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Energy Poverty in Addis Ababa City, Ethiopia

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Abstract
This paper analyzes multidimensional energy poverty in Addis Ababa city. The multi-dimensional energy poverty index is used to estimate the energy poverty in the city, using cross sectional data from 466 households in 2012/13. The result indicates that 57.9% of the city households suffer from multi-dimensional energy poverty. It means that households have little or no access to clean cooking energy, have no their own energy appliances and do not use energy appliances. The households do not benefit much from modern energy sources. The study also identified that households with high education level, who own refrigerator, posses their own electric meter and have higher income are less likely to be energy poor. Thus, improving the status of households in possessing these resources is essential to enhance their access to energy.
Keywords: Energy poverty, energy sources, multi-dimensional poverty, Addis Ababa.

1. Introduction

Energy is one of the basic elements of economic and social development. It contributes to health and education service delivery, and helps to meet the basic human needs such as food and shelter (IEA, 2006). There are traditional and modern energy sources. Traditional energy sources are firewood, charcoal, crop residues and animal waste. They are also referred as biomass energy and are obtained from natural environment. The modern energy sources are kerosene, LPG and electricity. These energy sources are collectively termed as modern or commercial energy sources (Leach, 1987). Modern energy services have important role in improving production and productivity. They relieve millions of women and children from daily burden of water fetching and firewood collection. They can help to extend the working time, increase individual income, invest children's time in schooling and deliver health services to the community (World Bank, 2000).

The number of people who depends on traditional energy sources in the world is estimated to be 2.7 billion of the global population in 2009. Among these, 2.6 billion people are from developing countries, 653 million people of which are from Sub-Saharan Africa. In case of Ethiopia, more than 67 million people are dependent on biomass energy to meet their cooking, heating, lighting and hygiene needs (UNDP, 2009; IEA, 2010; DGEP, 2011; and CSA, 2012). Regarding access to electricity, 1.32 billion people in the world lacks access to electricity. From this, 1.3 billion people are from developing countries, of which 586 million people are from Sub-Saharan Africa. In Ethiopia, more than 46 million people live without access to electricity. Generally, 51% of the population of developing countries, 78 % of Sub-Saharan African population and 93% of Ethiopian population use biomass energy for their domestic use. Moreover, 25% of developing countries population, 69% of Sub-Saharan African countries population and 63 % of Ethiopian population have no access to electricity (UNDP, 2009; IEA, 2010; DGEP, 2011; and EPA, 2012). However, such heavy dependency on biomass energy sources creates deforestation, land degradation, soil erosion and climate change (World Bank, 2000; Alemu, et. al, 2008; and Yonas, et. al., 2013).

2. Literature Review

Energy poverty is defined as inability to cover basic energy cost to keep homes adequately warm, cook food and have light. It can be also defined as the absence of sufficient choices for affordable, reliable, high quality, safe and environmental benign energy services to support economic and human development (Reddy, 2004). Although many researchers have similar ideas in the definition of energy poverty, they fail to agree on what exactly is the minimum level of energy poverty line and below which a household can be classified as energy poor (Pachauri, et.al, 2004; Dhanuska, 2008; and Betchani, et, al., 2013).

For example, Bravo, et, al. (1979) measured energy poverty in terms of physical energy amount and identified 27.4 kilograms of oil equivalent (kgoe) per household per month as the minimum amount.

Goldemberg, (1990) defined 32.1 kgoe per household per month as the minimum amount, while Modi, et.al. (2005) computed 50 kgoe per household per month for cooking and lighting as energy poverty line. Foster, et, al. (2000) estimated a minimum level of energy for rural and urban households. They estimated the minimum amount for rural households to comprise two bulbs, five hours service for radio use while for urban areas with additional appliances such as television and refrigerator use, the minimum energy level is estimated to be 50kgoe . All these works used the minimum amount of energy for estimation of energy poverty line in terms of physical amount without considering economic aspects.

ESMAP,(2002), Pachauri, et.al.(2004), DGEP,(2011), Patil (2011), ESCAP (2012) and Betchani, et.al. (2013) estimated energy poverty in terms of economic aspect. Economic energy poverty is at a level when households' energy expenditure is more than 10% of the disposable income, excluding transportation costs (WEO, 2004). These researches considered economic or expenditure aspect of energy poverty, but they did not consider other factors like accessibility, affordability and classification of energy for domestic activities.

Mirza et. al. (2010) in their energy poverty study applied new method for estimation of energy poverty in terms of access to different energy sources such as firewood, charcoal, kerosene and LPG at household level. This energy poverty model is a bit complex to estimate for each energy source inconvenience index using energy inconvenience excess and energy short fall at household level. The model emphasizes much on how to access different energy sources, without considering the affordability and supply of energy.

Nussbaumer, et. al. (2011) developed the multi-dimensional energy poverty index (MEPI) and estimated energy poverty for African countries in terms of incidence and intensity of energy poverty, and reported that the energy poverty line is at 0.30. According to their finding, 65% of Zambian, 70% of Cameron and 90% of Ethiopian are energy poor multi-dimensionally. Similarly, ESCAP,(2012) estimated multi-dimensional energy poverty index for South and East Asian countries and Edoumiekumo, et, al.(2013) also used the Nussbaumer, et.al.(2011) model to estimate multi-dimensional energy poverty index for Nigeria. MEPI focuses on measuring modern cooking fuels, indoor air pollution from burning of firewood and charcoal, access to electricity, services provided using own energy appliances for domestic energy activities.

From the forgoing discussion, it is clear that the empirical works on estimation of energy poverty are limited in scope and coverage. Some works by Bravo, et. al. (1979), Goldemberg (1990), Modi, et.al (2005) and Foster, et.al (2000) estimated energy poverty in terms of physical quantity, while other researchers such as ESMAP (2002), Pachauri, et.al.(2004), Mirza et.al. (2010), DGEP (2011), Patil (2011), ESCAP (2012) and Betchani, et,al (2013) estimated energy poverty on the basis of economic or access to energy aspect. This study estimated energy poverty by adapting approaches of multi-dimensional energy poverty measurement.

3. Methodology

3.1. The study area

Addis Ababa is the largest city in Ethiopia with the total area of 54,000 hectares or 540 km^2. The city lies on the altitude of 2,300 meters (7,546 feet) and located at 9°1′48″N, 38°44′24″E latitude. The city highest point is found at Entoto Mountain at 3,000 meters (9,800 ft) above sea level in the north periphery. The lowest point is found around Bole International Airport, at 2,326 meters (7,631 ft) above sea level in the southern periphery (CGAA-BPACSP, 2010). Addis Ababa has a Subtropical highland climate zone, with temperature up to 10 °C differences, depending on elevation and prevailing wind patterns. The mean annual maximum and minimum temperature for Addis Ababa is 22.8 C^0 and 10.0 C^0, respectively. The mean annual rain fall is around 1,118.4 mm with the maximum of 132 rainy days per year (NMA, 2011).

According to 2007 Ethiopian census, Addis Ababa city population was estimated to be 2,739,551, of whom 1,305,387 were men and 1,434,164 were women. In the city, 662,728 households were living in 628,984 housing units, with average family size of 4.1 persons. The 2012 estimate of population of the city was 3,033,284 living within 739,829 households. The population density of the city was 5,617 persons per kilo meter square (CSA, 2008 and CGAA, 2013).

The residents of Addis Ababa use both modern and traditional energy sources for domestic energy activities. The sources are firewood, charcoal, animal dung, sawdust, barks, roots, leaves, kerosene, LPG and electricity (GTZ-Sun, 2010). Many factors were considered for selecting the study area. The key reasons for selecting Addis Ababa city are: steady growth of the population of the city, shortage of firewood, charcoal, kerosene and LPG, and the accompanying rise of their prices, and the sustainability challenges of energy supply. The other important energy feature of the city is that there are some peri-urban *kebeles* that have no access to electricity. In these places, there is less expansion of electricity grid, price fluctuation of different energy sources, and physical inaccessibility of kerosene and LPG.

There is also an increasing shortage of firewood in the city due to the imbalance between the supply and demand for the source due to depletion of the forest in the periphery of the city. The city is however still a good market for biomass energy supplies from its surroundings. Besides, the city is strategically located to access different kinds of energy sources like fire wood, charcoal, kerosene, LPG, electricity and even other varieties of energy sources like animal dung, leaves, barks, etc. The fact that the city is inhabited by people of different income groups makes ita marketplace for diverse kind s of energy sources.

3.2. Data sources

The study used primary data that were collected from 466 households in 2012/13. The study employed a multistage stratified random sampling technique to identify data sources. The multistage random sampling technique is used for large scale enquiry covering large geographical area such as a state, large or medium city. Addis Ababa city is the largest city in Ethiopia and has ten sub cities and 116 urban and peri-urban *woredas* (CGAA, 2013). In the first stage of multi-stage sampling, sub-cities were selected randomly from stratified sub-cities, in the second stage *woredas* from each sub-city were selected randomly and finally households from each *woreda* were selected randomly.

For sampling purposes, the sub cities were categorized into two strata based on the following criteria: geographical location (distance from the center), boundaries with surrounding rural areas, size of geographical areas, population density and economic activities. Stratum one (outer sub cities) has six sub cities, namely, Gullele, Kolfe Keranyo, Nefas Silk, Akaki- Kality, Bole and Yeka. Those sub-cities with long distance from the center (Menilik II Square) border with rural areas in Oromia region, have large geographical areas, are sparsely to densely populated (on average 4,576.3 persons per Km^2) and the major economic activities of the people are trade, services, transport, hotel, manufacturing, urban agriculture and animal husbandry.

Stratum two (inner sub-cities) has four sub cities that include Arada, Kirkos, Lideta and Addis Ketema. These four sub cities have short distance from the center, have no border with rural areas, have small geographical areas, are located relatively at the center of the city, densely populated with average of 35,794.5 Persons/Km^2, and the major economic activities of the people are trade, services, transport, hotel and tourism.

After classifying the city into strata, three sub cities (50%) were randomly selected from the first stratum, i.e. Gullele,Yeka and Akaki-Kality sub cities and two sub-cities (50%) from second stratum - Arada and Lideta. After selecting the five sub cities, 50% of *woredas* were also selected randomly from each selected sub-city. Accordingly, 26 woredas, 466 households were randomly selected from the sub-cities for the study. The number of sample households for each *woreda* is proportional to the respective *woreda* household population.

3.3. Model specification

3.3.1. Multi-dimensional Energy Poverty Index (MEPI)

Following the works of Nussbaumer, et.al.(2011), ESCAP,(2012) and Edoumiekumo, et, al (2013), the MEPI was determined using five dimensions with thirty three variable indicators of energy deprivation. The multi-dimensional energy poverty approach measures the proportion of the population that is multi-dimensionally energy poor (incidence) and the average intensity of their deprivation of energy (Intensity). Multi-dimensional poverty can be estimated by multiplying the incidence of poverty by the average intensity of energy deprivation. In the case of this study, five dimensions of energy poverty indicators were generated from the average indicator weights as derived from the works of the authors mentioned above, and the dimensions are outlined as given below.

1. Energy for cooking activities: A household is deprived of modern cooking fuel if its main cooking fuel is not modern energy sources (kerosene, LPG or electricity), for which a value of 1 is assigned or otherwise 0. The deprivation index is weighted by 0.25.
2. Indoor air pollution: A household is relying on traditional energy sources (fire wood and charcoal) and do not use modern stoves for burning them; it is assigned the value 1, otherwise 0. The deprivation index is weighted by 0.15.
3. Access to electricity: A household does not have its own electric meter to access electricity in his /her home, for which it is assigned the value 1, otherwise 0. The deprivation index is weighted by 0.30.
4. Owning energy appliances: A household does not have energy appliances for cooking, baking, heating, washing, entertainment, education, telecommunication, etc, and it is assigned the value 1, otherwise 0. The deprivation index is weighted by 0.15.
5. Using energy appliances: A household does not use different energy appliances for cooking, baking, heating, washing, entertainment, education, telecommunication, etc, and it is assigned the value 1, otherwise 0. The deprivation index is weighted by 0.15.

Accordingly, for a household to be identified as energy poor, the combination of those deprivation counts has to exceed a pre-defined threshold line, which is 0.3. And this is interpreted that the household does not use modern energy source for cooking (kerosene, LPG and electricity), is affected by an indoor pollution from burning traditional energy sources without using improved cooking stoves, has no its own electric meter, has no its own devises and do not use energy appliances (refrigerators, electric stoves, LPG stoves, etc,), entertainment or education appliances (TV and Radio) and telecommunication appliances (mobile phone, internet services) for domestic activities.

The energy poverty incidence is then measured through head count employing the following equation.

$$HCR = \left(\frac{NEP}{NEP+NNEP}\right)W_i$$

Where: HCR is the Head Count Ratio from total households (Incidence of energy poverty)

NEP is the Number of Energy Poor

NEP + NNEP is the Number Energy Poor and Energy non-Poor.

W_i is the estimated weight

Energy poverty intensity is also estimated using the following equation

$$A = \sum_{i=1}^{n} Ci(k)/q$$

Where: A is the intensity of energy poverty

$\sum_{i=1}^{n} Ci(k)$ is the average of censored weighted deprivation or

Σci = which is the sum of weighted deprivation of person i who suffers from energy poverty

k =Multi-dimensional energy poverty line for African countries as suggested by Nussbaumer, et.al.(2011). Thus, if k=0.3, it implies that a person is considered as energy poor. I.e. she /he has no access to modern energy sources for cooking or does not benefit from modern energy sources.

q is average of un-weighted deprivation of energy count , i.e. incidence of energy poverty or head count.

A person is an energy poor if her/his weighted deprivation count c_i exceeds k; therefore, $c_i(k)$ is set to zero when $c_i \leq k$ and equals MEPI= c_i when c_i>k. Thus, c(k) represent the censored vector of deprivation count and it is different from c in that it counts zero deprivation for those not identified as multi-dimensionally energy poor. Then MEPI is calculated as:

$$MEPI = \frac{HCR * \sum_{i=1}^{n} Ci(k)}{q}$$

It is interpreted as, if MEPI > 0.3, households are energy poor, which means that they are deprived of access to modern energy sources. I.e. households have little or no access to clean cooking energy, have no their own energy appliances and do not use different energy appliances.

If MEPI ≤ 0.3, households are energy non-poor. I.e. they benefit from access to modern energy sources, have access to clean cooking energy, have their own and use different energy appliances and do benefit from modern energy sources.

3.3.2. Econometric analysis of multi-dimensional energy poverty

The study households were first categorized into two groups (multi-dimensionally energy poor and multi-dimensionally energy non-poor) based on their total deprivation counts. Binomial logistic regression model was used to find the main determinant of household energy poverty. The logit model used for the analysis is written as

$$Prob(1|X_i) = L_i = \ln\left(\frac{Pi}{1-Pi}\right) = Z_i = \beta_1+\beta_i X_i + \varepsilon_i$$

Where: $Prob(1|X_i) = \ln\left(\frac{1}{0}\right) = 1$, if the household's weighted energy deprivation counts is ≤ 30% (for energy non-poor household).

$Prob(1|X_i) = \ln\left(\frac{0}{1}\right) = 0$, , if the household's weighted energy deprivation counts >30% (for energy poor household)

P_i:= the probability of being energy non poor,

$1-P_i$= the probability of being energy poor

$\ln\left(\frac{Pi}{1-Pi}\right) =$ log odds ratio of the two probabilities in favor of being energy non-poor

β_i parameters to be estimated,

X_i is a vector of household characteristics, while εi is an error term.

4. Results and Discussion

The multi-dimensional energy poverty index measures the proportion of the population that is multi-dimensionally energy poor (incidence) and the average intensity of their deprivation of energy. As per the findings of the study, proportion of households who do not use modern energy source (kerosene, LPG and electricity) for cooking/baking is estimated to be 70.4% (Table 1).

As shown in Table 1, households who rely on traditional energy without using improved stoves and as a result suffer from indoor air pollution comprise 34.33%. Similarly, 29.4% of the sample households do not have their own electric meter for accessing electricity. Households that do not have their own energy appliances consist of 59.2% of the sample households, while those who do not use any of energy appliances for cooking/baking, heating, entertainment, education and communication make up 60.9% of the sample households.

Table 1: Indicators and their weights for measuring energy poverty incidence

	Traditional energy user	Indoor air pollution from burning	Have no own electric meter	Have no own energy appliance	Use no energy appliance	Incidence of energy poverty(H)
Weight	0.25	0.15	0.3	0.15	0.15	1.00
%	70.4	34.33	29.4	59.2	60.9	
Weighted values	17.6	5.15	8.82	8.87	9.13	49.57

Source: Own computation

The finding also shows that 49.57 % of households are energy poor (i.e. in energy poverty incidence group). The poverty intensity is computed to be 1.17, which is greater than 0.3, indicating that the households are with high energy poverty intensity. Further, the MEPI is calculated to be 0.5799 or 57.99%. The result implies that these households have little or no access to clean cooking energy, do not have their own energy appliances and as well do not use energy appliances. This finding is similar with that of Nussbaumer, et.al.(2011), ESCAP(2012) and Edoumiekumo et, al.(2013). The remaining households, 42.01%, are multi-dimensionally energy non-poor, implying that they have access to clean cooking energy and use different energy appliances, thus benefiting from modern energy supply.

The results of logit model analysis indicated that household head/s education at post secondary level, owning refrigerator, owning electric meter, total amount of energy expenditure and total amount of household income are statistically significant (at 1 % level of precision) factors of the probability of multi-dimensional poverty.

The coefficient of household head's education level at post-secondary level is negative. It indicates that households with post-secondary education level are less likely to be energy poor than those with less post-secondary education level. This could be due to the possibility that more educated households earn more income enabling them to spend more for energy and use different energy appliances relative to households with less post secondary education.

The coefficient of owning refrigerator is negative, showing that households with own refrigerator are less likely to be energy poor than households without. This could be because these households cook more food at a time and store it in a refrigerator for long for later use. This practice helps households to save time, energy and income.

The negative coefficient of owning electric meter indicates that households with own electric meter are less likely to be energy poor than households without their own electric meter. This is probably because households with own electric meter can access electricity easily any time they want and enable them to use different energy appliances like stove, refrigerator, Tv, etc.

The coefficient of total energy expenditure is negative. It indicates that households who spend more on energy are less likely to be energy poor than those who spend less on energy. That means, higher energy expenditure by households implies that these households have opportunities to buy more types and amounts of energy especially modern energy than the traditional ones and use different energy appliances.

Since total energy expenditure is a proxy for income, its negative coefficient indicates that households with more income are less likely to be energy poor than household with less income. In other words, it shows that households with more income have better ability to use modern energy and purchase different energy appliances than the households with less income. A similar result was reported by Pachauri et.al (2004), Mirza et.al (2010), Nussbaumer et.al (2011), ESCAP (2012) and Edoumiekumo et, al (2013).

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Table 2. Logit and WLS Estimation of Multidimensional Energy Poverty

Explanatory variable	**Logit estimation of the household's weighted energy deprivation count: 1 if ≤ 0.30, otherwise, 0**	**WLS estimation of household's weighted energy deprivation count in percentage**
Age(log)	- 0.523 (1532)	0.001 (0.059)
Marital status	- 0.213 (0.320)	- 0.008 (0.012)
Family size(log)	1.458 (1.013)	0.188*** (0.039)
HH head post primary education level	0.275 (0.335)	0.017 (0.013)
HHs head post secondary education level	- 1.991*** (0.472)	- 0.064*** (0.014)
Own house	- 0.197 (0.330)	- 0.028** (0.012)
Own refrigerator	- 2.760*** (0.396)	- 0.195*** (0.013)
Own electric meter	- 2.276*** (0.412)	- 0.096*** (0.014)
Total energy expenditure (log)	- 4.228*** (1.581)	- 0.309*** (0.055)
Total expenditure(log)	- 3.454*** (1.149)	- 0.257*** (0.042)
Constant	24,672*** (4.927)	2.306*** (0.170)
Pseudo R^2	0.497	-
R^2	-	0.702
LR $chi^2(10)$	302.00(0.000)	-
F(10,455)	-	109.39(0.000)

*** Significance at 1%, ** significance at 5%, * significance at 10%, Figure in bracket is standard error
Source: Household survey, 2012.

Results of Weighted Least Square Estimation

After identifying the variables to be estimated for energy poverty estimation, Ordinary Least Square (OLS) method is used to estimate the explanatory variables on continuous dependent variables of average energy deprivation counts. Multicolinearity[1] is tested through VIF[2], TOL[3] test and Spearman[4] correlation coefficient matrix for energy poverty model. The results of the tests show that there is no high correlation coefficient among the explanatory variables. Heteroscedasticity[5] is also tested by Breusch-Pagan test. The test assures the presence of heteroscadasticity (has no constant variance in the ε_i). OLS regression was thus not best linear unbiased estimators (BLUE) when the error terms have no constant variance. As a result, the Weighted Least Square(WLS) method was used for estimation of energy poverty as

$$MEPI_{average} = \beta_1+\beta_i \log X_i + \varepsilon_i$$

Where $MEPI_{average}$ is multi-dimensional energy poverty index in average

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[1] Multicolinearity shows the existence of perfect or exact linear relationship between two or more explanatory variables in the regression model.

[2] Variance inflating factor measures the speed with which variance and covariance increase .It is computed as VIF $=\frac{1}{1-r2}$, Where: r^2 is Correlation Coefficient ,then , VIF=1.78 , r^2=0.44

[3] TOL =1/VIF or 1-r^2 = 1/1.78 = 0.56

[4] . All Spearman's correlation coefficients are below 0.8.

[5] The probability distribution of random variables (u_i) is the same over all observation of x, and in particular that the variance of each u_i is that same for all values of the explanatory variables $Var(u_i) = E\{ (u_i – E(u_i) \}^2 = E(u_i)^2 = \delta^2$= Constant variance. Heteroscedasticity is also tested by Breusch-Pagan test as $Chi^2(10)$= 26.50(0.000)

β_i is parameter to be estimated,
X_i is a vector of household characteristics and
ε_i is an error term.

As can be seen in Table 2, family size, household head education level at post-secondary level, owning refrigerator, owning electric meter, total energy expenditure and total household income are found to be significant factors of multi-dimensional energy poverty.

The coefficient of family size is positive, indicating that households with large number of family members have higher weighted deprivation counts of energy. It means that, if the family size increases by one member, keeping other variables constant, household's weighted energy deprivation count increases by 0.188%. This implies that large family size has less opportunity or possibility to use modern energy sources and to buy different energy appliances than small family.

The coefficient of household head's education level at post-secondary level is negative, indicating that households with heads of higher education level have less weighted deprivation counts of energy poverty than households with heads of less education. It means, if the household's head education upgrades to post-secondary level, keeping other variables constant, household's weighted energy deprivation count decreases by 0.064%. This can be due to the increased earning by educated families that enables them to use more modern energy and different energy appliances (refrigerator, stove, etc) compared to those households with less educated heads.

The coefficient of owning refrigerator is negative. It indicates that households who own refrigerator have less weighted energy deprivation counts than households without. It means, if households probability to own refrigerator increases, keeping other variables constant, household's weighted energy deprivation count decreases by 0.195%. This might be due to the situation that refrigerator helps to preserve the cooked food for long period of time, leading to reduced energy budget and food cooking frequencies and thus saving households' time.

The negative coefficient of owning electric meter shows that households who own electric meter have less weighted energy deprivation counts. It means that if households own electric meter, keeping other variables constant, household's weighted energy deprivation count decreases by 0.096%. This might be due to the easy access to electricity any time, permitting the households to use more electric power and energy appliances.

The coefficient of households' total energy expenditure is negative. It indicates that households with higher energy expenditure have less weighted energy deprivation. If a household's energy expenditure rise by 1%, other variables held constant, household's weighted energy deprivation count decreases by 0.309%. This can be attributed to households' ability to spend more money to buy more types of modern energy and different energy appliances for domestic activities.

The negative coefficient of households' total expenditure, proxy of income, indicates that households with more income have less weighted energy deprivation. It means that if a household's income increases by 1%, keeping other variables constant, household's weighted energy deprivation count decreases by 0.257%. This could be because higher income creates more demand for modern energy sources and enables households to purchase different energy appliances.

5. Evaluation of Energy Poverty Regression Model

In logit regression analysis, the log-likelihood ratio which is distributed as a chi-square is computed to test the overall performance of the model. As we have seen in Table 2, the LR/ chi-square is 302.00. It is statistically significance, rejecting the null hypothesis that the overall explanatory variables in the model could not explain the dependent variable. Thus, the predictor variables in the logistic regression model are collectively important in explaining the behavior of energy poverty in Addis Ababa city. Besides, the Pseudo R-square value is 0.49, implying that the model can explain 49 percent of the energy poverty in the city.

In Weighed Least Square analysis, the overall significance test of the model, F-test, is computed to be 109.39 (Table 2) which is statistically significant indicating that the given predictor variables in the model are collectively important and explain the behavior of energy poverty in Addis Ababa city. In addition, the Coefficient of determination or R–square value is 0.70 which indicates that the model explained about 70 percent of the energy poverty model.

6. Concluding Remarks

In Addis Ababa city, 57.9 % of households are energy poor multi- dimensionally, for the amount of energy they utilize is below the energy poverty line. The energy-poor households use traditional energy sources for cooking activities and are affected by indoor air pollution from burning of traditional energy sources without using improved cooking stoves. They do not have their own electric meter and energy appliances, and they do not use electrical energy appliances (refrigerators, electric stoves, LPG stoves, etc,), entertainment and/or education appliances (TV and Radio) and telecommunication appliances (e.g. mobile phone and internet services). The key energy poverty factors identified by the study include family size, household head's education level at post

secondary, owning refrigerator, owning electric meter, total energy expenditure and total household income.
The findings imply the importance of enhancing households' income, education, ownership of electric meter, since they are instrumental for households to transit from use of traditional energy sources to use of modern energy sources. In this context, finding ways of lowering prices of modern energy appliances through different mechanisms and encouraging local assembly and manufacturing of refrigerator and other electrical appliances is useful. Besides, promoting access to electric power through own or cooperative electric meter is also important dimension to consider in enhancing households' access to energy.

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