Determinants of Home Lighting Fuel Choices in Rwanda: A Discrete Choice Analysis

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Abstract: Renewable technologies such as solar present some of the possibilities for indoor and outdoor lighting in the remotest rural Africa where grid connections may take ages. This paper examined the key determinants that drive household lighting fuel using a nationally representative sample (14,415 households) across Rwanda. Results from a multinomial probit regression show that rural location, house ownership, household wealth, and nonfarm work are some of significant factors that influence lighting fuel choices in Rwanda. Robustness of the results indicates that household wealth levels and other regional differences are likely to influence choice probability for using clean energy sources such as solar confirming the need to prioritise wealth generation. The study’s findings suggest the need for joint efforts by government and non-state actors to prioritise household wealth generation, promotion of non-farm activities and improvement of infrastructures to reduce rural-urban bias and differences across the regions, assuming that wealth will motivate rural households to switch to clean energy sources.

Key words: Fuel choices, choice probability, Rwanda, households, clean energy.

1. Introduction

Overdependence on using traditional cooking fuels is closely linked to indoor pollution, environmental degradation, and high opportunity cost for women and children that end up affecting household welfare [1]. Energy is considered as a basic need and literature demonstrates correlation of absolute poverty with poor use of modern energy [2]. 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 [3]. The future outlook shows that vulnerable population that depends on biomass number is likely 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 [4]. 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 [5, 6]. However, successful uptake of clean energy technologies largely is linked to consumer demand and energy choices mostly from the household sector. Therefore, this paper utilized the latest EICV4 2013/14 data set that captures micro economic information to analyze lighting fuel choices of Rwandan households 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 [7] 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 1,871 inhabitants per square kilometer as of 2012 [8]. 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 [9]. 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 less than 200,000 inhabitants; an agglomeration at least 10,000 but less than 30,000 inhabitants. By 2012, Rwanda had 21 urban areas, 10 municipalities, 10 agglomerations with 7 emerging urban areas [10].

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 solar attributed to improved accessibility and availability that may induce fuel switching [11]. This implies that the household sector can offer an attractive market and prospect for diffusion of commercial clean energy 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 [12, 13].

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” 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 [14, 15]. In simple terms, the hypothesis depicts a linear movement up on arbitrary ladder so 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 [16]. 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 [17]. 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 [18, 19]. For this study it was not possible to test the fuel stacking hypothesis since the EICV 4 dataset did not capture disaggregated information on fuels regarding their primary and secondary usage that would have permitted further analysis.

2. Materials and Methods

2.1 The Research Conceptual Framework

The study grouped the lighting fuels in four categories based on energy ladder hypothesis [11, 20]. Specifically, the paper focused on analyzing household energy choice probability for solar in the modern fuel category; batteries in the transition fuel category and wood in the traditional fuels category in order to understand the prospect of accelerating modern energy services uptake in Rwandan homes [21] as depicted in Fig. 1.

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 wealth in form of an index. The household wealth index
calculated by principal component analysis (PCA) based on quantity of selected durable goods owned by households such as radios, benches, television, bicycles; quality of water supply and sanitation facility (toilet quality) and flooring materials (beaten earth, cemented floor, wooden floor) [22, 23]. Thereafter, four wealth quintiles were developed from the household scores that were used to categorise the socioeconomic status of the sampled households. According to Ref. [24], the only caveat with PCA is that it relies on using the first principal component of a set of variables that is a linear index of all the variables that capture the largest amount of undefined “common information” from relevant variables that are identified based on the discretion of the researcher’s judgement which is a drawback. The advantage is that it gives objectivity of the weights.

2.2 Data Source

To model the fuel choices of the Rwandan households and factors influencing their decisions for using the lighting fuels in their homes, the study utilized the household responses from secondary data collected during a 12-month cycle from October 2013 to October 2014 by National Institute Statistics of Rwanda [25]. Specifically, the survey data consisted of a nationally representative sample of 14,419 households but for this study we only considered 14,415 households that had fully captured a variety of information on key variables for the research study 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 was built on the previous household living condition surveys which started in 2001 known by its French acronym of “Enquête Integrales les Conditions de Vie des Ménages (EICV1)” and are done on regular basis. This survey was conducted by the National Institute of Statistics Rwanda (NISR) with joint financial supporters from with development partners such as
World Bank, African Development Bank, European Union and UK aid to provide vital information regarding the poverty and living conditions in Rwanda as a way of monitoring progress towards implementation of the Poverty Reduction Strategy and other Government policies. The main sampling frame consisted of primary sampling units (PSUs) drawn from 2012 Rwanda census Enumeration Areas (EAs). In this census, each EA was categorized as urban, semi-urban, peri-urban or rural. The urban areas included the Kigali-Ville and the district capitals. The smaller towns that had service facilities and markets were classified as semi-urban. The distinct feature that classified peri-urban areas was that they had the characteristics of rural areas, but were found on the periphery of urban areas and were earmarked for future development. In the final sampling frame, the semi-urban areas were put in the urban strata whilst the peri-urban areas were put with the rural strata. Hence, the final distribution of the sampling frame comprised of 17.2% urban households and 82.8% rural households across all 5 provinces of Rwanda.

2.3 Empirical Modeling

2.3.1 Multinomial Logit versus Multinomial Probit Models

This study adopts a discrete choice modeling approach by assuming that the individual household $i$ is an economic agent facing a consumer basket of fuel products (suppose there are $m$ alternatives that are latent variables). The choice of Multinomial Probit (MNP) over Multinomial Logit (MNL) or other Random parameters model depends on the working assumptions of the error terms despite that both models give similar results [26, 27]. We assume that there was no expected order of progression with respect to the fuel choice. This implies that what was observed among the four types of fuels that were selected for analysis could not be easily ordered in terms of comfort, ease of use and efficiency as has been the case with other scholars who employ ordered probit and logit models [27]. In this paper, households’ choice from four fuel types was estimated using MNP and was suitable because the outcome variable included four distinct unordered fuel alternatives and not multiple responses from the outcome variable and therefore fuel stacking was not tested [27-29]. The only caveat for MNP is that there is no specification testing due to its inherent complexity characterized by intractability of probability expressions for greater than four alternatives compared to MNL which requires a Hausman specification test [30, 31]. However, this study still adopted MNP due to its strength and also because the analysis only considered four fuel alternatives and therefore operating within safe limit [30]. Theoretically, error terms from logit model take a logistic distribution whilst those of probit model are assumed to be normally distributed [30]. According to Refs. [32, 33], suppose that a particular lighting fuel is chosen from a set of “$m$” alternatives by household “$i$” to maximize household utility and its indirect utility derived from each of the $m$ alternatives is depicted by $U_{im}$ that consists of observables ($X_i \phi_m$) such as age of household head and education level of the household head and other relevant household characteristics, and unobservable ($u_{im}$). The MNP model is now formally specified in Eq. (1) as follows:

$$U_{im} = X_i \phi_m + u_{im}$$

where the unobservable ($u_{im}$) is assumed to have a normal distribution with $u \sim N[0, \Sigma]$ and $\phi_m$ is a vector of unknown parameters. Supposing there are $m$ sets of lighting fuel alternatives, then the probability that individual household selects the first lighting fuel alternative is expressed as follows:

$$p_{i1} = \Pr(u_{i1} - u_{i1} < X_i \phi_1 - X_i \phi_2 \text{ and } u_{i1} - u_{i1} < X_i \phi_1 - X_i \phi_3 \text{ and } u_{i1} - u_{i1} < X_i \phi_1 - X_i \phi_4)$$

$$= \Pr[u_{i1} < X_i (\phi_1 - \phi_2) \text{ and } u_{i1} < X_i (\phi_1 - \phi_3) \text{ and } u_{i1} < X_i (\phi_1 - \phi_4)]$$

where $u_{i1} = u_{i2} - u_{i1}; u_{i3} = u_{i3} - u_{i1}; u_{i4} = u_{i4} - u_{i1}$ and likewise, we can get expressions for probabilities of second, third and fourth alternatives in a similar manner.
Furthermore, we assumed that \( u_{im} \) has a joint normal density function depicted as \( f(u_i) \) where \( f(u_i) = f(u_{i1}, u_{i2}, u_{i3}, u_{i4}) \) and has the mean vector equal to zero (0) with a corresponding variance covariance matrix expressed as follows:

\[
\Sigma = \begin{bmatrix}
\sigma_{i1}^2 & \cdots & \sigma_{i14}^2 \\
\vdots & \ddots & \vdots \\
\sigma_{i41}^2 & \cdots & \sigma_{i44}^2
\end{bmatrix}
\]

Lastly, Eq. (2) shows that the choice probability is a cumulative distribution, which is the probability that the difference in the random component of the utility from two lighting fuel alternatives is below the corresponding cumulative probability for the third, fourth lighting fuel alternatives or any general case can be derived following the same procedure [34]. Finally, one can express the log likelihood function for a sample of “n” independent households with “m” alternatives following the same procedure as shown in Eq. (3) using simulation methods in any statistical software package. This study utilized the Stata 14 software package by using the mprobit [varlist] command and further post estimation commands. Usually, the general practice in estimating the MNP is to choose one fuel choice category to be a reference for comparison purpose.

In this study, the first MNP model without region effects was estimated as shown in \( M_1 \) whilst the second model that included regional effects was estimated as shown in \( M_2 \) as expressed in Eqs. (4) and (5) respectively. Lastly, further testing of the robustness of the results of this study was done by regressing wealth index alone as a covariate in the household fuel choice Eq. (6) using a separate regression to know whether wealth status is the most dominant factor or not for the household lighting fuel choices. This is key in energy policy discourse to prioritise the pertinent needs within a given country. All the three models that were estimated are expressed as follows:

\[
\begin{align*}
M_1 &= \phi_0 + \phi_1 X_1 + \phi_2 X_2 + \phi_3 X_3 + \phi_4 X_4 + \\
& \quad \phi_5 X_5 + \phi_6 X_6 + \phi_7 X_7 + \phi_8 X_8 + \epsilon_i (4) \\
M_2 &= \gamma_0 + \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 X_4 + \gamma_5 X_5 + \\
& \quad \gamma_6 X_6 + \gamma_7 X_7 + \gamma_8 X_8 + \gamma_9 X_9 + \gamma_{10} X_{10} + \epsilon_i (5) \\
M_3 &= \alpha_0 + \alpha_1 W + \nu_i (6)
\end{align*}
\]

where:

- \( M_1 \) = household fuel choice equation in Eq. (4)
- \( M_2 \) = household fuel choice equation in Eq. (5)
- \( X_1 \) = rural/urban location
- \( X_2 \) = household size
- \( X_3 \) = age
- \( X_4 \) = education
- \( \phi_2 \) = estimated parameters of Eq. (4)
- \( \alpha_1 \) = error term of Eq. (4)
- \( \nu_i \) = error term of Eq. (6)
- \( \epsilon_i \) = error term of Eq. (5)

3. Results and Discussion

We first present results from the descriptive statistics analysis which is followed by results from MNP regression and other details on regarding tests for robustness of the results.

3.1 Descriptive Statistics for Household Characteristics and Lighting Fuel Choices

In terms of the Rwandan household energy choice, Table 1 shows that the highest proportion (45.02%) of households used batteries with bulbs as main lighting fuel. This was seconded by kerosene (18.60%), then electricity (18.01%) with solar panels (1.78%) being the lowest on the frequency of use as main primary energy source for lighting. Other fuels such as candles (7.07%) and fuelwood (9.52%) constituted smaller
proportions of the total sample. These household energy choices show the possibility of accelerating adoption of clean energy sources since the majority of the households depend on the transitional fuels. We also carried a further examination of the lighting fuel choices based on household location (rural versus urban) as possible key determinant. Batteries with bulbs were found to be the most dominating energy source for lighting followed by kerosene and fuelwood for rural households and those belonging to lower and medium wealth levels. However, the story is different for urban households which showed that electricity (70.45%) was the most dominant energy source for lighting followed by kerosene (10.73%) then batteries with bulbs (7.49%). The different pattern in household fuel use corresponded by household wealth quartiles showed that the cross-sectional energy ladder concept may hold for lighting fuel choices in Rwanda. The use of fuelwood decreased with higher wealth levels whilst the use of transitional fuels first rose up and then reduced again. This finding is in agreement with similar Kenyan study conducted by Lay et al. [35].

Further investigation on the distribution of the solar panels by wealth quartiles showed different observation to that of Jacobson [36] in 2006 who found that Kenyan households using solar tend to be rich but not the richest. Instead, our findings indicated that majority of households using solar panels seemed to be the richest belonging to the highest wealth level category.

Brief summary statistics of independent variables that were hypothesized to influence lighting fuel choices among the Rwandan households are presented in Tables 2 and 3. The inclusion of these variables was informed by literature on lighting fuel choices [12, 35] and also related energy studies [37, 38]. Some of the variables such as ownership of dwelling, gender of the household head, education and farm work are dummies. The average age of household head was 45 years whilst the average household size was 4. A correlation matrix for the independent variables that were used in the MNP estimation showed no serious multicollinearity as reported in Tables A1 and A2 in the appendix. The variance inflation factor (VIF) values for each of the independent variables were less than 10 which is a rule

| Lighting fuel source | Overall | Q1 | Q2 | Q3 | Q4 | Urban | Rural |
|----------------------|---------|----|----|----|----|-------|-------|
| Electricity          | 18.01   | 0.92 | 3.0 | 12.38 | 55.77 | 70.45 | 8.14 |
| Solar panel          | 1.78    | 0.22 | 0.97 | 2.72 | 3.19 | 0.44 | 2.03 |
| Batteries with bulbs | 45.02   | 55.72 | 57.50 | 47.64 | 19.21 | 7.49 | 52.09 |
| Fuelwood (firewood, dungs etc.) | 9.52 | 18.98 | 10.29 | 6.35 | 2.47 | 1.80 | 10.98 |
| Kerosene             | 18.60   | 17.40 | 20.53 | 23.53 | 12.94 | 10.73 | 20.08 |
| Candles              | 7.07    | 6.77 | 7.71 | 7.38 | 6.41 | 9.11 | 6.69 |
| Household distribution | 2,284 | 12,131 | |

Source: Authors’ calculations based on EICV4 survey data (2013/2014).

| Variables                  | Means | Standard deviation |
|----------------------------|-------|---------------------|
| Household size             | 4.51  | 2.07                |
| Female household head      | 0.25  | 0.43                |
| Ownership of dwelling      | 0.82  | 0.38                |
| Age of household head      | 45.04 | 15.98               |
| Rural location             | 0.84  | 0.36                |
| Wealth index               | 1.21  | 2.01                |
| Education                  | 1.25  | 0.43                |
| Farm work                  | 1.20  | 0.40                |
### Table 3  List of variables and definitions and hypothesis for influencing household lighting fuel choice.

| Variable’s name          | Description                                      | Expected sign |
|--------------------------|--------------------------------------------------|---------------|
| Household size           | Number of people in the household                | ±             |
| Female household head    | Dummy (1 if female 0 otherwise)                  | -             |
| Age of household head    | Age of the household head (years)                | +             |
| Wealth index             | Wealth index of household                        | ±             |
| Education                | Dummy (household head has ever been to school = 1, 0 = otherwise) | ±             |
| Ownership of dwelling    | Dummy (1 = household owns its dwelling, 0 = otherwise) | +             |
| Region                   | Dummies for all provinces in Rwanda              | ±             |
| Rural location           | Household situated place (1 if urban 0 otherwise) | +             |
| Farm work                | Dummy (1 = household head has farm work, 0 = otherwise) | -             |

of thumb of threshold for potential near perfect collinearity.

### 3.2 Factors Influencing the Household Lighting Fuel Choice

The MNP regression model was fitted with Rwandan household choice for three types of fuels namely; solar panels, batteries with bulbs and fuel wood with and without regional effects separately. This was to ensure robustness of the MNP regression results to get a full picture of the choice process for the specified fuels in Rwanda. The marginal effects for the choice of the three lighting fuels from the first model without regional effects and second model with regional effects are reported in Tables 4 and 5 respectively. The estimated coefficients ($\phi_i$) are presented in Tables A3 and A4 in the appendix, where other fuels (electricity, kerosene and candles) were used as the reference fuel category for the MNP estimation. The marginal effects of the first model (Table 4) show that household size had no significant effect on choice of solar panels despite having positive effects. However, rural location and ownership of a dwelling had positive significant effects on choice for solar panels at 1% level of significance. This reveals that being a rural household and also being a house owner lead to an increase in the probability choice for solar panels by 1.0% and 0.6% respectively. This study’s finding supports the notion that rural-urban difference is key to adoption of solar whilst we found weak evidence for education in influencing the choice probability for using solar panels. As for the significance of household wealth at 1% level of significance, the results showed that households belonging to poorer and middle and wealth status levels were less likely to choose solar panels, compared to the richest wealth level status. This result is different from that of Jacobson [36] who found that those who adopted solar PV belonged to the richer category but not the richest category. We also found negative significant influence of farm work on choice for solar panels. Those households that reported to have worked on their farm were less likely to choose solar panels implying that farm work decreased the choice probability for solar by 1.2%.

In case of batteries with bulbs, the results showed that rural location (33.5%) and ownership of dwelling (8.8%) had bigger marginal effects compared to the rest of the other significant factors such as household size (0.9%), age of household head (0.1%), education (3.5%) in increasing the choice probability. Additionally, household wealth broken down into poorer (26.2%), middle (26.8%) and richer wealth status (19.9%) compared to the richest category had bigger effects in increasing the choice probability for using battery with bulbs as depicted by the respective percentage average points indicated in the brackets. However, female household headship and farm work had negative significant effects of choice for using batteries with bulbs having decreased the choice probability by 8.0% and 15.7% respectively.
Looking at the case of fuelwood, the results indicate that household size had weak significance effect on the probability of choosing fuelwood by decreasing the choice probability for fuelwood by 0.2%. Whereas, rural location (6.1%), education (1.1%), age of household head (0.1%), female headship (2.0%) and household wealth especially belonging to poorer (14.6%), medium (7.4%) and richer (3.7%) category increased the choice probability for fuelwood having bigger effects seconded by rural residence.
Finally, the model with regional effects (Table 5) produced similar results to that of first model that did not capture the regional differences, substantiating that these findings were not driven by variation within regions of Rwanda. Considering eastern province as the reference region, households located in the southern and western provinces were more likely to use solar panels as the main lighting fuel by 1.3 and 1.9 percentage points respectively. Kigali and Northern Province had no significant effect on the choice of using solar panels. However, all the provinces including Kigali had significant effects on choice probability for batteries with bulbs and fuelwood. These regional effects imply that some provinces might have better infrastructure and easy access to the modern fuels such as solar panels and batteries with bulbs. These study’s findings support the notion that the rural-urban difference, ownership of dwelling, household wealth, farm work and some regional factors play a critical role by influencing the choice probability of household energy choices. These factors had significant effects on adoption probability for solar panels at 1% and 5% level of significance. In terms of magnitude of effects, the results show that ownership of dwelling increased choice probability to use solar by 0.5 percentage points and 7.8 percentage points to that of batteries with bulbs whilst it was found to be insignificant on the choice probability of using fuelwood.

4. Conclusion

This research study presented a framework for analyzing determinants of solar photovoltaics and household lighting fuel choices by employing a multinomial probit model using a nationally representative household level dataset. The study further categorized the households into different levels of wealth status via a principal component analysis to examine household wealth effects and other relevant factors on choice probability for lighting fuels namely: solar panels, batteries with bulbs and fuelwood taking other fuels (electricity, kerosene and candles) as a reference category. In addition, consideration was also given to some regional factors to investigate further whether there could be regional differences that affect the household lighting fuel choice. Household wealth also played an important role in pertaining clean energy uptake in the households. The data of the choice probability for using solar panel as the main source of lighting fuel decreased steadily in terms of percentage points of the marginal effects. Some of the significant factors that negatively influenced choice probability for solar included house wealth, and non-farm work whilst female household headship and Kigali residence were some of the significant factors that negatively affect the choice probability of using batteries. However, poor household wealth levels, residence in southern and western provinces and rural location were some of factors that drive choice probability for using fuelwood in the homes. This study shows mixed evidence regarding fuelwood under traditional being the most dominant fuel for the poor households. This paper found that batteries with bulbs categorized as transitional fuel were the most dominant fuels for lighting to households belonging to both lower and the middle wealth status levels.

The robustness of the result suggests the need for government and non-state actors to have joint efforts in prioritizing generation of household wealth, non-farm enterprises and improvement of infrastructures to reduce rural-urban bias and regional differences assuming that wealth and reduction in regional differences may help households to switch to clean energy sources [36]. Finally, some caution needs to be exercised when interpreting these study findings since we used only the cross-section data set that does not capture time in order to examine other fixed effects that may also influence fuel choices in homes to allow renewable energy transition process. As such, these findings just imply correlation not causality. Due to this limitation, we were not able to use dynamic discrete models to analyze the expected behavior.
following the Lucas critique which allows making predictions [39]. Again, inclusion of other important variables such as tastes, attitudes, perception and awareness levels about clean energy technologies would be helpful despite having an education variable alone that may not adequately capture them.

Compliance with Ethical Standards
Not applicable.

Conflict of Interest
All the authors declare that they have no conflict of interest.

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**Appendix**

Table A1 Collinearity diagnostics.

| Variable’s name | VIF | Tolerance |
|-----------------|-----|-----------|
| Household size  | 1.21| 0.8248    |
| Female household head | 1.29| 0.7748    |
| Age of household head | 1.37| 0.7299    |
| Wealth_poorer   | 1.98| 0.5062    |
| Wealth_middle   | 1.86| 0.5384    |
| Wealth_richer   | 1.72| 0.5813    |
| Owner_occupied  | 1.35| 0.7396    |
| Education       | 1.27| 0.7845    |
| Rural location  | 1.59| 0.6306    |
| Farm work       | 1.43| 0.6989    |
| **Mean VIF**     | 1.51|           |

Table A2 Correlation matrix.

| Variables    | hhsize | femHH | Province | Owner_occ | agehh | Farm work | Wealth index | Rural | Educ2 |
|--------------|--------|-------|----------|-----------|-------|-----------|--------------|-------|-------|
| hhsize       | 1.0000 |       |          |           |       |           |              |       |       |
| femHH        | -0.2622| 1.0000|          |           |       |           |              |       |       |
| Province     | 0.0402 | -0.0136| 1.0000   |           |       |           |              |       |       |
| Owner occupied| 0.2424| -0.0044| 0.1818  | 1.0000   |       |           |              |       |       |
| agehh        | 0.0704 | 0.3194| 0.0075  | 0.2657   | 1.0000|           |              |       |       |
| Farm work    | -0.0490| -0.0826| -0.2476 | -0.3339 | -0.0371| 1.0000    |              |       |       |
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Table A2 to be continued

| Variables     | Wealth index | Rural | Educ2 |
|---------------|--------------|-------|-------|
|               | 0.2219       | -0.1492 | -0.0545 |
|               | -0.1630      | 0.3027 | 0.2822 |
|               | -0.0980      | 0.3497 | 0.0634 |
|               | -0.0222      | 0.1077 | 0.1121 |
|               | 0.3232       | -0.4951 | 0.3767 |
|               | 1.0000       | -0.4768 | -0.0848 |

hhsize = household size, femHH = female household head, agehh = age of household head, educ2 = education of household head.

Table A3 Estimated $\beta$’s for solar panel, batteries, and fuelwood from multinomial probit model without regional effects.

| Variables                | Solar panels $p$-value | Batteries with bulbs $p$-value | Fuelwood $p$-value |
|--------------------------|------------------------|--------------------------------|-------------------|
| Household size           | 0.0337                 | 0.061                          | 0.0287***         |
| Wealth_poorer           | -0.5425***             | 0.000                          | 1.3786***         |
| Wealth_middle            | -0.1534                | 0.142                          | 1.2025***         |
| Wealth_richer           | 0.1006                 | 0.226                          | 0.8301***         |
| Female head              | -0.1323                | 0.170                          | -0.2710***        |
| Age of household head    | 0.0036                 | 0.172                          | 0.0046            |
| Farm work                | -0.7393***             | 0.000                          | -0.5962***        |
| Education of head        | -0.0961                | 0.329                          | 0.1441***         |
| Rural                    | 1.2727***              | 0.000                          | 1.5355***         |
| Owner occupied           | -0.4406***             | 0.001                          | 0.3552***         |
| Intercept                | -2.7876***             | 0.000                          | -2.2214***        |
| Sample size (N)          | 14,415                 |                                |                   |

The estimates were obtained using MNP regression with electricity, kerosene plus candles as the reference case, where, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4 Estimated $\beta$’s for solar panel, batteries, and fuelwood from multinomial probit model with regional effects.

| Variables                | Solar panels $p$-value | Batteries with bulbs $p$-value | Fuelwood $p$-value |
|--------------------------|------------------------|--------------------------------|-------------------|
| Household size           | 0.0324                 | 0.076                          | 0.0089            |
| Wealth_poorer           | -0.6178***             | 0.000                          | 0.0542***         |
| Wealth_middle            | -0.2409*               | 0.022                          | 0.0518***         |
| Wealth_richer           | 0.0476                 | 0.579                          | 0.0500***         |
| Female head              | -0.1058                | 0.285                          | 0.0436***         |
| Age of household head    | 0.0021                 | 0.439                          | 0.0012***         |
| Farm work                | -0.6899***             | 0.000                          | 0.0504***         |
| Education of head        | -0.0753                | 0.456                          | 0.0426***         |
| Rural                    | 1.2037***              | 0.000                          | 0.0680***         |
| Owner occupied           | 0.4222**               | 0.002                          | 0.0515***         |
| Kigali                   | -0.3675***             | 0.269                          | 0.0946***         |
| Southern                 | 1.8783***              | 0.000                          | 0.0454***         |
| Western                  | 0.0589***              | 0.000                          | 0.0469***         |
| Northern                 | 0.7246***              | 0.000                          | 0.0521***         |
| Intercept                | -3.3321***             | 0.000                          | 0.1264***         |
| Sample size (N)          | 14,415                 |                                |                   |

The estimates were obtained using MNP regression with electricity, kerosene plus candles as the reference case, where, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 