UNIVERSITY OF WAIKATO

Hamilton
New Zealand

Migration, Remittances and Cooking Fuel Usage in Sri Lanka: The Mediating Role of Household Wealth

J.M.D. Sandamali Wijayarathne, Gazi M. Hassan and Mark J. Holmes

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Corresponding Author

J.M.D. Sandamali Wijayarathne
School of Accounting Finance and Economics
Waikato Management School
University of Waikato
Private Bag 3105
Hamilton 3240
New Zealand
Email: jw406@students.waikato.ac.nz

Gazi M. Hassan
School of Accounting Finance and Economics
Waikato Management School
University of Waikato
Email: gmhassan@waikato.ac.nz

Mark J. Holmes
School of Accounting Finance and Economics
Waikato Management School
University of Waikato
Email: holmesmj@waikato.ac.nz

Abstract

The Sustainable Development Goal (SDG) 7 ensures universal access to affordable, reliable, and modern energy services by 2030. However, one-third of the world's population still lacks access to clean cooking fuel, and it will account for 2.3 billion by 2030. The transition from solid to clean, modern fuel is challenging because it is influenced by various factors, with household income being one of the most influential. Nowadays, the overwhelming majority of people in low and middle-income countries heavily rely on migrant remittances as a source of income, and this will have a favourable impact on clean cooking fuel choice. To explore this, we use three waves of Sri Lankan Households' Income and Expenditure Survey data (2009, 2012, and 2016). The results of propensity score matching analysis reveal that migrants use about 5% more clean fuel for cooking than non-migrants. Furthermore, we use the instrumental variable approach and the log of the distance to the nearest bank as the instrument to address the endogeneity of remittances. Accordingly, the control function estimates show that a 10% increase in migrant remittances increases clean cooking fuel use by 3.2%. The instrumental variable mediation analysis results find that household wealth significantly mediates this relationship. The findings suggest that policies encouraging migrant remittances can assist in developing and implementing energy policies to achieve SDG 7 by 2030.

Keywords

clean fuels

solid fuels

remittances

migration

household wealth

sustainable development goals

JEL Classification

F22, F24, Q40, R20

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1. Introduction

About 2.8 billion people worldwide use solid fuels like firewood, biomass, and crop residue for cooking, endangering human health and the environment (United Nations, 2020). Incomplete combustion of these fuels emits extremely harmful greenhouse gases and directly contributes to indoor air pollution (Balakrishnan et al., 2018; Muller & Yan, 2018). Indoor air pollution has been designated as the world's ninth-largest health risk, accounting for 1.6 million premature deaths each year (Ritchie & Roser, 2020). Therefore, the United Nations has adopted Sustainable Development Goal (SDG) 7, ensuring access to affordable, reliable, and modern energy for all by 2030. Modern or clean fuels such as electricity, Liquefied Petroleum Gas (LPG), and solar power are thought to be the golden thread that connects economic growth, human development, and environmental sustainability together (IEA, 2017). As a result, countries are prompted to switch from solid to clean fuels, irrespective of their level of development.

However, present trends indicate that SDG 7 will not be met, as 2.3 billion people will lack access to clean fuels and cooking technologies by 2030 (United Nations, 2020). As a result, researchers are interested in examining the causes of the energy transition, and most have identified household income as a significant determinant (Amoah, 2019; Dash et al., 2018; Ye & Koch, 2021). Households can raise their income from internal and external sources. Migrant remittances, or financial and in-kind transfers made directly by migrants to their families in the origin countries, are currently among the most prominent external income sources (Hassan, 2020; IOM, 2019b). Migrant remittances to Low and Middle-Income Countries (LMICs) reached USD 554 billion in 2019, with a 4.7% increase over the previous year, making them the largest source of foreign exchange revenue (World Bank, 2020).

As a result, migrant remittances have a great potential to be used as a source of income to encourage clean fuel consumption. A few studies have looked into the impact of migrant remittances on fuel consumption (Hassan, 2020; Manning & Taylor, 2014; Taylor et al., 2011; Ye & Koch, 2021). However, a clear link between migrant remittances and clean fuel usage is challenging to establish as many factors drive the use of remittances. For example, remittance is a flow variable rather than a stock, and therefore, it may not promote clean energy spending directly even if it induces current expenditure. Thus, if energy spending is to be induced, it must be more closely related to stock variables like education and health (Hassan, 2020).

Despite this, previous research shows that migrant remittances substantially affect household wealth (Baiyegunhi & Hassan, 2014; Rahut et al., 2016), whereas household wealth significantly influences clean fuel consumption (Adams & Cuecuecha, 2010; Mahapatro, 2016). This would happen because wealth is a stock variable rather than a flow variable, and therefore, it is likely to influence the use of clean fuel. As a result, this paper integrates two distinct pieces of literature: remittances and energy, through household wealth. Based on this background, this study seeks to address three research questions: (1) does clean cooking fuel consumption differ between migrants and non-migrants? (2) do migrant remittances influence the type of cooking fuel used? (3) does household wealth mediate the relationship between migrant remittances and the type of cooking fuel used?

As a result, this study has threefold contributions to the literature. First, to the best of our knowledge, this will be the pioneering study to employ household wealth as a mediating variable to examine the impact of migrant remittances on the type of cooking fuel used. The paper's uniqueness stems from integrating two disparate research areas, namely remittances and energy, through household wealth. Second, this will be the first study to compare the use of clean fuel for cooking between migrant and non-migrant households, based on nationally representative panel data from over 58,000 households. Third, this paper isolates migrant remittances as a driver of household fuel choice, which has received less attention in earlier research.

The remainder of this paper is organized as follows. Section 2 briefly reviews the relevant literature. Sections 3 and 4 outline the data and variable descriptions and the empirical model. Section 5 describes the results and discussion. Finally, section 6 concludes the paper and discusses the policy implications.

2. Literature Review

Solid fuels produce harmful gases such as carbon dioxide (CO_2), carbon monoxide (CO), and particulate matter ($PM_{2.5}$), endangering human health and the environment (Desai et al., 2004; Smith & Mehta, 2003). Due to the extremely negative implications of using solid fuels, extensive research has been performed to determine the factors that induce households to move from solid to cleaner fuels. Household income[1], household wealth[2], price of fuels[3], head and spouse characteristics[4] (age, gender, marital status, and education level), household size[5], number of children[6] and females[7], housing characteristics[8] (water and sanitation facilities, type of wall, roof, and floor), residential area[9] (urban vs rural), accessibility and availability of fuels[10], and taste preferences[11] are among the major determinants highlighted by these researchers.

Furthermore, the energy transition process is explained by two primary theories; the *energy ladder hypothesis* and the *energy stacking theory*. The energy ladder hypothesis states that when a household's socioeconomic status improves, particularly their income, they shift from solid fuels to transitional fuels and eventually to cleaner fuels (Heltberg, 2004;

[1] Amoah, 2019; Dash et al., 2018; Ravindra et al., 2019; Song et al., 2018; Ye & Koch, 2021

[2] Baiyegunhi & Hassan, 2014; Ouedraogo, 2006; Rahut et al., 2016
[3] Baiyegunhi & Hassan, 2014; Guta, 2014; Ravindra et al., 2019; Sharma et al., 2020
[4] Mensah & Adu, 2015 ; Sharma et al., 2020 ; Baiyegunhi & Hassan, 2014
[5] Sharma et al., 2020 ; Baiyegunhi & Hassan, 2014; Mensah & Adu, 2015
[6] Baiyegunhi & Hassan, 2014
[7] Dash et al., 2018; Rahut et al., 2016 ; Rahut et al., 2017
[8] Heltberg, 2005; Sharma et al., 2020
[9] Mensah & Adu, 2015; Rahut et al., 2016
[10] Mensah & Adu, 2015; Sharma et al., 2020; Song et al., 2018
[11] Dash et al., 2018; Heltberg, 2005; Ravindra et al., 2019; Sharma et al., 2020.

Hosier & Dowd, 1987; Leach, 1992). On the contrary, energy stacking theory asserts that as a person's economic status improves, they consume a portfolio of energy sources, including more clean fuels (Amoah, 2019; Heltberg, 2005; Ravindra et al., 2019; Sharma et al., 2020). Therefore, both theoretically and empirically, household income has been recognised as the most crucial driver of clean fuel use.

Most LMICs currently rely on international migration, i.e., a movement of people away from their habitual residence across an international boundary, to supplement their income (IOM, 2019a). The New Economics of Labour Migration (NELM) theory states that migration is not an individual decision but rather a family decision to improve socioeconomic conditions and well-being in one's home country (Stark & Bloom, 1985). Numerous studies have been conducted to discover the causes for migration and the benefits it brings, notably in terms of health and education.

However, although energy access and its use are essential aspects of people's socioeconomic conditions and welfare (Broto et al., 2017), it is rarely acknowledged as a factor in migration decisions and benefits. As a result, the link between international migration and the usage of clean fuels is currently a point of contention among scholars, but it remains restricted. Scott et al. (2018) argue migration can help to achieve SDG target 7.1, ensuring universal access to modern, reliable, and affordable energy. Manning and Taylor (2014) showed that migration aids the transition from fuelwood to gas for cooking in Mexico. Similarly, migrant families in Guatemala use multiple cooking fuels than non-migrants (Taylor et al., 2011). However, no research has been done to investigate how migration affects the various types of fuels used at the household level.

The effects of migration on clean fuel consumption in origin countries can be seen in three ways: (1) reducing the number of females; (2) transferring knowledge and skills; and (3) sending remittances. First, if a family has many female migrants, the household might switch to clean fuels because fuelwood collecting diminishes as the number of females falls (Scott et al., 2018). Second, migrant resilience to fuel access obstacles or shocks can be improved with knowledge from other contexts (Maller, 2011). Most migrant-heavy households have higher average income levels, enabling better access to modern energy services. Moreover, migrants working in more advanced countries can experience and gain knowledge about the benefits of using clean energy such as solar home systems, modern electrical appliances, and modern cooking methods. Thus, migrants can transfer this knowledge to their families while they remain in their place of destination or, more significantly, when they return (Scott et al., 2018), and this was validated by Sulthana (2015).

Finally, migrant remittances are inextricably related to migration, and they provide economic support and self-insurance to millions of households in underdeveloped nations at the micro-level (Akçay & Demirtaş, 2015; Taylor, 1999). Much evidence suggests that remittance recipients have a higher standard of living than non-remittance recipients, owing to better social conditions. Remittance recipients, for example, are more likely to use modern, clean fuels than non-remittance recipients. In Bangladesh, Hassan (2020) discovered that remittances enhance the likelihood of utilizing LPG for cooking by recipient households. In Ghana, Bukari et al. (2021) found that the negative impact of energy poverty on household health expenses is considerably mitigated through remittances. According to Mendelson (2013), remittance income is used for various sustainable energy technologies in developing countries. In Ecuador, a clean energy technology programme has been coupled with a financial remittance mechanism to boost rural energy access (IFAD, 2009). Moreover, households in Morocco use remittances for short-term and long-term energy consumption (Akçay & Demirtaş, 2015), and in Tajikistan, remittances are used to pay for energy services (World Bank, 2015). Also, the 3x1 Migrant Program in Mexico directs remittances to invest in local development, such as electrification projects (Orozco & Lapointe, 2004).

In theory, with an increase in income, two underlying factors cause households to switch to cleaner fuel sources (Hanna & Oliva, 2015). First, because solid fuels are inherently inferior goods and clean fuels are normal goods, the substitution effect towards clean fuels can outweigh the wealth effect due to greater household well-being. Second, awareness of the adverse health consequences of using dirty fuel will strengthen the substitution effect of clean fuels. The source of income, in general, do not affect the extent of the substitution effect. Yet, the rise in household income from specific sources, such as migrant remittances, could affect the substitution effect in some circumstances. Because remittances are usually invested in boosting human capital, they are more cautious about safeguarding their health capital (Hassan, 2020).

However, establishing a clear link between remittances and the use of clean fuel remains a challenge theoretically or empirically, prompting further investigation. As a result, this paper adds a new dimension and integrates two distinct pieces of literature: remittance and energy, through household wealth. Household wealth is generally measured by the wealth index, and it incorporates the long-term impacts of household well-being. The wealth index is often constructed using the number of durable household assets, water and sanitation facilities, and housing characteristics like the number of bedrooms, house ownership, housing area, type of wall, roof, and floor (Balen et al., 2010; Chasekwa et al., 2018; Gupta et al., 2017; Guta, 2014; Rahut et al., 2016; Song et al., 2018).

Most studies have discovered a significant positive association between household wealth and clean fuel use in the energy literature. Rahut et al. (2016) stated that wealthy families with permanent floors, roofs, and walls were more likely to use cleaner fuels. Having more rooms and piped water also enhances the possibility of using clean fuels (Arthur et al., 2010; Heltberg, 2004, 2005). Furthermore, in Nigeria, Baiyegunhi and Hassan (2014) show that families who reside in traditional dwellings are more likely to use clean fuels. According to Lay et al. (2013), homeowners utilize more clean fuels than tenants. Nevertheless, some studies have found the contrary (Ouedraogo, 2006; Pundo & Fraser, 2006).

Research on migrant remittances, on the other hand, indicates that they have a significant impact on household wealth. Households that receive remittances are more likely than non-recipients to invest in productive assets (Adams & Cuecuecha, 2010; Ajaero et al., 2018; Ajefu, 2018; Mahapatro, 2016; Yousafzai, 2015). Specially in housing, land, education, health, and repay debts (Abainza & Calfat, 2018; Ajaero et al., 2018; Mahapatro, 2016; Mahapatro et al., 2017), and therefore, they are benefited from higher living standards.

Given this context, the following hypotheses are tested in this study.

H_1: Migrant families use more clean fuel for cooking than non-migrant families

H_2: Migrant remittances and clean cooking fuel have a direct, positive relationship

H_3: Migrant remittances and transitional cooking fuel have a direct, positive relationship

H_4: There is a direct, positive relationship between migrant remittances and household wealth

H_5: Household wealth and clean cooking fuel have a direct, positive relationship

H_6: Household wealth and transitional cooking fuel have a direct, positive relationship

H_7: Household wealth mediates the relationship between migrant remittances and use of clean fuel for cooking

H_8: Household wealth mediates the relationship between migrant remittances and use of transitional fuel for cooking

H_9: Household wealth mediates the relationship between migrant remittances and use of solid fuel for cooking

3. Data and Variable Description

Sri Lanka is an intriguing study context to investigate the issues of energy and migration. Because although the country achieved universal access to electricity in 2019, clean cooking remains a challenge, with nearly 15 million people (69%) relying on biomass to cook (IEA, 2021). Jayasinghe et al. (2021) also found that the most pressing issue of energy poverty in Sri Lankan households is a lack of access to modern cooking fuel. Furthermore, worker remittances account for 8.8% of the Gross Domestic Product, amounting to USD 7104 million (CBSL, 2020).

3.1 Data Description

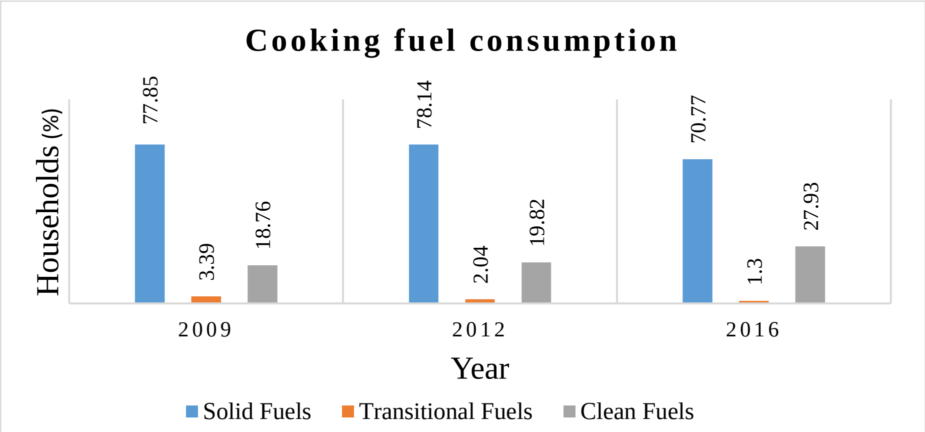
This study uses three waves of (2009, 2012, and 2016) Household Income and Expenditure Survey (HIES) data. The Department of Census and Statistics in Sri Lanka conducts HIES every three years and provides the essential socioeconomic indicators. It uses direct interviews and a survey questionnaire to collect data on demographics, income, expenditure, school education, health, and household assets.

The survey's sample design is stratified into two stages, and urban, rural, and estate sectors in each district serve as selection domains for stratification. A selection of 2500 primary sampling units was chosen from the sampling frame for the survey at the primary stage. From each primary sampling unit, 10 housing units were chosen for the survey. In 2009, 2012, and 2016, the total sample sizes were 23 641, 25 319, and 25 640 dwelling units. However, only 19 958, 20 540, and 21 756 households replied each year, for a total of 62 254 households, and we ended up with 58 061 households for the study after making all of the necessary changes.

3.2 Variable Description

The dependent variable of the study is cooking fuel consumption. Based on the energy ladder theory, we divide cooking fuel choice into three categories: (1) solid fuels (fuelwood, saw/paddy husk, and other); (2) transitional fuels (kerosene); and (3) clean fuels (LPG and electricity). Figure 1 shows the distribution of households by primary cooking fuel consumption in Sri Lanka.

Figure 1: Cooking Fuel Consumption



According to Figure 1, most Sri Lankan families use solid fuels as their primary cooking fuel, but this has declined over time (from 78% in 2009 to 71% in 2016). The proportion of households using transitional fuels has decreased over the three survey periods, whereas the proportion of households using clean fuels has steadily increased (18.76%, 19.82%, and 27.93% for 2009, 2012, and 2016 respectively).

The independent variable of the study is migrant remittances. To have better-behaved data distributions, we use the natural logarithm (log) of remittances to validate normality. We use the household wealth index as the mediating variable in the relationship between migrant remittances and the type of cooking fuel used. The study's control variables include the other household[12] income, age of the head[13] and the spouse (log), gender of the head (male and

[12]Household is defined as a group of persons who live together and has a common arrangement for cooking.

[13] Head of household is a person who usually resides in the household and is acknowledged by the other members of the household as the head of the household.

female), education of the head and the spouse (no schooling, primary, secondary, and tertiary), head's employment sector (government, private, and other sectors), household size[14], the number of children under the age of five, the number of females, the residential sector[15] (urban, rural, and estate sector), and the districts (25 districts). In addition, categorical variables were dummy coded, with each of them having the following reference categories: solid fuels for cooking fuel type, female for head's gender, no schooling for education, other sectors for head's employment sector, estate sector for residential area, and Colombo district for district variable.

The descriptive statistics of the variables studied are reported in Table 1. It shows that around 8% of families have at least one migrant member, with an average remittance of SL Rs.15,566 (US$ 77.06, converted to US$1 = SL Rs.202). The average wealth quintile is 3, indicating that the most families are middle-income. Males account for the majority of the heads of households. The head and spouse are, on average, 51 and 46 years old, respectively. The head has a grade 9 education, whereas the spouse has an average grade 7 education. The average household size is four individuals, comprising two women. Rural areas account for 70% of all households. The average distance from the house to the nearest bank is 2.47 kilometres.

Table 1: Descriptive statistics

Variable	Mean	Std. Dev.
Cooking Fuel Type	1.467	0.833
Migrant Remittances	15565.6	102184.1
Migrants	0.081	0.273
Household Income	98018.72	949094.8
Wealth Index Quintiles	2.999	1.418
Head Gender	1.245	0.43
Head Age	51.45	14.05
Head Education	8.819	3.999
Head Employment Sector	1.594	1.19
Spouse Age	45.805	12.623
Spouse Education	6.666	5.334
Household Size	4.183	1.718
Female Number	2.16	1.173
Children Number	0.252	0.527
Urban Sector	0.224	0.417
Rural Sector	0.703	0.457
Distance to the bank	2.47	1.891

[14] Household size refers to the number of persons usually living in the household, including boarders and servants.

[15] Rural sector includes all the areas other than the areas governed by Municipal Councils (MCs) and Urban Councils (UCs) and the estate sector (Census and Statistics Department, 2012)

4. Empirical Model

This study addresses three research questions. We begin by identifying the differences between migrants and non-migrants in their use of clean fuel for cooking. To accomplish this, we employ the Propensity Score Matching (PSM) method (Arsenijevic & Groot, 2018; Clément, 2011; Démurger & Wang, 2016). Second, we examine the impact of migrant remittances on the type of cooking fuel used. For that, we use a control function approach due to the possible endogeneity of remittances (Petrin & Train, 2010; J. Wooldridge, M., 2015). Finally, we utilize instrumental variable mediation analysis to determine how household wealth mediates this relationship (Dippel, 2017; Joffe et al., 2008). We use Principal Component Analysis (PCA) to construct the household wealth index (Chasekwa et al., 2018; Filmer & Pritchett, 2001; Vyas & Kumaranayake, 2006) (see Appendix B).

4.1 Propensity Score Matching Method (PSM)

The primary purpose of using PSM analysis is to quantify the average effect of migrant households (treatment group) on non-migrant households (control group) who have similar characteristics. The estimated average impact on the treated group can be derived as follows.

Suppose the treatment (T_i) is equal to "1" if household "i" receives remittances and if not "0". Y_{i1} is the potential outcome of household i who receive remittances and otherwise Y_{i0}. The difference between the outcome indicator of the treatment group and the control group is then used to calculate the average treatment effect for the i^{th} household.

$$\Delta Y_i = E\left(Y_{it|}\, T_i = 1\right) - \left(Y_{i0|}\, T_i = 1\right) \tag{1}$$

The main assumption of the PSM analysis is the Conditional Independence Assumption (CIA), which states that treatment selection is exclusively dependent on observed variables (Caliendo & Kopeinig, 2008; Nannicini, 2007; Rosenbaum & Rubin, 1983). The observed variables are denoted by X and can be expressed as follows.

$$\left(Y_{i0|}\, T_i\right) \perp T_{i|}\, X_i \tag{2}$$

Equation 2 shows, given X_i, the outcome of the control group can approximate the counterfactual outcome of the treated group in the absence of treatment. Accordingly, the outcome is given as:

$$E\left(Y_{i0|}\, T_i = 1,\ X_i\right) - \left(Y_{i0|}\, T_i = 0,\ X_i\right) \tag{3}$$

This illustrates the propensity score represents the probability of treatment conditional on a vector of observable characteristics and may be interpreted as the one-dimensional summary of the set of observable variables, which is expressed as:

$$P\ (Xi) = Pr(\ T_i = 1|X_i\ ) \tag{4}$$

The estimation of the counterfactual is given as:

$$E\left[\left(Y_{i0|}\, T_i = 1, P(X_i)\right)\right] = E\,[\left(Y_{i0|}\, T_i = 0, P(X_i)\right)] \tag{5}$$

Finally, the average treatment effect for i[th] household is measured as follows.

$$\Delta Y_i = E\left[\left(Y_{i0|}\, T_i = 1, P(X_i)\right)\right] = E\,[\left(Y_{i0|}\, T_i = 0, P(X_i)\right)] \tag{6}$$

4.2 Control Function Approach

To analyze household cooking fuel choices, we employ a random utility model. Accordingly, a household chooses between three mutually exclusive cooking fuel options: solid, transitional, and clean, to maximize their utility. The utility that household n obtains from alternative j is given by (Petrin & Train, 2010; Vadean et al., 2019):

$$U_{nj} = V\left(Rem_{nj}, X_{nj}, \beta_n\right) + \varepsilon_{nj} \tag{7}$$

where U_{nj} is the utility that depends on observed factors, Rem_{nj} stands for the amount of remittances received by the household n, X_{nj} is a vector 14 of exogenous variables that affect the utility derived from choice j, β_n is the parameters that present the taste of households, and ε_{nj} is the unobserved utility.

However, the amount of remittances a household receives is most likely endogenous (Adams & Cuecuecha, 2013; Demirgüç-Kunt et al., 2011). In choice models, the control function (CF) approach is one of the most effective and straightforward ways to deal with endogeneity (Petrin & Train, 2010; Piracha et al., 2013; J. M. Wooldridge, 2015). The CF method is a robust two-step approach in which the amount of remittances is represented as a function of observed and unobserved parameters in the first phase as follows:

$$Rem_{nj} = W(Z_n, X_n, \gamma) + \mu_{nj} \tag{8}$$

where ε_{nj} (in equation 7) and μ_{nj} are independent of Z_n and X_n, but ε_{nj} and μ_n are correlated. The vector Z_n contains a set of instruments that are correlated with Rem_n but not enter directly the utility function U_{nj}. Following Petrin and Train (2010), it is decomposed into a part that can be explained by a general function of μ_n and a residual:

$$\varepsilon_{nj} = CF(\mu_n, \lambda) + \tilde{\varepsilon}_{nj} \tag{9}$$

where $CF(\mu_n, \lambda)$ denotes the control function with parameters λ. We specify the control function as linear in μ_n (i.e., $F(\mu_n, \lambda) = \lambda\mu_n$), giving utility the following form:

$$U_{nj} = V\left(Rem_{nj}, X_n, \beta_j\right) + \lambda\mu_{nj} + \tilde{\varepsilon}_{nj} \tag{10}$$

Conditional on μ_n, the probability that household *n* chooses alternative *i* is equal to:

$$P_{ni} = \iint I(U_{ni} > U_{nj} + \lambda\mu_n + \tilde{\varepsilon}_{nj} \ \forall \ j \neq i) \mathrm{f}(\beta_n, \tilde{\varepsilon}_n) \mathrm{d}\beta_n \mathrm{d}\tilde{\varepsilon}_n \tag{11}$$

where f (.) is the joint density of β_n and $\tilde{\varepsilon}_n$ and I (.) is the indicator function.

In this way, the control function is added to the conventional choice model as an extra explanator variable. The model is estimated in two steps. First, Equation 8 is estimated by OLS with the endogenous variable (Rem_n) as the dependent variable and the exogenous variable and the instrument (i.e., Z_n and X_n) as explanatory variables, following the exclusion restriction procedure of the instrument. Then, using the estimated parameters ŷ from the OLS regression, the residual is calculated as ($\hat{\mu}_{nj} = Rem_{nj} - W(Z_n, X_n, \gamma)$). In the second step, the choice model is estimated using multinomial logit regression (see Appendix C) by taking $\hat{\mu}_n$ as an additional covariate.

The choice of an appropriate instrument that satisfies both instrument relevance and exclusion restriction criteria is crucially essential to address the endogeneity of remittances. Regarding this, the choice of an instrumental variable differs across various studies. Some important studies have employed *distances* such as *the distance to the railway station* (Adams & Cuecuecha, 2010, 2013; Ambrosius & Cuecuecha, 2016), or *the distance to the city* (Demirgüç-Kunt et al., 2011) as the instrument depending on the study context and the data availability.

For this reason, we use *the log of distance to the nearest bank* as the instrument. Many studies have used this instrument to examine the association between financial inclusion and energy poverty (Awaworyi Churchill et al., 2020; Koomson & Danquah, 2021; Koomson et al., 2020). However, this is the first study to use the distance to the nearest bank as an instrument in migration (remittance) research because most migrant families are financially inclusive, with bank accounts and access to banking to perform routine banking operations such as withdrawing cash from remittance receipts. Furthermore, due to the rapid expansion of global money transfer infrastructure and lesser restrictions, most remittances are now channelled through official banking sources (Ahmed et al., 2021; Guermond, 2022). Thus, it is reasonable that migrant households will be relocating closer to a bank to lower the transaction costs of frequent visits to a bank or other financial institutions. As a result, we predict that the log of remittances and the distance to the nearest bank will have a negative first-stage relationship.

More significantly, the *distance to the nearest bank* satisfies the two conditions of a valid instrument: relevance and exogeneity (Stock & Watson, 2007; J. Wooldridge, M., 2015). If the instrument is more relevant, it can explain the greater variation in the endogenous regressor (log of remittances) without necessarily being correlated with the unobserved factors that influence the outcome variable (cooking fuel type). This criterion is satisfied when the first stage F statistics exceed the rule-of-thumb value of 10 (Stock & Yogo, 2005). The second condition, exogeneity, explains that the instrument cannot directly affect the type of cooking fuel and can only affect the type of cooking fuel through remittances to obtain a consistent estimation. Since there are no direct tests for the exclusion restriction, we run auxiliary regressions to help us identify variables in our model that could be potential exclusion restriction violators because they are correlated with the instrument. Afterwards, we incorporate them into the empirical model as covariates to ensure they have no direct relationship with the dependent variable of the structural equation. The process provides a credible identification and supports the instrument's validity (see Table A.1 and A.2 in Appendix A).

4.3 Instrumental Variable Mediate Model (IV Mediate)

One of the primary objectives of this study is to determine the mediating effect of the wealth index on the association between migrant remittances and the type of cooking fuel used. We observed that remittances and wealth index are endogenous variables using the endogeneity test (the predicted residual is significant in the second stage). Since both the treatment variable and the mediators are endogenous, a single instrumental variable is sufficient to determine the causal and mediation effects (Dippel, 2017; Joffe et al., 2008). Following that, we employ the IV mediate model with a single instrument (Dippel et al., 2020; Dippel et al., 2019).

First, we define the linear equations for remittances (Equation 13), wealth index (Equation 14) and cooking fuel type (Equations 15 - 17) as follows:

$$lnDB = \varepsilon_{DB} \, , \tag{12}$$

$$lnRem = \beta_{Rem}^{DB}.DB + \varepsilon_{Rem} \quad , \tag{13}$$

$$WI = \beta_{WI}^{DB}.DB + \varepsilon_{WI} \, , \tag{14}$$

$$CF_1 = \beta_{Rem}^{DB}.DB + \beta_{WI}^{DB}.DB + \varepsilon_{CF1} \, , \tag{15}$$

$$CF_2 = \beta_{Rem}^{DB}.DB + \beta_{WI}^{DB}.DB + \varepsilon_{CF2} \, , \tag{16}$$

$$CF_3 = \beta_{Rem}^{DB}.DB + \beta_{WI}^{DB}.DB + \varepsilon_{CF3} \, , \tag{17}$$

where DB is the log of distance to the nearest bank (instrumental variable), $lnRem$ is log of migrant remittances (treatment), WI is wealth index (mediator), CF is cooking fuel type (outcome, where 1,2 and 3 are solid, transitional and clean fuels, respectively) and $\varepsilon_{WI}, \varepsilon_{Rem}, \varepsilon_{II}, \varepsilon_{EP1}, \varepsilon_{EP2}, \varepsilon_{EP3}$ are error terms, respectively. We assume ε_{DB} is statistically independent from other error terms.

The direct effect is given by the coefficient $DE = \beta_{EP}^{II}$, the indirect effect is given by the coefficient multiplication $IE = \beta_{II}^{Rem}.\beta_{EP}^{II}$, and total effect is the sum of these two terms $TE = \beta_{EP}^{II} + \beta_{II}^{Rem}.\beta_{EP}^{II}$.

5. Results & Discussion

5.1 Propensity Score Matching (PSM) Results

This section compares how migrants and non-migrants use clean fuel for cooking. We employed the PSM model, with migrants serving as the treatment group (8%) and non-migrants serving as the control or comparison group. We use the migrants as a dummy variable, coding "1" for migrants and "0" for non-migrants. To estimate propensity scores, we selected 13 covariates[16] to avoid reverse causality and to have no effect on household expenditure patterns. However, household income was not included as a covariate since it directly impacts household expenditure patterns, leading to endogeneity bias (Clément, 2011).

As the first step of estimating the propensity score, we used probit regression to identify the relationship between covariates and the treatment variable. The results are shown in Table 2 and the explanatory power of the probit model is satisfactory, with a probability Chi-squared value less than 0.05 (Prob > Chi2 is 0.000) and a McFadden Pseudo R-squared value of 13.54%.

Table 2: Probit estimation for propensity score

Migrants	Coefficient	Standard Error	z	P > z
Wealth Index	0.087	0.004	19.73	0.000
Head Male	0.280	0.028	10.06	0.000
Head Age (log)	-0.425	0.032	-13.41	0.000
Head Education	-0.004	0.002	-1.95	0.052
Head Government Sector	-0.473	0.035	-13.48	0.000
Head Private Sector	-0.227	0.021	-10.80	0.000
Spouse Age (log)	-0.117	0.010	-11.94	0.000
Spouse Education	-0.042	0.003	-13.02	0.000
Household Size	-0.061	0.007	-8.39	0.000
Female Number	0.299	0.010	28.80	0.000
Children Number	-0.143	0.019	-7.29	0.000
Urban Sector	0.105	0.037	2.80	0.005
Rural Sector	-0.078	0.035	-2.24	0.025
Psedo R-square	0.1354			
Log likelihood	-14096.029			
LR Chi2	4413.71			
Number of Observations	58,061			

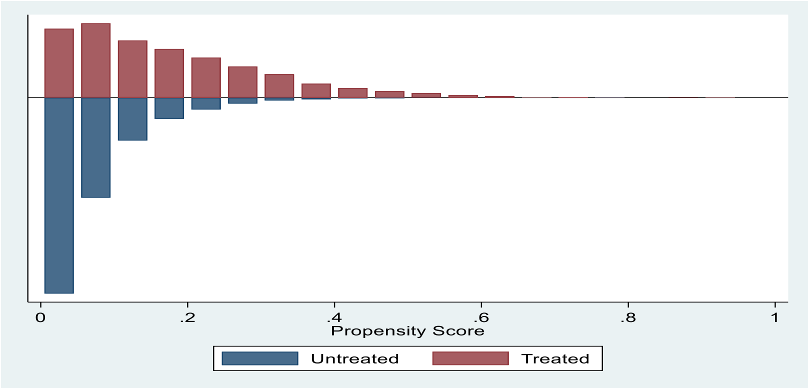
The findings suggest that all other covariates are significantly associated with the treatment group at the 5% significance level, apart from the head's education level. For example,

[16] Wealth index, head and spouse characteristics (gender, age, education, and employment sector), household characteristics (household size, number of children, and number of females), and residential sector (urban and rural).

the wealth index, gender of the head, number of females, and urban sector are positively associated with the treatment group, whereas other covariates are negatively associated.

Next, we ensure the condition for common support by examining whether the propensity scores in the treatment and control groups are overlapping and balanced. To ensure this, we divided the observations into five propensity score quintiles (see Figure 2).

Figure 2: Distribution of propensity score across treatment and control groups



The propensity score distributions of the two groups in the graph include 58,061 observations (4,693 treated and 53,368 untreated). The results reveal that the degree of overlap is satisfactory as the mean propensity score is equivalent in the treatment and comparison groups within each of the five quintiles in our final propensity score specification (Imbens, 2004).

After creating a balanced propensity score, we calculated the Average Treatment Effects on the Treated (ATT) to compare treatment and control groups, and the estimates are shown in Table 3.

Table 3: Propensity Scores for unmatched and matched sample

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Clean Fuel	Unmatched	0.343	0.212	0.131	0.006	20.84
	Matched /ATT	0.343	0.296	0.048	0.010	4.56

The mean difference between migrants and non-migrants in choosing clean fuel was measured using a T-test, and it was shown to be significant. According to the unmatched analysis, migrants are 13.1% more likely to use clean fuels than non-migrants. Using the matching method, or ATT, migrants use 4.8% more clean fuel for cooking than non-migrant households.

To check the robustness of the results, we computed the Average Treated Effect (ATE) and Average Treated Effect on Treated (ATET) using the same covariates. The ATE was calculated using two estimators: nearest-neighbour (nn) matching and propensity score (ps) matching. The results are depicted in Table 4.

Table 4: ATE and ATET values from Propensity Score Matching

Variable	AI Robust		z	p
Clean Cooking Fuel	Coefficient	Std. Error		
ATE (nn matching)	0.055	0.010	5.50	0.000
ATE (ps matching)	0.068	0.010	7.09	0.000
ATET	0.048	0.010	4.89	0.000

According to the nearest-neighbour matching and propensity score matching, migrant households use 5.5% and 6.8% more clean fuels for cooking than non-migrant households, respectively. Notably, the ATET produces the same results as the ATT, and all the results are consistent with the ATT's estimates.

The PSM approach is based on the Conditional Independence Assumption (CIA), which states that treatment selection is exclusively dependent on criteria that the researcher can observe (Caliendo & Kopeinig, 2008; Nannicini, 2007). However, if unobserved variables affect treatment assignment and potential outcome variables simultaneously, a hidden bias might arise. If hidden biases are present, matching estimators are not robust. Therefore, to address this issue, we use simulation-based sensitivity analysis, and it is recommended to use an additional binary variable to calculate the matching estimator (Nannicini, 2007). Thus, we use *house ownership* as an additional covariate with the nearest-neighbour matching estimation to calculate ATT. The ATT value was 0.059, and it indicates that migrant households use 5.9% more clean fuels for cooking than non-migrant households, which is consistent with our previous results.

Overall, the findings reveal that migrants use more clean fuels for cooking than non-migrants, rejecting the first (H_1) null hypothesis. This finding is consistent with the findings of Manning and Taylor (2014) in Mexico. They discovered that migration boosts gas expenditure by around 160% while decreasing their reliance on firewood in rural households. This could be because migrant families are experiencing increased labour shortages, especially in terms of female numbers, thereby raising the implicit cost of firewood. Furthermore, migrants utilize more modern energy sources due to greater remittances and the transfer of energy-related knowledge (Scott et al., 2018). However, Taylor et al. (2011) observed that migrant households in Guatemala use various fuels and cooking methods rather than a complete transition from fuelwood to LPG. These findings suggest that the type of cooking fuel used by migrants differs depending on the study context. Yet, our findings demonstrate 'energy access' as a factor in migration decision-making and one of the benefits of migration that is not addressed in the migration theories.

5.2 Control Function (CF) Results

The main objective of this study is to identify the impact of remittances on the use of clean fuel for cooking. Since remittance is endogenous, we use the CF approach to address the endogeneity. As described in Section 3.2, the *log of the distance to the nearest bank* was used as the instrumental variable, and an OLS regression was run with the instrument under each of the three models, taking log remittance as the dependent variable. The F-test value for all the models is greater than 10, suggesting that the instrument is valid according to the rule of thumb (J. Wooldridge, M., 2015). Then we predicted the OLS residual and substituted it into the multinomial logit model as an additional covariate in the second stage for each model separately. The results are presented in Table 5.

Table 5: CF Estimates

Variables	**Model (1)**		**Model (2)**		**Model (3)**	
	Clean Fuels	Trans. Fuels	Clean Fuels	Trans. Fuels	Clean Fuels	Trans. Fuels
Migrant Remittances (log)	3.378*** (0.170)	3.361*** (0.431)	3.169*** (0.246)	2.781*** (0.628)	2.930*** (0.242)	2.640*** (0.610)
Head's Characteristics						
Gender	3.241*** (0.170)	3.315*** (0.431)			-0.138*** (0.103)	-2.187*** (0.252)
Age (log)	1.313*** (0.075)	0.744*** (0.180)			2.171*** (0.152)	1.093*** (0.372)
Marital Status	1.191*** (0.109)	1.814*** (0.246)			2.112*** (0.211)	2.091*** (0.511)
Primary Education	-0.282** (0.111)	-1.067*** (0.190)			-0.147 (0.116)	-0.682*** (0.199)
Secondary Education	0.775*** (0.117)	-1.445*** (0.218)			0.591*** (0.127)	-0.901*** (0.239)
Tertiary Education	2.958*** (0.122)	-1.253*** (0.381)			2.494*** (0.126)	-0.499 (0.378)
Employment Sector - Government	2.381*** (0.115)	2.024*** (0.308)			1.734*** (0.127)	1.067*** (0.332)
Employment Sector - Private	1.172*** (0.089)	1.788*** (0.224)			0.494*** (0.068)	0.702*** (0.166)
Spouse's Characteristics						
Age (log)			0.342*** (0.048)	0.278*** (0.131)	0.352*** (0.055)	0.383*** (0.130)
Primary Education			1.541*** (0.152)	2.022*** (0.423)	2.156*** (0.203)	2.222*** (0.472)
Secondary Education			3.532*** (0.210)	2.618*** (0.566)	3.833*** (0.274)	2.294*** (0.668)
Tertiary Education			6.934*** (0.356)	3.161*** (0.104)	5.885*** (0.370)	2.901*** (0.097)

Other Characteristics					
Other Household Income (log)		-1.164*** (0.125)	-1.164*** (0.125)	-1.072*** (0.120)	-1.292*** (0.299)
Household Size		0.377*** (0.043)	0.494*** (0.108)	0.398*** (0.046)	0.507*** (0.113)
Number of Females		-1.560*** (0.130)	-1.596*** (0.332)	-1.552*** (0.134)	-1.595*** (0.337)
Number of Children		0.293*** (0.028)	0.359*** (0.068)	0.761*** (0.055)	0.606*** (0.136)
Urban Sector		2.348*** (0.105)	2.492*** (0.200)	2.101*** (0.081)	2.576*** (0.203)
Rural Sector		1.676*** (0.085)	1.228*** (0.278)	1.455*** (0.114)	1.358*** (0.295)
District Dummy	Yes	Yes		Yes	
First Stage F Statistic	97.38	293.68		249.86	
Psedo R squared	0.2121	0.2628		0.2884	
No. of Observations	57,931	57,931		57,931	

Notes: Robust standard errors in parentheses; ***,**, and * represent significant at the 1%, 5% and 10% levels, respectively. Solid fuel has been used as the base category for cooking fuel. Model 1 considers only the head's characteristics, Model 2 includes spouse's and other household characteristics, and Model 3 considers all the characteristics as the control variables.

Table 5 shows that remittances enhance the use of clean and transitional fuels for cooking in all models, compared to solid fuels. According to our base model (Model 3), a 10% increase in remittances boosts clean fuel use by 3.22% and transitional fuel use by 2.9%. These findings reject the second and third null hypotheses (H_{02} and H_{03}), indicating that remittances positively and directly affect clean and transitional fuel choice. The results align with those of earlier studies conducted in various circumstances. For example, Hassan (2020) discovered that a 10% increase in remittance income could improve the likelihood of adopting LPG by 2% for cooking in rural Bangladesh. He stated that high revenue from remittances and increased health awareness make modern energy more affordable. In Morocco, Akçay and Demirtaş (2015) found that short-term and long-term remittances impact for about 1% of variation energy usage of households, but they did not highlight the impact of remittances on various energy sources or their causes.

5.3 Mediation Analysis

One of the objectives of this paper is to identify the mediating role of household wealth in the relationship between remittances and the type of cooking fuel used. Since the treatment (remittance) and the mediator (wealth index) are endogenous, we used an IV Mediate model to identify this mediation effect, and the results are depicted in Table 6.

Table 6: IV Mediation Results

Pathways	Direct Effect	Indirect Effect	Total Effect
Remittances to Clean Fuels	0.326*** (0.082)		
Remittances to Transitional Fuels	0.033** (0.014)		
Remittances to Solid Fuels	-0.359*** (0.089)		
Remittances to Wealth Index	1.793*** (0.447)		
Wealth Index to Clean Fuels (*controlled for the treatment*)	0.181*** (0.018)		
Wealth Index to Transitional Fuels (*controlled for the treatment*)	0.018*** (0.006)		
Wealth Index to Solid Fuels (*controlled for the treatment*)	-0.199*** (0.019)		
Remittances to Wealth Index to Clean fuels	0.002*** (0.001)	0.324*** (0.086)	0.326*** (0.082)
Remittances to Wealth Index to Transitional fuels	-0.000 (0.000)	0.033** (0.015)	0.033** (0.014)
Remittances to Wealth Index to Solid fuels	-0.002*** (0.001)	0.357*** (0.095)	-0.359*** (0.089)

Notes: standard errors in parentheses; ***,**, and * represent significant at the 1%, 5% and 10% levels, respectively.

IV Mediate generates the results not only for the mediating effect but also for the direct effect of all the variables in the model. As a result, the findings support the CF estimates, demonstrating that a 10% increase in remittances raises clean and transitional fuels by 0.358% and 0.036%, respectively, while decreasing solid fuel use by 0.394%.

Furthermore, the findings indicate that a 10% increase in remittances boosts household wealth by 1.97%. This reveals that the fourth null hypothesis is also rejected (H_{04}), suggesting a significant positive link between remittances and household wealth. Many pieces of evidence suggest that remittance recipients have more wealth than non-remittance recipients. For example, remittances enable Nigerian (Ajaero et al., 2018; Ajefu, 2018) and Bangladeshi households (Mahapatro, 2016) to acquire and accumulate productive and non-productive goods and increase the asset index. Likewise, various empirical studies found that remittances enhance the wealth of migrant families through their investment in housing (Abainza & Calfat, 2018; Adams & Cuecuecha, 2010), education (Adams & Cuecuecha, 2010; Mahapatro et al., 2017), and health (Mahapatro et al., 2017). This finding also follows the NELM theory, which claims that migration is a family decision to improve socioeconomic conditions and well-being in one's home country (Stark & Bloom, 1985), and this can be realised through increased wealth.

Further, a unit increase in the wealth index increases the clean and transitional fuel usage by 0.181 units and 0.018 units, respectively. As a result, the fifth (H_{05}) and sixth (H_{06}) null hypotheses are rejected, confirming that wealth has a direct, positive effect on clean and transitional fuel consumption. The finding is similar to the results of previous studies in various settings. Rahut et al. (2016) observed that wealthier families in Bhutan use and rely more on clean energy sources such as electricity and LPG. In addition, families in rural China with a higher wellness index consume more modern fuels (Song et al., 2018). This could be related to the fact that wealthier households can afford the extra cost of using modern fuels compared to solid fuels. Furthermore, members of affluent families have greater access to education, and as a result, they are aware of the negative health effects of solid fuel consumption. Therefore, they use more clean and transitional fuels for cooking than the less-wealthy families.

Finally, the results reveal that the wealth index explains 35.6% of the total effect of remittances on clean fuel use by rejecting the seventh null hypothesis (H_{07}). In other words, the total effect shows that every 10% increase in remittances raises clean fuel use by 0.358%. The direct effect estimates that 0.002% of this increase is because of remittances itself, and it is statistically significant. This would happen because, as migrant remittances grow, they are more inclined to spend remittances on home improvements. As a result, migrant families are more likely to adopt modern cooking methods and technologies, which ultimately enhance the use of advanced fuels for cooking. Moreover, the wealth index accounts for 36% and 39.2% of the total effect of remittances on transitional fuel use (H_{08}) and solid fuel use (H_{09}), respectively. These findings exemplify the study's fundamental contribution, integrating two distinct pieces of literature on remittance and energy through household wealth.

5.4 Robustness Check

To check the robustness of the results, we employed the GSEM as it enables multinomial logistic modelling with robust error with clusters. Further, it simultaneously measures the direct, indirect, and total effects when including mediating variable/s (Liu et al., 2020; Pei et al., 2020; Silverstein & Bengtson, 2018). The GSEM results show that a 10% increase in remittances increases clean fuel use by 0.035% and transitional fuel use by 0.037% (see Table A.3 in Appendix A). The GSEM results are consistent with the previous results. However, the impact of remittances on cooking fuel choice becomes substantially stronger after accounting for endogeneity.

6. Conclusion and Policy Implications

This research examines the impact of migration and remittances on the usage of cooking fuels using three waves of Sri Lankan Household Income and Expenditure surveys. It also brings together two previously unrelated pieces of literature on remittances and energy through household wealth. According to PSM analysis, migrants are at least 5% more likely to use clean fuels for cooking than non-migrants. According to CF analysis, a 10% increase in remittances boosts clean and transitional fuel use by about 3% compared to solid fuels. Furthermore, the

IV mediation analysis shows that remittances increase household wealth, which in turn, increases the use of clean cooking fuels, indicating that household wealth has a significant mediating impact on the relationship between migrant remittances and cooking fuel use.

The current study results have significant implications for meeting SDG 7 by 2030. Policymakers can utilize overseas inward migrant remittances as a strategic tool in formulating a financial, legal, and regulatory framework to achieve SDG 7. This can be accomplished through a variety of strategies. First, strengthen the ability of the financial services sector to channel remittances into a variety of sustainable energy technologies, like fuel-efficient cooking appliances. Second, direct remittances towards energy development projects in rural areas, such as electrification and solar power. Third, provide incentives such as lowering the cost of remittance transactions or lowering taxes on modern cooking equipment for migrant families to invest in modern cooking methods and technologies. Furthermore, educational authorities can develop programs to enhance awareness of the negative impacts of using dirty fuels on human health and environmental sustainability, particularly for women who undertake most household chores. These actions will promote clean fuel use and help to achieve SDG 7 as expected.

While this article examines a number of significant control variables that influence migration and remittances, data restrictions have limited the examination of some factors that may influence cooking fuel choice, such as fuel prices. Therefore, future researchers could look into how fuel prices affect this scenario. Moreover, they might also think about how migrant knowledge, skills, and experience in the destination country influence their decision to use clean fuel for cooking.

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Appendices

Appendix A – Tables

Table A.1: OLS Regression

Remittance (log)	Model 1	Model 2	Model 3
Distance to the Bank (log)	-0.097	-0.070	-0.073
	(0.018)	(0.017)	(0.017)
First-Stage F Statistic	97.38	293.68	249.86
Number of Observations	57,931	57,931	57,931

Notes: Robust standard errors in parentheses; ***,**, and * represent significant at the 1%, 5% and 10% levels, respectively.

Table A.2: Test of the Exclusion Restriction

	Lighting Source (Clean = 1)	Access to Electricity (Yes = 1)	Access to Safe Drinking Water (Yes = 1)
First-Stage Regression Distance to the Nearest Bank (log)	-0.106***	-0.274***	-0.073***
Second-Stage Regression Cooking Fuel Use	0.031	-0.060	0.028
Wald Test of Exogeneity (Cragg-Donald Wald F)	83.90***	44.26***	94.86***

Notes: Robust standard errors in parentheses; ***,**, and * represent significant at the 1%, 5% and 10% levels, respectively. The instrumented variable, remittance, is measured in log remittance. All specifications include a vector of controls that include other household income, heads' characteristics (age, gender, marital status, education, and employment sector), spouses' characteristics (age and education), household size, number of children, number of females, residential sector and district dummies.

Table A.3: GSEM Results

Explanatory Variables	Transitional Fuels	Clean Fuels
	0.034***	0.032***
Migrant Remittances (log)	(0.009)	(0.004)
Wealth Index	0.002	0.616***
	(0.019)	(0.009)
Head's Characteristics		
Gender (Female = 0)	-0.180*	0.009
	(0.105)	(0.054)

Marital Status (Never Married = 0)	0.106	-0.055
	(0.188)	(0.103)
Age (log)	-0.417***	-0.337***
	(0.113)	(0.062)
Primary Education (No Schooling = 0)	-0.147	0.137
	(0.151)	(0.107)
Secondary Education (No Schooling = 0)	-0.134	0.589***
	(0.155)	(0.106)
Tertiary Education (No Schooling = 0)	-0.356	1.219***
	(0.384)	(0.133)
Government Sector (Other sectors = 0)	-0.286**	0.085*
	(0.135)	(0.045)
Private Sector (Other sectors = 0)	0.047	-0.068**
	(0.070)	(0.034)
Spouse's Charateristics		
Age (log)	-0.105*	-0.162***
	(0.059)	(0.036)
Primary Education (No Schooling = 0)	0.490**	0.208
	(0.224)	(0.141)
Secondary Education (No Schooling = 0)	0.301	0.367***
	(0.220)	(0.138)
Tertiary Education (No Schooling = 0)	-0.755	0.823***
	(0.643)	(0.164)
Household and Other Characteristics		
Household Size	0.014	-0.181***
	(0.025)	(0.014)
Number of Children Under 5	0.089	0.309***
	(0.064)	(0.029)
Number of Females	-0.142***	0.014
	(0.038)	(0.018)
Other Household Income	-0.009	0.051***
	(0.020)	(0.011)
Residential Sector		
Urban Sector (Estate = 0)	2.450***	1.558***
	(0.199)	(0.087)
Rural Sector (Estate = 0)	0.458**	-0.133
	(0.203)	(0.085)
District Dummy	Yes	
Year Dummy	Yes	
Log psedolikelihood	-134 031.66	
Number of Observations	58,061	

Notes: standard errors in parentheses; ***,**, and * represent significant at the 1%, 5% and 10% levels, respectively. Solid fuel has used as the base category for cooking fuel.

Appendix B - Principal Component Analysis (PCA)

This study uses PCA to construct the household wealth index based on literature (Chasekwa et al., 2018; Filmer & Pritchett, 2001; Vyas & Kumaranayake, 2006). The PCA is one of the most popular multivariate statistical techniques that exact only the most crucial information from the observed data and develop the set of new orthogonal variables called principal components.

PCA makes uncorrelated components from an initial set (suppose n) of correlated variables, and those components are considered linear weighted components of the initial variables (Vyas & Kumaranayake, 2006). The derivation of principal components from a set of variables X_1 to X_n are as follows:

$$PC_1 = \alpha_{11}X_1 + \alpha_{12}X_2 + \ldots + \alpha_{1n}X_n$$

$$PC_m = \alpha_{m1}X_1 + \alpha_{m2}X_2 + \ldots + \alpha_{mn}X_n$$

where α_{mn} represents the weight for the m^{th} principal component and n^{th} variable, the weight for each component are ordered from 1 to m. The first components (PC_1) shows the largest possible variation in the original data, which is subject to the sum of squared weights ($\alpha^2_{11} + \alpha^2_{12} + \ldots + \alpha^2_{1n}$). The second component is entirely uncorrelated with the first component and shows the additional variation subject to the same constraint. Likewise, each additional component explains the further variation at a decreasing rate. Element is given by the eigenvector of the correlation matrix or covariance matrix. The eigenvalue measures each principal component's variance and indicates the percentage of variances in the total data explained. Fewer components are required if there is a higher degree of correlation among the original variables in the data (Vyas & Kumaranayake, 2006).

Following the rule of thumb, we first select the variables in the data set with a frequency of between 5% and 95% to include in the PCA. Then we looked at the correlation and eliminated any variables with a correlation of less than 1.0 or greater than 0.9. Finally, we use the 12 households' durable assets (ownership of radio, TV, VCD, sewing machine, washing machine, refrigerator, cooker, electric fan, computer, telephone, motor bicycle and car), type of wall, type of roof, the number of bedrooms, and the housing area to measure the household wealth. The sample adequacy is satisfied by the Kaiser-Meyer-Olkin measure value of 0.90 (kmo > 0.6). The wealth index, which has a 4.85 eigenvalue and a cumulative variation of 30.28%, is chosen as the first principal component.

Appendix C - Multinomial Logistic Regression Model

The MNL model follows random utility theory (RUT). The RUT states that every individual is a rational decision-maker and selects the best among alternatives to maximize utility (McFadden, 1978). Therefore, a household chooses the primary cooking fuel from various energy sources that yield the highest utility (Mensah & Adu, 2015). For instance, assume that the i^{th} household has three fuel alternatives (solid, transitional and clean fuels), and the household chooses the fuel "j" to maximize the utility in the time period t (t = 1,2,3) with a random effect can be described as follows:

$$V_{ijt} = X_{it}\beta_j + u_i + \varepsilon_{ijt} \quad (18)$$

where X_{it} is a vector of explanatory variables for each household's cooking fuel preference, β_j is a vector of cooking fuel choice-specific coefficients, u_i is an unobserved heterogeneity of household characteristics, and ε_{ijt} is an independently and identically distributed random error term. Thus, the conditional probability that household i chooses cooking fuel j in time t with unobserved household heterogeneity is:

$$\Pr(f_{it} = t_j | x_{it}, u_i) = \frac{\exp(x_{it}\beta_j + u_{ij})}{1 + \sum_{k \neq B} (x_{it}\beta_k + u_{ij})}, j \neq B \quad (19)$$

where B denotes the base outcome of the cooking fuel type. The equation shows that the probability of choosing a cooking fuel type is conditional on the set of household-level effects and the observable household characteristics (Choumert-Nkolo et al., 2019).