2012), the emergency of multidimensional energy poverty index (MEPI) is the other important development in the measurement of energy poverty. The approach includes dimensions like indoor air pollution, access to clean cooking fuel, access to clean energy source for lighting and access to media and communication and it can be customized for the context of any study area selected.

The second stage in measuring poverty is aggregation. This will help us get an index representing the level of poverty in a given study area. Different aggregation techniques are used by different approaches. In income poverty, head count ratio, poverty depth ratio, poverty severity ratio are used as indexes that can represent level of poverty in the study area (Foster et al., 1984). In multidimensional approaches adjusted headcount ratio, adjusted poverty gap ratio and adjusted poverty severity ratio are used (Alkire and Foster, 2011).

But, the need to be concerned about poverty line will disappear once poverty is conceptualized as a fuzzy predicate. The advantage of such moves is so as to understand the deprivation level of all those who are included in the study area. As a result, there will be no household or individual which will be left out of the analysis just because it manages to be just above the poverty line.

2.1.6 Using Fuzzy Set Poverty Measurement as an Extension to Multidimensional Approach

According to Qizilbash (2006), poverty can manage to fulfill all three major characters of a vague predicates, and its multidimensional nature contribute a lot for it. These characters include absence of clear borderlines that indicate where exactly the predicate poor applies or not [1], the presence of borderline cases [2], and the application of Sorties paradox [3]. Thus, as Fustier (2006) has put it, it is justifiable to use fuzzy set approach to measure poverty. Though the introduction of fuzzy logic dates back to **?**, its application to poverty studies was first pioneered by Cerioli and Zani (1990) work. Based on a fuzzy set theory, truth comes in degrees, and rather than representing the poverty status of a given household or

[1] This one denies the use of crisp borderlines used as thresholds to differentiate poor from non poor.

[2] Here, the truth value of vague predicates does not only include definite truth and false, but also indefinite degree of truth in between

[3] Increasing a given household's degree of membership to poverty only with small fraction will not make its level of poverty any worse, but if the action is undertaken repetitively, the small fractions will pile up enough to make the household reach 100% membership value or to be absolutely poor.

individual only with crisp values, zero and one, which represent definite falsehood and truth, what is more informative is to assign values for indefinite truth values that represent varying degree of memberships in between (Fustier, 2006).

Ever since its first application by Cerioli and Zani (1990) on poverty analysis, number of contributors are improving the way fuzzy set theory is applied to poverty studies. After the totally fuzzy and absolute approach of Cerioli and Zani (1990), Cheli and Lemmi (1995) introduce the totally fuzzy and relative approach. Later Betti and Verma (1999), improve the way weights are constructed, and later, Betti et al. (2006), show cased how to undertake longitudinal poverty analysis using fuzzy sets.

According to (Costa and De Angelis, 2008), the major objective of any fuzzy set approach in measuring multidimensional poverty is first to determine the level of deprivation faced by each household in each selected indicators. And second one is aggregating the level of deprivation in each of a given dimensions and determine household's deprivation per dimension. And the third one is aggregating deprivations in all dimensions selected and determine overall level of poverty being experienced by the given household. The last step is estimating the average poverty index of the population in the study area, and decomposing the results to see which dimensions contribute the most to the overall level of poverty in the study area Costa and De Angelis (2008).

Though each fuzzy set methodology used in measuring poverty follow the five major steps as mentioned by Costa and De Angelis (2008), their difference comes in the choice of three major factors. And these are choice of membership function, weighting scheme and method of aggregation.

Membership functions

Membership functions are used to determine the level of deprivation which is also called deprivation score faced by each household in each selected indicator. The concept of membership functions comes from the very definition of poverty as a vague concept and the need to represent its vagueness numerically. According to Qizilbash (2006), there are three views of vagueness; the first one is epistemic view which assumes that though vague predicates do not have clear borderlines that determine the places where the predicate do and do not apply, the reason for it is nothing but ignorance. The second view is supervaluationism which emerge to answer the problem of higher order vagueness, and the last one is degree theory which assumes the presence of more than two truth values to any given vague predicate (Qizilbash, 2006). Among the three, the degree theory was found to be ideal in measuring vague predicates. The approach assumes that beside the two extremes, definite falsehood and definite truth, for a given predicate's truth value, we can find indefinite truth values in between. And fuzzy set theory is used to assign numerical values to these indefinite truth values or degrees of truth (Fustier, 2006). Fuzzy set theory was first proposed by **?**, and ever since then it has been applied to number of applications in different disciplines, and its application in poverty measurement was first introduced by (Cerioli and Zani, 1990).

And membership functions of fuzzy set theory are used to execute the task of assigning numerical values to those who are claimed to be definitely poor, those who are definitely not poor and infinite cases in between which will be represented by their relative degree of poverty. Different fuzzy set approaches propose different membership functions. Proposed by Cerioli and Zani (1990), the pioneering poverty membership function is the so called totally fuzzy and absolute (TFA) approach. According to **?**, to deal with continuous indicators like income, the concept of transitional zone can be used as in equation 2.1.

$$\mu_{ij} = \begin{cases} 1, if d_{ij} < Z_1 \\ \frac{Z_2 - d_{ij}}{Z_2 - Z_1}, if Z_1 \leq d_{ij} < Z_2 \\ 0, if d_{ij} \geq Z_2 \end{cases} \tag{2.1}$$

Where μ_{ij} is the level of deprivation score of i^th household in j^th dimension, d_ij is the performance of i^th household in j^th dimension, and Z_1 and Z_2 represent the bounds which Cerioli and Zani (1990) referred to as transition zone.

For categorical indicators they assume that the categories of any given indicator will be equally spaced and the deprivation score in these dimensions are determined as in 2.2.

$$\mu_{ij} = \frac{C - C_i}{C - 1}, where 1 < C_i \leq C \tag{2.2}$$

Where C is the highest integer assigned to the category which represent the better performance in the given indicator, and C_i is an integer assigned to the any other category. μ_{ij} will represent the deprivation score that ranges from 0 for those who are not deprived to 1 for those who are absolutely deprived in the dimension.

Up on the criticisms on Cerioli and Zani (1990), Cheli and Lemmi (1995) propose the totally fuzzy and relative (TFR) approach. The approach is based on the assumption that the deprivation score in each indicator must be determined not only based on the performance of a given individual but also by the performance of others in the study area (Cheli and Lemmi, 1995). As a result the deprivation score will be dependent on the distribution of the deprivation in the given study area and that is why it is called totally fuzzy and relative.

Later Betti and Verma (1999), introduce an adjustment to the TFR approach of Cheli and Lemmi (1995) by introducing the need to include Lorenz curves especially in determining deprivation score in indicators with continues nature (Betti and Verma, 1999, 2008).

There are other improvements made to the membership functions used in fuzzy set theories which include Martinetti (1994), and the emergency of the integrated fuzzy and relative (IFR) approach by Betti et al. (2006), and the latter one has shown how to apply the membership functions of IFR approach in the case of multidimensional poverty.

Weights

Cerioli and Zani (1990) is not only pioneering in determining membership function, but also in proposing how to assign weights to indicators. According to Cerioli and Zani (1990), equal weights shall be assigned to all dimensions while weights for indicators under each dimension must be based on the distribution of deprivation in that given indicator across the population in the study area. Thus, we can claim that though the membership function they propose is absolute in nature, they at least have tried to incorporate its relatively through the weights.

$$w^{cz}_{k} = log(n/\sum \mu_{ij} n_i) \tag{2.3}$$

Where W_k is the weight to be assigned to the k^{th} attribute, n is the sample size included in the study, μ_{ij} is the level of deprivation of i^{th} individual on j^{th} attribute, and n_i represent weight assigned to i^{th} individual in the sample.

Given the above formula for the weights, we should be careful in defining weights as an indicator for the level of importance of a given indicator. Rather it is something that represent the level of distribution of deprivation among the population at least for (Cerioli and Zani, 1990).

The method is formulated in the way the weight will be an inverse function of the degree of deprivation among the population. Based on the formula above, if every household in the study area is found to be completely deprived in the given indicator, the weight to be assigned for the corresponding indicator will become zero. And it will be unnecessary to include it in the analysis. And also if there are no households which are deprived in the given indicator, the formula will be undefined, and thus such indicators must also be excluded. If smaller numbers of households are found to be deprived with smaller degree, the highest will be the weight assigned. And for those dimensions over which most of households are deprived in higher degree are going to be penalized by lower weight (Cerioli and Zani, 1990).

The other weighting scheme is the one proposed by Betti and Verma (1999). Here also all dimensions included in the study will be assigned with equal weights, and the weight to be assigned to indicators within each dimension must be based not only on the distribution of deprivation in the study area but also on the level of correlation among the indicators. The introduction of any indicator which is uncorrelated with the existing ones will not majorly affect the percentage of weights that is already assigned for the existing indicators, and on the other hand, these values will definitely be reduced with the introduction of indicator with high degree of correlation.

Aggregation

Once the membership function for the degree of deprivation in each dimension is determined, so as to reach to a single index that represent the overall level of energy poverty faced by each household, we need to aggregate dimension level deprivations. To execute such objectives, we have three major aggregation operations, namely intersection, union and average. But before selecting among these three operators, we have to agree on the set of rules that should guide such operators. These guides are used to enable fuzzy set operators satisfy some required axioms and properties.

According to Betti and Verma (2008), fuzzy set operators has to be prepared in the way they can be generalization of the corresponding crisp set operations. If this quality is going to be satisfied, the former can easily be reduced to the later one, or in the case of dichotomous dimensions, the fuzzy membership function in [0, 1] rage will be easily converted to 0, 1 dichotomy.

The other required quality is the need to satisfy required boundary conditions which are also called marginal constraints. For example, if we are going to undertake poverty analysis with only two dimensions, A with degree of deprivation represented by a and degree of non derivation represented by $1-a$, and dimension B with degree of deprivation represented by b and degree of non derivation represented by $1-b$, degree of deprivation in AB must satisfy the marginal constraint presented below in table 2.1.

Table 2.1: Marginal constraint

		Dimension B		
		Poor	*Nonpoor*	constraint
Dimension A	*Poor*	$a \bigcap b$	$a \bigcap (1-b)$	a
	Nonpoor	$(1-a) \bigcap b$	$(1-a) \bigcap (1-b)$	$(1-a)$
constraint		b	$(1-b)$	1

Important qualities also include the need to be monotonic and commutative etc where the details are available at (Fustier, 2006).

Each having their own advantage, the three basic set of rules that guide fuzzy set operations are standard, algebraic and bounded operations. According to Betti and Verma (2008) compared to the other two, the standard approach is ideal when the membership function associated with each dimension represent similar state, like either all represent the degree of deprivation, or all represent degree of non deprivation. When these preconditions are fulfilled, the operator will provide us with the largest possible or the most loose intersection which can be labeled as I_max, and the smallest possible or the most tight union which can be labeled as U_min. But, according to Betti and Verma (2008), the operator will fail to pass the marginal constraints stated on table 2.1 above. On the other hand, if membership functions represent different states like one represent degree of deprivation while the other represent degree of non deprivation, bounded operations will be more efficient(Betti and Verma, 2008). According to Betti and Verma (2008), though algebraic operations can pass the marginal constants from the table 2.1 above, when the membership functions of the two or more dimensions included represent similar state, it will produce underestimated intersection values, and when the membership functions represent dissimilar state, it will produce overestimated intersection values.

To overcome the limitations of all three fuzzy set operation rules, Betti and Verma (2008), by combining the best of all three rules,come up with operation rules called composite operators. According to cite Betti and Verma (2008), the operator will take on the methods used by the standard operator when membership functions of each dimension represent similar state (degree of deprivation), and the operator will take on the methods as used by bounded operator when membership functions represent rather different state. Thus, the required marginal constraint presented in table 2.1 will take the following form.

Table 2.2: Marginal constraint used in Betti and Verma (2008)'s composite operator

		Dimension B		
		Poor	*Nonpoor*	constraint
Dimension A	*Poor*	$min(a,b)$	$max(0,a-b)$	a
	Nonpoor	$max(0,b-a)$	$min(1-a,1-b)$	$1-a$
			$1-max(a,b)$	
constraint		b	$1-b$	1

Even though we are going to apply only the operation method in the first cell, which of course is the intersection method used in standard operators, for the case deprivation overlap in each cross sectional period, the whole set of the composite operator proposed by Betti and Verma (2008) is going to be critically needed to undertake fuzzy longitudinal analysis.

Since, the appropriate set of rule that can result in aggregation techniques with desirable character has been selected, let us see methods of aggregation techniques that are going to be applied so as to aggregate degree of dimension in each deprivation to a single poverty index that represent each households degree of energy poverty.

Each having there own advantage, there are three alternative methods of aggregation, namely average, intersection and union. And, in this research, i have applied all three forms so as to explore the different sides of poverty experienced by each household.

Average

Also referred as compensatory aggregation, according to Betti and Verma (2008), averages are used as aggregation technique when all form of deprivation in each dimension or indicator are important, and they are compensatory for each other. This method is used in aggregating each household's degree of deprivation in each indicator so as to reach the degree of deprivation they face in each dimension. In aggregating the degree of deprivation across all dimensions, since equal weight is attached to each dimension, arithmetic mean is used to take the average.

Intersection

Also called intensive deprivation or deprivation overlap in Betti and Verma (2008), finding the intersection of deprivation across dimensions will show us the extent of simultaneous deprivation faced by households.

$$\begin{aligned} \mu_i &= (\mu_{1,i} \bigcap \mu_{2,i} \bigcap \mu_{3,i} \bigcap \mu_{4,i}) \\ \mu_i &= min(\mu_{1,i}, \mu_{2,i}, \mu_{3,i}, \mu_{4,i}) \end{aligned} \tag{2.4}$$

Union

According to Betti and Verma (2008), the result of such aggregation is called extensive deprivation. And it is used to see households propensity to experience positive degree of deprivation at least in one of selected dimension.

$$\begin{aligned} \mu_i &= (\mu_{1,i} \bigcup \mu_{2,i} \bigcup \mu_{3,i} \bigcup \mu_{4,i}) \\ \mu_i &= max(\mu_{1,i}, \mu_{2,i}, \mu_{3,i}, \mu_{4,i}) \end{aligned} \tag{2.5}$$

2.2 Empirical Literature Review

It is important to investigate the level of energy poverty experienced by households so as to come up with policy options. And growing number of researches are being conducted in different parts of Africa, and they show very high level of energy poverty experienced by households and the level is higher for those households in the rural parts. Here, i have presented some of the researches from different areas of the continent, and show how especially those who live in the rural areas require a due attention.

Ye and Koch (2021) applying the income poverty measurement approach of Foster–Greer–Thorbecke (FGT)index to measure energy poverty in South Africa, they found that the three FGT indices, headcount, poverty depth and severity are all to be around 50% indicating not only the incidence but also the intensity of energy poverty is very high. But, they follow only uni dimensional approach to measure energy poverty.

Mbewe (2018) applying both the uni dimensional energy expenditure approach and multidimensional energy poverty measurement (MEPI) approaches, they tried to show the extent of the problem among the low income earners of South Africa, and they indicate a declining trend in energy poverty index measured in both approaches. Compared to those in urban areas, low income households in the rural parts of the country face higher but slowly declining level of energy poverty. Even though they have showed the progress being made over a period of time, they did not show which factors are determinants of energy poverty experienced by households of the study area.

Using static logistic regression, Ismail and Khembo (2015) has showed the determinants energy poverty measured through expenditure approach. They found expenditure pattern, race, education level, household and dwelling size, location of the household and access to electricity significantly affecting energy poverty.

Ogwumike and Ozughalu (2016) investigate the level of energy poverty experienced by Nigerian households using multidimensional energy poverty measurement approach, and found 75% of households experiencing the problem where the rural residents experience level of energy poverty that is almost twice as much as the urban residents. The logistic regression they used show determinants like household size, educational level, gender and age of household head, income poverty, region of residence, and proportion of working members in the household to affect households probability of becoming energy poor. But, they undertake a static analysis leaving us without information about the longitudinal behavior of energy poverty experienced by Nigerian households.

Poverty is not a one time phenomenon that can only be studied through static analysis which can show us the extent of the problem only in a given point of time. Rather, dynamic analysis is required in order to understand its nature over longer period and be able to decide if households are experiencing either persistent or transitory poverty. The same is true for the case of energy poverty, and though it is in its early stage, growing number of researches are being conducted in different study areas to investigate presence of dynamics in households energy poverty, for example see (Adusah-Poku and Takeuchi, 2019; Alem and Demeke, 2020; Drescher and Janzen, 2021; Munro et al., 2020; Phimister et al., 2015).

Phimister et al. (2015) undertook an energy dynamic analysis for the case of Spain. Measuring energy poverty through energy expenditure approach of Boardman (2013), and the subjective measure approach which includes difficulty of heating home, difficultly of paying bills, and housing condition as dimensions, they have shown the dynamics in energy poverty using entry and exit rates estimated from Markov transition matrix. And they found, 44% of those who experienced energy poverty in the expenditure approach and 52% of those who were in energy poverty in subjective measure approach were found to experience a persistent energy poverty. And 55% and 47.8% of those who experience expenditure based and subjective energy poverty respectively were found to exit from being poor in the next period. But, here we have to remember both approaches have used energy poverty lines to identify those who are energy poor and non poor. And as Brown et al.

(2020) households which send the highest share of their disposable income on affording energy services will be faced with the decision of reducing expenditures on other household needs and even energy expenditures, and can push them to the vicious cycle of energy poverty. And we can undertake a dynamic analysis that can show how being energy poor in one period can influence the probability of being energy poor on the next period. While this type of analysis are missing from Phimister et al. (2015), we can find huge in depth analysis made to it in the works of (Drescher and Janzen, 2021) and (Alem and Demeke, 2020).

Drescher and Janzen (2021) measuring energy poverty using Boardman (2013) expenditure based and perceived energy poverty approaches, they have investigated the presence of persistence and dynamics in energy poverty for the case of Germany. Using spells approach to identify weather energy poverty is a transitory or a chronic problem, they have reached to the conclusion that energy poverty in Germany has a transitory nature with 78% of households experience it only temporarily. Using random effect probit model to show the presence of state dependence in energy poverty, they have shown that those households which were energy poor in one period are 7.4% more likely to experience it during the next period. Further, using multinomial logit regression, they have shown the determinants of transitory or chronic poverty.

According to Phimister et al. (2015), dynamics of energy poverty might differ depending on the way the level of energy poverty is measured in the first place as different factors can affect the dimensions included. And the dimensions to be used to analyze energy poverty in developing countries must be selected based on the context of the study area. In Africa, even though, growing number of researches are being made on energy poverty, most of them conduct a static analysis (for example see (Ismail and Khembo, 2015; Mbewe, 2018; Ogwumike and Ozughalu, 2016; Olang et al., 2018; Ozughalu and Ogwumike, 2019; Ye and Koch, 2021) etc), and only few has considered its dynamic nature (for example see (Adusah-Poku and Takeuchi, 2019; Alem and Demeke, 2020; Munro et al., 2020)).

Researches like Adusah-Poku and Takeuchi (2019); Bersisa (2019) show the progress in energy poverty by comparing the level of energy poverty indexes across two or more period of times. They fall short of bringing any numerical evidence on households probability to stay in or leave out of energy poverty over long period of time. On the other hand a research by Alem and Demeke (2020) undertook a brief analysis on the dynamic nature of energy poverty in the major towns of Ethiopia, and with the application of random effect probit analysis show households which are energy poor in one period are 16.4% more for the case of Barnes et al. (2011) based and 9.8% more for the case of Nussbaumer et al. (2012) based MEPI likely to stay in energy poverty during the next period.

When we come to the rural and small towns of Africa, in depth analysis made on the dynamics of energy poverty is missing. Beside this, the dynamic analysis made both for the case of developed world like in Drescher and Janzen (2021); Phimister et al. (2015) and for the case of developing countries like in Alem and Demeke (2020) have all depend on the poor non poor dichotomy of energy poverty using some predetermined energy poverty line, and the dynamic analysis requires random effect probit regression as the dependent variable is zero and one dummy representing the probability of being energy poor or non poor. But, the situation will get complex once energy poverty is perceived as a fuzzy concept and the FMEPI representing households energy poverty status become a continuous fractional number bounded between zero and one.

There are growing number of researches being conducted in the case of energy poverty in Ethiopia. Bekele et al. (2015), conducted a research on multidimensional energy poverty in Addis Ababa using primary data from 466 sampled households. They used access to clean cooking fuel, ownership of energy appliances and the use of modern energy appliances as selected dimensions. With poverty cutoff of 30%, they found that 57.9% of households suffer from multidimensional energy poverty during their survey period 2012/13. They also undertook a logit analysis to investigate the effect of selected socioeconomic and demographic factors on the probability of experiencing multidimensional energy poverty. They found that household head's educational level, ownership of private electric meter, and level of income to significantly and negatively affect the probability of being energy poor.

One of the draw backs of this paper is the fact that it is confined to small geographical area, and this made it impossible to conclude about the situation of the problem in other major towns of the country. And the other limitation is that they used only headcount ratio to aggregate and determine level of energy poverty of the town. They report just the number of household which are found above a certain poverty line while leaving indexes like adjusted headcount ratio which can tell not only the incidence but also the intensity of energy poverty. Besides, it is a cross sectional analysis which is not able to show the potential progress made overtime and possible impact of unobserved heterogeneity on energy poverty.

Alem and Demeke (2020), conducted a research on the persistence of energy poverty among households of major towns of Ethiopia using data from the three rounds of Ethiopian Urban Socio Economic Survey (EUSS). Their paper has tried to show the persistence of energy poverty among the households of major towns of the country after measuring energy poverty using three alternative approaches. The first approach they applied is Modi et al. (2005) approach, which depends on minimum amount of energy consumed by major energy requiring household activities. And based on this approach they found that 21% of sampled households to be energy poor throughout the three survey periods. The second approach they applied is Barnes et al. (2011) energy demand based approach. And based on this approach, they found 60% of households to be energy poor throughout all survey periods. The last approach they applied is multidimensional energy poverty analysis, and based on this approach they found that 26% of sampled households being energy poor throughout all survey periods. And by applying random effect dynamic Probit model, they confirmed that across all three energy poverty measuring approaches, being energy poor in one period has a positive and significant impact on the probability of becoming energy poor in the next period. Their analysis also indicated the huge impact of energy price on households' energy poverty. And they show that households will shift to consume solid fuels when they are faced with raise in price in modern fuels.

The major limitation of this paper is that, it is urban focused which makes it unlikely to conclude about the nature of the situation nation wide. The other important factor that is missed out of this paper is the vary nature of the predicate poverty. Instead of treating it as a fuzzy concept and investigate issues like state dependence and responses to the change in price after wards, they tend to stick to the poor non poor dicotomization using already determined energy poverty lines.

Bersisa (2019) conducted a research on energy poverty in rural and small towns of Ethiopia using data from two rounds of Ethiopian socio economic survey (ESS). Using indoor air pollution, type of cooking fuel, source of lighting and access to entertainment and education as dimensions of energy poverty, he tried to determine the level of multidimensional energy poverty in the selected study area. Using 33% of average deprivation as a poverty cutoff, the results of its analysis indicates the presence of severe energy poverty in study area which did not change much over the two survey periods. 74% of households were found facing multidimensional energy poverty in 2011/12 and this declined only to 73.2% in 2012/13. Type of cooking fuel used was found to be the major contributor for the overall level of energy poverty in the area with its contribution being 43.2% during the first survey and 40.43% during the second survey. He also undertook a logit regression to determine the effect of selected socioeconomic and demographic factors on households' probability of becoming energy poor. And, he found that household size and living in rural areas affect the chance of becoming energy poor significantly and positively while number of rooms per household and households' income size affecting it significantly but negatively.

But here, though we have to accept the idea of incorporating multiple dimensions that represent multifaceted deprivation households would face in their energy use, we have to question on what bases 33% of deprivation is selected as a energy poverty line. According to number of researchers on fuzzy poverty, the selection of this level of deprivation as a poverty line does not have any theoretical or analytic background. It is more of an arbitrary assignment. Again know a days the third round of Ethiopian socioeconomic survey is available and must be incorporated into the analysis so as to get updated on the extent of the problem.

Thus, the analysis made in this thesis are made with the objective of investigating the possible progress or leap backs that happened in rural and small towns of the country ever sine the last research, Bersisa (2019), made using data from only two of ESS surveys, and expand the energy persistence analysis made across the major towns of the country by Alem and Demeke (2020) in to the rural and small towns of the country, and plus add to the existing energy poverty studies by incorporating not only its multidimensional but also its vague nature. This research has also tried to solve the problem of inclining to probit/logit analysis in investigating the determinants of fuzzy multidimensional poverty by using the appropriate dynamic fractional regression.

Chapter 3

Methodology

3.1 Source of data

For this research, I used data from Ethiopian Socioeconomic Survey (ESS). ESS is a panel survey prepared by Ethiopian Central Statistical Agency (CSA) in collaboration with World Bank's Living Standards Measurement Study (LSMS) teams. So far data from two panel data sets are available on World Bank's open data access. I used the first panel data set which is constructed of three rounds of data surveys.

ESS use two stage probability sampling technique; where in the first stage primary sampling units or also called enumeration areas (EAs) are selected and in the second stage households from each EA are selected.

According to CSA et al. (2017), the first round of survey (ESS1) was made in 2011-2012, and it covered 3,969 households sampled across the rural and small towns of the country. The second round of survey was made in 2013-2014, and this time the survey covered sampled households from the first round of survey plus new sampled households from large and medium towns of the country. The total sample size increased to 5,469 out of which 3,969 were those which were already included during the previous survey. During this survey, from 3,969 sampled households of the previous survey, 3,776 households were covered making the panel attrition rate at this stage 3.45% and the panel success rate 95.14%. The third round of survey was made in 2015-2016. During this survey, all households sampled during the second survey were expected to be covered, but only 4,954 were observed. And in the panel data set which is constructed for this research data only from the rural and small towns of the country was needed, and the panel attrition at this stage (in the third survey) is 8.31% with success rate of 91.69% and reducing the sample size to

3,639 households. Thus, the analysis made on this research is made based on information from 3,639 households which were observed during all three rounds of ESS.

Here, according to CSA et al. (2017), ESS's sample size taken from regions of the country namely Afar, Benishagul-Gumz, Dire Dawa, Gambella, Harari and Somalia, are found not being representative for their population size. As a result, the report recommends merging samples from these regions and form one category labeled as ”other regions”. Thus, the same measure is taken in this research, and the analysis results are based on sample from five regions; Tigray, Amhara, Oromiya, Southern Nations and Nationalities (SNNP) and other regions.

3.2 Descriptive Statistics

I have used descriptive statistics like frequency and standard errors to show the distribution associated with some of selected socio economic and demographic factors in the study area. And two way tables are used to show the energy source and cooking technologies used by households in the study area.

3.3 Fuzzy Set Approach

There are alternative methods of measuring poverty in general and energy poverty in particular. But, as I have clearly mentioned it in previous chapters, these approaches come with drawbacks like trying to focus only on access to energy for the purpose of cooking and lighting, being dependent on predetermined energy poverty line, ignoring the vague nature of poverty etc. And further, their application require data from variables like price associated with energy sources, expenditure on affording modern energy sources and services, quantity of total and end use energy consumption. And when these are not available, an opportunity costs are used as proxies for those traditional energy sources that are available for free. But, unfortunately ESS does not contain such variables for example households expenditure on electricity was not included the during first survey, time spend by household members on collecting firewood is included but the information it can convey is less satisfactory compared to other surveys which are used as source of data set in researches of Modi et al. (2005) and Barnes et al. (2011) papers which clearly show the application of using minimum energy requirement and energy demand based analysis of energy poverty. Thus, I decided that understanding the fuzzy and multidimensional version of the problem is more important and more applicable given the availability of data, the limitation of other approaches, and nature of poverty in general.

Based on the availability of data and frequently used dimensions in other related papers in the case of developing countries like Alem and Demeke (2020); Bekele et al. (2015); Bersisa (2019); Mbewe (2018); Olang et al. (2018); Ozughalu and Ogwumike (2019) and most importantly the pioneering one in the area which is Nussbaumer et al. (2012), I have selected dimensions and indicators as indicated on the table of appendix 1 A to study fuzzy multidimensional energy poverty in rural and small towns of Ethiopia. As it is indicated on the table, all dimensions and indicators selected are categorical. And numerical values that represent each ordered category of a given dimension or indicator was supposed to be calibrated in the way it can be suitable to calculate degree of deprivation (Costa and De Angelis, 2008). Thus, for each indicator, the largest integer value is given to the category which represents the highest possible performance, and the lowest value is given to the category which represent the lowest performance.

3.3.1 Totally Fuzzy and Relative Approach (TFR)

The major development after the totally fuzzy and absolute approach of Cerioli and Zani (1990) is the totally fuzzy and relative approach of Cheli and Lemmi (1995). According to Cheli and Lemmi (1995), the totally fuzzy and absolute approach (TFA) of Cerioli and Zani (1990) has number of draw backs that need to be improved in order to make sure that poverty is clearly defined as a fuzzy concept. The first criticism forwarded byCheli and Lemmi (1995) is on the TFA attempt to avoid dichotomy used in the traditional crisp poverty analysis yet by introducing another two bounds which according to Cerioli and Zani (1990) is intended to create transition zone. But, according Cheli and Lemmi (1995) such claim will not go with the name associated with the approach; totally fuzzy. The second criticism made by Cheli and Lemmi (1995) is on the method used by in TFA to determine the membership function of a given household in a specified indicator based only on the considered household's performance. But, Cheli and Lemmi (1995) claims membership function must be prepared in the way they can also incorporate the distribution of deprivation in a particular indicator/ dimension across the households of the study area. TFA attempt to incorporate the relative nature of poverty through the methods used to attach weights among the indicators of a given dimension, and Cheli and Lemmi (1995) has also inherited the same approach to augment the relativity that is tried to be addressed through membership functions. But, in this research, improved weighting methods used in Betti and Verma (2008) are applied and will enable us to control for not only the distribution of deprivation among the households of the study area but also for the possible correlation between indicators of a given dimension.

As it has been indicated in table Al on the appendix, four dimensions are used to study the multidimensional nature of energy poverty. Two dimensions, indoor air pollution and media and communication, have two indicators under each while other dimensions, fuel and lighting are represented by only one indicator each. Moreover, indicators and dimensions used in this study are all categorical. Thus, the membership functions that are going to be used to represent the deprivation degree of each household in each indicator/dimension has to be adjusted in the way it can address the categorical yet fuzzy nature of deprivation in these indicators.

Costa and De Angelis (2008) has generalized the steps to be used in the analysis of poverty which is conceptualized as a vague concept, in this thesis too those steps are followed in order to reach to a single poverty index that represent the fuzzy multidimensional energy poverty level of the rural and small tows of Ethiopia.

Step one:

Before all the other steps are executed, first it is important to assign successive integer values to represent each categories of a specified indicator. Here, as Costa and De Angelis (2008) has clearly mentioned it, the process has to be uniform across all indicators in the way that the lowest integer will be associated with a category which represent the worst possible performance in the indicator, and the highest integer will be associated with a category of the best possible performance. The first dimension selected in this study which is indoor air pollution is represented by two indicators, type of kitchen and oven used by households. And the performance of households in the type of kitchens used in rural and small towns of Ethiopia is summarized under four categories. And while assigning integer values for the categories,the integer four is assigned to those households which cook in modern kitchens and one is assigned to those which use the same space both for living and cooking. The performance of households in their use of oven is summarized under three categories and the integer three is assigned to households which use Electric mitads and one is assigned to those who use traditional. The second dimension used is type of cooking fuel, and though households of the study area are found to use multiple alternatives of fuels as their main cooking fuel, here in this study they are summarized under three categories, and those which use solid fuels are assigned with integer value one and those which use electricity are assigned with three. When we come to the forth dimension which is source of energy for lighting, the alternatives used by households in the study area area categorized in to three , where light from electricity is represented by the integer three, light from unclean sources like firewood are assigned with the integer one.

Step two:

The second step is to select the appropriate membership function so as to determine the degree of deprivation each household face in each selected indicators. Here, given the fact that all indicators selected are categorical in nature, the integer values we have attached in step one need to be converted in to fractional values that are going to be limited between zero and one boundary. Here the vagueness of poverty in the case of multidimensional poverty is manifested in the vagueness of indicators used in the analysis (Fustier, 2006). For categorical indicators used in this study, unlike the membership function proposed by Cerioli and Zani (1990), which considers the rank of categories to represent an equally spaced metric variable, Cheli and Lemmi (1995) approach which instead go with the distribution of deprivation in that given indicator among households of the study area is selected. Thus, based on Cheli and Lemmi (1995) the membership function for deprivation in a given indicator for a given household is computed as presented in equation 3.1.

$$g(d_{ik}) = g(d_k^{(c)}) = \begin{cases} 0 & if d_{ik} = d_k^{(C)}; C = The best catagory \\ g(d_k^{(c+1)} + \frac{H(d_k^{(c)}) - H(d_k^{(c+1)})}{1 - H(d_k^{C})}; & if d_{ik} = d_k^{c}; c < C \end{cases} \tag{3.1}$$

Where $g(d_k^{(c)})$ represents degree of deprivation associated with the category in which a given household i happens to be in the k_{th} indicator of dimension d, C represents the best possible category of a given indicator K, $H(d_k^{(c)}$ represents the cumulative distribution of value associated with the category of the given household i, and $H(d_k^{(c+1)})$ represent the cumulative distribution associated with the next best category, and $H(d_k^{C})$ represent the cumulative distribution associated with the best category of the given item k.

Step three:

As it is indicated on table A1 in the appendix, two of the dimensions selected, indoor air pollution and access to media and communication are represented by more than one indicators. And the degree of deprivation in each indicator generated using TFR approach in step two needed to be aggregated so as to get degree of deprivation in the dimension that host them. Thus, we need to aggregate degree of deprivation in type of kitchen and type of oven used so as to get degree of deprivation in indoor air pollution. And also we need to aggregate degree of deprivation in access to media and access to communication devices so as to get degree of deprivation in access to media and communication. The other two indicators used in the study, type of main cooking fuel and source of energy used for lighting are considered both as indicator and dimension, thus they will not need any aggregation in this stage.

So as to complete the task the weight that is going to be attached with each indicator has to be determined first. And as it has been mentioned in number of researches made applying the fuzzy set approach to study multidimensional poverty(for example see (Betti and Verma (2008); Cheli and Lemmi (1995)), here too all dimensions selected to study multidimensional energy poverty are assigned with equal weight so as to indicate all dimensions selected are equally important for the energy well being of households. And these weights are further distributed between indicators of each dimension. Though Cheli and Lemmi (1995) has used Cerioli and Zani (1990) method to assign weights to indicators of a given dimension, here in this research, i have applied method of Betti and Verma (2008) which consider not only the distribution of deprivation in the indicator, but also the possible correlation among the indicators of the dimension that hosts them.

$$w^{cz}_{k} = log(n/\sum d_{k,i} n_i) \tag{3.2}$$

Where w^{cz}_{k} is the weight to be assigned to the K^{th} indicator using Cerioli and Zani (1990) approach, n is the population size, $d_{k,i}$ is the level of deprivation of i^{th} household in k^{th} indicator of d^{th} dimension, and n_i represents the sample weight attached with the i^{th} household.

$$w^{b}_{k} = \left(\frac{1}{1+\sum_{k=1}^{K} \rho_{k,k'} | \rho_{k,k'} < \rho_H}\right) x \left(\frac{1}{1+\sum_{k'=1}^{K} \rho_{k,k'} | \rho_{k,k'} >= \rho_H}\right) \tag{3.3}$$

Here $\rho_{k,k'}$ level of correlation between between two indicators, ρ_H is a threshold. Thus, the overall weight will be the combination of the two equations mentioned above.

$$w^{bv}_{k} = \left(w^{cz}_{k}\right) . \left(w^{b}_{k}\right) \tag{3.4}$$

Given the above formula for the weights, we should be careful in defining weights as a representatives for the level of importance of a given indicator. Rather it is something that indicate the level of distribution of deprivation among the population(Cerioli and Zani, 1990).

once we decide the weight to be attached with each indicators of a given dimension, we can determine the deprivation score for each dimension as weighted average as indicated in 3.5.

$$S_{d,i} = \frac{\sum_{k \in d} w_k(d_{ki})}{\sum w_k} \tag{3.5}$$

Where $S_{d,i}$ is the deprivation score of i^{th} household in d^{th} dimension, w_k is the weight assigned to the k^{th} indicator of d^{th} dimension.

Step five

Here degree of deprivation in indoor air pollution, type of main cooking fuel used, source of energy for light and access to media and communication are aggregated for each household in order to get their respective degree of energy poverty. To do so there are three alternative methods of aggregation, integration, union and average. Since each can tell us the different side of energy deprivation faced by households, all are applied in this study. After assuming that all dimensions have equal importance for the energy well being households, we can aggregate deprivation scores in each dimensions as indicated below.

$$u_i = \left(\frac{\sum_d w_d S_{d,i}}{\sum_d w_d} \right) \tag{3.6}$$

Where u_i is the fuzzy multidimensional energy poverty status of household i, w_i is the weight attached to dimension d and $S_{d,i}$ is the deprivation score of household "i" in dimension "d". And using intersections, we can generate the level of simultaneous deprivation or what is called intensive deprivation in Betti and Verma (2008) as follows.

$$u_i = I_{min}(S_{1,i}, S_{2,i}, S_{3,i}, S_{4,i}) \tag{3.7}$$

And using unions,we can determine the level of energy poverty which is also called extensive deprivation in Betti and Verma (2008).

$$u_i = U_{max}(S_{1,i}, S_{2,i}, S_{3,i}, S_{4,i}) \tag{3.8}$$

Step six

Once, we become able to determine the fuzzy multidimensional energy poverty index of each household, we have to aggregate it in order to come up with a single index that represent average degree of energy poverty in the study area.

$$EPI = \frac{\sum_{i=1}^{N} \mu_i n_i}{\sum_{i=1}^{N} n_i} \tag{3.9}$$

3.3.2 Fuzzy set Longitudinal Analysis

Like the traditional crisp poverty analysis, the fuzzy set approach can be adjusted in to longitudinal analysis which can enable us to infer important longitudinal nature of poverty like households chance to ever experience poverty, never expedience poverty, or stay in poverty for the majority of the study period and rate of re-entry and exit. And according to Betti et al. (2006) such important factors can be found using joint membership functions which are going to be constructed from the cross sectional membership functions which are used in determining the fuzzy multidimensional energy poverty index above. And the construction of joint membership functions are guided by composite operators of citetbetti2008fuzzy as stated in table 2.2 above.

As suggested in Betti et al. (2006), here too the degree values which represent each household's degree of energy poverty will be taken to represent households propensity to be energy poor or having degree of truth that equals one in each dimension. And, its complement will represent the propensity of not being energy poor (having zero membership degree, or having zero degree of truth). **Ever in poverty**
Propensity to experience some positive degree of deprivation atleast once through out all the study period can be calculated for each household as in 3.10.

$$U_{T,i} = max(\mu_1, \mu_2, \mu_3) \tag{3.10}$$

Never in poverty
Given the international and national level efforts being made on achieving universal access to clean, efficient and modern energy, through time households might end up not experiencing energy deprivation of any degree across all of the dimensions selected over longer period of time. For each household such propensities of never experiencing energy poverty will be found as in 3.11. And, it has to be noted that these propensities are nothing but the

complements of the propensities to ever experience energy poverty.

$$\begin{aligned} \bar{U}_{T,i} &= min(\bar{\mu}_{1,i}, \bar{\mu}_{2,i}, \bar{\mu}_{3,i}) \\ \bar{U}_{T,i} &= 1 - max(\mu_{1,i}, \mu_{2,i}, \mu_{3,i}) \\ \bar{U}_{T,i} &= (1 - U_{T,i}) \end{aligned} \tag{3.11}$$

Persistent poverty(poor in all periods)

Given the fact that the rate of electrification is far behind in the rural and small towns of the country and the access to clean cooking fuels is far from showing drastic improvement, households in such areas will be faced with deprivation in these dimensions over longer period of time. Households propensity to experience positive degree of energy poverty across all time periods will be computed as in 3.12.

$$I_{T,i} = min(\mu_{1,i}, \mu_{2,i}, \mu_{3,i}) \tag{3.12}$$

Where $I_{T,i}$ represent propensity to be energy poor in all periods and $\mu_{t,i}$ represent household i degree of energy poverty in each cross sectional period t.

Once household level of these propensities are found, we can aggregate the results across the population by finding their population weighted average.

Rate of re-entry and exit

Betti et al. (2006) come up with the following methods to compute re-entry and exit rate when poverty is rather conceptualized as a vague predicate and fuzzy set approach is used to measure it. Thus, before we determine the overall re-entry and exit rate in the study area, first we have to compute each household's contribution to the overall re-entry rate and exit rate as follows. Then the individual contributions are aggregated so as to get the overall re-entry rate in the study area.

Given that we have data only from three time periods, we can compute the rate of exit only during the last survey period. And, as it is mentioned earlier, the results are going to be based on the membership functions not on the count. Thus, as forwarded by Betti et al.

(2006), the re-entry rate can be calculated as in equation3.13.

$$RER_i = \left(\frac{\mu_1 \bigcap \bar{\mu}_{t-1} \bigcap \bar{\mu}_t}{\mu_1 \bigcap \bar{\mu}_{t-1}} \right) = \left(\frac{max[0, min(\mu_1, \mu_t) - \mu_{t-1}]}{max[0, \mu_1 - \mu_{t-1}]} \right) \tag{3.13}$$

Where RER_i is the contribution of household i to the overall re-entry rate of the study area. And the contribution of each household for the overall exit rate of the study area will be computed as in equation3.14.

$$ExitR_i = \left(\frac{(\mu_1 \bigcap \mu_{t-1}) \bigcap \bar{\mu}_t}{(\mu_1 \bigcap \mu_{t-1})} \right) = \left(\frac{max[0, min(\mu_1, \mu_{t-1}) - \mu_t]}{min(\mu_1, \mu_{t-1})} \right) \tag{3.14}$$

Where $ExitR_i$ is the contribution of household$i$ to the overall exit rate, μ_1 is the degree of poverty membership for household i during the first period, μ_{t-1} is the degree of poverty membership for household i during the second period, and μ_t is the degree of poverty membership during the last period.

In order, to get the overall re-entry and exit rate in the study area, all we have to do is to find the weighted average where the weights are those sample weights which are attached with each household.

3.4 Dynamic Fractional Regression

Due to the conceptualization of energy poverty in its multifaceted nature, and the use of fuzzy set analysis due to its vague nature, households in this study are no longer identified as being energy poor or non poor using some predetermined energy poverty line. Rather, each household is represented by a value that indicates its degree of membership in being energy poor. These values will be among the possible infinite fractional numbers between the two limits (zero and one) that indicate where the level of a given household's energy poverty is. Further, households will have positive probability of having zero degree of membership to energy poverty if they are going to be found not deprived in any of the dimensions selected. On the flip side, if households are going to be found deprived in all dimensions, they will have 100% (or represented by one) degree of membership to energy poverty. As a result, the econometric regression to be undertaken shall support the presence fractional dependent variable with substantial number of observations at the two corners; zero and one while also managing to include one period lagged value of the dependent variable as a determinant.

The first option is to apply log odds transformation to the dependent variable before undertaking the regression. This transformation will make the dependent variable to assume continuous values which are not bounded as it used to be. Then the regression can be executed using ordinary least squares (OLS) with careful interpretation of coefficients since after the transformation the dependent variable will take on negative values (Villadsen and Wulff, 2018). Though it is logical to apply this approach for required analysis with fractional dependent variable, it will automatically fail once the dependent variable begins to have substantial number of observations at the two corners; zero and one (Loudermilk, 2007; Papke and Wooldridge, 1996). Due to the presence of households with zero or one degree of energy poverty, it will be inappropriate to apply the method in the case this study.

The other option is to apply beta regression. First applied by Ferrari and Cribari-Neto (2004), the whole model is dependent on the assumption that the dependent variable will follow a beta distribution. Even it has been applied in longitudinal analysis by handling panel data through beta distributed generalized linear mixed model (GLMM), for example see (Hunger et al., 2012). But the method is highly criticized for its poor handling of observations at the corner (Papke and Wooldridge, 1996; Ramalho et al., 2011; Villadsen and Wulff, 2018).

A pioneering approach in dealing with fractional dependent variables which incorporate observations at the two corners is the one proposed in Papke and Wooldridge (1996), and it applies standard logit framework under qusi-maximum likelihood estimation. But, it can be applied only with cross sectional data set, and modifications are required for the case of panel data set (Papke and Wooldridge, 1996, 2008). Papke and Wooldridge (2008) propose an approach to deal with fractional dependent variables in the case of panel data regression. Here, even though it will be possible to generate consistent estimates while dealing with the fractional nature of the dependent variable, the model has not proposed methods to deal with initial condition problem that could result if the lagged dependent variable is going to be included as explanatory variable. Thus, dealing with dynamic fractional regression will require a method that can deal with not only the nature of the dependent variable but also the possible correlation the lagged dependent variable can create with the unobserved heterogeneity (Papke and Wooldridge, 2008).

To fill this gap, Loudermilk (2007) introduce the use of two limit random effect tobit regression with fractional dependent variables while treating endogenity problem that can result due to the correlation of the lagged dependent variable and the unobserved heterogeneity with the application of simple solutions to initial condition problem in dynamic nonlinear regression as suggested in Wooldridge (2005).

Usually, the use of tobit regression with fractional dependent variable is criticized for resulting in inconsistent estimates. And as stated in Ramalho et al. (2011); Villadsen and Wulff (2018) most of this inconsistency is the result of absence of substantial number of observations at the two corners in most variables with fractional values. Thus, it is necessary to make sure the selected dependent variable has substantial number of observations not in one but at both corners if tobit regression is going to be used.

Since I have applied three alternative methods of aggregation, average, intersection and union, three alternative FMEPI representing households energy poverty are generated. Though all FMEPI generated have a fractional nature, it will be appropriate to select among them in order to undertake a dynamic regression via two limit random effect tobit regression with unobserved heterogeneity so as to investigate the presence of state dependence in energy poverty. Here selection is needed since we need to avoid inconsistency that could result from the use of tobit regression with fractional dependent variables with values which are bounded n zero and one limit, but lack observations at the two corners (Ramalho et al., 2011).

While using averages as a method of aggregating deprivation scores in each dimension, even though, 1482 observations across the three survey periods are found to be deprived in all dimensions selected, only 15 observations are found not deprived in all dimensions. As a result, I found it inappropriate to represent the households' degree of energy poverty determined through these aggregation technique in the two limit random effect tobit regression which require substantial number of observations at the two corners.

While using unions as a method of aggregation, FMEPI are found to be concentrated at the right corner. Using this method, across the three survey period 10,809 observations were found having degree of energy poverty that is 100%. And only 15 observations were found on the left corner, zero. And the overall standard deviation associated with this variable is only 0.0543 making it risky to use it as a dependent variable representing households level of energy poverty.

Representing households' energy poverty using intersections to aggregate degree of deprivation faced in each dimension will convey information about the minimum possible deprivation to be faced by a given household across all dimensions, or what is called simultaneous deprivation or intensive deprivation (Betti and Verma, 2008). And using this aggregation technique, across the three survey periods, 1482 observations which make 13.58 % of the total observation were found with FMEPI of one , and 3856 observations which make upto 35.32% of the total observations are found with FMEPI of zero. And the fact that now we have substantial number of observations at the two corners, zero and one, it will be possible to use two limits random effect tobit regression with the following model specification.

Let us begin our model with latent variable setup.

$$y_{it}^{*} = x\beta + y_{i,t-1}\,\rho + c_i + \mu_{it} \tag{3.15}$$

$$\mu_{it}|(x_{it}, y_{i,t-1}, c_i) \sim N(0, \sigma_{\mu}^{2}) \tag{3.16}$$

Where x represents the set of strictly exogenous explanatory variables which represent the socio economic and demographic factors of households in the rural and small towns of Ethiopia. And these includes sex of household head, age of household head, literacy of household head, proportion of female household members aged seven and above, proportion of children aged seven and above, number of elderly household members, number of available room per household, access to large weakly market, access to main road, log of real income per adult equivalent, log of real monthly energy expenditure, region, area of residence. Further in equation 3.15, $y_{i,t-1}$ represents one period lagged value of energy poverty, and it is used to investigate the presence of state dependence in energy poverty, c_i represents the time invariant household specif unobserved effects and μ_{it} represents normally distributed error term with zero mean and constant variance.

Given that y^*_{it} is latent variable, and our dependent variable has two corner values at zero and one, the observed y will be

$$y_{it} = \begin{cases} 0, if y^*_{it} \leq 0 \\ y^*_{it}, if 0 < y^*_{it} < 1 \\ 1, if y^*_{it} \geq 1 \end{cases}$$

Know, had c_i was normally distributed with zero mean and constant variance, and had we were able to assume it as an exogenous, the standard random effect tobit regression would have been put to work Verbeek (2008). But, with the presence of the lagged dependent variable, $y_{i,t-1}$, as an explanatory, treating c_i the same way as in the case of random effect tobit regression will lead us to the famous initial condition problem. Thus, before we proceed with the estimation, the time invariant unobserved heterogeneity must be modeled.

The problem of initial condition emerges because the stochastic process that generates the dependent variable which in the case of this study is energy poverty can not be observed from the the very beginning, or households in the study area have been experiencing energy poverty long before the survey that generate the panel data set was started (Verbeek, 2008). As a result, there will be a correlation between the unobserved effects and the lagged dependent variable, and business as usual can not be conducted using the random effect non linear models, tobit or probit. And if so, it will result in biased and inconsistent estimates (Wooldridge, 2005).

There are alternative methods of dealing with initial condition problem.Heckman (1987) proposes to treat initial conditions of the dependent variable as endogenous explanatory variable and model its density functions conditioned on other explanatory and the unobserved heterogeneity. But, Wooldridge (2005) has criticized the approach for its computational difficulty to obtain parameter estimates and average partial effects. The other technique is to apply fixed effects and systematically treat the unobserved effect, but this will get us to the incidental parameter problem as the number of cross sectional elements N is large in the panel data set while the time period is limited to three.

Wooldridge (2005) propose a solution by introducing need to formulate the auxiliary distribution of unobserved individual heterogeneity conditioned on the initial condition and the time dummies of all other exogenous explanatory variables. And given its flexibility, opportunity it gives for straight forward estimation, and the possibility of getting average partial effects,the same approach is used to deal with initial condition problems in this study too. Thus, the density of c_i is specified as

$$D(c_i|y_{i0},x_i) = \gamma_0 + \gamma_1 y_{i0} + \gamma_2^{'} x_i + a_i \tag{3.17}$$

$$a_i|y_{i0},x_i \sim N(\gamma_0 + \gamma_1 y_{i0} + \gamma_2^{'} x_i, \sigma_a^2) \tag{3.18}$$

Where y_{i0} is the initial degree of energy poverty experienced by a household, x_i is time dummy of the explanatory variables, and a_i is the new unobserved heterogeneity with that has no correlation with the lagged dependent variable. And the new latent model will be

$$y_{it}^{*} = x\beta + y_{i,t-1}\rho + \gamma_0 + \gamma_1 y_{i0} + x_i\gamma_2 + a_i + \mu_{it} \tag{3.19}$$

Density of y_{it} conditioned by x_{it}, $y_{i,t-1}$,y_{i0} and a_i will be

$$P(y_{it} = 0|x_{it},x_i,y_{i,t-1},y_{i0},a_i) = \Phi\left(\frac{-x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2^{'} x_i - a_i}{\sigma_\mu}\right) \tag{3.20}$$

$$P(y_{it} = 1|x_{it},x_i,y_{i,t-1},y_{i0},a_i) = \Phi\left(\frac{x\beta + y_{i,t-1}\rho + \gamma_0 + \gamma_1 y_{i0} + \gamma_2^{'} x_i + a_i - 1}{\sigma_\mu}\right) \tag{3.21}$$

and

$$\frac{\partial P(y_{it} \leq y|x_{it},x_i,y_{i,t-1},y_{i0},a_i)}{\partial y} = \frac{1}{\sigma_\mu}\phi\left(\frac{y_{it} - x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2^{'} x_i - a_i}{\sigma_\mu}\right) \tag{3.22}$$

Thus, the density of y_{it} would become

$$f_t\left(y_{it}|x_{it},x_i,y_{i,t-1},y_{i0},a_i\right) = \Phi\left(\frac{-x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2' x_i - a_i}{\sigma_\mu}\right)^{n[y_{it}=0]} \times \Phi\left(\frac{x\beta + y_{i,t-1}\rho + \gamma_0 + \gamma_1 y_{i0} + \gamma_2' x_i + a_i - 1}{\sigma_\mu}\right)^{n[y_{it}=1]} \times \frac{1}{\sigma_\mu}\phi\left(\frac{y_{it} - x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2' x_i - a_i}{\sigma_\mu}\right) \tag{3.23}$$

Now, given these densities the joint distribution of y_it will be generated as proposed by (Wooldridge, 2005) as follows.

$$f\left(y_{i1,\ldots,y_iT|x_i,y_{i,t-1},y_{i0},a_i}\right) = \prod_{t=1}^{T} f_t\left(y_{it}|x_{it},x_i,y_{i,t-1},y_{i0},a_i\right) \tag{3.24}$$

And the log likelihood function to be used in estimating the partial effects will be generated by integrating the distribution of y_{it} against the distribution of a_i.

$$L = \sum_{i=1}^{N} log\left\{\int\left[\prod_{t=1}^{T} f_t\left(y_{it}|x_i,y_{i,t-1},y_{i0},a_i\right)\right]\frac{1}{\sigma_a}\phi\left(\frac{a}{\sigma_a}\right)da\right\} \tag{3.25}$$

And given the assumption of normal distribution, the expected value of y_{it} can be found as

$$E(y_{it}|x_{it},x_i,y_{i,t-1},y_{i0},a_i) = \Phi\left(\frac{x\beta + y_{i,t-1}\rho + \gamma_0 + \gamma_1 y_{i0} + \gamma_2' x_i + a_i - 1}{\sigma_\mu}\right) + \left[\Phi\left(\frac{1 - x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2' x_i - a_i}{\sigma_\mu}\right) - \Phi\left(\frac{-x\beta - y_{i,t-1}\rho - \gamma_0 - \gamma_1 y_{i0} - \gamma_2' x_i - a_i}{\sigma_\mu}\right)\right] \times E\left(y_{it}|x_{it},x_i,y_{i,t-1},y_{i0},a_i,0 < y_{it}\right) \tag{3.26}$$

Deriving this with respect to needed variables will give use partial effects. But due to the presence of unobserved effects the partial effects generated through this process will not give important information by them selves, instead partial effects averaged across the distribution of the unobserved effect must be estimated(Wooldridge, 2005).

let

$$m(x_{it}, x_i, y_{i,t-1}, y_{i0}, a_i; \theta) = E(y_{it}|x_{it}, x_i, y_{i,t-1}, y_{i0}, a_i) \tag{3.27}$$

$$\{r(x_i, y_{i,t-1}, y_{i0}, a_i) = E\left[\int m(x_{it}, x_i, y_{i,t-1}, y_{i0}, a_i; \theta) h(c|y_{i0}, x_i; \gamma)\, dc\right] \tag{3.28}$$

$$\hat{r} = \frac{1}{N}\sum_{n=1}^{N} E\left[m(x_{it}, x_i, y_{i,t-1}, y_{i0}, a_i; \theta)|y_i 0, x_i\right] \tag{3.29}$$

Derive this with respect to the explanatory and will give us the average partial effects.

Chapter 4

Results and Discussion

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics of Variables on Household Characteristics

Below on table 4.1, I have presented the descriptive statistics of variables that represent selected socioeconomic and demographic characteristics of households in the rural and small towns of Ethiopia, and these are used as explanatory variables in the econometric analysis. As I have mentioned it earlier, among households covered by ESS, I have selected those who were included during all three surveys. When we observe the distribution of this sample over regions of the country, except for region Tigray which contributed about 10% of the sample, the rest take nearly equal sample share. Here, it will be important to remember the last region which is mentioned as "other region" is the combination of samples from smaller regions of the country. The sample proportions of the regions remain the same throughout the three rounds of surveys. And also we can see that most of sampled households come from rural areas of the country and cover about 88.54% of the data while the rest 11.46% are sampled from small towns of the country. And this distribution remained the same over the three rounds of surveys.

As it can be seen from the table 4.1, during the first survey, 76.2% of the households are found to be headed by males, and their share in households headship did not show much change over the three rounds of surveys. Age of household heads was 44.4 years on average in 2011/2012, and this rose to 46.9 and 47.9 in 2012/2013 and 2015/2016 survey years respectively. When we come to household heads' literacy, those who are illiterate take the majority across all three survey periods.

During 2011/2012, the average proportion of female household members was 41.85%

and it reached to 45.46% during the last survey. Number of rooms per household was 1.69 on average during the first survey and it has increased to 1.79 during the second and to 1.828 during the third survey period. Both access to large weakly market and access to main road improve over time. But even during 2015/16 survey period, 83.18% of sampled households were without access to main asphalt road in their village.

Table 4.1: Descriptive statistics of variables on household characteristics

Variables	2011/12		2013/14		2015/16	
	Mean	Stand.Dev.	Mean	Stand.Dev.	Mean	Stand.Dev.
Male	76.2	0.426	0.76	0.4274	0.757	0.4289
Female	23.8	0.426	0.24	0.4274	0.243	0.4289
Head's age	44.4	15.5116	46.16	15.32	47.9	15.14
Illiterate	0.6457	0.4783	0.6492	0.47727	0.6405	0.4798
Literate	0.3543	0.4783	0.3508	0.47727	0.3595	0.4798
Proportion of female aged seven and above	0.4158	0.2254	0.4900	0.3164	0.4546	0.2730
Proportion of children aged seven and above	0.2687	0.2256	0.3345	0.2708	0.3015	0.2360
Number of elderly	0.1481176	0.3906	0.1737	0.4336	0.1997	0.4398
Number of rooms	7.3491	12.0311	7.8683	7.8683	7.617	20.670
Access to large weekly mkt	0.4885	0.4999	0.5298	0.4992	0.5887	0.4921
No access to large weekly mkt	0.5114	0.4999	0.4702	0.4992	0.4112	0.4921
Access to main road	0.1378	0.3447	0.1504	0.3575	0.1690	0.3748
No access to main asphalt road	0.8621	0.3447	0.8495	0.3575	0.8309	0.3748
Log of real income per adult equivalent	8.349028	0.6662	8.4331	0.6168	8.5025	0.6319
Log of real monthly energy expenditure	3.15483	1.315787	3.3092	1.2378	3.2625	1.284
Tigray	0.1050	0.3066	0.1050	0.3066	0.1050	0.3066
Amhara	0.2146	0.4106	0.2146	0.4106	0.2146	0.4106
Oromiya	0.2031	0.4023	0.2031	0.4023	0.2031	0.4023
SNNP	0.2564	0.4367	0.2564	0.4367	0.2564	0.4367
Other	0.2210	0.4149	0.221	0.4149	0.2210	0.4149
Small town	0.1146	0.3186	0.1146	0.3186	0.1146	0.3186
Rural	0.8854	0.3186	0.8854	0.3186	0.8854	0.3186

4.1.2 Descriptive Statistics on Deprivation Per Dimension

Here i have presented two way tables[1] to see households deprivation under selected dimensions and indicators. And, the two way tables were preferred over the one way tables so as to infer information that can pave our way to further analysis to be made using the fuzzy set analysis and the dynamic regression.

Table 4.2 below presents choice of cooking fuel by households which use alternative sources of light which are grouped under electricity and other. The intention is to see if electricity is going to be used for all household activities that require energy once it is accessed.

As it is shown on the table, during the first survey 17.5% of sampled households used electricity for lighting. And among these households, only 0.63% of them use it for cooking purpose too. And, among those households which light their home at night using electricity, 95.87% of them choose solid fuels for cooking purposes. And from solid fuels firewood dominated with 81.72%. And we can also observe only 1.43% of them used Kerosene for cooking. During the same survey period, 82.5% of households are found to use sources other than electricity for lighting. And from these households, the large majority, which cover up to 98%, relay on solid fuels for cooking. 0.03% of them use Kerosene while 0.09% uses electricity, solar or butane gas for cooking.

Know let us see if the situation has improved during the second survey period. During 2013/2014 survey period, percentage of households which use electricity for lighting has increased from what it used to be during the first period and reached to 23.7%, and among them those who use it for cooking purpose increased to 2.45%, which is an improvement from 0.63% in the first survey. Solid fuels still dominate cooking fuels with 93.34% of households with access to electricity stick with them for cooking. When we come to households which do not use electricity for lighting, solid fuels still dominate with 99% with the majority of it contributed by households using firewood.

[1]To make the explanations of the two way tables presented in this section more clear, let me summarize the way they are constructed. In each cell there are two numbers; the top ones representing frequency while the bottom ones represent percentage. The three rows at the bottom of the table represent total number and percentage of households with attributes represented by each column during each round of survey. And the last column represents number of households with attributes represented by each row.

During the last survey, households which use electricity for lighting further increased and reached 36.4%. But when we ask if the same happened to percentage of households which use it both for lighting and cooking purposes, even though the frequency has increased, the percentage remains the nearly the same as the previous survey.

As it is also shown by the increasing share of households using electricity for lighting purposes,according to Bank (2020), in Ethiopia, overall access to electricity has increased from 33.36% in 2010 to 42.9% in 2016. And the rural coverage has increased from 22.4% in 2010 to 32.36% during 2016. According to Bank (2020), between the year 2010 and 2016, a period which cover the Ethiopian Growth and Transformation Plan I(GTPI), GDP per capita of the country more than doubled, reaching to $717.12 from the initial $341.55. During the same period, the county's energy production increased from 2000MW to 4000MW. But, the results of the descriptive statistics shows, despite the improvements mentioned earlier, the use of electricity for cooking purpose did not seem improve while households' access to it keeps increasing over time. And this confirms Muller and Yan (2018) conclusion that households in developing countries of Africa will keep on using traditional energy sources for core household activities while they tend to use modern energy sources for those activities that are considered to be of least prioritized. Here on the scale of prioritizing in the need for modern energy , according to Kowsari and Zerriffi (2011)cooking and heating comes first and is followed by lighting and entertainment and information.

Number of theories have tried to give an explanation to what seems to be common behavior of energy demand for electricity among households of developing countries. That is even despite the presence of an improvement in the level of households income, they do not to seem to use modern fuels for all household tasks that require energy. And this is best explained by fuel stacking behavior. And, number of researches which are made on households energy demand in Ethiopia has shown the presence of this behavior in Ethiopia too(Alem et al., 2016; Guta, 2012; Mekonnen and Köhlin, 2009). And these researches have indicated reasons like availability of traditional fuels for free, unreliability of modern fuels, relatively higher cost required to use modern fuels and the appliances they require, local custom and in applicability of modern fuels to cook traditional dishes etc as the reasons behind. As Bersisa (2019) has put it, works has to be made so as not only to increase physical accessibility of modern fuels but also their economic accessibility and reliability.

Table 4.2: Type of cooking fuel used by those households with and without access to electricity

Source of light	wave	Main Cooking Fuel: Collected Firewood	Purchased Firewood	Charcoal	Crop Residue	Dung Manure	Sawdust	Kerosene	Butane/gas	Electricity	Solar Energy	None	Other	**Total**
Electricity	Wave1	254 0.4025	260 0.4120	45 0.0713	19 0.0301	24 0.0380	3 0.0048	9 0.0143	0 0.00	4 0.0063	0 0.00	9 0.0143	4 0.0064	631 1
	Wave2	437 0.5105	259 0.3026	40 0.0467	34 0.0397	29 0.0339	0 0.00	11 0.0129	2 0.0023	21 0.0245	0 0.00	19 0.0222	4 0.0046	856 1
	Wave3	830 0.6264	270 0.2038	49 0.0370	60 0.0453	47 0.0355	1 0.0008	2 0.0018	1 0.0008	31 0.024	4 0.03	16 0.0121	14 0.016	1325 1
Other sources than electrcity	Wave1	2,572 0.8654	84 0.0283	8 0.0027	101 0.0340	160 0.0538	0 0.00	9 0.0030	1 0.0003	1 0.0003	1 0.0003	8 0.0027	27 0.0091	2,972 1
	Wave2	2,387 0.8639	83 0.03	13 0.0047	88 0.0318	166 0.0601	0 0.00	16 0.0043	1 0.0004	0 0.00	0 0.00	1 0.0004	12 0.0043	2,763 1
	Wave3	1,927 0.8328	53 0.0229	11 0.0048	120 0.0519	158 0.0683	3 0.0013	7 0.0030	1 0.0004	0 0.00	3 0.0013	7 0.003	24 0.0104	2,314 1
Total	Wave1	2,826 0.7843	344 0.0955	53 0.0147	120 0.0333	184 0.0511	8 0.0008	18 0.005	1 0.0003	5 0.0014	1 0.0003	17 0.0047	31 0.0086	3,603 1
	Wave2	2,824 0.7803	342 0.0945	53 0.0147	122 0.0337	195 0.0539	0 0.00	3 0.0008	21 0.0058	0 0.00	21 0.0058	20 0.0055	16 0.0044	3,619 1
	Wave3	2,757 0.7576	323 0.0888	60 0.0165	180 0.0495	205 0.0563	4 0.0011	9 0.0025	2 0.0005	31 0.0085	7 0.0019	23 0.0063	38 0.0104	3,639 1

Wave 1 Pearson chi2(11) = 1.2e+03 Pr = 0.000
Wave 2 Pearson chi2(9) = 841.2672 Pr = 0.000
Wave 3 Pearson chi2(11) = 495.3191 Pr = 0.000

The other important point that has to be noticed with the popularity of traditional fuels among households is the inevitability of indoor air pollution. And beside the use of traditional fuels,the problem is magnified with the type of kitchen and oven used. According to Smith et al. (2000), the pollutants concentration indoor is varied with the type of kitchen type type of fuel used, and they has proved that those who cook using solid biomass fuel in indoor kitchen are four times more exposed to hazardous pollutants that can cause severe respiratory problems than those who use clean fuel.

Table 4.3 below shows type of kitchen used by households which use different types of cooking fuels. During the first survey period 42.19% of households use no kitchen for cooking indicating these households use the same space both for living and cooking purposes. This percentage showed a decline in the next two surveys and become 32.66%

and 27.84% respectively. The percentage of households using modern kitchen was the lowest in every period, but it showed a slightest of increment overtime. The use of separate but traditional rooms in the same housing unit has increased overtime. And the use of traditional kitchens outside the housing unit has also increased.

During the first wave, among households which use solid fuels for cooking, 42.07% of them use their living space also for cooking, 23.91% of them cook in traditional kitchen inside the housing unit, and 33.43% of them use traditional kitchen outside their housing unit. Less than one percent of them get the privilege to cook in modern kitchens.

The use of the same space for cooking and living among those who use solid fuels for cooking has decreased over the next two surveys and reached to 28% during the last survey. Though the rate is small, the use of separate traditional kitchens inside and outside the housing units has increased over the period of two surveys and during the last survey it reached to 32.61% and 37.72% respectively. Even though it is still less than one percent, the use of modern kitchens among solid fuel users has shown an improvement over the next two surveys.

The figures show that despite the improvement over time, there is huge vulnerability for indoor air pollution in the rural and small towns of the country. And this has the potential to affect the health of especially women and children who spent most of their day time with the task of cooking (Smith and Mehta, 2003).

The large majority of those who use liquid fuels for cooking do not have any room dedicated for cooking purpose in all three rounds of the survey. But it has shown reduction overtime from what it was 73.68% in the first survey to 50% in the last survey.

Table 4.3: Type of kitchen used by households which use different cooking fuels

Main cooking fuel	wave	No kitchen	Traditional kitchen inside house	Traditional kitchen outside house	Modern kitchen inside house	Modern kitchen outside house	Total
		Type of kitchen used					
Solid	Wave1	1,485 0.4207	844 0.2391	1,180 0.3343	11 0.0031	10 0.0028	3,530 1
	Wave2	1,155 0.3265	1,043 0.2948	1,306 0.3691	15 0.0042	19 0.0054	3,538 1
	Wave3	988 0.2804	1,149 0.3261	1329 0.3772	35 0.0099	22 0.0062	3,523 1
Liquid/bio gas	Wave1	14 0.7368	0 0.00	5 0.2632	0 0.00	0 0.00	19 1
	Wave2	14 0.5385	7 0.2692	5 0.1923	0 0.00	0 0.00	26 1
	Wave3	5 0.50	2 0.20	3 0.30	0 0.00	0 0.00	10 1
Electricity	Wave1	1 0.1667	1 0.1667	2 0.3333	1 0.1667	1 0.1667	6 1
	Wave2	2 0.952	5 0.2381	8 0.3810	6 0.2857	0 0.00	21 1
	Wave3	1 0.0263	5 0.1316	24 0.6316	7 0.1842	1 0.0263	38 1
Total	Wave1	1,500 0.4219	847 0.2377	1,187 0.3339	12 0.0034	11 0.0031	3,555 1
	Wave2	1,171 0.3266	1,055 0.2943	1,319 0.3679	21 0.0059	19 0.0053	3,585 1
	Wave3	994 0.2784	1,156 0.3237	1,356 0.3237	42 0.0118	23 0.0064	3,571 1

Wave 1 Pearson chi2(8) = 109.9128 Pr = 0.000
Wave 2 Pearson chi2(8) = 292.2637 Pr = 0.000
Wave 3 Pearson chi2(8) = 121.5511 Pr = 0.000

Once we have seen where households prefer to cooking using different type of fuels, let us see what type of technology they tend to use in order to cook.

As it can be seen from table 4.4 below, throughout the three surveys, majority of households are found to be using traditional mitad[2] for baking injera/bread. During the first survey the figure was 89.28% and it showed slight increment and reached to 91.37% in the last survey. From options in traditional mitad, removable ones are dominant. The use of

[2]Ethiopian traditional cooking stove mainly used for baking

improved rural technologies was low during each survey periods, while the percentage of households using electric mitad was below one percent during the first two surveys.

During the first survey among those households which use solid fuel as their main cooking fuel, 89.65% of them use traditional mitads for baking injera/ bread while only 2.49% of them use improved rural technology. Among those which use traditional mitad the ones that use removable mitad take the majority with 69.65%. During the next round of surveys, the use of traditional mitad among solid fuel users show slight increment reaching to 92.03% in the second and to 92.10% in the last round. The use of improved rural technology remained below 3% throughout the surveys. Here we can see some positive percents in the use of electric mitad among those who use solid fuels for cooking. This might be because in Ethiopian tradition, the main dishes have two parts; the first one is the sauce and the second one is injera or bread with which the sauce is eaten. Traditionally injera/bread is baked every two and three days while sauces require daily cooking. Thus, some households will relay on less expensive fuels to do the daily cooking and might prefer electricity to bake injera/ bread.

When increasing the rate of electrification and access to other modern energy sources face bottlenecks, the use of improved rural cooking stoves are usually seen as a solution, since they are capable of reducing amount cooking fuels required (usually firewood, charcoal), reduce indoor air pollution by using chimney, and avoid direct exposure of the cookers to the open fire (Arora et al., 2020). But, the dominance of traditional mitad, both renewable and non renewable, among those who use solid fuels is an indicator of a very early stage in the introduction of improved rural technologies in the study area. And this will result in a consequence that can manifest itself in the form of exposure to respiratory health problems, fire hazards, and environmental impacts.

When we come to those using liquid fuels to cook, the majority of households seems to use no oven, indicting they do not prepare injera/bread at home. But their percentage fall from 63.16% in the first survey to 36.36% in the last. And the use of traditional mitad for cooking has shown an increment from 21.05% in the first round to 54.55% in the last round.

Majority of households which use electricity for cooking seem to use electric mitad for baking. The highest percentage was registered during the second survey with 80.95%, but it declines back to what it was in the first round.

Table 4.4: Type of oven used by households which use different cooking fuels

Main cooking fuel	**wave**	Traditional mitad removable	Traditional mitad non removable	Improved rural technology	Electric mitad	None	**Total**
		Type of oven used for baking injera/bread					
Solid	Wave1	2458 0.6965	707 0.2003	88 0.0249	6 0.0017	270 0.0765	3,529 1
	Wave2	2620 0.7410	634 0.1793	71 0.0201	12 0.0034	199 0.0563	3,536 1
	Wave3	2508 0.7107	742 0.2103	102 0.0289	12 0.0034	165 0.0468	3,529 1
Liquid/bio gas	Wave1	4 0.2105	2 0.1053	1 0.0526	0 0.00	12 0.6316	19 1
	Wave2	11 0.4231	1 0.0385	0 0.00	1 0.0385	13 0.5	26 1
	Wave3	6 0.5455	1 0.0909	0 0.00	0 0.00	4 0.3636	10 11
Electricity	Wave1	2 0.3333	0 0.00	0 0.00	4 0.6667	0 0.00	6 1
	Wave2	2 0.0476	3 0.1429	0 0.00	17 0.8095	0 0.00	21 1
	Wave3	7 0.1842	5 0.1316	0 0.00	25 0.6579	1 0.0263	38 1
Total	Wave1	2464 0.6933	709 0.1995	89 0.0250	10 0.0028	282 0.0793	3,554 1
	Wave2	2,632 0.7346	238 0.1781	71 0.0198	30 0.0084	212 0.0592	3,583 1
	Wave3	2521 0.7046	748 0.2091	102 0.0285	37 0.0103	170 0.00475	3,578 1

Wave 1 Pearson chi2(8) = 1.0e+03 Pr = 0.000
Wave 2 Pearson chi2(8) = 1.7e+03 Pr = 0.000
Wave 3 Pearson chi2(8) = 1.6e+03 Pr = 0.000

Table4.5 below presents to which type of cooking oven households tend to go with their preferred type of kitchen. During the first survey, among those households that do not have any room dedicated for cooking, 83.23% of them use traditional mitad for baking injera/ bread while only 2.28% of them use improved rural technology. And this does not show any improvement over the next two surveys. It even has gotten worse for the use of improved rural technology. Here, the problem is twofold since the households are not only cooking and living in the same space but they are also cooking using unimproved technologies. The smoke that come out of the fuels has nowhere to go but to stay at home for longer and household members will breathe this air which has huge concentration of pollutants (Smith et al., 2000). Unlike those who use separate rooms for cooking which make women and little children exposed to related problems, here all household members will become vulnerable (Smith et al., 2000).

Among those households that use traditional kitchen inside the housing unit, during 2011/12 survey 93.78% of them use traditional mitad for baking injera/ bread while only 1.64% of them use improved rural technology and less than one percent of them use electric mitad. In this case too, we can hardly observe improvements over the next two surveys with the use of traditional mitad at 94.71%, use of improved rural technology at 1.13% in 2013/14 survey, and use of traditional mitad at 94.87% and use of improved rural technology at 1.28% in 2015/16 survey. The use of electric mitad remained below one percent.

Among those households which have traditional kitchens outside the housing unit 92.83% of them use traditional mitad, and it showed very small improvement over the next surveys with 92.35% in the second and 91.46% in the last survey. The use of improved rural technologies remains low throughout the three surveys, and the use of electric mitad remained below one percent during the first two surveys and exceed one percent and reached to 1.68% during the last survey.

Table 4.5: Type of oven used by households using different type of kitchen

Type of kitchen	**wave**	Traditional mitad removable	Traditional mitad non removable	Improved rural technology	Electric mitad	None	**Total**
		Type of oven used for baking injera/bread					
No kitchen	Wave1	1,069 0.6951	211 0.1372	35 0.0228	0 0.00	223 0.1450	3,530 1
	Wave2	891 0.7443	148 0.1231	5 0.0042	6 0.005	152 0.1265	1,202 1
	Wave3	719 0.7028	170 0.1662	11 0.0108	2 0.0020	121 0.1183	1,023 1
Traditional kit inside	Wave1	602 0.7066	197 0.2312	14 0.0164	2 0.0023	37 0.0434	852 1
	Wave2	602 0.7066	199 0.1877	12 0.0113	9 0.0085	35 0.0330	1,060 1
	Wave3	5 0.50	813 0.6949	297 0.2538	15 0.0128	40 0.0342	1,170 1
Traditional kit outside	Wave1	811 0.6770	301 0.2513	45 0.0376	4 0.0033	37 0.0309	1,198 1
	Wave2	933 0.6999	298 0.2236	54 0.0405	9 0.0068	39 0.0293	1,333 1
	Wave3	972 0.7095	281 0.2051	68 0.0496	23 0.0168	26 0.0190	1,370 1
Modern kit inside	Wave1	6 0.5	2 0.1667	1 0.833	3 0.25	0 0.00	12 1
	Wave2	8 0.3810	5 0.2381	0 0.00	6 0.2857	2 0.0952	21 1
	Wave3	16 0.3636	10 0.2273	7 0.1591	9 0.2045	2 0.0455	44 1
Modern kit outside	Wave1	3 0.2727	3 0.2727	3 0.2727	1 0.0909	1 0.0909	11 1
	Wave2	11 0.55	4 0.2	0 0.00	0 0.00	5 0.25	20 1
	Wave3	20 0.83	1 0.0417	2 0.0833	1 0.0417	0 0.00	24 1
Total	Wave1	2,491 0.6898	714 0.1977	98 0.0271	10 0.0028	298 0.0825	3,611 1
	Wave2	2648 0.7283	654 0.1799	71 0.0195	30 0.0083	233 0.0641	3,636 1
	Wave3	2,540 0.6995	759 0.2090	103 0.0284	40 0.0110	189 0.0521	3,631 1

Wave 1 Pearson chi2(16) = 518.8788 Pr = 0.000
Wave 2 Pearson chi2(16) = 416.3260 Pr = 0.000
Wave 3 Pearson chi2(16) = 395.3275 Pr = 0.000

4.2 Fuzzy analysis

In the previous section, i have presented where households in the study area are regarding their performance in each selected indicators and dimensions. Here the results of fuzzy multidimensional energy poverty index (FMEPI) of rural and small towns of Ethiopia during each survey is presented. And the results are further decomposed in to indicators so as to identify those which contribute the most for the overall level of energy poverty in the study area.

After determining the level of each household degree of deprivation in each selected indicator through Cheli and Lemmi (1995) membership function, these results are aggregated for those dimensions with more than one indicators. Here, the weights are calculated as suggested by (Betti and Verma, 2008). Now once deprivation per dimension is determined for each household, here is where alternative methods of aggregation techniques are applied so as to reach a single figure that can represent each household's level of fuzzy multidimensional energy poverty. After determining the household poverty index the next step is determining the overall poverty index of the study area through weighted average of each households energy poverty index.

Using three alternative methods of aggregation, average, intersection and union, table 4.6 below presents fuzzy multidimensional poverty index of households in the rural and small towns of Ethiopia across the three ESS survey periods, and decomposes the results in to six of the major indicators selected. The table contains information under the columns of Indicators, [3], Index,[4] Contribution,[5] and Share [6].

Average

[3]The column titled Indicators contains, type of kitchen which is one of the indicators under the indoor air pollution dimension, type of oven used, which is also found under the dimension of indoor air pollution (Simple weighted average of the two can give us deprivation score of indoor air pollution dimension), type of cooking fuel, type of energy source of lighting, households access to media and communication.

[4]Index represents level of average deprivation among households in each given indicator. What makes it different from the values mentioned in the descriptive statistics is that when the later one report the percentage of households which use certain type of energy source, the Index represents the average level of deprivation in particular dimension among households of the study area

[5]Contribution represents the absolute contribution of each indicator to the overall level of energy poverty in the study area.

[6]Share represents the relative share of deprivation in each dimension to the overall level of energy poverty in the area.

The first aggregation technique applied is just to average deprivation faced in each dimension as shown in equation **??** so as to reach to a single FMEPI. In the process, so as to indicate the equal importance of all dimensions selected, equal weight is assigned for each. And, the resulting FMEPI of the study area during the first survey period is calculated to be 79.98% indicating on average any given household in the study area was facing 77.51% of average deprivation during the time. FMEPI declines over the next two successive survey periods reaching to 75.89% during the second and 72.41% during the last survey. This is an indicator for the presence of very high but declining level of energy poverty in the study area. The fact that the figure has declined over time is an indicator for the presence of progress being made in some of dimensions selected while the fact that the level of the poverty index is still very high is a pointer to the handwork left to be done in some other dimensions. So let us see which indicators contribute the most for energy poverty.

The highest level of deprivation index was registered in the type of cooking fuels used by households, and throughout the three survey periods it managed to be above 98%. This indicates the presence of large number of households which use solid fuels for cooking and their choice has not changed much over the years that extend from 2011/12 to 2015/16. These results are reaffirmations for the findings from the descriptive analysis made in the previous section. When we come to the contribution of this dimension to the overall level of energy poverty in the study area, we will find it to be the highest contributor both in terms of absolute and relative contributions. Besides, its relative contribution even looks to grow over the three rounds of survey periods. This very high contribution which is even rising overtime is an indicator for the possible presence of decline in deprivation in some other dimensions while there happens to be a stagnant situation regarding deprivation in the type of cooking fuel used. Here, we can rise number of factors that can contribute for such results. As it is also shown by the descriptive statistics above, majority of households, which make up to more than 75% in each survey, relay on collected firewood for cooking. Even though, it requires further investigation for the case of the study area selected here, other researches indicate high price of modern fuels as one of the factors that influence households to stick to traditional fuels. For example Alem and Demeke (2020) has showed that households in the major towns of Ethiopia tend to choose solid fuel (in their case charcoal) over modern fuels following surge in the price of the kerosene. The other contributor might be the high start up cost required have modern energy fuel using cooking stoves. Besides Kowsari and Zerriffi (2011) states factors like local tradition of cooking using traditional fuels, absence of regular pattern of income among the factors that influence households to stick to traditional fuels. These and the fact that traditional fuels, mostly collected firewood is accessed free of charge might cause high deprivation score and high contribution it to the overall level of energy poverty in the study area.

While the situation in the use of clean cooking fuel is not being improved, deprivation in access to clean energy sources is rather improving over time. On average a given household was expected to face 76.05% of deprivation in this dimension, but this value sharply declined over time and reached 47.63% during the last survey. As a result, both the relative and absolute contribution of deprivation in this dimension has declined too. And, this is a manifestation for the progress being made in addressing clean energy for lighting in rural and small towns of the country. These results go along with the increasing electrification rate both in the rural and urban areas of the country.

Deprivation in indoor air pollution is contributed by two major indicators; type of kitchen and oven used for cooking. Among these indicators lower weight assigned is to the type of cooking oven used showcasing that large number of households have higher deprivation score in this indicator. Average deprivation experienced by the households in this indicator keeps being above 94% throughout the three survey periods. Given the lower weight assigned to it, the absolute and relative contribution of deprivation in this indicator looks to be very small. But this should not mislead policy makers to conclude that the indicator should be given of little attention. In fact, it should be underlined that the situation is in fact created by rather higher level of deprivation in that indicator.

When we come to where households cook, deprivation in this indicator, though it is declining over time, it still shows how much work is needed to improve the situation.

Accessing information via radio and TV looks to get worse over time with average deprivation in this indicator has increased from 64.36% during the first period to 71.26% during the last. Along with the worsening deprivation scores the absolute and relative contributions to overall poverty also has increased over the three rounds of survey periods. On the other hand communication through mobile phones and fixed line telephones seems to improve overtime as average deprivation in this indicator is being lowered and also its contribution for energy poverty of the study area.

Here level of high deprivation score and slow progresses in the two dimensions; indoor air pollution and type of cooking fuel is an indicator for higher exposure of households to indoor air pollution.

Intersection

The second aggregation technique used is intersection. Also called intensive deprivation or deprivation overlap, it will show us the minimum degree of deprivation a given household is expected to experience in each selected dimension. Given the situation in access to clean energy source for lighting and access to information through communication devices are improving over time, the average deprivation overlap score of the study area is also improving. During the first survey, a given household in the study area was found to be facing with 47.64% of intensive deprivation, or on minimum it was facing 47.64% degree of derivation in each selected dimension. But, in the last survey, the a given household in the study area was faced with 34.61% of degree of deprivation in each selected dimension. Though these magnitudes are smaller than the energy poverty index we found using average as technique of aggregation, the information they convey is rather strong. The energy deprivation overlap index that even tend to reach 50% during the first survey is an indicator for the absence of substantial number of households with zero degree of deprivation in each dimension.

Union

The third aggregation technique used is union. Showing the maximum degree of deprivation a given household faces in one or more of selected dimension, FMEPI calculated to the study area indicates the presence of worst and not improving situation among the dimensions selected. The score keeps being closer to 100% during each survey, and it is not surprising given high degree of average deprivation score in dimensions of type of cooking fuel and type of oven used.

Table 4.6: Deprivation level, weight and contribution to total, by item (indicators) in TFR approach

Average												
Item	**Index**			**Weight**			**Contribution**			**Share**		
	Wave1	**Wave2**	**Wave3**	**Wave1**	**Wave2**	**Wave3**	**Wave1**	**Wave2**	**Wave3**	**Wave1**	**Wave2**	**Wave3**
Kitchen	0.6778	0.6546	0.6532	0.1679	0.1779	0.1805	0.1223	0.1165	0.1179	0.1529	0.1535	0.1628
Oven	0.9673	0.9702	0.9485	0.0695	0.0721	0.0821	0.0672	0.0699	0.0778	0.0840	0.0921	0.1074
Fuel	0.9959	0.9926	0.9865	0.2500	0.2500	0.2500	0.2489	0.2482	0.2466	0.3112	0.3270	0.3419
Light	0.7605	0.6593	0.4763	0.2500	0.2500	0.2500	0.1901	0.1648	0.1191	0.2377	0.2172	1786
Media	0.6436	0.6914	0.7126	0.1349	0.1112	0.1006	0.0868	0.0696	0.0717	0.1085	0.0917	0.0987
Communication	0.7329	0.6021	0.5293	0.1151	0.1388	0.1494	0.0845	0.0899	0.0791	0.1057	0.1185	0.1106
Total				1.000	1.000	1.000	**0.7998** (0.0038)	**0.7589** **(0.0040)**	**0.7241** **(0.0044)**	1.000	1.000	1.000
INTERSECTION												
Total				1.000	1.000	1.000	**0.4764** (0.0061)	**0.4149** **(0.0078)**	**0.3461** **(0.0077)**			
UNION												
Total				1.000	1.000	1.000	**0.9996** (0.00017)	**0.9977** **(0.0005)**	**0.9963** **(0.0007)**			

4.2.1 Longitudinal Analysis of Fuzzy poverty

Depending on the concept of composite operators which fulfill the marginal constraints the following results are found to represent the persistence and transition of fuzzy energy poverty in rural and small towns of Ethiopia.

At least during one of the survey periods a given household in the study area was faced with 84.93% average deprivation across the dimensions selected, and in each dimension it was experiencing degree of deprivation that reaches 60.13%. And During each survey period, a given household of the study area was faced with a degree of deprivation that reaches to 100% at least in one of the dimensions selected in this in this study. The propensity of never experiencing deprivation is too small in all methods of aggregation. The other important fining is in the results of re-entry and exit. For those households which were not facing any average deprivation across all dimensions selected, their propensity to re-enter in to poverty is 98.11%. Or if we define energy poverty as the propensity of experiencing some minimum level of deprivation in each dimension selected, for those households with 0% level of intensive deprivation, their propensity to experience a degree of deprivation that is greater than zero is 70.90%. In the extensive deprivation, for households with no deprivation, the chance of being deprived at least in one of the dimensions selected is 89.71%. Compared to the re-entry rates the exit rates are smaller in the case of aggregation technique of average and union. And these numbers are indicators for the slow progress made in the sector. The exit rate in the case of FMEPI is very high. The propensity of those households which were experiencing energy poverty to exit from intensive poverty is 83.63%. This is mainly due to the improvement being made in access to improved energy source for lighting and access to communication devices.

Table 4.7: Deprivation level, weight and contribution to total, by item (indicators) in TFA approach

Method of Aggregation	**Longitudinal Analysis**				
	Ever in poverty (being deprived atleast once)	**Persistent poverty (being deprived at all period)**	**Never in poverty (no deprivation)**	**RE-Entry rate**	**Exit rate**
Average	0.8493 (0.0020)	0.6641 (0.0023)	0.1507 (0.0020)	0.9811 (0.0010)	0.4224 (0.0043)
Intersection	0.6013 (0.0045)	0.3986 (0.0045)	0.2253 (0.0035)	0.7090 (0.0078)	0.8368 (0.0056)
Union	0.9998 (0.0007)	0.9995 (0.0004)	0.00017 (0.0007)	0.8971 (0.0321)	0.1875 (0.0494)

4.3 Dynamic Fractional Regression Outputs

Before jumping straight to the main regression outputs of the model selected in the methodology part, let us see what could go wrong if other alternatives are used instead.

4.3.0.1 Pooled OLS

As it is indicated on table B.2, the model happens to be adequate even with only one percent level of significance, but it fails to pass the Ramsey's reset (specification) test. And also the fitted values generated after the estimation happens to exceed a unitary interval. As Wooldridge (2010) has stated it, using pooled OLS to deal with dynamic regression will make the estimates upward biased, and here too, the estimated coefficient for the lagged dependent variable looks to be upward biased compared to the random effect tobit regressions with the unobserved heterogeneity. Determinate like household heads sex, age, marital status, literacy level, and living in other regions of the country happens to affect the degree of deprivation overlap significantly while they are insignificant determinants in the random effect tobit regression with unobserved heterogeneity. There are number of reasons that can possibly cause these problems. Firstly, the linear regression model focusing only on the continuous nature of the dependent variable ignores the fact that households also have some positive probability of being at the two corners; zero and one (Papke and Wooldridge, 1996). Secondly, the estimation used by pooled regression ignores the effect of individual specific time invariant factors that could cause energy poverty (Wooldridge, 2010). And Thirdly, the endogeneity problem that will result from the correlation of the unobserved heterogeneity with the lagged dependent variable included as explanatory will cause the coefficients of the explanatory variable to be inconsistent and upward biased (Wooldridge, 2010). But despite all these, the pooled OLS regression has indicated that there is some level of state dependence in energy poverty in the study area.

4.3.0.2 Pooled tobit regression

Here, we have upgraded the pooled OLS regression and tried to recognize the bounded nature of the dependent variable by using pooled tobit regression. As it is indicated on table B.2, the model is found to be adequate even with one percent level of significance. And it manages to pass the Ramsey's reset test with five percent level of significance. The fitted values, respecting the unitary interval of the dependent variable, are bounded between zero and one. And determinants like household's sex, literacy, marital status, log of real energy expenditure, and living in other regions of the country happens to have significant effect on the degree of deprivation overlap while these determinants are insignificant for the case of random effect tobit regression with unobserved heterogeneity. Even though the model had incorporated the bounded nature of the dependent variable, it doesn't consider the possible effect of unobserved heterogeneity. And it has not managed to solve the initial condition problem that can result from the presence of lagged dependent variable as explanatory resulting in inconsistent and biased estimates. Despite all these, the model has indicated the presence of some degree state dependence in energy poverty.

4.3.0.3 Random effect tobit regression with out considering initial condition

Here, this model will try to solve the drawbacks of pooled OLS regression which bypass the fractional but bounded nature of the dependent variable, and that of pooled tobit regression which ignores unobserved heterogeneity that are inherited with the use of panel data set. The other important test provided with this estimation is the likelihood ratio test which helps to choose among the pooled or random effect tobit regression and show the need to consider the unobserved heterogeneity in the analysis Wooldridge (2010). And the test rejects the pooled tobit regression and accepts the presence of unobserved heterogeneity effect on the dependent variable. According to Greene (2000); Verbeek (2008), the basic assumption behind this approach is that unobserved heterogeneities are randomly distributed with zero mean and constant variance. But, this will fall into question with the presence of lagged dependent variable as explanatory and the resulting initial condition problem Wooldridge (2010). That is why as we can see from 4.8, when we compare the coefficients of the lagged energy poverty, the one generated in random effect tobit regression with out modeling unobserved heterogeneity looks upward biased compared to the random effect model that treat the initial condition problem that comes along with it.

4.3.0.4 Random effect tobit regression with unobserved effect

Here, we have expand the random effect tobit regression model by incorporating unobserved effects. As we can see form the table B.2, like the previous models, this one also manages to be adequate even at one percent level of significance, and it passes Ramsey's specification test.

The coefficients of this regression which are generated through maximum likelihood estimation can not be directly interpreted. And it is attributed to the presence of unobserved heterogeneity, and as Wooldridge (2005) has showed it, they need to be averaged across the distribution of these unobserved heterogeneity.

But, before we explain the average partial effects, we will be faced with the question of solving problems that can result from heteroscedasticity and non normality of the error term. According to Wooldridge (2010), homoscedastic and normally distributed error terms are the two basic assumptions over which the consistency of tobit regression estimates depend. Unlike other linear models which allow their standard errors to be robust to such problems, applying the same procedure here will rather make the estimated coefficients inconsistent and indicate the use of wrong model specification (Wooldridge, 2010). On the same book Wooldridge (2010), indicates the standard errors of pooled tobit regression can be made robust to heteroscedasticity problems. Thus, i have used pooled tobit regression and augmented it with the use of unobserved heterogeneity after modeling it the same way as used in random effect tobit regressions Wooldridge (2005) to check if the random effect tobit regression that can not be made robust to the specification problems can produce consistent results after bootstrapping it with 500 replications.

Thus, in order to check if the standard errors of the average partial effects of the random effect tobit regression with unobserved heterogeneity can be made robust to heteroscedasticity problem after bootstrapping it with 500 replication, as it is indicated on C.1, I have tried to compare the average partial effects generated after bootstrapping with 500 replication of random effect tobit regression with unobserved heterogeneity, pooled tobit regression with unobserved heterogeneity but without robusted standard errors, and pooled tobit regession with unobserved heterogeneity and robusted standard errors. And the results show

- The standard errors generated after the pooled tobit regression with unobserved heterogeneity with and without robusted standard errors are different, but their standard errors of APE generated after 500 replication avoid the difference generated earlier.
- Coefficients of the pooled tobit and random effect tobit regression with unobserved heterogeneity are different.

- The APE of the random effect tobit regression and the pooled tobit regression are pretty much the same in terms of sign and significance and are very close in magnitude.

4.3.1 State dependence in energy poverty

After controlling for unobserved effect, the random effect tobit model was estimated as indicated in the model specification[7]. The output of the random effect tobit regression with unobserved effect indicates the presence of state dependence in energy poverty. When the degree of energy poverty measured in in terms of degree of deprivation overlap or degree of intensive energy poverty increase by 1% during the first period, the degree of energy poverty to faced during the second period will rise by 3.8% marginally. And this will lead us to accept the hypothesis made at the beginning of the research with even one percent of level of significance. This is consistent with the finding of Alem and Demeke (2020) in the case of major towns of Ethiopia where a state dependency of 9.8% in multidimensional energy poverty is found. Even though we can not compare the results since the dependent variables are of different nature, we can detect the presence of the problem across the country. Despite it requires further investigation, beside the unobserved heterogeneity, as Kowsari and Zerriffi (2011) indicated it, many factors can be associated with households continuous presence in energy poverty. This includes the high economic cost of affording modern cooking utensils, the presence of unreliable and expensive electricity, and free access to collected firewood.

The initial condition included in the regression has reduced the estimated coefficient of the lagged dependent variable below the magnitude estimated by other methods and is happened to be a significant determinant. As Wooldridge (2005) indicate it, the significance of the initial degree of poverty is an indicator for the presence of correlation between unobserved heterogeneity and the initial condition. Initial energy poverty can contribute up to 7% for households degree of energy poverty. As Alem and Demeke (2020) clearly

[7] While the coefficients of the lagged energy poverty, the initial level of energy poverty and other strictly exogenous variables together with their standard errors are presented, the coefficients associated with the time dummy of each exogenous variables which was made part of the original regression is not presented here so as to save space.

indicated it missing out this factors can lead to a misleading policy recommendation trough their bias on the lagged dependent variable.

The other interesting factor is the marginally positive and significant effect proportion of female household members aged seven and above has on households degree of energy poverty. In many developing countries these household members are highly engaged with many of household chores which includes the task of cooking and firewood collection. According to Kes and Swaminathan (2006) the availability of free labour at home will make households to prefer free energy sources like collected firewood, and there by this increases households reliance on solid fuels and traditional way of cooking. And, the average partial effect estimates of the random effect tobit regression made here indicates when the proportion of female household members increases by one percent, household's degree of energy deprivation overlap or the degree of energy poverty intensity will increase by 3.65% marginally. Despite the expectation of the same result for the case of proportion of children aged seven and above, the variable tend to be a marginally significant but negative determinant for households energy poverty.

The other variable that happens to have marginally significant effect on households degree of energy poverty is the number of available rooms per household. And averaged across the distribution of the unobserved heterogeneity, when the number of available rooms per household increase by one, households degree of energy poverty will reduce by 1.77%.

The other important factor that happens to have marginally significant effect on households' energy poverty in rural and small towns of the country is the log of real income per adult equivalent. Increasing households real income per adult equivalent happens to cause marginally significant and negative change on households degree of energy poverty. In fact averaged across the distribution of the unobserved heterogeneity, increasing households real income per adult equivalent by one percent happens to reduce households degree of energy poverty by 3.98%. In order to see the extent a rise in income per adult equivalent has on households energy poverty, as it is indicated in table4.10, i have tried to break the results in to six different levels of income percentile that ranges between five to ninety nine percent. In table 4.10, coefficients represent average partial effects associated with the effect of each income percentile on households energy poverty while the standard errors are bootstrapped standard errors generated after 500 replications. The results indicate as the income percentile increase marginally the degree of energy poverty faced by households will decline, but the rate of change between the percentiles is so small that the difference between the lowest percentile, 5% and the highest percentile 99% is only 0.42%. This indicates the action to be made on improving households income can have an impact on reducing the degree of energy poverty households face. But, relaying only on reducing the income poverty (improving households income) to solve the problem of energy poverty will not result in the intended level of change.

Table 4.8: Results Across Alternatives

Variables	POOLED OLS	POOLED TOBIT With out CRE	XTTOBIT with out CRE	XTTOBIT with CRE	APE XTTOBIT
Lagged poverty	**0.2658 (0.0133)	0.4458*** (0.02411)	0.3063*** (0.0263)	0.1461*** (0.0326)	0.0386*** (0 .00947)
Initial poverty	- (-)	- (-)	- (-)	0.2408 (0.0302)	0.0700 *** (0 .00948)
Household head's sex	0.0473*** (0.0124)	0.0764*** (0.0235)	0.0762 (0.0230)	0.0451 (0.0481)	0.0157 (0 .0147)
Household head's age	0.00067**** (0 .0003)	0.0010 (0.0005)	0.0117 (0.0005)	0.0007 (0.001)	0.00044 (0 .0004)
Proportion of female household members aged seven and above	0.0293 (0 .0169)	0.0592*** (0.0319)	0.0638 (0.029)	0.1304** (0.0531)	0.0365** (0 .01524)
Proportion of children aged seven and above	-0.0148 (0 .0165)	-0.0339*** (0.0317)	-0.0325 (0.030)	-0.1137** (0.0544)	-0.0369 ** (0 .0167)
Number of elderly	-0.0072 (0.0132)	-0.0227 (0.0112)	-0.0017 (0.0245)	-0.0395 (0.0350)	-0.0129 (0.0083)
Marital status of household head					
Married	0.1618*** (0.0282)	0.2554*** (0.0647)	0.2553*** (0.0510)	0.0418 (0.0849)	0.0126 (0.0267)
Divorced	0.1612*** (0.0319)	0.2444*** (0.03711)	0.2516*** (0.0586)	0.1000 (0.0960)	0.030092 (0.0293)
Separated	0.1049*** (0.0391)	0.1237 (0.0896)	0.1246 (0.0785)	0.0137 (0.1207)	0.0082 (0.0411)
Widowed	0.1488 (0.0338)	0.2315 (0.0698)	0.2416*** (0.0559)	0.0289 (0.0914)	0.004 (0.004)
Number of rooms	-0.0279 *** (0.0075)	-0.0885*** (0.009)	-0.0882*** (0.0078)	-0.0519*** (0.0138)	-0.0177*** (0.0042)
Literacy	-0.0559*** (0.0093)	-0.1141*** (0.0178)	-0.1174 (0.0174)	-0.1000 (0.0185)	-0.0137 (0.0095)
Lnripae	-0.0058 (0.0038)	-0.0668*** (0.0087)	-0.0741*** (0.0078)	-0.1307 (0.0201)	-0.0398*** (0.0062)
Lnexpenditure on energy	-0.00267*** (0.0036)	-0.0570*** (0.0071)	-0.050 (0.0065)	-0.0075 (0.0102)	-0.0050 (0.0031)
Continued on next page					

Table 4.9: Continued from the previous

Variables	POOLED OLS	POOLED TOBIT With out CRE	XTTOBIT with out CRE	XTTOBIT with CRE	APE XTTOBIT
Access to the main road	0.0175 (0.010)	-0.0386 (0.0219)	0.0416 (0.020)	-0.0196 (0.0374)	-0.0068 (0.011)
Access to large weakly market	0.0225 (0.0079)	-0.0362 (0.0141)	-0.0301 (0.0142)	-0.0184 (0.0233)	-0.0019 (0.0063)
Rural	0.16874*** (0.01150)	0.5537*** (0.0419)	0.6236*** (0.0354)	0.5507*** (0.0395)	0.1377*** (0.0130)
Amhara	0.1923*** (0.0253)	0.1377*** (0.0130)	0.2085*** (0.0281)	0.1993*** (0.030)	0.0527*** (0.0080)
Oromiya	0.1170*** (0.0137)	0.2244*** (0.0278)	0.2437*** (0.0291)	0.2409*** (0.0315)	0.0626*** (0.0084)
SNNP	0.1822*** (0.129)	0.3054*** (0.0256)	0.3319*** (0.0279)	0.3243*** (0.0305)	0.08461*** (0.0083)
Other	0.0272*** (0.0129)	0.0368*** (0.0269)	0.0477*** (0.0285)	0.0370 (0.0311)	0.0069 (0.008)
Year 2015/16	-0.0589*** (0.0072)	0.1267*** (0.0139)	-0.1214*** (0.0130)	-0.03316*** (0.0041)	-0.1011*** (0.0144)

Table 4.10: APE associated with different income percentile

Percentile of lnincome per adult equivalent	coefficient	Bootstrap standard error
5% log(1072.961)	-0.0460***	0.0068
25% log(3057.501)	-0.0482***	0.0076
50% log(4540.942)	-0.0489***	0.0078
75% log(6856.978)	-0.0494***	0.0078
95% log(10064.57)	-0.0498***	0.0079
99% log(20748.33)	-0.0503***	0.0013
APE diff (99%-5%)	-0.0042***	

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

Analyses made in this paper are undertaken with the aim of understanding fuzzy multidimensional energy poverty in rural and small towns of Ethiopia, and investigating the presence of state dependence in it over time. And the results indicate the presence of high but slowly improving energy poverty in the study area. And this is mainly manifested by the fall in fuzzy multidimensional energy poverty index (FMEPI) calculated after using averages as method of aggregation. FMEPI that used to be close to 80% during the first survey declined to 72.41% during the last survey. But, FMEPI calculated after applying intersection and union tell us more about if the improvement is satisfactory enough. The level of FMEPI calculated after intersection which also represent the level of intensive deprivation or deprivation overlap in energy poverty falls from 47.64% to 34.61% indicating the presence of drastic change at least in one or more of dimensions. Looking at decomposition of FMEPI, we can see that deprivation in source of energy for lighting and access to communication is positively improving over time. Thus, we can conclude that these are the two reasons for the improvement in the level of intensive deprivation over time. When we come to the third type of FMEPI measured using union as a method of aggregation, given that it is representative for the presence of extensive deprivation or experiencing deprivation atleast in one dimension, its value is not declining from 99% over time. And this is an indicator for the presence of one or more dimensions where majority of households in the study area are deprived with high degree over longer period of time. And this is confirmed by the decomposition made on FMEPI which shows the average deprivation score in the dimension that represent type of cooking fuel is close to 99% through out the study period.

The descriptive statistics also indicates solid fuels are the most popular type of cooking fuel used across all periods, and among them collected firewood taking the majority share.

The longitudinal fuzzy set analysis made also further cement these results above. Re-entry rates that exceed 70% across all methods of aggregation indicates households high propensity to slip back to energy poverty. On the other hand exit rates are low for the case of FMEPI calculated with the application of averages and unions as a method of aggregation which indicates households low propensity to exit. But, exit rate associated with intensive deprivation is high indicating fast progress in some of the dimensions selected which in the case of this study area is contributed by improving use of modern energy sources for lighting purpose and increasing access to communication devices.

The dynamic fractional analysis made with the application of random effect tobit regression confirms the presence of state dependence in energy poverty. Level of initial energy poverty experienced, percentage of female household members aged seven and above, living in rural areas and being resident of regions of Amhara, Oromiya and SNNP are found to have a marginally significant and positive effect on households intensive energy poverty. On the other hand, number of elderly, number of rooms available, income and year of survey bring a significant but negative effect on households intensive energy poverty.

5.2 Recommendation

All the analysis made above have indicated the presence of high level of energy poverty in the rural and small towns of the country which show only slow rate of decline over the three rounds of survey. Among the dimensions selected deprivation in access to clean cooking fuel is the highest which is followed by deprivation in indoor air pollution. There is a state dependence which is confirmed by the dynamic analysis undertaken. Thus based on the findings of the analysis made in this paper, I have given the following recommendations

- The results of the descriptive statistics and the decomposition of results in the fuzzy set analysis indicate that most of the work being done in the residential energy sector is to increase access to electricity. This is shown with decreasing deprivation in access to clean energy source for lighting while deprivation in access to modern cooking fuels is very high and show no improvement over time. Thus, I recommend the rush only to increase the access must be complemented with making it both economically affordable and reliable so that its popularity as a cooking fuel can increase.

- Cooking in separate rooms is showing an improvement over time with households having separate rooms as kitchen both inside and outside the living area is increasing. This will improve the indoor air quality in the living area. But, the use of improved ovens even in the form of improved rural technology is still far from showing an improvement. And this will make the quality of indoor air polluted especially for women and children who spend most of their time cooking. Thus, I recommend that beside investing on the expensive process of generation or importation and distribution of modern energy fuels, the energy poverty faced by households in rural and small towns of the country can be improved by introducing improved rural technologies. And as a result the dissemination of these improved rural cooking technologies needs to be improved.

- The results of the random effect tobit regression indicates the presence of state dependence in energy poverty in the study area. This indicated the need to make a huge mobilization of resource in order to increase access to modern energy sources for all household tasks that require energy. And the introduction of efficient and affordable rural technologies must be considered, and huge awareness creation programmes that introduce the need to separate the living and cooking areas has to be made. Because, unless these measures are taken to curb the problem today, the problem will persist for longer than intended by dragging households in to vicious cycle of energy poverty.

- The dynamic analysis we undertake has shown that income per adult equivalent has a significant effect on the degree of energy poverty faced by households. Thus, I recommend programmes that can increase households income has to be improved as they can improve households energy poverty situation.

Appendix A

Dimensions and Indicators Used in the Study

Table A.1: Dimensions and indicators used for fuzzy analysis in the research

Indicator	Categories on available on ESS	Categories used in fuzzy analysis	Reason to merge the categories	Values to be assigned to categories
Type of Kitchen	No kitchen	No kitchen		1
	Traditional kit. inside the house	Traditional kit. inside house		2
	Traditional kit. outside the house	Traditional it. outside the house		3
	Modern Kit. inside house	Modern kitchen	Small number of households with modern kitchen in either case	4
	Modern kit. outside the house			
Type of oven	Traditional removable	Traditional mitad	Both are unimproved technologies with no chimney	1
	Traditional non removable			
	Improved rural technology	Improved rural technology		2
	Electric mitad None	Electric mitad		3

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Table A.1 – *Continued from previous page*

Indicator	Categories on available on ESS	Categories used in fuzzy analysis	Reason to merge the categories	Values to be assigned to categories
Type of fuel	Collecting fire wood	Solid fuel	Based on energy ladder theory, these fuels are suspected of emitting smoke while using. Used in related papers	1
	Purchase fire wood			
	Charcoal			
	Crop residue / leaves			
	Dung / manure			
	Sawdust			
	Other specify			
	None			
	Kerosene	Liquid fuel	Based on the energy ladder theory, these are clean but not sustainable	2
	Butane / gas			
	Electricity	Electricity	Based on the energy ladder theory, these are clean and sustainable	3
	Solar energy			
	Bio gas			
Source of light	Electricity meter - private	Light from Electricity	Clean, and provide enough amount of light during night time	3
	Electricity meter - shared			

Continued on next page

Table A.1 – *Continued from previous page*

Indicator	Categories on available on ESS	Categories used in fuzzy analysis	Reason to merge the categories	Values to be assigned to categories
	Electricity from generator			
	Solar energy	Light from alternative source	Though clean they are less reliable	2
	Bio gas			
	Electrical battery			
	Lantern			
	Light from dry cell with switch			
	Kerosene light lamp (imported)	Light from unimproved source	Unclean	1
	Kerosene lamp (local kuraz)			
	Candle/wax			
	Fire wood			
	Other specify			
Access to media	Availability of either TV or radio	Access		2
		No access		1
Access to communication	Availability of either mobile or telephone	Access		2

Continued on next page

Table A.1 – *Continued from previous page*

Indicator	Categories on available on ESS	Categories used in fuzzy analysis	Reason to merge the categories	Values to be assigned to categories
		No access		1

Appendix B

Model Specification Tests

Table B.1: Specification tests

Variables	POOLED OLS	POOLED TOBIT With out CRE	XTTOBIT with out unobserved effect	XTTOBIT with unobserved effect	APE XTTOBIT
Model Adequacy					
F(22, 3411) **Prob > F**	426.41 (0.0000)				
F(22, 6152) **Prob > F**		172.48 (0.0000)			
Wald chi2(22) **Prob > chi2**			2972.18 0.0000		
Wald chi2(53) **Prob > chi2**				2664.92 0.0000	
Ramsey reset test					
F(2, 3411) **Prob > F**	18.76 (0.0000)				
F(2, 6149) **Prob > F**		4.94 (0.0072)			
chi2(2) **Prob > chi2**			2.64 0.2671		
chi2(2) **Prob > chi2**				7.92 0.0191	
Continued on next page					

Table B.2: Specification$_{c}ontinued$

Variables	POOLED OLS	POOLED TOBIT With out CRE	XTTOBIT with out unobserved effect	XTTOBIT with unobserved effect	APE XTTOBIT
Goodness of fit					
GOF	0.6604	0.2971	0.2988	0.3085	
Min fit	-1.137263	0.0000396	0.0000437	1.58e-15	
Max fit	0.8224511	.8733064	.8457053	0.8311683	
/sigma		0.4760*** (0.0079)			
LR test of Sigma_u=0					
chibar2(01) **Prob >= chibar2**			74.87 0.0000	92.09 0.0000	

Appendix C

APE across alternatives

Table C.1: APE difference across alternatives

Variables	APE of XTTOBIT	APE of POOLED TOBIT Without ROBUST STANDARD ERROR	APE of POOLED TOBIT With ROBUST STANDARD ERROR
Lagged poverty	0.0386 *** (0 .00947)	0.0833*** (0.0083)	0.2152*** (0.0083)
Initial poverty	0.0700 *** (0 .00948)	0.0697*** (0 .009)	0.0697*** (0.0092)
Household head's sex	0.0157 (0 .0147)	0.0149 (0.014)	0.0149 (0.014)
Household head's age	0.00044 (0 .0004)	-0.0003 (0.0003)	-0.0003 (0.0003)
Proportion of female household members aged seven and above	0.0365** (0 .0152)	0.0377*** (0.0156)	0.0377*** (0.0156)
Proportion of children aged seven and above	-0.0369 ** (0 .0167)	-0.0396*** (0.0166)	-0.0396*** (0.0166)
Number of elderly	-0.0129 (0.0083)	-0.009*** (0.0112)	-0.009*** (0.087)
Marital status of household head			
Married	0.0126 (0.0267)	0.0085 (0.2710)	0.0085 (0.2710)
Divorced	0.0300 (0.0293)	0.0217 (0.0298)	0.0217 (0.0298)
Separated	0.0082 (0.0411)	0.0039 (0.0422)	0.0039 (0.0422)
Widowed	0.0085 (0.0291)	0.004 (0.004)	0.2152*** (0.0340)
Number of rooms	-0.0154 *** (0.000)	-0.0177*** (0.0042)	-0.0177*** (0.0042)
Literacy	-0.0110 (0.0094)	-0.0137 (0.0095)	-0.0137 (0.0095)
Lnincome	-0.0391*** ((0.0000))	-0.0398*** (0.0062)	-0.0398*** (0.0062)
Lnexpenditure on energy	-0.0024 (0.0031)	-0.0050 (0.0031)	-0.0050 (0.0031)
Access to the main road	-0.0061 (0.011)	-0.0068 (0.011)	-0.0050 (0.0031)
Access to large weakly market	-0.0051 (0.0061)	-0.0019 (0.0063)	-0.0019 (0.0063)
Rural	0.1587*** (0.0137)	0.1377*** (0.0130)	0.1377*** (0.0130)
Continued to next page			

Table C.2: Continued from the previous

Continued from the previous			
Variables	**APE of XTTOBIT**	**APE of POOLED TOBIT Without ROBUST STANDARD ERROR**	**APE of POOLED TOBIT With ROBUST STANDARD ERROR**
Region			
Amhara	0.0578 *** (0.0085)	0.0527*** (0.0080)	0.0527*** (0.0080)
Oromiya	0.0578 *** (0.0085)	0.0527*** (0.0080)	0.0527*** (0.0080)
SNNP	0.0954*** (0.0088)	0.08461*** (0.0083)	0.08461*** (0.0083)
Others	0.0097** (0.0091)	0.0069 (0.008)	0.0069 (0.008)
2015/16 (year of last survey)	- 0.030*** (0.0040)	-0.03316*** (0.0041)	-0.03316*** (0.0041)

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