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The direct rebound effect for two income groups: The case of Paraguay

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Abstract

We estimate the direct rebound effect (DRE) for all energy services requiring electricity for their provision in Paraguayan households. Using recent panel data from 2001 to 2017, we estimate the magnitude of the DRE at the province and municipality levels. Because we estimate the DRE through the own-price elasticity of electricity demand, we not only provide the first empirical evidence of the DRE for Paraguay, a developing country, but also update the study of Paraguay's residential electricity demand. Our findings suggest a positive DRE emerges after an improvement in energy efficiency, but the magnitude of the DRE does not completely reduce the resulting energy savings. We find a lower DRE in low-income households, which may be explained by two factors: electricity is not the main source of energy for most low-income households, and most clandestine electricity connections are from low-income households. Paraguay is one of the countries with the highest generation of electricity per capita through hydroelectric plants. However, this electricity supply does not match electricity consumption, especially in low-income households, because of distribution issues in relation to energy sources.

Keywords

Direct Rebound Effect, Electricity Consumption, Energy Services, Low-Income Households, Panel Data.

1. Introduction

Empirical evidence shows an improvement in energy efficiency leads to a lower than proportional reduction in energy savings due to behavioral responses from consumers, which is known as the rebound effect. This effect reduces the amount of energy savings but also involves an improvement in social welfare because energy service consumption increases as the effective cost is reduced by the energy efficiency improvement (direct rebound), and less income must be used to purchase the same energy services, which increases the income available to consume other energy goods and services (indirect rebound). Thus, appraisal of the rebound effect depends on the size of consumers' benefits relative to the environmental costs of the energy savings reduction and the associated pollutant emissions (Sorrell, 2018). In addition, the literature suggests the rebound effect is greater in low-income groups because their demand for energy services is far from their satiation levels (Milne and Boardman, 2000; Sorrell, 2007). Therefore, the purpose of this article is to estimate the direct rebound effect (DRE) for electricity in two income groups in Paraguay at the department (province) and district (municipality) levels.

This paper contributes to the literature in four ways. First, this paper provides the first empirical evidence of the DRE for Paraguay, a developing country. Second, it updates the study of the Paraguayan residential electricity demand (Westley, 1984) because we estimate the DRE through the own-price elasticity of electricity demand. Third, it provides updated and useful information to Paraguayan policymakers at the province and municipality levels. Finally, it fosters the debate about the potential difference in the size of the DRE for different income groups. No unanimous definition of energy poverty has been established to date; however, the existing literature combines the concepts of an energy ladder (from the less advanced to most advanced energy sources) and energy equity to define energy poverty (Sovacool, 2014). The study of the size of the DRE for different income groups may facilitate better assessments of this issue.

This paper is arranged as follows. Section 2 reviews empirical evidence related to this research; Section 3 explains the methodology and the variables used to estimate the DRE for Paraguay, as well as the data employed for each variable; Section 4 shows the econometric model estimated and includes a discussion of results; and Section 5 presents the conclusions and policy implications.

2. DRE in Developing and Middle-Income Countries

To contextualize our study, this section summarizes empirical evidence of the DRE for developing countries with a particular focus on Paraguayan neighboring countries. We focus on studies applying econometric methods to estimate the DRE for residential energy services.

Given the existing empirical evidence, the DRE for most energy services is expected to be around 30% in developed countries (Greening et al., 2000). However, according to the literature, the rebound effect in developing countries tends to be greater. Possible explanations for this finding include the following:

(i) In developing countries, the demand for energy services is far from residents' satiation levels (Sorrell, 2007).

(ii) Residents experience rapid accumulation of energy-using technologies and more energy-intensive consumption due to a high growth rate (van den Bergh, 2011).

(iii) Energy is relatively more expensive given residents' low wages; thus, energy conservation may induce a larger re-spending effect (van den Bergh, 2011).

Labidi and Abdessalem (2018) estimated a DRE of 81.7% for electricity end uses in Tunisia through a panel data model with fixed effects for 21 cities and 5 nonconsecutive years (1995, 2000, 2005, 2010). The magnitude of the effect is relevant for the energy service of refrigeration because this service has accounted for the greatest share of residential electricity consumption since 1984 (Labidi and Abdessalem, 2018). Alvi et al. (2018) found DREs of 42.9% and 69.5% for residential electricity consumption in Pakistan in the short term and the long term, respectively. They used an error-correction model with time series data from 1973 to 2016. If consumers respond the same way to a decrease in energy prices as they do to more efficient energy systems (given both decrease the effective cost of energy services), then the own-price elasticity of electricity demand can be used as a proxy of the DRE. Thus, regarding Paraguayan neighboring countries, Casarin and Delfino (2011) estimated own-price elasticity values of 10% and 20% for the residential electricity demand in Greater Buenos Aires (Argentinian capital) in the short term and the long term, respectively. They found increases in the stock of air conditioners and regulatory tariffs that fixed the electricity price for several years tended to increase residential electricity demands. These results may also be relevant for Paraguay because it has a warmer climate than Buenos Aires. In addition, the National Administration of Electricity (ANDE, n.d.) fixed electricity prices for Paraguayan households. Villareal and Moreira (2016) estimated an own-price elasticity of electricity demand between 23% and 44% for Brazilian households. These values are relevant for the energy services of electric showers and refrigeration because they account for a considerable share of residential electricity consumption in Brazil (EPE, n.d.). Comparing the electricity demand among these countries is particularly pertinent because Paraguay shares the ownership of two hydroelectric plants, including one with Argentina (Yacyreta) and the other with Brazil (Itaipu). Furthermore, in relation to the empirical evidence of the DRE for other developing countries, the magnitude of the DRE for Buenos Aires–Argentina and for Brazil is relatively small. However, according to the Handbook of Statistics of the United Nations Conference on Trade and Development (UNCTAD), these two neighboring countries of Paraguay may be considered to have more advanced economies among developing countries (UNCTAD, n.d.).

Regarding studies differentiating among income groups, Zhang and Peng (2017) presented a study similar to ours by estimating the DRE of China's residential electricity consumption for two income regimes and for two cooling degree day (CDD) levels. In line with the literature, which suggests a higher DRE in low-income groups, they found a greater DRE under a low-income regime (68%) than under a high-income regime (55%). Moreover, for CDD levels, the authors found a greater DRE under a high CDD level (90%) than under a low CDD level (75%).[1] They also highlighted the relevance of the stock of space cooling devices in explaining residential electricity consumption, which may be the case in Paraguay. Similarly, Liddle and Huntington (2020) analyzed the residential electricity demand for high- and middle-income countries and found smaller price elasticity, greater income elasticity, smaller heating elasticity, and larger cooling elasticity for middle-income countries than for high-income/Organisation for Economic Co-operation and Development (OECD) countries.[2] Regarding price elasticity, according to Liddle and Huntington (2020), many non-OECD countries have subsidies for electricity price, thus diminishing the price response. Furthermore, they argued most non-OECD countries present only the average electricity price and not the actual price charged to the different types of subscribers, which may affect the results for middle-income countries. We explain how we addressed this issue in the next section.

To our knowledge, no consensus has been established among researchers regarding how a change in price or an improvement in energy efficiency (depending on the case) may affect energy consumption for different income groups. Because empirical evidence indicating whether the DRE is greater in low-income households is inconsistent, the results of this research can provide insight into this topic. Most revised studies have highlighted the relevance of the stock of electric conversion devices in explaining the consumption of residential electricity, as well as the subsidized prices, especially for low-income households. However, relating the energy poverty

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[1] They also found a greater DRE under a heavy rainfall regime (86%) than under a light rainfall regime (68%).

[2] Paraguay was included as a middle-income country in their data set.

literature to DRE estimation may facilitate an understanding of the potential differences among the reactions of different income groups to improvements in energy efficiency or to changes in energy prices.

3. Methodology and Variables

Because we estimate the DRE through the own-price elasticity of electricity demand, we should consider the assumptions involved when analyzing our results. These assumptions are as follows (Sorrell, 2007; Sorrell and Dimitropoulos, 2007):

1. Symmetry—Consumers respond the same way to a decrease in energy prices as they do to more efficient energy systems[3] because more efficient systems reduce the effective cost of energy services.
2. Exogeneity—Energy prices do not affect energy efficiency. To fulfill this assumption, the period analyzed must be characterized by stability or decreases in energy prices because increasing energy prices may induce an improvement in the energy efficiency of energy systems.
3. Constant energy efficiency—The efficiency of an energy system does not change with the amount of energy service used.

The main definition of the DRE is the efficiency elasticity of the demand for useful work (Berkhout et al., 2000; Sorrell, 2007; Sorrell and Dimitropoulos, 2007). Nevertheless, we use the own-price elasticity of electricity demand as a proxy for the DRE given data availability issues (Freire-González, 2010; Wang et al., 2014, 2016; Bordón Lesme et al., 2020). See Sorrell (2007, 2009) and Sorrell and Dimitropoulos (2007) for further DRE estimation methods. The primary definition of the DRE is as follows:

$$\eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1 \tag{1}$$

The first term, $\eta_{\varepsilon}(E)$, represents the efficiency elasticity of the demand for energy, and the second term, $\eta_{\varepsilon}(S)$, is the efficiency elasticity of the demand for useful work. For the residential case, examples of useful work are residential energy services such as heating, lighting, or cooking.

Following previous research on the topic (Freire-González, 2010; Chitnis et al., 2013; Zhang and Peng, 2017; Alvi et al., 2018; Belaïd et al., 2018; Labidi and Abdessalem, 2018), we use a double

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[3] In our case, the energy systems are residential energy conversion devices.

logarithmic functional form to estimate the DRE for residential energy services requiring electricity in Paraguay. The model is as follows:

$$ln\left(\frac{E_{it}}{hh_{it}}\right) = \alpha + \beta_1 ln(P_{E_{it-1}}) + \beta_2 lnP_{LPG_{it}} + \beta_3 lnCDD_{it} + \beta_4 lnHDD_{it} + \beta_5 lnY_{it} + \beta_6 ln(\frac{E_{it-1}}{hh_{it-1}}) + \varepsilon_{it} \qquad (2)$$

where it represents the data of each geographic subdivision (i) per time period (t) for each variable. The dependent variable $\left(\frac{E_{it}}{hh_{it}}\right)$ is the average electricity consumption; $P_{LP}{}_{it}$ denotes the price of liquefied petroleum gas (LPG); Y_{it} represents the income variable; and CDD_{it} and HDD_{it} are climate variables—CDDs and heating degree days (HDDs), respectively. Our variable of interest, the price of residential electricity, changes depending on the amount consumed and is therefore charged after consumption $(P_{E_{it-1}})$. Finally, (E_{it-1}/hh_{it-1}) is the lagged dependent variable, and ε_{it} represents the error term.

Regarding the income groups, two price categories exist in Paraguay, and both have their own price levels according to the amount of electricity consumed by a household. Low-income households are registered under price category 141, which corresponds to a subsidized price at the ANDE.[4] Appendix 1 and Appendix 2 illustrate the price categories per consumption level and the corresponding discount rate for low-income households registered in the social tariff program. The LPG price is the same for all households and does not change with the amount consumed.

Household disposable income and the climate variables (CDDs and HDDs) are available only at the province level and are therefore the same for all estimations.

The dependent variable is available for both income groups and both geographic subdivisions. Thus, we estimate the coefficients of the equation for both types of households, low-income and non-low-income households, at the province and municipality levels. For all models, the monetary variables are constant at 2017 prices. Table 1 depicts the data development process for all variables.

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[4] To be registered under that price category, households must provide legal documents to the ANDE office that prove a certain income level. See https://www.ande.gov.py/infodata.php?catid=6#.X8FQBc1Kg2w for further details.

Table 1. Definitions of the Variables of the Model

Variable	Definition	Availability	Time	Data Sources	Expected Coefficient Sign
$\left(\frac{E_{it}}{hh_{it}}\right)$	Average electricity consumption. Aggregate electricity consumption per municipality and province divided by the registered subscribers at the municipality and province levels.	Data at the municipality and province levels. Data available for low-income and non-low-income households.	Annual (2001 to 2017)	Administración Nacional de Electricidad (Ande, n.d.)	Positive for the lagged dependent variable $(\frac{E_{it-1}}{hh_{it-1}})$
$(P_{E_{it}-1})$	The real price charged at both geographic levels. We calculate the real price charged to consumers by allocating the price categories for both income groups according to their kWh range of consumption. For low-income households, after allocation to the price categories, we calculate the corresponding discount. See Appendices 1 and 2.	Data at the municipality and province levels. Data available for low-income and non-low-income households.	Annual (2001 to 2017)	Administración Nacional de Electricidad (ANDE, n.d.)	Negative
$P_{LPG_{it}}$	The real LPG price.	Data at the national level. The same data for both income groups at both geographic levels. Data available from 2005 to 2017.	Annual (2005 to 2017)	SIEN Statistics – Viceministerio de Minas y Energía (n.d.)	Negative
CDD_{it}	Cooling degree days. A base temperature of 22 degrees Celsius (see Appendix 3 for further details about the calculation) (Calculating Degree Days, n.d.)	Data at the province level. The same data for both income groups at both geographic levels.	Daily data aggregated into annual data (2001 to 2017, with gaps)	Dirección de Meteorología e Hidrología (n.d.)	Positive
HDD_{it}	Heating degree days. A base temperature of 21 degrees Celsius (see Appendix 3 for further details about its calculation) (Calculating Degree Days, n.d.)	Data at the province level. The same data for both income groups at both geographic levels.	Daily data aggregated into annual data (2001 to 2017, with gaps)	Dirección de Meteorología e Hidrología (n.d.)	Positive
Y_{it}	Real household income.	Data at the province level. The same data for both income groups at both geographic levels.	Annual (2001 to 2017, with gaps)	Dirección General de Estadística, Encuestas y Censos (n.d.)	Positive

* Some daily data for the minimum and maximum temperatures are missing for most provinces. Therefore, some provinces have data gaps in some years (unbalanced panel). There are 47 total annual gaps among the sample.

* Only five provinces do not have missing annual income data. Therefore, the remaining provinces have gaps in most years for this variable (unbalanced panel). There are 138 total annual gaps among the sample.

* For the prices of electricity and LPG, the consumer price index (CPI) falls under the same category according to the Central Bank of Paraguay. This CPI is at the national level. The income variable was already obtained with 2017 constant prices according to Dirección General de Estadística, Encuestas y Censos (DGEEC, n.d.).

4. Econometric Model Estimation

Following equation (2), we estimate our model at the province and municipality levels for both income groups (low-income and non-low-income households). The Hausman test confirms differences exist between fixed and random effect estimators in all models at both geographic levels (Table 2). Therefore, we prefer fixed effect estimates for all models.

Evidence for Paraguay may differ from other empirical evidence of the DRE, especially evidence for developed countries. The nominal price of electricity was the same from 2005 to 2016; that is, the ANDE fixed the price during those years. The only change, which occurred in 2017, was the addition of price subcategories four, five, and six for category 142 (non-low-income households), which correspond to the prices without social tariff discounts, as shown in Appendix 1. Thus, we assumed the price and consumption of electricity in Paraguay could not be cointegrated over time. Nevertheless, we performed the Pedroni residual cointegration test for the four models. As expected, almost all the statistics confirmed the null hypothesis of no cointegration, as shown in Table 3. Therefore, we do not apply an error-correction model for our estimates.

In the models for low-income households at the municipality and province levels, we exclude the HDD variable because this type of household does not use electricity for the energy service of space heating. We exclude the income variable in Model 3 because it is not significant. Moreover, we retain the LPG price variable in Model 4 because it is significant at the 10% level. We include the lagged dependent variable in the models to deal with autocorrelation. We also add cross-section weights in the models to address potential cross-section heteroskedasticity. Similar specifications have been used widely in previous research (Sorrell and Dimitropoulos, 2007).

Table 2. Hausman Test of Model 1 to Model 4

Correlated Random Effects – Hausman Test			
Cross-Section Random:	**Chi-Sq. Statistic**	**Chi-Sq. df**	**Prob.**
Model 1	326.0419	6	0.0000
Model 2	202.9900	5	0.0000
Model 3	30.4818	4	0.0000
Model 4	20.7580	5	0.0009

Note: Test performed after using random and fixed effects for each model.

Table 3. Cointegration Test for Model 1 to Model 4

Alternative Hypothesis: Common AR Coefficients (within-dimension)								
	Model 1		Model 2		Model 3		Model 4	
	Prob.	**Weighted Stat Prob.**	**Prob.**	**Weighted Stat Prob.**	**Prob.**	**Weighted Stat Prob.**	**Prob.**	**Weighted Stat Prob.**
Panel v-Statistic	0.9966	0.9992	0.9988	1.0000	0.1258	1.0000	0.6915	0.8790
Panel rho-Statistic	1.0000	1.0000	1.0000	1.0000	0.7572	0.6441	0.9191	0.9402
Panel PP-Statistic	0.8269	0.0000	0.0000	1.0000	0.0004	0.0105	0.1554	0.5637
Panel ADF-Statistic	0.6222	0.9389	1.0000	1.0000	0.5497	0.7351	0.6180	0.7766

Alternative Hypothesis: Individual AR Coefficients (between-dimension)				
	Model 1	Model 2	Model 3	Model 4
	Prob.	**Prob.**	**Prob.**	**Prob.**
Group rho-Statistic	1.0000	1.0000	0.9822	0.9956
Group PP-Statistic	0.0000	0.7255	0.0000	0.6322
Group ADF-Statistic	1.0000	1.0000	0.8551	0.4580

Note: The test was performed after using random and fixed effects for each model.

4.1. Results

Table 4 shows the results of the estimations of the residential electricity demand models. Models 1 and 3 correspond to non-low-income households, whereas Models 2 and 4 correspond to low-income households.

Table 4. Empirical Estimates of Households' Electricity Demand in Paraguay

Dependent Variable: $ln(E_{it}/hh_{it})$		Municipality Fixed Effects		Province Fixed Effects	
		Non-Low-Income Households (Model 1)	Low-Income Households (Model 2)	Non-Low-Income Households (Model 3)	Low-Income Households (Model 4)
α	Coef.	4.5606***	0.3668	−0.3251	−0.5795
	Std.Err	(0.3878)	(0.3008)	(1.0308)	(1.1278)
$(ln(P_{E_{it}} - 1))$	Coef.	−0.5972***	−0.1786***	−0.2302***	−0.1379*
	Std.Err	(0.0232)	(0.0162)	(0.0634)	(0.0597)
$lnP_{LPG_{it}}$	Coef.	0.0410**	−0.0925***	0.1132***	−0.0565
	Std.Err	(0.0156)	(0.0127)	(0.0275)	(0.0326)
$lnCDD_{it}$	Coef.	0.2514***	0.2567***	0.2508***	0.3044**
	Std.Err	(0.0183)	(0.0221)	(0.0389)	(0.0980)
$lnHDD_{it}$	Coef.	0.0162***			
	Std.Err	(0.0038)			
lnY_{it}	Coef.	0.0164**	0.1287***		0.0927*
	Std.Err	(0.0062)	(0.0103)		(0.0399)
$(ln(E_{it-1}/hh_{it-1}))$	Coef.	0.5751***	0.7819***	0.8654***	0.8333***
	Std.Err	(0.0179)	(0.0153)	(0.0563)	(0.0529)
Periods		13	13	13	13
Cross-sections		189	187	16	16
Observations		1235	1207	165	85
Panel		Unbalanced	Unbalanced	Unbalanced	Unbalanced
Weighted Statistics					
R2		0.9957	0.9826	0.9922	0.9800
Prob (F-Statistic)		0.0000	0.0000	0.0000	0.0000
Durbin–Watson Stat		2.2026	2.3132	2.3336	2.5061
Unweighted Statistics					
R2		0.9561	0.8134	0.9879	0.7730
Durbin–Watson Stat		2.4575	2.8149	2.8039	3.2068

Note: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

Regarding the models for non-low-income households (Model 1 and Model 3), the coefficients of the own-price elasticity of electricity demand have a negative sign between 23% and 60%, with a significance level of 0.001; that is, an increase in the price of electricity reduces its consumption. The climate variables show a positive sign at a significance level of 0.001. Thus, as the temperature reaches below or above some thresholds, the consumption of electricity for cooling and heating devices increases. Furthermore, the CDD coefficient is significant at both geographic levels, whereas the HDD coefficient is not significant at the province level. At the municipality level, where both are significant, the CDD coefficient has a greater magnitude. Thus, the impact of space cooling devices on electricity consumption may be greater than that of space heating devices. Therefore, an increase in the stock of air conditioners may increase the residential electricity demand (Casarin and Delfino, 2011; Liddle and Huntington, 2020). Regarding this issue, Appendix 4 and Appendix 5 show space cooling accounts for a greater share of electricity consumption than space heating. The income variable is significant only at the municipality level, with a 0.01 significance level, and it has a positive sign; that is, as income increases, residential electricity consumption also increases. The lagged dependent variable suggests electricity consumption in period $t-1$ has a positive effect on the current period because it has a positive sign significant at the 0.001 level.

The LPG price coefficients have significance levels of 0.01 and 0.001 at the municipality and province levels, respectively. The sign of the coefficients indicates a substitutive relationship between electricity and LPG for the demand of residential energy services; that is, an increase in LPG prices increases electricity consumption in the residential sector in non-low-income households. Therefore, space heating and cooking (energy services commonly provided by LPG, firewood, or charcoal) would be replaced by electricity.

Regarding the models for low-income households (Model 2 and Model 4), the coefficients of the own-price elasticity of electricity demand also have the expected negative sign and are 18% at the municipality level and 14% at the province level. At the province level, the coefficient is significant at the 0.05 level, whereas at the municipality level, the coefficient is significant at the 0.01 level. The HDD coefficient is not significant at the municipality or the province level. Nevertheless, the next section shows low-income households mostly use firewood for space heating services (Figure 1), whereas middle- and high-income households mostly use electricity for this energy service (Appendix 4 and Appendix 5). Furthermore, the CDD coefficient has a positive relationship with residential electricity consumption, with significance levels of 0.001 and 0.01 at the municipality and province levels, respectively. The coefficients of income and the lagged dependent variable also have positive relationships with residential electricity consumption. In this case, the income variable is significant at both geographic levels, with significance levels of 0.001 (municipality) and 0.05 (province). The lagged dependent variable is significant at the 0.001 level for both geographic levels.

For low-income households, LPG price coefficients have a complementary relationship (negative sign) with respect to residential electricity demand. That is, an increase in the price of LPG would reduce electricity consumption. The potential income constraint could explain this relationship. Moving up the energy ladder by changing their energy consumption from traditional energy sources to electricity could be expensive because of the capital cost of the more efficient, electrically run conversion devices (Van der Kroon et al., 2013). Thus, as shown in the next section (Figure 1), low-income households may prioritize the substantial energy services of cooking and water heating because both can be provided by traditional energy sources instead of the modern energy services provided by electricity (Sovacool, 2014).

Therefore, considering the assumptions explained in Section 3, the DRE of electricity for Paraguay could be between 23% and 60% for non-low-income households and between 14% and 18% for low-income households. That is, because of an improvement in electricity efficiency with respect to a scenario where there are no behavioral responses from consumers, the electricity savings would be reduced up to 60% and 18% in non-low-income and low-income households, respectively.[5] Moreover, the significant influence of LPG price in explaining residential electricity consumption is consistent with the finding of Bordón Lesme et al. (2020). They estimated the DRE of residential electricity for Spain and found other energy sources influenced it.

Because we estimate the DRE for a collection of energy services that require electricity, our results are more relevant for the energy service with the greatest share of electricity consumption. Hence, for low-income households, our results are more relevant for the energy service of food preservation because this energy service amounts to 37.3% of the total electricity consumption of this income group. For non-low-income households, the magnitude of the DRE is more relevant for the energy services of space cooling and water heating because both energy services have the greatest share of electricity consumption in the high-income and middle-income households (29.6% and 25.8%), respectively. See Appendix 6 for further details.

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[5] Usually, energy efficiency improvements are due to more efficient conversion devices.

Moreover, for all models, the exogeneity assumption should not be a source of bias because the period analyzed is characterized by stable electricity prices (the ANDE fixed the prices). However, the symmetry assumption may provide an upper bound for the magnitude of the DRE because consumers could easily notice the electricity prices instead of searching for the improvements in electricity efficiency.

4.2. Discussion of the Results

The magnitude of the DRE for non-low-income households, which is between 23% and 60%, falls in the range of the expected values of the DRE for developed countries at approximately 30% (Greening et al., 2000; Sorrell, 2009; Freire-González, 2017). Intriguingly, the magnitude of the DRE for low-income households is between 14% and 18%. When comparing both types of households, we observe the DRE for electricity is lower in low-income households because the own-price elasticity of electricity demand is lower for these households. This feature is present at both the municipality and province levels, which may seem counterintuitive because the literature suggests the DRE should be higher in low-income groups, given their demand for energy services is far from their satiation levels (Milne and Boardman, 2000; Sorrell, 2007). Appendix 7 shows the robustness checks for models 1 to 4[6], which reinforce the finding that there is a lower DRE for electricity in low-income households. We identify two factors that may explain this peculiarity of our results.

i. Electricity is not the main energy source for most low-income households:

As Figure 1 shows, electricity accounts for only 16% of total residential energy input consumption[7] in low-income households, whereas charcoal (41%) and firewood (34%), which are traditional energy sources (van der Kroon et al., 2013), account for 75% of this total. However, these energy sources are used primarily for cooking, an energy service that accounts for 67% of total residential energy input consumption in low-income households. Notably, reliance on traditional energy sources for cooking and the lack of access to a bare minimum of electricity are methods for measuring energy poverty (Sovacool, 2014).

Thus, Paraguay presents an unusual case relative to other developing economies because it has one of the highest per capita electricity generation levels through hydropower, given it shares ownership of two hydroelectric power plants with its neighboring countries: Itaipu in Brazil and

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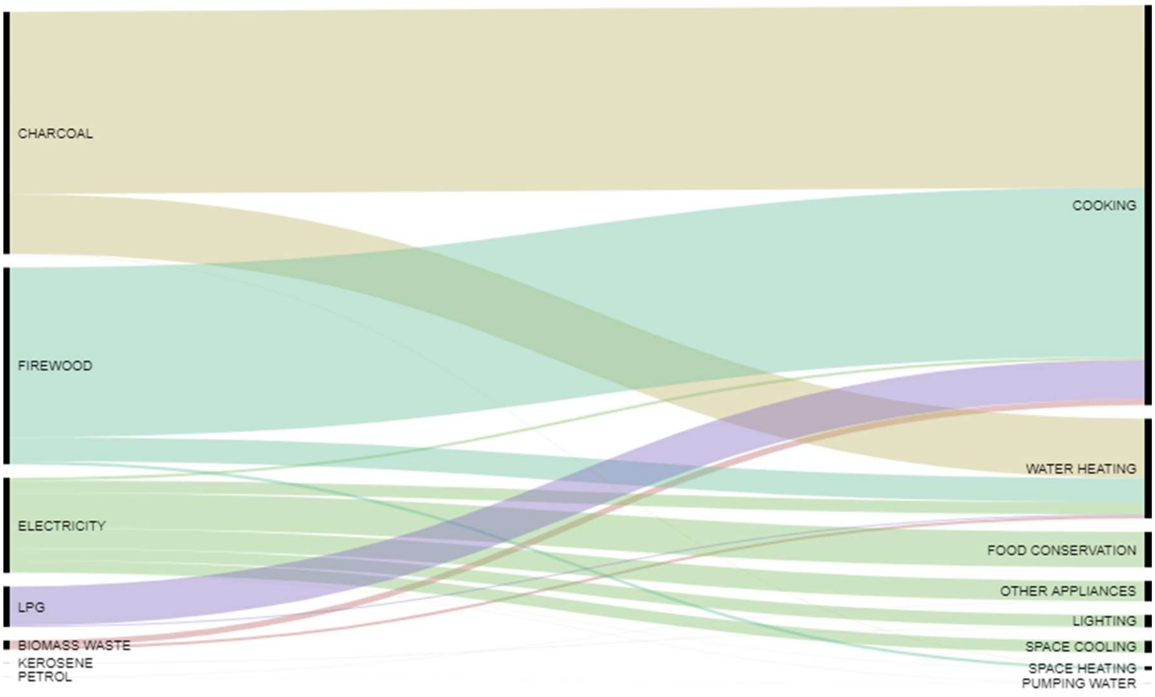
[6] For comparison purposes, we leave out the variables with a lower significant level in the original models, as well as some coefficients that were not present in models 2 to 4.

[7] Energy input is the energy before its transformation into useful energy.

Yacyreta in Argentina (Blanco et al., 2017).[8] However, this electricity supply does not match electricity consumption, especially in low-income households (Figure 1). Furthermore, according to the (IEA , n.d.), 99.3% of the Paraguayan population has access to electricity. Thus, compared to other developing areas in which the percentage of electricity access is relatively small, such as developing Asian countries and most African countries (IEA, n.d.), Paraguay has high electricity supply and access. Therefore, in Paraguay, the issue may be moving up the energy ladder by increasing electricity consumption, especially in low-income households, rather than access to the electricity grid. Thus, Paraguayan households may benefit from consuming a cleaner and more effective energy source (e.g., electricity) instead of traditional energy sources (e.g., charcoal and firewood). First, electricity requires less energy input per energy service. Second, electricity reduces household drudgery, which is associated with increasing economic development levels. Third, electricity alleviates indoor air pollution caused by the inefficient use of biomass, which improves health, especially among women and children. Finally, reduced drudgery and cleaner cooking methods provided by electricity are relevant to gender equality (Barnes et al., 2014, p 16). This discrepancy between the supply of and access to electricity and electricity consumption by low-income households can be explained by distribution issues related to the relevance of different energy sources for different income groups, an issue analyzed in the energy poverty literature (Halff et al., 2014).



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[8] Itaipu and Yacyreta have annual average production levels of 98,287 GWh and 20,867 GWh, respectively (Blanco et al., 2017).

Figure 1. The share of energy input per energy service in Paraguayan low-income households of 2011. Source: Personal elaboration from BNEU (n.d.).

ii. Clandestine electricity connections:

Most clandestine electricity connections are from low-income households. Thus, these households do not react to prices, which may result in low elasticity. Appendix 4 and Appendix 5 match the energy input with the share of energy services for middle- and high-income households. The consumption of modern energy sources tends to increase as income increases, which is consistent with the energy ladder model. Furthermore, high-income households still use some traditional energy input in their bundle of energy sources, as the energy stacking model suggests (Van der Kroon et al., 2013)[9]; this may also be explained as cultural factor (Masera et al., 2000). However, the fact that most clandestine electricity connections are from low-income households (Figure 2) indicates that in Paraguay, the use of traditional energy sources may be due to income constraints, which is an energy poverty indicator. In Paraguay, most low-income households are located in slums; thus, most of these households do not have a property title (RAP, n.d.). Without this document, they cannot ask for a legal electricity connection to the ANDE, which may be another reason most clandestine electricity connections are from low-income households.

Given points i and ii, electricity price and potential improvements in electricity efficiency would not affect low-income households as much as they would affect non-low-income households.

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[9] The energy ladder and energy stacking are models analyzed in the energy poverty literature.

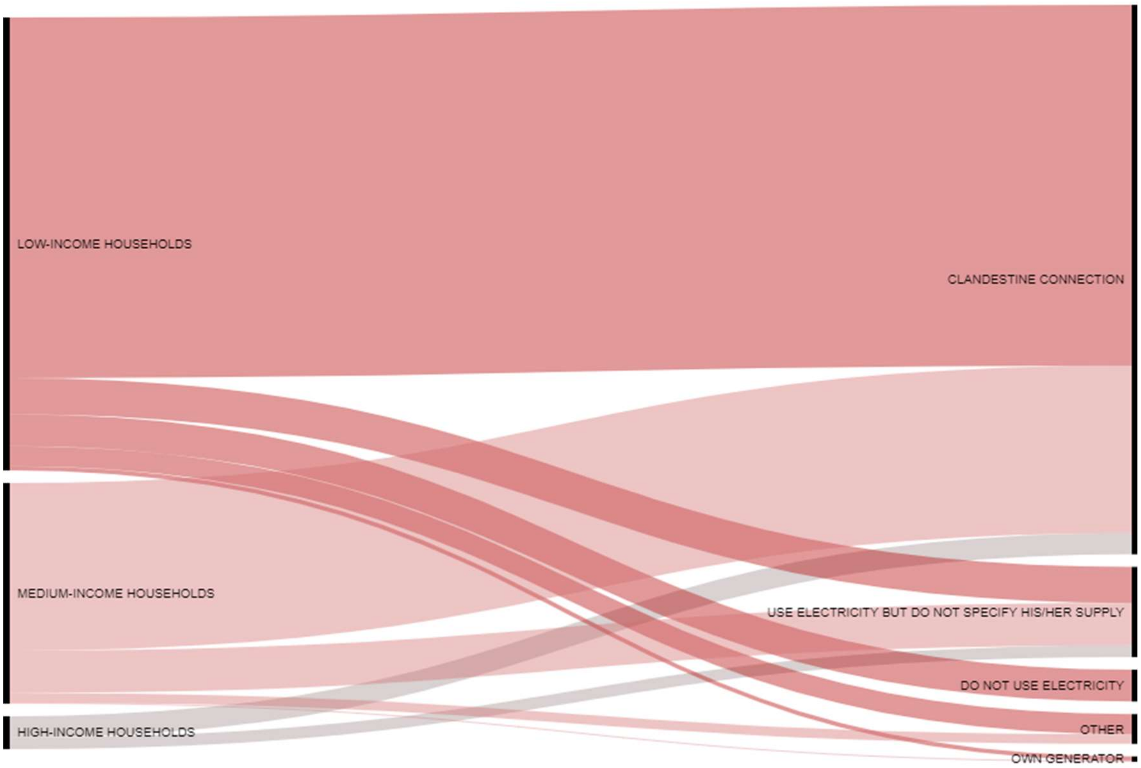

Figure 2. Clandestine electricity connection per income level.

5. Conclusions and Policy Implications

The literature on DREs suggests low-income groups show a greater increase in energy consumption than high-income groups after an improvement in energy efficiency, given their level of energy consumption is far from their satiation levels (Milne and Boardman, 2000; Sorrell, 2007). However, the results of this research show a lower DRE in the low-income group for energy services requiring electricity for their provision in Paraguay. We find DREs between 14% and 18% in low-income households and between 23% and 60% in non-low-income households for residential electricity consumption in Paraguay. We identify two factors that may explain our results. First, electricity is not the principal energy source for most low-income households. Second, most clandestine electricity connections are from low-income households, leading to limited reactions to price changes in this group. Moreover, considering the two points highlighted, the results of DREs for non-low-income households are more comparable to other empirical DRE results than to our results for low-income households.

Interestingly, Paraguay's electricity supply provided by Itaipu and Yacyreta surpasses its electricity demand because Paraguay is one of the largest exporters of hydropower electricity in the world (Blanco et al., 2017). The discrepancy between the supply of electricity and its consumption, especially in low-income households, can be explained by distribution issues related to the share of different energy sources for different income groups; this is an issue analyzed in the energy poverty literature (Halff et al., 2014). Thus, our results introduce a new line of research by exploring the relationship between the DRE and energy poverty. In further research, gathering available data regarding the prices of firewood and charcoal (the principal energy sources for Paraguayan low-income households) would be relevant. Likewise, the specific factors affecting only the poverty-stricken group, such as the two points highlighted in this research, should be considered in further analyses.

Another novelty of this study is that it provides the first empirical evidence of the DRE for Paraguay, a developing country. Empirical evidence of the DRE in the South American region is lacking because most studies focus on the determinants of electricity demand rather than residential DREs for electricity (Bendezú and Gallardo, 2006; Casarin and Delfino, 2011; Agostini et al., 2012; Orejuela et al., 2015; Villareal and Moreira, 2016; Laureiro, 2018). Furthermore, because we estimated the DRE through the own-price elasticity of electricity demand, we are also updating the study of the Paraguayan residential electricity demand. Given this estimation method, food preservation is the energy service associated with the greatest electricity consumption for low-income households; by contrast, space cooling and water heating account for the greatest consumption for non-low-income households. In further research, the DRE for each energy service should be estimated by differentiating each energy service according to the required energy source (Hunt and Ryan, 2014). Moreover, data availability permitting, introducing the efficiency of each energy service into the price of the corresponding energy source may reduce the classical assumptions of the DRE through price elasticity (Hunt and Ryan, 2014).

Finally, our findings suggest alternative energy policies to the social tariff discount for residential electricity should be implemented to alleviate energy poverty. Despite the existing electricity discounts for low-income households, electricity is not their main energy source. Therefore, given our results, linking electricity consumption barriers to the level of electricity access may improve energy poverty measurements. These potential consumption barriers may explain why electricity is not the main energy source for low-income households in a country rich in hydroelectricity such as Paraguay. Consequently, our research provides a new path to expand the understanding of energy poverty issues as well as magnitude estimations of DREs by combining both concepts.

6. Acknowledgments

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Appendix 1. Paraguayan Electricity Prices for Households, Category 142

Number	Monthly Range of Consumption	Price	Unit of Measure
1	0–50 kWh	311.55	G/kWh
2	51–150 kWh	349.89	G/kWh
3	151–300 kWh	365.45	G/kWh
4	301–500 kWh	403.82	G/kWh
5	501–1000 kWh	420.27	G/kWh
6	> 1000 kWh	435.51	G/kWh

Source: Personal elaboration with data from https://www.ande.gov.py/docs/tarifas/PLIEGO21.pdf.

Appendix 2. Paraguayan Electricity Prices for Households, Category 141

Number	Monthly Range of Consumption	Price	Unit of Measure
1	0–50 kWh	311.55	G/kWh
2	51–150 kWh	349.89	G/kWh
3	151–300 kWh	365.45	G/kWh

Source: Personal elaboration with data from https://www.ande.gov.py/docs/tarifas/PLIEGO21.pdf.

Number	Monthly Range of Social Tariff Consumption	Discount Rate. Law N° 3480/2008
1	0–100 kWh	75%
2	101–200 kWh	50%
3	201–300 kWh	25%

Source: Personal elaboration with data from https://www.ande.gov.py/docs/tarifas/PLIEGO21.pdf.

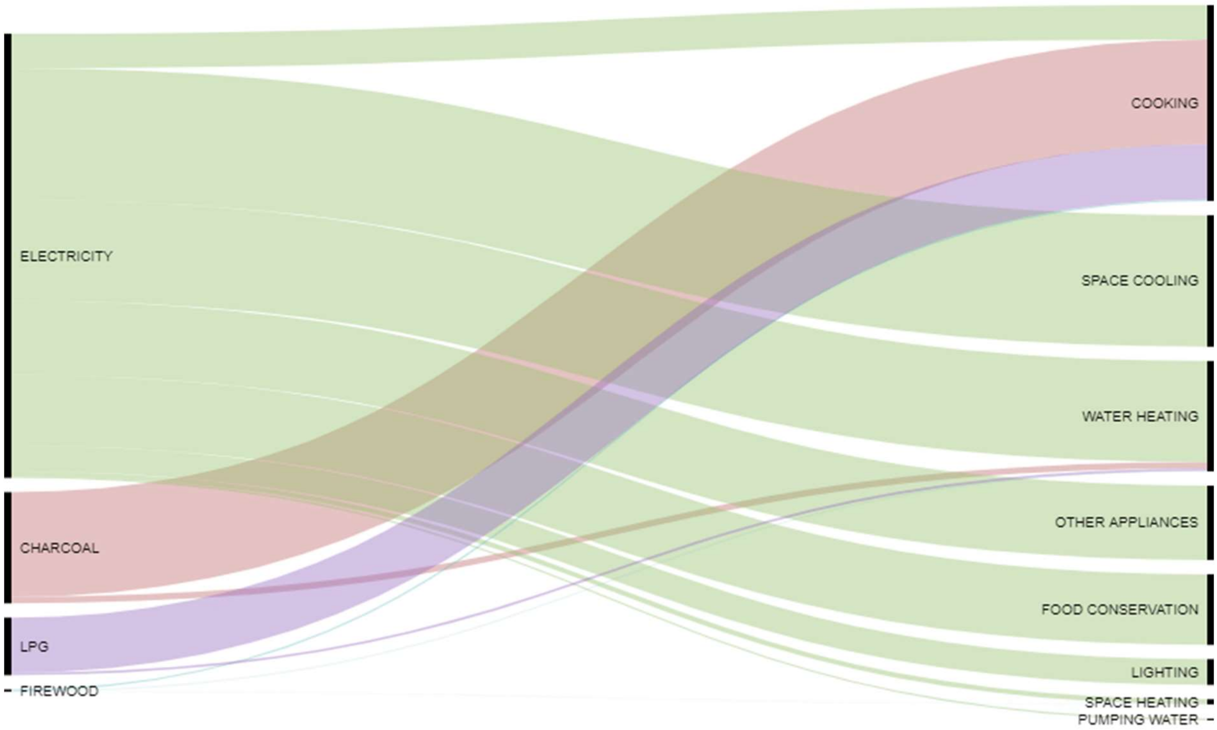
Appendix 3. Calculation Methods for the Climatic Variables

Condition	**Heating Degree Days Formula**
$T_{min}>T_{base}$	HDD = 0
$(T_{max}+T_{min})/2>T_{base}$	HDD = $(T_{base}-T_{min})/4$
$T_{max}>=T_{base}$	HDD = $(T_{base}-T_{min})/2-(T_{max}-T_{base})/4$
$T_{max}<T_{base}$	HDD = $T_{base}-(T_{max}+T_{min})/2$

Condition	**Cooling Degree Days Formula**
$T_{max}<T_{base}$	CDD = 0
$(T_{max}+T_{min})/2<T_{base}$	CDD = $(T_{max}-T_{base})/4$
$T_{min}<=T_{base}$	CDD = $(T_{max}-T_{base})/2-(T_{base}-T_{min})/4$
Tmin>Tbase	CDD = (Tmax+Tmin)/2-Tbase

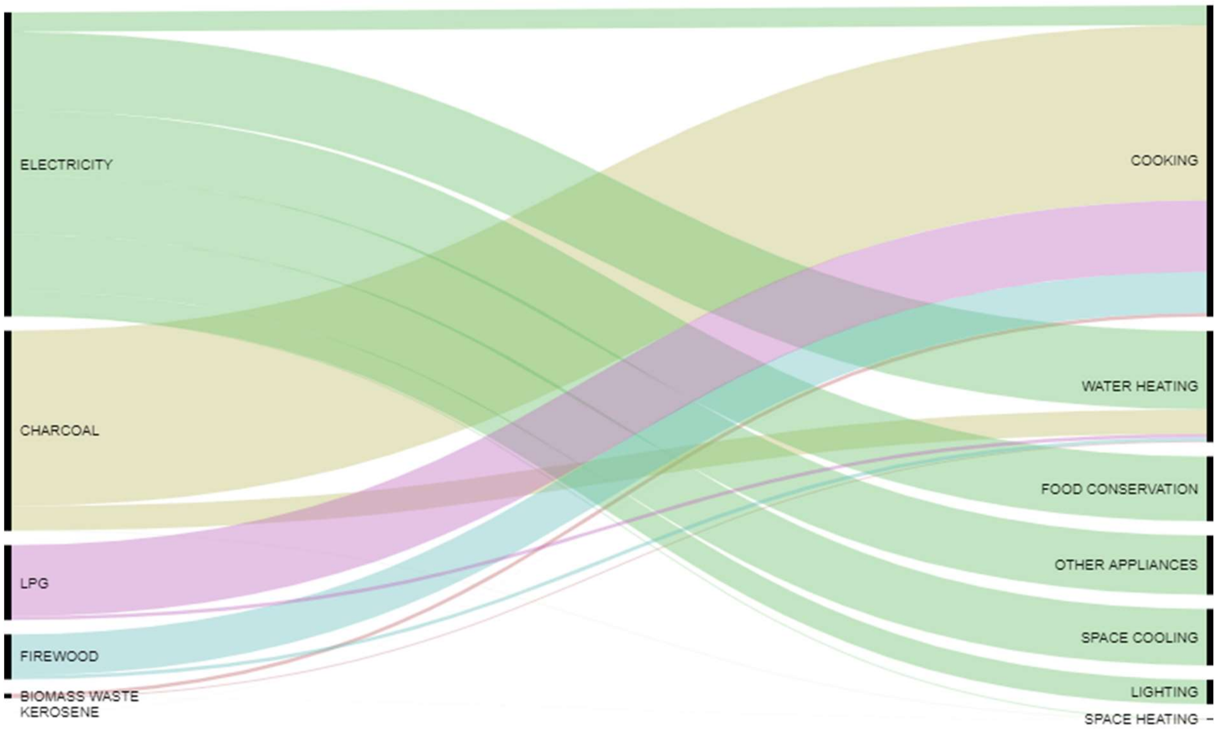
Source: (*Calculating Degree Days*, n.d.).

Appendix 4. Share of Energy Sources’ Input per Energy Services in Paraguayan High-Income Households of 2011



Source: Personal elaboration with BNEU data.

Appendix 5. Share of Energy Sources' Input per Energy Services in Paraguayan Medium-Income Households of 2011



Source: Personal elaboration with BNEU data.

Appendix 6. Data on Energy Sources' Input per Income Level of 2011

ENERGY SOURCE	ENERGY SERVICE	INCOME LEVEL	Data (toe)
ELECTRICITY	SPACE COOLING	HIGH INCOME	10375
CHARCOAL	COOKING	HIGH INCOME	8262
ELECTRICITY	WATER HEATING	HIGH INCOME	7970
ELECTRICITY	OTHER APPLIANCES	HIGH INCOME	5861
ELECTRICITY	FOOD PRESERVATION	HIGH INCOME	5574
LPG	COOKING	HIGH INCOME	4349
ELECTRICITY	COOKING	HIGH INCOME	2716
ELECTRICITY	LIGHTING	HIGH INCOME	2031
CHARCOAL	WATER HEATING	HIGH INCOME	507
ELECTRICITY	SPACE HEATING	HIGH INCOME	387
LPG	WATER HEATING	HIGH INCOME	188
ELECTRICITY	PUMPING WATER	HIGH INCOME	127
FIREWOOD	COOKING	HIGH INCOME	120
FIREWOOD	WATER HEATING	HIGH INCOME	41
FIREWOOD	SPACE HEATING	HIGH INCOME	13
CHARCOAL	SPACE HEATING	HIGH INCOME	3
CHARCOAL	COOKING	MIDDLE INCOME	34776
ELECTRICITY	WATER HEATING	MIDDLE INCOME	15573
LPG	COOKING	MIDDLE INCOME	14149
ELECTRICITY	FOOD PRESERVATION	MIDDLE INCOME	12850
ELECTRICITY	OTHER APPLIANCES	MIDDLE INCOME	11732
ELECTRICITY	SPACE COOLING	MIDDLE INCOME	11180
FIREWOOD	COOKING	MIDDLE INCOME	8188
ELECTRICITY	LIGHTING	MIDDLE INCOME	4861
CHARCOAL	WATER HEATING	MIDDLE INCOME	4828
ELECTRICITY	COOKING	MIDDLE INCOME	3878
FIREWOOD	WATER HEATING	MIDDLE INCOME	720
LPG	WATER HEATING	MIDDLE INCOME	709
BIOMASS WASTE	COOKING	MIDDLE INCOME	705
BIOMASS WASTE	WATER HEATING	MIDDLE INCOME	205
ELECTRICITY	SPACE HEATING	MIDDLE INCOME	174
CHARCOAL	SPACE HEATING	MIDDLE INCOME	58
KEROSENE	COOKING	MIDDLE INCOME	14
BIOMASS WASTE	SPACE HEATING	MIDDLE INCOME	13
LPG	SPACE HEATING	MIDDLE INCOME	3
CHARCOAL	COOKING	LOW INCOME	52915
FIREWOOD	COOKING	LOW INCOME	49211
CHARCOAL	WATER HEATING	LOW INCOME	17248
LPG	COOKING	LOW INCOME	11401
ELECTRICITY	FOOD PRESERVATION	LOW INCOME	10299
FIREWOOD	WATER HEATING	LOW INCOME	6964
ELECTRICITY	OTHER APPLIANCES	LOW INCOME	5859

ELECTRICITY	WATER HEATING	LOW INCOME	3537
ELECTRICITY	LIGHTING	LOW INCOME	3512
ELECTRICITY	SPACE COOLING	LOW INCOME	3448
BIOMASS WASTE	COOKING	LOW INCOME	1777
FIREWOOD	SPACE HEATING	LOW INCOME	898
BIOMASS WASTE	WATER HEATING	LOW INCOME	817
ELECTRICITY	COOKING	LOW INCOME	811
LPG	WATER HEATING	LOW INCOME	351
CHARCOAL	SPACE HEATING	LOW INCOME	122
KEROSENE	LIGHTING	LOW INCOME	81
ELECTRICITY	PUMPING WATER	LOW INCOME	75
PETROL	OTHER APPLIANCES	LOW INCOME	55
ELECTRICITY	SPACE HEATING	LOW INCOME	54
PETROL	PUMPING WATER	LOW INCOME	22
BIOMASS WASTE	SPACE HEATING	LOW INCOME	10
CHARCOAL	OTHER APPLIANCES	LOW INCOME	6

Source: Personal elaboration with BNEU data.

Appendix 7. Robustness Checks

Dependent Variable: $ln(E_{it}/hh_{it})$		Municipality Fixed Effects		Province Fixed Effects		
		Non-Low-Income Households (Model 1)	Low-Income Households (Model 2)	Non-Low-Income Households (Model 3)	Low-Income Households (Model 4)	Low-Income Households (Model 4.1)
α	Coef.	3.9259***	1.7465***	3.6763***	2.0249**	2.5176***
	Std.Err	(0.1629)	(0.2210)	(0.4001)	(0.7016)	(0.2899)
$(ln(P_{E_{it}}-1))$	Coef.	-0.4492***	-0.3084***	-0.4220***	-0.3271***	-0.3017***
	Std.Err	(0.0089)	(0.0105)	(0.0233)	(0.0337)	(0.0302)
$lnP_{LPG_{it}}$	Coef.	Without	Without	Without	Without	Without
	Std.Err					
$lnCDD_{it}$	Coef.	0.1877***	0.1001***	0.1944***	0.0964	Without
	Std.Err	(0.0162)	(0.0283)	(0.0397)	(0.0936)	
$lnHDD_{it}$	Coef.	Without				
	Std.Err					
lnY_{it}	Coef.	Without	Without		Without	Without
	Std.Err					
$(ln(E_{it-1}/hh_{it-1}))$	Coef.	0.6737***	0.8570***	0.6884***	0.8343***	0.8472***
	Std.Err	(0.0091)	(0.0093)	(0.0249)	(0.0309)	(0.0261)
Periods		16	16	16	16	16
Cross-sections		189	187	16	16	16
Observations		2517	2479	210	210	256
Panel		Unbalanced	Unbalanced	Unbalanced	Unbalanced	Balanced
		Weighted Statistics				
R2		0.9842	0.9230	0.9892	0.9264	0.9280
Prob (F-Statistic)		0.0000	0.0000	0.0000	0.0000	0.0000
Durbin–Watson Stat		2.1357	1.8623	2.1376	1.7809	1.7723

	Unweighted Statistics				
R2	0.9579	0.8479	0.9867	0.8577	0.8674
Durbin–Watson Stat	2.3057	2.2009	2.1869	2.1944	2.0791

Note: ∗$p < 0.05$; ∗∗$p < 0.01$; ∗∗∗$p < 0.001$

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