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Are Urban Rwandan Households using Modern Energy Sources? An Exploration of Cooking Fuel Choices

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ABSTRACT

This study employed a discrete choice framework to explore cooking energy use patterns amongst urban Rwandan households using the latest EICV 5 microeconomic survey dataset. Specific analysis focused on choices for three primary cooking fuels namely: firewood, charcoal and liquidified petroleum gas. The findings show that ordered model provided better prediction for primary fuel choices rather than the secondary choices for multiple fuel users with income as a key determinant. Furthermore, asset index, house ownership, geographical location, number of rooms, household size and household head labor market participation were some of the non-price factors that significantly affected the choice probability for using charcoal as transitional fuel and liquidified petroleum gas as a modern fuel in Rwandan country context. Robustness test of the results emphasizes the need for government in collaboration with modern energy suppliers to have clean energy use campaigns and do market segmentation through repackaging of smaller gas cylinders so that many low- and middle-income households become aware and use modern energy services. This is essential to ensure good prospect of energy transition for the developing country case context amidst urbanization and climate change.

Keywords: Energy; Households; Urban; Rwanda; Fuel
JEL Classifications: D12, O12, Q420

1. INTRODUCTION

Most governments and development practitioners are deeply concerned with heavy use of traditional fuels closely linked to indoor pollution, environmental degradation, and high opportunity cost for women and children that eventually affect household wellbeing in general (IRENA, 2019). For most developing countries, energy is increasingly becoming a very scarce commodity and literature demonstrates correlation of absolute poverty with poor use of modern energy (Sher et al., 2014). There is no consensus on universal definition of energy poverty. However, what is prevalent in all definitions of the energy poverty is that it depicts a situation whereby there are insufficient choice sets of getting adequate access to sustainable modern energy services and products (IRENA, 2019). To date, the Sub Saharan Africa region and other developing countries face limited access to affordable and clean energy sources. It is estimated that 2.5 billion people depend on solid fuel from traditional biomass fuels such as crop residues and firewood for cooking and heating which are associated with indirect adverse health effects (Buba et al., 2017). This number is projected to reach 2.7 billion by 2030 implying that depletion of forest and environmental degradation might be inevitable if proper and timely policy measures are sluggish (IEA, 2006). As such, promotion of clean energy technologies is vital to facilitate energy transition in order to improve accessibility and utilization of modern energy services to reduce state of energy deprivation (Morrissey, 2017; Bhattacharyya, 2012).

However, successful uptake of cleaner cooking technologies largely is linked to consumer demand and energy choices mostly from the household sector. Therefore, this paper utilized the latest

EICV5 2016/17 data set that captures micro economic information to analyze cooking fuel choices of urban households in Rwanda within the context of urbanization and migration. This study contributes to literature by expanding the scope of the urban context research gap that was left by (Marathe and Eltrop, 2017) who only considered Kigali city. Their findings showed big differences on electricity utilization among different socioeconomic groups and dwelling types. The country has experienced rapid urban growth that is accompanied by demographic growth and migration to urban spaces with resettlement of displaced people and returnees from neighboring countries such as Burundi and Democratic Republic of Congo following the end of 1994 genocide. Recent statistics show that urban population rose from 4.6% in 1978 to 16.5% in 2012 with an average urban density of 1871 inhabitants/km^2 as of 2012 (MINIFRA, 2015). The annual growth rate for urban population is pegged at 4.1% whilst the country's vision 2020 highlighted a target of reaching an urbanization rate of 35% in 2020 (NASIR, 2012). The urban planning and building department in Rwanda defined a city to have a population of at least 200,000 inhabitants; a municipality at least 30,000 but <200,000 inhabitants; an agglomeration at least 10,000 but <30,000 inhabitants. By 2012, Rwanda had 21 urban areas, 10 municipalities, 10 agglomerations with 7 emerging urban areas (UNHabitat, 2020).

This research study is timely and pertinent considering the country's urban rapid growth. This growth may stimulate a big surge in demand for household fuels coupled with dynamic urban lifestyles which has policy implications. Urban households have an added advantage of exposure towards a variety of choices for modern commercial fuels such as LPG attributed to improved accessibility and availability that may induce fuel switching (Farsi and Filippini, 2007). This implies that the household sector can offer an attractive market and prospect for diffusion of commercial clean energy cooking technologies. However, so many factors do influence household fuel choices and differ depending on context, level of transition by the households and the prevailing energy sources available to households based on a cross section energy ladder (Smith and Urperlainen, 2014; Pachauri and Jiang, 2008).

1.1. Energy Ladder Versus Energy Stacking Models

Theoretical explanation on household utilization of different fuels is classified into two schools of thought. First, the "energy ladder hypothesis" which states that household income and fuel switching are linked by postulating that poor households are more likely to use traditional fuels than wealthy household counterparts mainly due to their income differences (Toole, 2015; Van Der Kroon, 2013). In simple terms, the hypothesis depicts a linear movement up on arbitrary ladder such that any household shift from lower level to the next upper level corresponds to rising household income levels. For instance, high dependency of using traditional fuels reflects a poor household energy status (mainly because of low income levels) and is usually associated with the lowest weight of the energy ladder (Masera et al., 2000). Another school of thought referred as "fuel stacking or energy transition" asserts that utilization of both clean and unclean energy fuel sources still occurs regardless of household high-income levels for various reasons (Heltberg, 2005). Reasons for multiple fuel use by households in developing countries are attributed not only to economic factors but also non-economic factors as well which are deeply connected to culture, social or security purpose to ensure uninterrupted supply to always meet household demands (Mekonnen and Kohlin, 2009; Pachauri and Spreng, 2004). For this study it was possible to test the fuel stacking hypothesis since the EICV 5 dataset captured information regarding primary and secondary cooking fuels that permitted further analysis.

1.2. Survey Approaches and Methods on Cooking Fuel Choice

The existing literature has documented a variety of studies that have analyzed household cooking energy choices and patterns in different regions based on two methodological approaches. The first approach consists of studies that usually look at possible future scenarios and therefore focus on analyzing the energy demand together with factors that influence household cooking fuel choices to make projections using either econometric techniques (Daioglou et al., 2012; Van Ruijven et al., 2011) or simulation by least cost optimization to arrive at the optimal cooking energy choices (Pachauri et al., 2013; Ekholm et al., 2010). However, these methods do not handle fully multiple cooking fuel utilization and fuel stacking that is prevalent in poor economies which is a limitation (Masera et al., 2000). Recent development of a MESSAGE-Access model which was used to assess household cooking energy choices in South Asia and Central America brings an array of hope to overcome this limitation as a new demand model (Pachauri et al., 2018; Cameron et al., 2016). This new approach not only incorporates fuel stacking but also permits further calibration on using household survey data to assess household cooking fuel choice patterns. Nevertheless, such approach is still limited to be carried in most developing countries including the present study due to insufficient data on energy prices and expenditures.

The second methodological approach focuses mostly on the investigation of energy ladder hypothesis validity using discrete choice frameworks (Buba et al., 2017; Farsi and Filippini, 2007; Heltberg, 2005). However, these studies reveal mixed evidence regarding income and choice of fuel type especially in the sub Saharan Africa and other developing country context. Emphatically, both recent and old studies show that demographic characteristics, economic status, public awareness, geographical location, wealth, household preferences, access to modern infrastructures play a role in determining household cooking fuel choices (Makonese et al., 2018; Hiemstra-Van der Horst and Hovorka, 2008; Madubansi and Shackleton, 2007; Arnold et al., 2006). Therefore, this paper assessed household preferences towards clean cooking fuels and energy use patterns in Rwanda, one of the low-income countries in the Sub-Saharan African region to see prospect of improving access of commercial modern cooking fuels along the urban domestic sector. This is a unique country specific case study which informs policy design and decision-making process towards promotion of clean cooking fuels especially in the Sub Saharan African region to support the sustainable goal number 7 agenda of ensuring affordable and clean energy sources. The paper used the newly released household survey data to provide country empirical evidence that is still limited. But why did the households choose a certain type of cooking fuel, what factors influenced these choices; what household characteristics made more probable to use traditional fuels that are deemed to be unclean than other modern energy sources such as LPG and charcoal that are regarded as clean energy sources for cooking in their homes? These were some of the guiding research questions.

2. MATERIALS AND METHODS

2.1. The Research Conceptual Framework

The study grouped the cooking fuels in three categories based on energy ladder hypothesis (Cameron et al., 2016; Toole, 2015; Farsi and Filippini, 2007). Specifically, the paper focused on analyzing household energy choice probability for LPG in the modern fuel category; charcoal in the transition fuel category and wood in the traditional fuels category in order to understand the prospect of accelerating modern cooking energy services uptake in Rwandan homes. The analytical approach was in three phases. First, the descriptive statistics analysis was carried out not only to help the researchers and readers understand energy use patterns but also to see the relationship that may exist between fuel choices and household income including multiple fuel use. The second part examined the linear and nonlinear relationships that may exist between cooking fuel choices versus household characteristics. Final part of the analysis focused on testing the robustness of the results.

2.2. Research Design and Data Collection

The study utilized the urban household responses from Rwanda Integrated Household Living Survey dataset for the year 2016 /17 (EICV5). This study focused on 2434 urban households that were drawn using the 2012 Rwanda Population and Housing Census as sampling frame for enumeration areas as primary sampling units. In this Census, each Enumeration Area was categorized as urban, semi-urban, peri-urban or rural (NASIR, 2018). The current population of Rwanda is pegged at 12.93 million with <30% living in urban areas (World Population Review, 2020). The EICV 5 data does not document energy prices and physical quantities of the fuels which is a limitation. However, its strength is that it captured a variety of information such as access to basic services, household durables, employment details, household demographics, household consumption, expenditure, and income over a calendar month. The nationally representative sample built on the previous household living condition surveys which started in 2001 known by its French acronym of "Enquête Integrals les Conditions de Vie des Ménages (EICV1)" and has been done on regular basis. Stata 14 as a statistical package software was used for descriptive statistics analysis and econometric estimation whilst the Microsoft Excel was used for graphics. Brief summary statistics of Independent variables that were hypothesized to influence cooking fuel choices among these urban households are presented in Table 1.

Table 1: Socioeconomic characteristics of the respondents

Variable	Obs	Mean	Std. Dev.
Log consumption per adult equivalent	2434	13.00	0.88
Log asset value	2434	8.86	3.41
Received environmental information	2434	0.40	0.49
Detached house	2434	0.63	0.48
Participant in the labour market	2434	0.57	0.50
Household size	2434	4.33	2.37
Male head	2434	0.76	0.43
Age of head	2434	40.70	13.99
Number of rooms	2434	3.45	1.61
Owner occupancy	2434	0.46	0.50
Tenant occupancy	2434	0.47	0.50
Education of head	2434	0.90	0.30
Number of children	2434	1.23	1.25
Number of elderly	2434	0.09	0.32
Electricity access	2434	0.75	0.44
Poor	2434	0.12	0.33

Source: Computed by author using EICV5

From Table 1, the distribution of the respondents shows that 76% were male heads and 24% were female heads. The mean household size was 4.33. The real annual consumption per adult equivalent (in January prices) which was used as a proxy measure of household income. Rwanda employs a basic-needs approach when measuring poverty in monetary terms. According to (NASIR, 2018), poverty was defined as insufficient consumption to satisfy food and non-food basic needs by using two poverty lines. Thus, households were classified as poor if they were below the poverty line of RWF 159,375 whilst that of extreme poverty line was computed at RWF 105,064. On poverty status, 12% of the households were classified as poor based on Rwandan poverty line of. With regard to occupational status, 46% were living in their own houses whilst 47% were renting houses. On education variable, 90% of the respondents have been to school. The inclusion of these variables was informed by literature (Mbaka et al., 2019; Adusah-Poku and Takeuchi, 2019). Some of the variables such as ownership of dwelling, gender of the household head, education, regional dummies. A correlation matrix for the independent variables that were used in the analysis showed no serious multicollinearity. The variance inflation factor (VIF) values for each of the independent variables was <10 which is a rule of thumb threshold for potential near perfect collinearity as reported in Table 1a in the Appendix.

2.3. The Empirical Model (Ordered Logit)

This study adopts an ordered discrete choice modeling approach by assuming that the individual household *i* is an economic agent facing a consumer basket of fuel product alternatives {depicted as latent variables, y_i^*, in equation (a)}. The choice of probit over logit or other random parameters model depend on the working assumptions of the error terms despite that both models give similar results (Nlom and Karimov, 2015; Greene, 2012). In this paper, the household fuel choices of four fuel types was estimated using ordered logit model based on the assumption that household energy consumption pattern followed a natural progression pattern (Farsi and Filippini, 2007). Theoretically, error terms from logit model take a logistic distribution whilst that of probit model are assumed to be normally distributed. Formally, assume that an individual's choice of primary cooking fuel is chosen from a set of "J" alternatives by household "i" to maximize household utility (Jumbe and Angelsen, 2006). It is assumed that the individual's choice of cooking fuel would be ranked based on efficiency, comfort and ease of use or convenience. The fuel choices would be determined also by a vector of household characteristics and other factors. The ordered logit model is specified in the equation (a) as follows:

$$y_i^* = X_i^* \beta + u_i \quad \text{(a)}$$

Where the unobservable (u_{nj}) for all "j" set of cooking fuel alternatives is identically and independently distributed having a Weibull distribution with $u \sim \exp[0, \Sigma]$ and β_{nj} is a vector of unknown parameters.

Rearranging expression (a) based on a hypothesis that the relationship between vector of household characteristics and the dependent variable is established by estimating a vector of parameters β using log-likelihood method gives the following maximizing log likelihood function.

$$\text{In}\,L(\phi) = \sum_{n=1}^{N}\sum_{j=1}^{J} y_{ni}\,\text{In}P_{nj} \quad \text{(b)}$$

The ordered logit model has m-1 cut -off points as threshold variables (not m categories) to avoid collinearity. For all probabilities to be positive, the threshold values are set to be $0 < \alpha_1 < \alpha_2 < \ldots. < \alpha_{m-1}$ and are estimated for each category. The ordered logit is a regression model where regressors do not include a constant. The individual probabilities are specified in expressions (c), (d), (e) and (f) as follows:

$$p_{i1} = pr(y_i = 1) = \frac{1}{1+\exp[-\alpha_1 + (x'\beta)]} \quad \text{(c)}$$

$$p_{i2} = pr(y_i = 2) = \frac{1}{1+\exp[-\alpha_2 + (x'\beta)]} - \frac{1}{1+\exp[-\alpha_1 + (x'\beta)]} \quad \text{(d)}$$

$$p_{i3} = pr(y_i = 3) = \frac{1}{1+\exp[-\alpha_3 + (x'\beta)]} - \frac{1}{1+\exp[-\alpha_2 + (x'\beta)]} \quad \text{(e)}$$

$$p_{i4} = pr(y_i = 4) = 1 - \frac{1}{1+\exp[-\alpha_3 + (x'\beta)]} \quad \text{(f)}$$

Where p_{i1} and p_{i4} are in reduced form because $\alpha_0 = -\infty$ and $\alpha_4 = \infty$; y_i are fuel alternatives such that 1= other fuels, 2= wood, 3= charcoal and 4= LPG. This study utilized the Stata 14 software package for simulations to get the probabilities and the marginal effects by using the "ologit [varlist]" command and further post estimation. Therefore, the first ordered logit model was estimated without disaggregation of income categories as shown in M_1 whilst the second ordered logit model included disaggregation of income categories (quintiles) as shown in M_2 as expressed in equation (g) and (h) respectively. This was done to assess the robustness of the results and get an insight in terms of different income groups. All the two models that were estimated are expressed as follows:

$$M_1 = \phi_0 + \phi_1 X_1 + \phi_2 X_2 + \phi_3 X_3 + \phi_4 X_4 + \phi_5 X_5 + \phi_6 X_6 + \phi_7 X_7 + \phi_8 X_8 + u_i \quad \text{(g)}$$

$$M_2 = \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 X_4 + \gamma_5 X_5 + \varepsilon_i \quad \text{(h)}$$

Where

M_1= Household fuel choice equation in equation (g)	M_2 = Household fuel choice equation in equation (h)
X_1 = Log annual household consumption per adult equivalent	X_{10} = Region
X_2= Household size	γ_s= estimated parameters from quintiles variables of equation (h)
X_3= Age of head	ϕ_s= estimated parameters of equation (g)
X_4= Education	u_i= error term of equation (g)
X_5= Male head	ε_i= error term of equation (h)
X_6= Marital status	
X_7= Asset index	
X_8= Electricity access	
X_9= Ownership of dwelling	

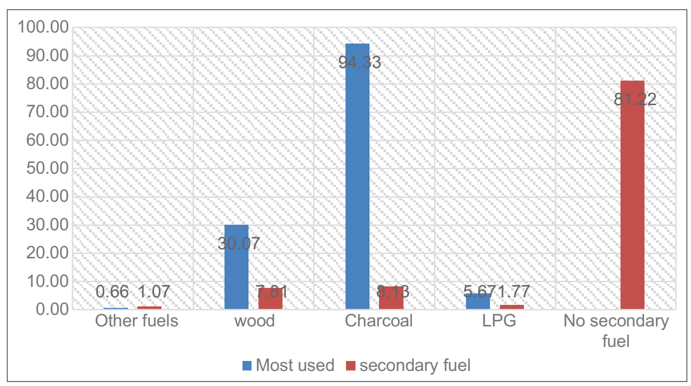
3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

This section presents the descriptive statistics first thereafter the econometric results from ordered logit regression analysis. In terms of clean energy access and energy consumption patterns, Figure 1 shows household cooking fuel consumption patterns amongest urban Rwandan households. It shows that few households use modern clean energy sources. For instance, under modern fuel category, 5.67% of households reported LPG as their primary fuel whilst 1.77% of households used it as a secondary fuel. The majority of the households (94.33%) used charcoal as a primary fuel for cooking activities and also majority of the households (8.13%) used it as a secondary fuel. This finding is not surprising since (Zulu and Richardson, 2012) found that charcoal was not only a primary source of household energy in urban communities but also is taken as a tradable commodity for household income generation. Charcoal is considered as a renewable energy source that is less polluting with fewer smoke emission compared to wood (Akpalu et al., 2011). Although this is the case, it attracts high opportunity cost for other economic livelihoods activities mostly for women and children thereby perpertuating gender and equity biases (Ekholm et al., 2010). However, a bigger proportion of the households (81.22%) did not have any secondary cooking fuel.

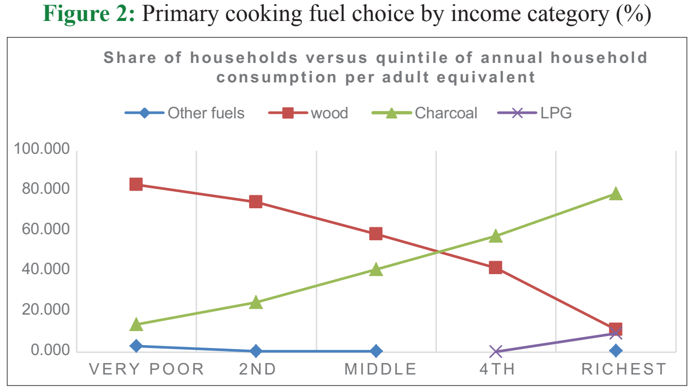
The choice of household cooking fuel is also linked to the income (proxied by annual household consumption per adult equivalent) and family size. Figure 2 indicates that high income levels reduces the probability of choosing traditional fuels (wood) while that of

Figure 1: Household cooking fuel consumption patterns (%)



Source: Computed by author using EICV5

Figure 2: Primary cooking fuel choice by income category (%)



Source: Computed by author using EICV5

modern fuels (LPG) and transitional fuels (charcoal) increases. This suggests that high income levels in Rwanda may be associated with fuel switching from traditional fuels to modern fuels. Thus, energy ladder hypothesis may hold in this situation.

3.2. Energy Ladder Versus Energy Stacking

However, regarding fuel stacking, the data showed that households practiced multiple fuel use and LPG which is a commercial energy is mainly used in the wealthy households with highest socioeconomic status depicted by the relationship between quintiles of household consumption expenditure and cooking fuel choices. Solid fuels still occupy large shares for both primary and secondary fuels categories across all the income categories. The Figure 3 shows that some rich and richest household use clean fuels, but the number is still small. In this case for easy assessment clean fuel referred to LPG, biogas, electricity and kerosene whilst solid fuels imply saw dust, wood, charcoal and crop residue).

Lastly, Figure 4 indicates that urban Rwandan households had a high rate of national grid connection (approximately 75%) but electricity was primarily used for home lighting and other purpose instead of cooking.

3.3. Factors Influencing the Cooking Fuel Choice

The ordered logistic regression model (Table 2) was fitted with household choice for three types of fuels namely; wood, charcoal

Figure 3: Fuel stacking by income category (%)

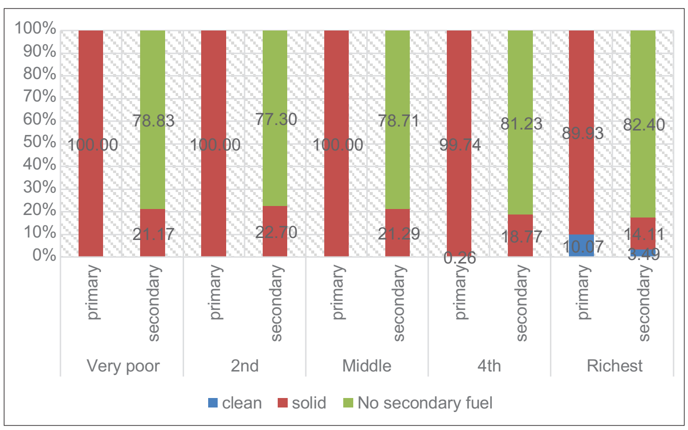
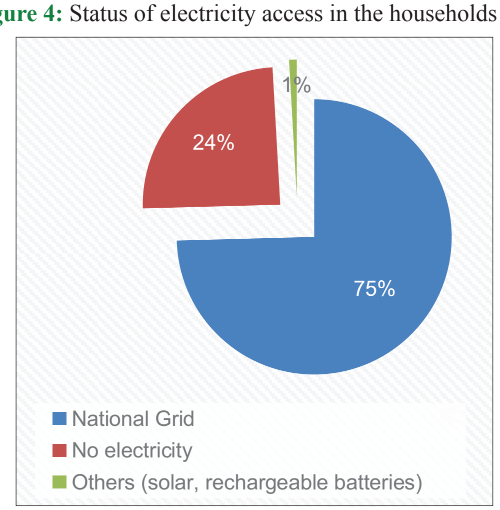


Figure 4: Status of electricity access in the households (%)



and LPG in the ascending order of 1, 2, 3 respectively. Further testing of the results involved estimating multinomial logit model(mlogit) specification to see if the assumption of ordered discrete choice modeling was feasible for the individual's choice on primary cooking fuel type based on efficiency, comfort and ease of use (Farsi and Filippini, 2007; Greene, 2012)[1]. The results showed that ordered logit model provided better prediction for household most used fuel choices (primary fuel) in both full sample (42.74%) and subsample (31.06%) of multiple fuel users[2]. However, the situation was different for multiple fuel users subsample. The non-ordered model (mlogit) provided better prediction for household secondary fuel choices (secondary fuel). This implies that for urban households, fuel ranking is critical when making decision regarding which cooking fuel to use most whilst for secondary the ranking does not matter. Since fuel switching process is both transitional and gradual in nature, it is important to understand these household preferences to inform the policy decision making process to improve clean energy service provision within a given country.

The results from Table 2 show some of the non-price factors which affect the household choice for cooking fuels in urban Rwanda. The parameters of these factors depict the position of the household on the energy ladder (household energy status). Overall, household income, household head labor participation, wealth status, residence in Kigali and western provinces had positive

1 Multinomial logit was estimated for full sample and multiple users subsample.

2 The results for multiple fuel users subsample are not presented here for brevity purpose but are available upon request.

Table 2: Ordered logit regression results

Fuel alternatives in ascending order: Wood, Charcoal, LPG	Coefficient	Std error
Log annual household consumption per adult equivalent	1.547***	0.108
Log asset value	0.137***	0.026
Received environmental information	−0.092	0.115
Detached house	−0.201	0.139
Labor participant head	0.350***	0.121
Household size	0.092**	0.043
Male head	−0.306**	0.143
Age of head	−0.031***	0.006
Number of rooms	−0.151***	0.049
Owner occupancy	−0.780***	0.142
Education of head	−0.028	0.200
Number of children	−0.033	0.066
Number of elderly	0.172	0.215
Kigali	1.908***	0.207
Southern	−0.228	0.215
Western	0.896***	0.209
Northern	0.415	0.237
Electricity access	−0.773***	0.155
Log likelihood	−1177.67	
Pseudo R squared	0.4274	
Percentage of correct prediction of chosen fuels		
Primary fuel for all the sample (2434) households	42.74%	
Both 1^{st} and 2^{nd} fuels for multiple-fuel users (457 households)	31.06%	

Table 3: Marginal effects for choice of wood, charcoal and LPG in Rwanda

Variables	Wood	Charcoal	LPG
Log annual household consumption per adult equivalent	−0.210*** (0.016)	0.198*** (0.015)	0.012*** (0.002)
Log asset value	−0.019*** (0.004)	0.018*** (0.003)	0.001*** (0.000)
Received environmental information	0.013 (0.016)	−0.012 (0.015)	−0.001 (0.001)
Detached house	0.027 (0.018)	−0.025 (0.017)	−0.002 (0.001)
Labor participant head	−0.048*** (0.017)	0.046*** (0.016)	0.003*** (0.001)
Household size	−0.013** (0.006)	0.012** (0.005)	0.001** (0.000)
Male head	0.039** (0.017)	−0.037** (0.016)	−0.003* (0.001)
Age of head	0.004*** (0.001)	−0.004*** (0.001)	0.000*** (0.000)
Number of rooms	0.020*** (0.007)	−0.019*** (0.006)	−0.001*** (0.000)
Owner occupancy	0.108*** (0.020)	−0.102*** (0.019)	−0.006*** (0.001)
Education of head	0.004 (0.027)	−0.004 (0.025)	0.000 (0.002)
Number of children	0.004 (0.009)	−0.004 (0.008)	0.000 (0.001)
Number of elderly	−0.023 (0.029)	0.022 (0.027)	0.001 (0.002)
Kigali	−0.261*** (0.029)	0.244*** (0.027)	0.018*** (0.003)
Southern	0.033 (0.032)	−0.031 (0.031)	−0.002 (0.001)
Western	−0.099*** (0.019)	0.090*** (0.016)	0.010*** (0.003)
Northern	−0.050** (0.025)	0.046** (0.023)	0.004 (0.003)
Electricity access	0.119*** (0.028)	−0.114*** (0.027)	−0.005*** (0.001)

These estimates were obtained from running ordered logit regression in Stata 14. Standard errors are in the parentheses. The levels of significance *P<0.05, **P<0.01, ***P<0.001

Table 4: Marginal effects by income category

Quintile	Wood	Charcoal	LPG
Very poor	0.468*** (0.050)	−0.436*** (0.059)	−0.076*** (0.012)
2nd	0.447*** (0.052)	−0.402*** (0.056)	−0.077*** (0.012)
Middle	0.457*** (0.049)	−0.406*** (0.052)	−0.082*** (0.013)
4th	0.325*** (0.057)	−0.271*** (0.054)	−0.067*** (0.012)

These estimates were obtained from running Ordered logit regression in Stata 14. Standard errors are in the parentheses. The levels of significance *P<0.05, **P<0.01, ***P<0.001

and significant effect as expected. However, owner occupancy, gender of household head, electricity access, number of rooms showed negative effects. On the otherhand, Table 3 presents the marginal effects of these factors that show the extent of how much these factors influence the household fuel choices in urban Rwanda. Looking at the case of fuelwood, the results indicated that household head labor market participation and household size had weak significance effects on the probability of choosing fuelwood by decreasing the choice probability for fuelwood by 4.8% and 1.3% at 1% and 5% levels of statistical significance respectively. Whereas, owner occupancy (10.8%), number of rooms (2%), electricity access (11.9%), age of household head (0.4%), female headship (3.9%) increased the choice probability for fuelwood with electricity access having bigger effects seconded by occupancy status. This finding shows that improved electricity access is not enough alone to promote fuel choices for clean energy sources and fuel switching. This finding is consistent with (Paudel et al., 2018) who found that Afghani households that had electricity access preferred animal dungs for cooking. However, this is contrary to what was found in Bhutan which is also a developing country (Bahadur et al., 2016). Reliability and availability of the electricity may be critical together with price factors and other social and risk perception reasons that were not captured by the available dataset.

However, being a resident of Kigali (24.4%), western province (9.0%), income (19.8%) and wealth (1.8%) had positive significant effect and increased choice probability for charcoal at 1% statistical level of significance. On contrary, female headship, age of household head (0.4%), number of rooms (1.9%), owner occupancy (10.2%), and electricity access (11.4%) decreased the choice probability for charcoal at 1% statistical level of significance. This finding supports the notion that regional differences and household socio economic status play a key role by influencing the choice probability for using transitional fuels such as charcoal.

In case of LPG, the results showed that income (1.2%), being a resident of Kigali (1.8%) and western province (1.0%) had bigger marginal effects compared to the rest of the other significant factors such as household size (0.1%), labor market participant head (0.3%) in increasing the choice probability. Some significant factors that reduced the choice probability for LPG include number of rooms (0.1%), owner occupancy (0.6%) and electricity access (0.5%).

Robustness testing of the results using different income categories (Table 4) show that households belonging to very poor (46.8%) and the middle class (45.7%) were more likely to choose wood, compared to the richest income category with bigger effects. This result supports the notion that traditional energy sources dominate the poor households unlike those with high socioeconomic status implying the household income does influence choice probability for cooking fuel consistent with what was found in Ghana (Karimu, 2015). Infact, very poor and the middle class were having large marginal effects across all the three fuel categories.

CONCLUSION

This research study presents findings from an ordered logit regression analysis on fuel choices and patterns of cooking fuels in urban Rwandan households using from EICV5 survey dataset. The study examined the choice probability of a household from selecting cooking fuel (wood, charcoal, LPG) whilst taking into consideration of socio-economic status and other household characteristics plus regional differences. The methodological aspect assumed a natural ranking of fuels depending on its efficiency, ease of use and cleanliness. The results from descriptive statistics and econometric analysis showed that the observed cooking fuel use patterns were consistent with the energy ladder hypothesis. This evidence suggests that natural order of progression, household income levels and other non-price factors play a key role in determining primary cooking fuel choices in the urban Rwanda. Other factors that influence fuel choices were asset index, house ownership, geographical location, number of rooms, household size and household head labor market participation significantly affected the propensity to use charcoal as transitional fuel and LPG as a modern fuel. The robustness testing of the results supports existing evidence in the literature which asserts that traditional fuel source (fuelwood) dominates in poor households. Charcoal, as a transitional fuel remains the most dominant primary fuel for cooking not only for lower- and middle-income household categories but also for the richest household category. The propensity to use charcoal and LPG as primary fuels decreased steadily by their percentage points of the marginal effects corresponding to the income category of the household. The highest income household households use mostly single fuel with no secondary fuel. This suggests a key policy implication of the need to intensify "clean energy use" campaigns project and strategic activities taking into consideration of regional differences. This will reduce regional biases to allow household energy transition to take place from primitive fuels to more advanced modern energy sources whilst encouraging poverty alleviation to improve household income status and affordability ceteris paribus (Paudel et al., 2018; Akpalu et al., 2011).

The limitation of these study findings is that these results imply correlation not causality since they are based on the cross-section data set that does not capture temporal effects of time variable in order to further examine renewable energy transition process in the households. As a result of this limitation, this paper could not employ dynamic discrete models to analyze the expected behavior following the Lucas critique which allows to make predictions (Tchereni, 2013; Aguirregabiria and Mira, 2010). For further research, it would be ideal to investigate key determinants for using clean energy sources in these households by employing a panel framework as datasets become available as well as inclusion of other important variables such as risk perception, social norms and awareness levels about clean energy technologies such as LPG.

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APPENDIX

Table 1a: Collinearity diagnostics

Variable's name	VIF	Tolerance
Household size	2.91	0.3432
Age of head	2.76	0.3626
Number of children	2.37	0.4212
Number of elderly	1.88	0.5309
Log of asset value	1.73	0.5784
Electricity access	1.59	0.6308
Owner occupancy	1.51	0.6632
Number of rooms	1.45	0.6891
Detached house	1.44	0.6962
Male head	1.40	0.7159
Poor	1.38	0.7260
Education of head	1.26	0.7966
Head is a labor market participant	1.23	0.8155
Received environmental information	1.08	0.9285
Mean VIF	1.70	