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Three essays on the direct rebound effect

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Contents

To my father, whom I miss every day

Epigraph

“The advent of cooking enabled humans to eat more kinds of food, to devote less time to eating, and to make do with smaller teeth and shorter intestines. Some scholars believe there is a direct link between the advent of cooking, the shortening of the human intestinal tract, and the growth of the human brain. Since long intestines and large brains are both massive energy consumers, it’s hard to have both. By shortening the intestines and decreasing their energy consumption, cooking inadvertently opened the way to the jumbo brains of Neanderthals and Sapiens.”

Harari (2014, p. 283)

1. Introduction

In this thesis, we provide three empirical essays on the direct rebound effect. The direct rebound effect can be defined as how the efficiency of an energy source conversion device affects the consumption of the energy service it provides. However, our focus is also to study if the efficiency of an energy source conversion device affects the consumption of others substitutes or complementary energy services which is provided by an alternative energy source conversion device.

Under certain assumptions, a suitable proxy for the direct rebound effect is the own-price elasticity of demand the energy source of the energy service considered. Therefore, in each essay we provide the shares of the energy services per energy source to show which energy services would be more affected by our estimation of the direct rebound.

In the first chapter, we estimate the magnitude of the direct rebound effect for electricity for households in Spain, considering the energy services provided by natural gas and diesel oil. Here, the energy services provided by natural gas and diesel oil affect the energy services provided by electricity with a complementary relationship. In this chapter, we find the first empirical evidence for this thesis suggesting a relationship between energy services through the efficiency of their energy source conversion devices. We find a magnitude of the direct rebound effect for the energy services provided by electricity between 26% and 35% in the short-run and 36% in the long-run, which are in line with the literature for a direct rebound effect of a developed country.

Moreover, as the empirical evidence of the direct rebound effect for developing countries is scarce, in the second chapter, we estimate the magnitude of the direct rebound effect, for two income groups, for electricity for households in Paraguay, considering the energy services provided by liquefied petroleum gas (LPG). Here, we find again empirical evidence suggesting a relationship between energy services through the efficiency of their energy source conversion devices. Thus, the energy services provided by LPG affect the electricity consumption with a substitute relationship in non-low-income households, and affect electricity consumption with a complementary relationship in low-income households. For low-income households the magnitude of the direct rebound effect we find is between 14% and 18%, and for non-low-income households the direct rebound effect magnitude we find is between 23% and 60%. Since the literature suggests a higher magnitude of the direct rebound effect in low-income households, we provide possible explanations for our results. First, electricity is not the main energy source for most low-income households. Second, most clandestine electricity connections are from low-income households.

In the third chapter, we estimate the magnitude of the direct rebound effect for natural gas for households in Spain, considering the energy services provided by electricity and diesel oil. Here, as in the previous two chapters, there is a significant relationship between energy services. Thus, the energy services provided by electricity affect natural gas consumption with a complementary relationship in the short-run and with a substitute relationship in the long-run. The energy services provided by diesel oil affect natural gas consumption with a substitute relationship in both short- and long-run. In this chapter, we also provide an updated set of assumptions for estimating the direct rebound effect through price elasticities given the relationship between energy services through the efficiency of their energy source conversion devices. We also find that, if the goal is to reduce natural gas consumption, it will be more effective to increase the efficiency of the energy services provided by electricity and diesel oil than to increase the efficiency of the energy services provided by natural gas. Here, we find a magnitude of the direct rebound between 79% and 89% in the short-run and between 42% and 64% in the long-run. This decreasing magnitude of the direct rebound effect for natural gas can be due to the fact that electricity can be a substitute of natural gas in the long-run and natural gas consumption seems to be an inferior good.

2. Chapter 1

Do household energy services affect each other directly? The direct rebound effect of household electricity consumption in Spain[1]

Abstract

We estimate the magnitude of the direct rebound effect (DRE) of households' electricity consumption in Spain, through an econometric estimation method of panel data. The results indicate a DRE between 26% and 35% in the short-run and around 36% in the long-run. Moreover, we find a significant influence of other energy sources that appear to be complementary to electricity consumption according to our estimation. Hence, our results suggest that an improvement in the energy efficiency of an energy service may affect its own energy consumption as well as the energy consumption of other energy services. This would entail a new source of DRE.

Keywords: Direct rebound effect, Complementary energy sources, Energy efficiency, Households' electricity consumption, Panel data

[1] This paper has been published in the journal *Energy Efficiency* on 26 august 2022. Bordón-Lesme, M., Freire-González, J., Padilla Rosa, E. (2022a) "Do household energy services affect each other directly? The direct rebound effect of household electricity consumption in Spain", *Energy Efficiency* 15(7), 1-21.

2.1. Introduction

Energy services can be understood as useful work or useful outputs obtained by energy conversion devices (Sorrell, 2007) or as Fell (2017, p. 137) stated: “Energy services are those functions performed using energy which are means to obtain or facilitate desired end services or states.” An example of an energy service would be “transportation”. The improvements in energy efficiency, due to innovation and technical change, decrease the effective cost of an energy service as it requires less energy to provide the same energy service, which leads to energy savings. However, as shown by empirical evidence, this decrease in the cost of the energy service causes behavioral responses from consumers, causing what is known in the literature as the direct rebound effect (DRE). Hence, the DRE can be defined as the consumer behavioral responses, following a reduction in the cost of energy services, due to an improvement of energy efficiency. This partially or fully reduces the initially expected energy savings, or in some cases, could even increase the energy consumption.

The purpose of this article is twofold. First, we obtain empirical evidence of the DRE for all the energy services that require electricity for their provision in Spanish households.

Second, the main contribution of this article is the consideration of alternative energy sources in the estimation of the DRE for the energy source of electricity for Spanish households. Using recent data, this paper delivers an estimated magnitude of the DRE in the consumption of electricity of Spanish households providing short- and long-run estimates. The results of this research will contribute to the empirical literature concerning the DRE in a developed country of the energy services provided by electricity in households. We will provide up to date evidence for the case of the residential sector in Spain since Freire González (2010) employed a similar estimation method to ours for the DRE of household electricity consumption in Catalonia.

There is also recent empirical evidence of the rebound effect for Spain by Cansino et al. (2022), who estimate the direct, the indirect, and the economy-wide rebound effect for 14 productive sectors, to estimate the DRE they also employed an econometric estimation method. They found a positive DRE for the 14 productive sectors.

Other recent empirical evidence related to the rebound effect for Spain is done by Cansino et al. (2019) and Román-Collado and Colinet (2018), whereas Román-Collado and Colinet Carmona (2021) focused on the Spanish region of Andalusia. They used a Logarithmic Mean Divisia Index I (LMDI-I) decomposition model to test how energy efficiency affects energy consumption in different economic sectors in Spain. Cansino et al. (2019) found that there are energy consumption savings after energy efficiency improvements. Román-Collado and Colinet (2018) highlighted the relevance of focusing on Spanish household energy consumption, as it became the most relevant energy consumption change in Spain with a 25.1% increase from 2000 to 2013. Román-Collado and Colinet Carmona (2021) found that, to achieve Spain's energy consumption targets, the energy consumption of Andalusia should reach the average Spanish energy consumption. The main additional contribution of this article is the consideration of alternative energy sources in the estimation of the DRE for the energy source of electricity for Spanish households.

As different economic variables tend to change over time, it is expected that the magnitude of the rebound effect varies through the years (Sorrell, 2007, 2018). Henceforth, this research will not only contribute to the DRE literature, but it will also provide updated and useful information to policymakers. An additional contribution of our paper is that we test the impact of the prices of other energy sources, which may be substitutes or complementary goods. If we find that household energy services affect each other directly this would involve a new source of DRE, which could open a new research line.

The study of the rebound effect is essential for policymakers whether they want to maximize energy and climate policy effectiveness by incorporating additional measures to tackle the rebound effect, such as energy taxation or tradable permits (Freire-González and Puig-Ventosa, 2014; van den Bergh, 2011) or if social welfare is a priority (as efficiency improvements in energy services would reduce its effective cost) rather than saving energy (Sorrell, 2018).

To put our analysis into context, we show next some empirical evidence of the DRE. We focus on the DRE estimation through econometric techniques for a collection of energy services supplied by electricity and natural gas in households. The empirical evidence that we review next does not consider alternative energy sources for the estimation of DRE of the energy source studied, with the only exception of Freire-González (2010). Nevertheless, his coefficient of the alternative energy source variable was not significant. Thus, by considering alternative energy sources that have significance in the estimation of the DRE of an energy source considered, our article would contribute to bridging the gap in the literature regarding this issue.

Under certain assumptions, the estimation of the own-price elasticity of domestic energy demand would reveal the DRE. In this approach, the estimation is based upon an overall

improvement in energy efficiency of energy services used by households (Sorrell, 2007). Hence, the DRE refers to all energy services run by energy source considered.
Table 1 summarizes some empirical evidence of the direct rebound for household electricity and gas consumption. One of the first studies to analyze the DRE of a collection of energy services was Freire-González (2010) for the case of Catalonia (Spain). He used panel data from the period 1991–2003 with a sample size of 43 Catalan municipalities. He found that the short- and long-run elasticities were 35% and 49% respectively. Several subsequent studies have analyzed the DRE for electricity consumption in households using the same econometric approach to estimate the short- and long-run elasticities.

The results of these studies for residential electricity consumption are in line with the theory suggesting that the DRE is expected to be greater in developing regions (Sorrell, 2007); since the DREs estimated for China, Tunisia, and Pakistan (Alvi et al., 2018; Labidi and Abdessalem, 2018; Wang et al., 2014; Zhang et al., 2017) were higher than those estimated for Catalonia (Spain) and Beijing (China) (Freire-González, 2010; Wang et al., 2016). Beijing is not only the capital of China, but also the second richest city of the country in per capita disposable income (Wang et al., 2016). Another recent measure of the DRE for domestic energy services was conducted by Belaïd et al. (2018). They found short- and long-run DREs of 60% and 63%, respectively, for all energy services supplied by residential gas in France. The size of both effects may seem large for a developed country considering the economic literature on the DRE. However, these results should be taken with caution, since they used average data for the whole country, which may not capture the heterogeneity among French regions. Table 1 indicates the findings of these studies.

The most common control variables used by the studies shown in Table 1 are the price of the energy source considered (electricity or natural gas), an income variable such as household disposable income or GDP, and the climatic variables such as heating- and cooling-degree days.

Table 1. Econometric estimates of direct rebound of all energy services in households that use electricity or gas.

Author/year	Country	Energy Source	Short-run	Long-run	Data	Estimation technique	Price coefficient of other energy sources
Freire-González (2010)	Catalonia (Spain)	Electricity	35%	49%	Panel: 1991–2002 Sample size: 43	Fixed effects and Error Correction Model	Price of Natural Gas, not significant
Wang et al. (2014)	China	Electricity	72%	74%	Panel: 1996–2010 Sample size: 30	Fixed effects and Error Correction Model	Not included in the model
Wang et al. (2016)	Beijing (China)	Electricity	16%	40%	Time series: 1990–2013	Fixed effects and Error Correction Model	Not included in the model
Zhang et al. (2017)	China	Electricity		72% on average. 68% low-income regime, 55% high income regime	Panel: 14 years (2000–2013) and 29 provinces of China	Linear panel model and panel threshold model	Not included in the model
Alvi et al. (2018)	Pakistan	Electricity	42.9%	69.5%	Panel: 1973–2016 Sample size: not specified	Fixed effects and Error Correction Model	Not included in the model
Labidi and Abdessalem (2018)	Tunisia	Electricity		81.7%	Panel: 1995, 2000, 2005 and 2010 Sample size: 21	Fixed Effect	Not included in the model
Belaïd et al. (2018)	France	Natural Gas	60%	63%	Time series: 1983–2014	OLS and ARDL	Not included in the model

Source: own elaboration.

2.2. Methodology and Data

2.2.1. Methodological developments on the estimation of the direct rebound

This subsection details the theoretical and methodological developments for the estimation of the DRE using econometric approaches. We follow the theoretical developments made by Berkhout et al. (2000), Sorrell (2007), and Sorrell and Dimitropoulos (2008). There is a consensus in the economic literature regarding the measurement of the DRE through the efficiency elasticity of the demand for useful work (Berkhout et al., 2000). This is the primary definition of the DRE:

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

Where $\eta_{\varepsilon}(E)$ is the efficiency elasticity of the demand for energy and $\eta_{\varepsilon}(S)$ is the efficiency elasticity of the demand for useful work. One definition of useful work or useful output is what consumers required in terms of an end-use service (Patterson, 1996). For example, a useful work measure of transportation service from private car ownership can be the calculation of passenger kilometers. This calculation can come from the product of the number of cars, the mean driving distance per car per year, and the average number of passengers carried per year (Sorrell and Dimitropoulos, 2008).

From this theoretical development, the different results found in the literature are the following:

(i) A zero DRE, when the efficiency elasticity of the demand for useful work equals to zero ($\eta_{\varepsilon}(S) = 0$). Hence, the efficiency elasticity of the demand for energy ($\eta_{\varepsilon}(E)$) is equal to minus one. This would imply that final energy savings are proportional to the efficiency improvement.

(ii) A positive DRE, when the efficiency elasticity of the demand for useful work is between 0 and 1 ($0 < \eta_{\varepsilon}(S) < 1$) and, therefore, the efficiency elasticity of the demand for energy is between 0 and -1 ($-1 < \eta_{\varepsilon}(E) < 0$) (Sorrell and Dimitropoulos, 2008). This implies that energy savings that are less than proportional to the improvement in energy efficiency. This is the most common outcome in the literature.

(iii) A positive DRE, causing an increase in energy consumption, when the demand for useful work is elastic ($\eta_{\varepsilon}(S) > 1$) and ($\eta_{\varepsilon}(E) > 0$). Thus, an improvement in energy efficiency increases energy consumption (what is known as backfire) (Saunders, 1992).

Under certain assumptions, the DRE can be measured indirectly, without data on energy improvements, through price elasticities (Sorrell, 2007; Sorrell and Dimitropoulos, 2007, 2008). First, symmetry: for a normal good, it is expected that rational consumers will respond in the same way to a decrease in energy prices as they do to an improvement in energy efficiency (and vice-versa) (Sorrell et al., 2009). Second, exogeneity: energy prices (P_E) are exogenous, so they do not affect energy efficiency (Sorrell, 2007). Under these assumptions, the DRE can be expressed as:

$$\eta_{\varepsilon}(E) = -\eta_{P_S}(S) - 1 \qquad (2)$$

Where the energy cost elasticity for useful work ($\eta_{P_S}(S)$) can be used as a proxy for the efficiency elasticity of useful work. It is expected that $\eta_{P_S}(S) \leq 0$ if useful work is a normal good (Sorrell and Dimitropoulos, 2008).

It is also possible to arrive at another definition for the DRE, through the estimation of the own-price elasticity of energy demand ($\eta_{P_E}(E)$).

$$\eta_{\varepsilon}(E) = -\eta_{P_E}(E) - 1 \qquad (3)$$

The additional assumption required for this definition (besides symmetry and exogeneity) is that energy efficiency does not change with the level of energy use (Sorrell and Dimitropoulos, 2008). To deal with endogeneity (energy efficiency affects energy costs and energy costs affect energy efficiency), empirical estimates can be addressed analyzing cointegration relationships between the variables (Freire-González, 2010a). Since periods of rising prices may induce improvements in efficiency, to avoid overestimating the size of the effect, empirical estimates must be based upon periods of stability or decrease of energy prices (Sorrell, 2007; Sorrell and Dimitropoulos, 2008; Sorrell et al., 2009).

We estimate the DRE through equation 3. Given the assumptions explained above, we use the own-price elasticity of electricity demand as a proxy for the efficiency elasticity of the demand for useful work of electricity (equation 1). Sorrell (2007) clarified that equation 1 requires energy efficiency data for the energy service considered, and for this type of data generally there is limited variation in energy efficiency providing results with large variance. On the other hand, equation 3 only requires data on energy prices, usually more available than data on energy efficiency, which provides a greater variation in the independent variable (Sorrell, 2007).

Most of the empirical evidence briefly reviewed in the introduction suggests that the DRE is lower than 100%, implying that there will be energy savings after an improvement in efficiency. However, it is important to point out that these estimates only measure the DRE without considering the indirect rebound effect; when both the direct and indirect rebound effect can be linked through a re-spending framework (Freire-González, 2011), leading to different rebounds at microeconomic level. In this framework, low estimations of the DRE give rise to the possibility that the indirect rebound effect reaches a wider range of values; likewise, high estimations of the DRE entails less potential fluctuation of the indirect rebound effect (Freire-González, 2017a). Given this relationship between both effects, it is not possible to confirm whether the direct and indirect rebound effect is greater or lower than 100% when only the DRE is measured. Freire-González (2017b) found direct and indirect rebound effects greater than 100% of energy efficiency in households in Cyprus, Poland, Belgium, Bulgaria, Lithuania, Sweden, Denmark, and Finland by using a combination of econometric estimations of energy demand functions, re-spending modeling, and generalized input–output of energy modeling.

A comprehensive way to jointly estimate the direct and indirect rebound is through the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980). These models, however, require a lot of information on consumption, expenditures, prices, and other variables from a basket of goods and services which is often not available. Chitnis and Sorrell (2015) estimated a direct and indirect rebound effect of 48% for electricity efficiency improvements in UK households through an AIDS, and using the same methodology, Lin and Liu (2013) found a direct and indirect rebound effect of 165.22% (backfire) in Chinese households.

The existing literature suggests that the magnitude of the DRE lies between 30% and 50% (Sorrell et al., 2009). As energy efficiency data is usually unavailable, most studies rely either on the elasticity of demand for energy services with respect to the price of energy or the elasticity of demand for energy with respect to the price of energy to estimate the DRE (Sorrell, 2007; Sorrell et al., 2009). Under the assumptions explained above, both approaches are accepted in the DRE literature (Freire-González, 2017b; Sorrell and Dimitropoulos, 2007). Regarding the term of the effects, Sorrel stated: “Rebound effects may be larger or smaller over the long-run as a greater range of behavioral responses become available” (Sorrell, 2018; p.14).

An additional issue to be considered in the estimation of the DRE is that different energy sources may be complementary or substitutes. Therefore, the price of other energy sources may be influencing the demand of a particular energy source and so, it should be taken into account in the estimation of the DRE. The only previous study that included the price of another energy source was Freire-González (2010), though he did not find it to be significant. We propose to include it in the model to obtain a more accurate estimation of the DRE. Moreover, in case of being significant it would open a new line of research, as it would involve evidence that there is an additional source of rebound to the ones usually considered in the literature.

2.2.2. Data

We obtained annual data from 2007 to 2016 for the 52 provinces of Spain for all the variables described. We obtained the price of domestic electricity and natural gas from the Eurostat (2016).[2] These prices do not vary between provinces, but they do over time. We gathered the information about heating oil prices from the Eurostat (2016).[3] We could not find data for renewable energy prices, which is mainly biomass. According to IDAE (Instituto para la Diversificación y ahorro de la Energía) the renewable energy sources used by Spanish households are the following: Biomass (96.6%), Solar Thermal (0.03%), and Geothermal (0.002%). In this sense, Vinterbäck and Porsö (2011, p. 9) stated that for Spain: "There is no official information or statistics about prices of wood pellets and briquettes. There are several independent organizations related to the wood sector (e.g. Confemadera, Cismadera, Cesefor) that handle internal data about prices, but these statistics are not available for all stakeholders but only for organization members and people registered on the webpage."

We assigned the price of electricity and natural gas considering their price categories. The price categories of each Spanish energy carrier (electricity and natural gas) are shown in Appendix 1. In the case of electricity consumption, we can find provinces that fell into two categories (Band DB and DC) along the 10 years, such as Álava, Burgos, and Cantabria. On the other hand, there are provinces whose price category remained the same during the 10 years, such as Barcelona and Madrid (Band DC), and Ávila and Cáceres (Band DB). This feature is also present in natural gas consumption. We captured this price variability for both energy sources (electricity and natural gas) considering the average household consumption per province per year to be the

[2] http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_204&lang=en

[3] https://ec.europa.eu/energy/en/data-analysis/weekly-oil-bulletin

dependent variable in the estimates. Heating oil is charged at the same price regardless of the amount used.

Given data availability issues, the household disposable income of each Spanish region, which was obtained from the National Institute of Statistics (INE, 2016),[4] is used as a proxy for the household disposable income per province. Nevertheless, we transformed all the monetary variables to constant 2016 prices by accounting for the inflation in each province.

We collected data on the minimum and maximum daily temperature of each province from the State Meteorological Agency of Spain (AEMET, 2016).[5] The base temperature chosen to calculate the heating and the cooling degree days are 21°C and 22°C respectively; Appendix 2 shows the formula used. Nevertheless, there is no consensus regarding the suitable values of the "threshold" or base temperature to define the comfort zone (Blázquez et al., 2013). In this sense, the base temperature for heating degree days was defined following the values chosen by Freire-González (2010) for his estimation of the DRE for Catalonia; and the cooling degree days base temperature was defined following the Spanish Technical System Operator (REE, 1998). Data on electricity consumption (the dependent variable in the estimates) and subscribers was obtained from the Ministerio de Industria, Comercio y Turismo (2016).[6]

The data collection process could be improved by collecting the specific price charged for each energy service. We estimate the DRE for a collection of energy services that require electricity, therefore, the DRE for each energy service is disguised into our results. It would also be desirable to enlarge the panel data by collecting data at the municipality level. However, the cost of collecting this specific type of data for Spain might exceed its benefits since different types of data used in different types of econometric estimation methods give an estimated magnitude of the DRE of around 30%, for a developed country (Sorrell and Dimitropoulos, 2007). Thus, given the present data availability, our results provide useful and robust information, especially regarding the direct influence that arises between households' energy services.

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[4] Instituto Nacional de Estadistica. (Spanish Statistical Office), www.ine.es/

[5] Agencia Estatal de Meteorología (AEMET). Sede Cataluña, from aemet.es/es/portada.

[6] https://energia.gob.es/balances/Publicaciones/.

2.2.3. Econometric models estimated

This subsection shows the econometric models estimated to measure the DRE. Following the proposal of Freire-González (2010), the estimation of the DRE was performed by obtaining the price and income elasticities using a double-logarithmic functional form for the demand of electricity consumption in households. A general household electricity demand model for Spain can be specified as follows:

$$ln\ (E_{it}/hh_{it}) = \alpha\ +\ \beta_1 lnP_{E_{it}} + \beta_2 lnP_{X_{it}} + \beta_3 lnY_{it} + \beta_4 lnCDD_{it} + \beta_5 lnHDD_{it} + \beta_6 ln\ (E_{it-1}/hh_{it-1}) \qquad (4)$$

Where E_{it}/hh_{it} is the aggregate electricity consumption divided by the number of households subscribed in period *t,* in province *i*; $P_{E_{it}}$ is the price of electricity in period *t,* in province *i*; $P_{X_{it}}$ is the price of other energy sources needed in Spanish households in period *t,* in province *i,* such as natural gas (*G*) and heating oil (*HO*); Y_{it} is the households' disposable income in period *t,* in province *i*; CDD_{it} and HDD_{it} are the cooling and heating degree days in period *t,* in province *i*, respectively; and E_{it-1}/hh_{it-1} is the average electricity consumption in period $t-1$, in province *i;* which captures the long-run effects.

We expect a negative sign in the coefficient accompanying the price of electricity, that is, an increase in electricity prices would reduce the electricity consumption. The relationship between electricity consumption and the price of other energy sources seems more complex. To identify whether electricity and the other energy sources are substitutes or complementary goods, we can focus on the energy services provided from each energy carrier. Considering the period 2010–2015, electricity is the major energy source in providing lighting and energy for appliances. This energy service amounts for approximately 74% of the total electricity consumption in Spanish households (IDAE, 2015). For space cooling services, electricity is the main energy source with 99% share (IDAE, 2015). Therefore, families do not have many possibilities of substituting the energy sources for these energy services. As regards, space heating, which is the energy service with the greatest share of energy consumption in Spanish households, electricity has a share of 7% (IDAE, 2015); biomass, natural gas, and heating oil being the most important energy sources. If we combined the energy services of space heating, water heating, and cooking, electricity amounts for 14% of the total energy consumption for those energy services (IDAE, 2015) (see Appendix 3 for further information). Nevertheless, most families just have one type of installation to provide each of these energy services and, therefore, there are not many possibilities for substituting the energy sources providing them. Households need not only electricity to satisfy their demand for energy services, but they also require other energy sources, such as natural gas and heating oil. Therefore, when we estimate the DRE of a collection of energy services provided by electricity, we could expect a negative (complementary) relationship between the other energy sources used in households and the residential electricity consumption. That is, an increase in the price of the other energy sources would tend to reduce the consumption of electricity.

Households' disposable income is expected to have a positive relation with electricity demand, as we consider that electricity is a normal good. Degree days measure the duration and intensity of warm or cold temperatures, along different periods. They are computed using a base temperature that should adequately separate the cold and heat branches of the demand–temperature relationship (Pardo et al., 2002). Concerning the weather variables, a wider temperature range is expected to have a positive influence on electricity consumption (Romero-Jordán et al., 2014), that is, the colder (warmer) the temperatures are from the base temperature, the greater is the use of heating (cooling) devices run by electricity. In this sense, HDD and CDD are expected to have a positive relationship with electricity demand. Regarding the lagged electricity consumption, a positive sign is expected, due to existing inertia in electricity consumption (Abel, 1990; Romero-Jordán et al., 2014). Given these relationships and the models used in previous studies concerning the direct rebound estimation in households, we presume that all relevant variables have been accurately included in the model.

2.2.3.1. Two-step error correction model

In the long-run, households' energy demand can be adjusted completely to changes in prices and income within the unit period, which is one year in our model (Sorrell and Dimitropoulos, 2007). On the contrary, in the short-run, households' energy demand has fewer adjustment possibilities. Therefore, to estimate both short- and long-run price elasticities in household electricity consumption, an error correction model (ECM) (Granger, 1981) is used to calculate the DRE (Alvi et al., 2018; Freire-González, 2010a). An ECM is an econometric model that deals with the cointegration of variables to obtain both short- and long-run estimators, and solve spurious relationships between them (Greene, 2003). For residential electricity demand, we can expect that households would respond not only to current values of independent variables but also to past values. As this effect might persist over time, an ECM with lagged variables is an appropriate model to deal with these potential endogeneity issues providing consistent estimations (Greene, 2003). In this case, the ECM is performed in two steps. First, a fixed effects model is estimated following this specification:

$$ln(E_{it}/hh_{it}) = \alpha + \mu_i + \beta_1 lnP_{E_{it}} + \beta_2 lnP_{X_{it}} + \beta_3 lnY_{it} + \beta_4 lnCDD_{it} + \beta_5 lnHDD_{it} + u_{it} \quad (5)$$

Where α represents the common fixed effect or constant; μ_i are the individual fixed effects. The fixed effects model has been estimated using a generalized least squares (GLS) method, correcting potential heteroskedasticity and autocorrelation problems by using cross-section weights. This model provides long-run elasticities. Second, the predicted residuals from estimating equation (5) have been saved and used as exogenous variable in a regression containing differenced endogenous and exogenous variables plus the lagged error term (ϑu_{it-1}), which is a specification of an ECM. The ECM model is specified as follows:

$$\Delta ln(E_{it}/hh_{it}) = \propto + \delta_1 \Delta lnP_{E_{it}} + \delta_2 \Delta lnP_{X_{it}} + \delta_3 \Delta lnY_{it} + \delta_4 \Delta lnCDD_{it} + \delta_5 \Delta lnHDD_{it} + \delta \Delta_6 ln(E_{it-1}/hh_{it-1}) + \vartheta_{it} u_{it-1} + \varepsilon_{it} \quad (6)$$

A significant and negative coefficient accompanying the error correction term ($\vartheta_{it} u_{it-1}$) would imply that the system corrects its previous period disequilibrium. Expected values of the error correction term are between 0 and -1. Table 2 shows that three of the eight statistics reject the null hypothesis of no cointegration, suggesting the existence of cointegration. The ECM has also been estimated assuming cross-section heteroskedasticity, that is, with a GLS specification. In both steps, the ECM has been estimated with the common coefficients to all provinces; the fixed effect of each province is displayed in Appendix 4.

The Hausman test confirms that there are differences between the random and the fixed effects estimators (Table 3). Hence, the fixed effects estimator is more suitable than the random effects to estimate the two steps ECM because Table 3 output rejects the null hypothesis of no correlation between the unique errors and the regressors. Likewise, Table 4 shows that the first step equation of the ECM, suggests that cross-section effects are significant. Moreover, the cross-section fixed effects test equation is relevant for all the variables.

2.2.3.2. System generalized method of moments

As previously stated, we expect a significant influence from past values of the explanatory variables on the current values of the dependent variable. To deal with this dynamic relationship, we can also estimate the model through a dynamic generalized method of moments (GMM) panel estimator. This estimator is consistent and unbiased if we assume that the unobserved heterogeneity (μ_i) is fixed (Wintoki et al., 2012).

To deal with potential endogeneity issues, the dynamic GMM estimators instrument current values of explanatory variables with their lagged values (Wintoki et al., 2012). According to Roodman (2009b), the dynamic GMM panel estimators, whether using difference or system GMM, are designed for situations when the time span *(T)* analyzed is relatively small with respect to the cross-sections *(N)*. Relating the econometric method to our data generating process, we can see that the individuals (52) are relatively large compared to the time frame (10).

We base our estimation on the system GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; Holtz-Eakin et al., 1988). This approach also addresses fixed effects, heteroskedasticity, and autocorrelation (Roodman, 2009a).

The dynamic model is specified as follows (Arellano and Bover, 1995; Baltagi, 2008; Blundell and Bond, 1998; Roodman, 2009a). See Roodman (2009a) for further details regarding the difference and system GMM:

$$y_{it} = \alpha y_{i,t-1} + \beta x'_{it} + \varepsilon_{it} \tag{7}$$

$$\varepsilon_{it} = \mu_i + \upsilon_{it}$$

$$E(\mu_i) = E(\upsilon_{it}) = E(\mu_i \upsilon_{it}) = 0$$

The two orthogonal conditions of the disturbance term are the fixed effects (μ_i) and the idiosyncratic shocks (υ_{it}) (Roodman, 2009b). For these conditions to be valid, the instruments must provide an exogenous source of variation on the explanatory variables. For example, past values of the explanatory variables that have no direct effect on the current dependent variable (electricity consumption per province) and only affect it through its effect on current values of the explanatory variables (Wintoki et al., 2012).

To remove the fixed effects (μ_i) from equation 7, Arellano and Bond's (1991) estimator subtracts the previous observation from the contemporaneous one which is known as "difference GMM":

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \Delta x'_{it}\beta + \Delta v_{it} \tag{8}$$

Nevertheless, the weakness of this estimator is that it increases data loss (due to the first difference transformation) especially in unbalanced panels (Roodman, 2009a). There is also a potential endogenous issue as the $y_{i,t-1}$ term in $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ is correlated with $v_{i,t-1}$ in $\Delta v_{it} = v_{it} - v_{i,t-1}$. Additionally, predetermined variables in x' could also add another endogeneity problem; as they might also be correlated with $v_{i,t-1}$ (Roodman, 2009b).

Arellano and Bover (1995) presented an alternative transformation of equation 7, by using forward orthogonal deviations. They proposed to subtract the average of all future available observations. For each $(T-1)$ observation, they subtract the mean of the remaining future observations available in the sample, instead of subtracting the previous observation from the contemporaneous one (Roodman, 2009a). Thus, only the last observation is kept out of the computation. For example: in a panel data of $(T = 3)$ the difference GMM produces one instrument per instrumenting variable and the system GMM produces two (Arellano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2009b). Arellano and Bover (1995), Blundell and Bond (1998), and Roodman (2009b) also demonstrated a weak instrumentation of difference GMM, especially if the variables are close to a random walk, system GMM being the favored alternative. System GMM augments difference GMM by estimating simultaneously in differences and levels, (Roodman, 2009b).

The system GMM estimator instruments the equation in levels with first-differenced variables in a "system" of equations that includes both equations in levels and differences (Wintoki et al., 2012):

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = \alpha + \kappa \begin{bmatrix} y_{it-p} \\ \Delta y_{it-p} \end{bmatrix} + \beta \begin{bmatrix} x'_{it} \\ \Delta x'_{it} \end{bmatrix} + v_{it} \tag{9}$$

Blundell and Bond (1998) contributed to the method by eliminating the fixed effect not through instrumenting differences with levels but instrumenting levels with differences (Roodman, 2009b). The assumption required for the system GMM is that changes in any instrumenting variable (w) are uncorrelated with the fixed effects $E(\Delta w_{it}\mu_i) = 0$ (Roodman, 2009b).

In the design of the instrument matrix, we assume the climatic variable Cooling Degree-Days to be strictly exogenous. For the appropriate instruments for predetermined variables we use: the lagged dependent variable, the price of electricity, and the natural gas price, with a lag limit of 2, and longer for the transformed equation, and lag 2 for the equation in levels (Roodman, 2009a).

Table 2. Pedroni Residual Cointegration Test

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-4.473	1.000	-4.633	1.000
Panel rho-Statistic	9.151	1.000	8.746	1.000
Panel PP-Statistic	-15.135	0.000	-14.542	0.000
Panel ADF-Statistic	NA	NA	NA	NA
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	11.627	1.000		
Group PP-Statistic	-27.688	0.000		
Group ADF-Statistic	NA	NA		

Table 3. Hausman Test

Correlated Random Effects – Hausman Test			
Test cross-section random effects			
Test Summary:	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random:	66.046	6	0.000

Table 4. Redundant Fixed Effects Tests

Test cross-section fixed effects				
Effects Test	**Statistic**	**d.f.**	**Prob**	
Cross-section F	49.126	(51.462)	0.000	
Cross-Section fixed effects test equation				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	**-2.303**	**0.410**	**-5.611**	**0.000**

$lnP_{E_{it}}$	-0.811	0.056	-14.388	0.000
$lnP_{G_{it}}$	0.064	0.033	1.938	0.053
$lnP_{HO_{it}}$	-0.331	0.051	-6.401	0.000
$lnCDD_{it}$	0.159	0.011	13.978	0.000
$lnHDD_{it}$	-0.219	0.019	-11.424	0.000
lnY_{it}	0.405	0.040	10.097	0.000

2.3. Results

In this section we show the obtained results, the first three columns of Table 5 provide the results of this article, the latter two are the corresponding robustness checks for the estimation method of the third column, which is the system GMM. The coefficients highlighted in bold font located in rows three, six, and nine are the coefficients of the variables of interest in this article. As we can see in Table 5, the sign and significance of the alternative energy sources (natural gas and heating oil) indicate a complementary relationship with electricity consumption.

As explained above, we also estimate the parameters for the relevant variables of the system GMM through Pooled OLS and Fixed Effects. These estimations will give us the suitable range of values of the lagged dependent variable (Bond, 2002; Roodman, 2009a). The p-values are below each coefficient. The standard errors are in parentheses below each p-value.

Regarding the ECM Model, the long-run coefficients of electricity price, natural gas price, and cooling degree days have a significance level of 1%. Alternatively, the coefficients of the price of heating oil, the heating degree days, and the households' disposable income have a significance level of 5%. The sign of the coefficients is as expected, that is, an increase in the price of electricity would reduce its consumption. In the same way, an increase in the price of heating oil and natural gas would reduce residential electricity consumption. This seems to corroborate that there is a complementary relationship between these energy sources in providing the collection of energy services needed in households. Blázquez et al. (2013) also found a significant and negative coefficient for the gas variable in their analysis of residential electricity demand in Spain, considering the period 2000 to 2008 and 47 Spanish provinces. They considered the number of gas consumers divided by the number of houses to use the gas penetration rate as a proxy for the gas price.

Climatic variables show a positive relationship with electricity consumption, that is, we could expect a greater use of heating and cooling devices run by electricity, as the weather gets cooler or hotter with respect to the base temperature. The income variable suggests that electricity consumption is a normal good, meaning that, the higher a household's disposable income gets, the higher the electricity consumption is.

Regarding the statistics values of the long-run ECM, the weighted Durbin-Watson Statistic estimated below 1.5 strongly indicates a positive first order serial correlation.

Regarding the second step of the ECM, which provides the short-run elasticities, the significance of the error correction term confirms that the series are cointegrated.

The significance level of 5% of the lagged dependent variable indicates that the electricity consumption in period $t-1$ has a positive effect on the electricity consumption in period t. Moreover, the value of the error correction term $(u_{it}-1)$ indicates that the system corrects its previous disequilibrium at a speed of 79%. In the short-run, we found no significance of the HDD_{it} coefficient, nor the income variable.
It is important to recall that the income variable is at the regional level and not at the province level, this data issue might explain the significance level of just 5% in the long-run and the no significance of the variable in the short-run.

Regarding the system GMM estimates, we also found a significance level of 1% for the coefficients of electricity price, natural gas price, and cooling degree days, all these three coefficients have the expected sign. The results of these estimates heighten the potential complementary relationship between different energy sources when providing the collection of energy services needed by households, especially for electricity and natural gas. The sign and significance of the lagged dependent variable confirm the dynamic setting of our model.

The lagged dependent variable coefficient seems a good estimate of the parameter; a useful check of it, when estimating through difference or system GMM, is to estimate the specified model through OLS and fixed effects. The first estimation will give us the upper bound limit and the latter the lower bound one (Bond, 2002; Roodman, 2009a) The coefficient of the lagged dependent variable of the system GMM estimate fell into this range of values (0.716> 0.596 >0.177).
The Hansen test failed to reject the null hypothesis of joint validity of the instruments. Additionally, for this specific test the conventional threshold of 0.05 and 0.10 when deciding whether a coefficient is significant or not should not be the only criterion. We should also treat with caution if the p-value is greater than 0.25 (Roodman, 2009b). The problem of too many instruments is that this impairs the efficiency of this test. This can overfit the endogenous variables and not succeed in taking out their endogenous component (Roodman, 2009a). In this sense, Roodman (2009b, p. 142) stated that: “The conventional thresholds (0.05 and 0.10) are liberal when trying to rule out correlation between instruments and the error term.” The Hansen test reported from our estimations is below 0.25. Furthermore, as regards this issue, a minimally

arbitrary rule of thumb found in the literature is that the number of instruments should be less than the number of groups (Roodman, 2009a), which is the case in our estimates (48<52).

The difference-in-Hansen of 0.766 also failed to reject the null hypothesis of joint validity of all instruments; this statistic tests the validity of additional moments restrictions necessary for system GMM (Heid et al., 2012). The Cooling Degree-days is a valid strictly exogenous instrument given its reported Hansen test.

By construction, a first order autocorrelation is expected, which is confirmed by the reported p-value of the $AR(1)$, which rejects the null hypothesis of no first order serial correlation. Furthermore, there is no evidence of a significant second order serial correlation $AR(2)$, as the null hypothesis was not rejected. This presumes a proper specification of the system GMM (Heid et al., 2012).

We use robust standard errors for the system GMM, we also use the one step system GMM results as we did not see major efficiency gains from the two steps. The p-value of the F-statistic of the five estimates rejects the null hypothesis that all slope coefficients are equal to zero. Hence, the estimated coefficients (excluding the constant) are jointly significant in explaining the household electricity consumption in Spain.

The estimated results suggest a direct rebound between 26% and 35% in the short-run and 36% in the long-run for all energy services supplied by electricity in households. That is, an overall costless exogenous (Gillingham et al., 2016) increase in electricity efficiency potentially entailing savings of 10 megawatts hour (Mwh) per year in electricity consumption, would be reduced by between 26% and 35% in the short-run and 36% in the long-run. This would decrease final electricity savings to between 7.4 and 6.5 Mwh per year in the short-run and 6.4 Mwh per year in the long-run.

Our findings are in line with previous studies concerning the DRE in households' electricity consumption, with a slightly higher DRE in the long-run than in the short-run. Our estimated DRE in Spanish households falls within the expected range in relation to the literature concerning this issue, around 30%; indicating electricity savings after the improvement in efficiency, as long as only the DRE is considered. Price elasticities are greater than income elasticities and weather variables' elasticities are smaller than the former two. Taking into consideration the findings of this article, which are in line with the results of Freire-González (2010) for Catalonia, one can expect a greater response from households to price changes than to changes in income or weather variables in Spain. This fact highlights the relevance of improvements in efficiency to obtain energy savings, since the own-price elasticity of energy demand can be the proxy of the DRE (Sorrell, 2007). In the same sense, the variation in the associated pollutant emissions in Spain might be greater when prices change than when other variables change.

Appendix 5 shows the robustness checks of the two econometric approaches we used. For the ECM approach, we specified a model using only the variables which have a significance level of 0.1% in the original model and so we drop the parameters of Heating oil Price, Heating Degree Days, and Income.

For the System GMM approach, we specified a fixed effect model without lags as instruments and without the lagged dependent variable. We also specified another System GMM without the lagged dependent variable to arrange a new set of instruments. We use the same lag limits as the original model.

Considering the variable of interest, which is the own-price elasticity of electricity demand, the resulting magnitudes from these models, with different specifications, are in the range of values shown in the literature between 30% and 50% (Freire-González, 2017b). Nevertheless, the alternative econometric models presented in Appendix V could overestimate the magnitude of our variable of interest because they estimate the econometric model without controlling some variables of the original model.

According to the literature, the estimation of the DRE through the own-price elasticity of energy demand could overestimate its magnitude (Sorrell, 2007). For most conversion devices, it is necessary to purchase new equipment to improve energy efficiency. Hence, if higher capital costs from more efficient conversion devices are not considered, the DRE could be overestimated to some extent. However, if the government promotes energy efficiency through subsidies, in order to make energy-efficient devices cheaper than the inefficient ones, the DRE may be underestimated (Sorrell, 2007; Sorrell and Dimitropoulos, 2008).

Regarding the symmetry assumption, Schimek (1996) found approximately equal magnitudes when estimating the DRE through the elasticity of the demand for travel with respect to fuel efficiency ($\eta_{\varepsilon}(S)$) and with respect to fuel prices ($\eta_{P_E}(E)$) (Sorrell and Dimitropoulos, 2007). The energy service considered in their study was transportation. In contrast, Wheaton (1982) found a significant larger magnitude of the DRE when estimating it with respect to fuel prices than with respect to fuel efficiency (Sorrell and Dimitropoulos, 2007). One possible explanation of this could be that energy prices are more salient for consumers than energy efficiency. Hence, the symmetry assumption, when estimating the DRE with respect to electricity prices, could give an upper bound magnitude. Concerning the exogeneity assumption, it should not be a source of bias since the period analyzed is based upon a period of stability in energy prices.

Table 5. Empirical estimates of the residential electricity demand in Spain

Dependent Variable: $ln(E_{it}/hh_{it})$		ECM		System GMM	Pooled OLS	Fixed Effects
		Long-Run	Short-Run (Δln)			
α		−1.923***	−0.001	−0.578***	−0.574***	−0.785*
		0.000	0.618	0.000	0.000	0.047
		(0.498)	(0.003)	(0.134)	(0.139)	(0.386)
$lnP_{E_{it}}$		**−0.358*** **	**−0.348*** **	**−0.261*** **	−0.378***	−0.418***
		0.000	0.000	0.000	0.000	0.000
		(0.039)	(0.045)	(0.049)	(0.068)	(0.088)
$lnP_{G_{it}}$		**−0.142*** **	**−0.129*** **	**−0.079** **	−0.016	−0.132**
		0.000	0.000	0.008	0.494	0.001
		(0.016)	(0.015)	(0.028)	(0.024)	(0.037)
$lnP_{HO_{it}}$		**−0.104** **	**−0.121** **			
		0.013	0.006			
		(0.042)	(0.044)			
$lnCDD_{it}$		0.061**	0.062***	0.048**	0.030**	0.080*
		0.001	0.000	0.004	0.009	0.030
		(0.018)	(0.013)	(0.015)	(0.011)	(0.036)
$lnHDD_{it}$		0.067*				
		0.034				
		(0.031)				
lnY_{it}		0.111*				
		0.042				
		(0.055)				
$\Delta ln(E_{it} - 1/hh_{it} - 1)$			0.092*	0.596***	0.716***	0.177**
			0.044	0.000	0.000	0.001
			(0.046)	(0.099)	(0.059)	(0.050)
$u_{it} - 1$			−0.790***			
			0.000			
			(0.061)			
R-squared		0.945	0.560		0.758	0.560
Prob (F-statistic)		0.000	0.000	0.000	0.000	0.000
Durbin-Watson stat.		1.470	2.048			
Number of Instruments				48		
Number of Groups		52	52	52		52
$AR(1)$ test ($p-$value)				0.012		
$AR(2)$test ($p-$value)				0.642		
Hansen Test of over-identification ($p-$value)				0.183		
Diff-in-Hansen tests of exogeneity ($p-$value)				0.766		

IV (lnCDD) Hansen Test excluding group				0.157		

Source: Own elaboration

We use asterisks alongside each coefficient to denote its significance:

* p<0.05 ** p<0.01 ***p<0.001

2.4. Conclusions

The purpose of this article is twofold. First, we obtain empirical evidence of the DRE for all energy services that require electricity for their provision in Spanish households. Second, the main contribution of this article is the consideration of alternative energy sources in the estimation of the DRE for the energy source of electricity for Spanish households. To do so, we add to the econometric estimation method the price of alternative energy sources. We have found significant coefficients for the prices of the alternative energy sources, that is, natural gas and heating oil have an influence on electricity consumption in the case of Spain. Improvements in energy efficiency in energy services that require natural gas or heating oil would increase the DRE for electricity given its complementary relationship. This is the main contribution of this article because, as explained in Table 1, previous estimations of the DRE do not consider alternative energy sources, with the only exception of Freire-González (2010), who found no significant coefficient for the variable of the alternative energy source for the case of Catalonia.

This newness in the estimation of the DRE opens a new line of research, by means of exploring the relationship between different sources of energy in the study of the different rebound effect channels, either direct, indirect, or economy-wide. In this sense, Hunt and Ryan (2014) developed a theoretical and empirical illustration of three household's energy sources, such as electricity, natural gas and oil products. Nevertheless, they assumed as an indirect rebound effect the changes in the demand for energy services that result from an increase in the efficiency of a different energy service. However, in this study we provide empirical evidence that the prices of natural gas and heating oil may have a direct influence on electricity consumption. The direct relationship between household energy services that we found open the study of a new source for the DRE, which will help to assess its magnitude (Greening et al., 2000). If there are no measures to tackle the DRE in Spain, our results indicate that electricity savings would be diminished.

Another contribution of this paper is that it is the first empirical analysis of this type for Spain because other research done for Spain focus on the economy-wide rebound effect (Duarte et al., 2018; Freire-González, 2020; Guerra and Sancho, 2010). Using recent data from all the provinces of Spain, a time frame of ten years, and controlling the weather variables by using information on all provinces' weather stations, we found a positive DRE with energy savings. We also provide the individual short- and long-run fixed effects of each Spanish province. Hence, our results provide useful information to policymakers at different levels. Since we estimated the DRE of a collection of energy services, the magnitude of the DRE of each of them is disguised (Sorrell and Dimitropoulos, 2007).

Our results are more relevant for the energy services of lighting and energy for appliances, as they dominate the consumption of electricity. Given the goals assumed by Spain in the EU context as regards energy efficiency and greenhouse gas emissions mitigation, Spanish policymakers should incorporate additional measures to tackle all sources of DRE to increase the effectiveness of the measures to produce electricity savings and reduce the associated pollutant emissions (Freire-González and Puig-Ventosa, 2014).

2.5. Appendix I Energy carrier price categories

Table 6: Electricity Price Categories.

Band	**Annual Consumption**
DA	Consumption < 1000 kWh
DB	1000 kWh < Consumption < 2500 kWh
DC	2500 kWh < Consumption < 5000 kWh
DD	5000 kWh < Consumption < 15000 kWh
DE	Consumption > 15000 kWh

Source: Own elaboration based on Eurostat (2016)
http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_204&lang=en

Table 7: Natural Gas Price Categories

Band	Annual Consumption
D1	Consumption < 20 GJ
D2	20 GJ < Consumption < 200 GJ
D3	Consumption > 200 GJ

Source: Own elaboration based on Eurostat (2016)
http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_204&lang=en

2.6. Appendix II Calculation method of the climatic variables

Table 8. Calculation of Heating and Cooling degree-days

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**
$T_{max}<T_{base}$	$CDD = 0$
$(T_{max}+T_{min})/2<T_{base}$	$CDD = (T_{max}-T_{base})/4$
$T_{min}<=T_{base}$	$CDD = (T_{max}-T_{base})/2-(T_{base}-T_{min})/4$
$T_{min}>T_{base}$	$CDD = (T_{max}+T_{min})/2-T_{base}$

Source: https://www.degreedays.net/calculation

2.7. Appendix III. Data on final energy consumption of Spanish households

Figure 1. Sources of energy for final energy consumption in Spanish households (Kidea (2010-2015). Source: IDAE (2015)

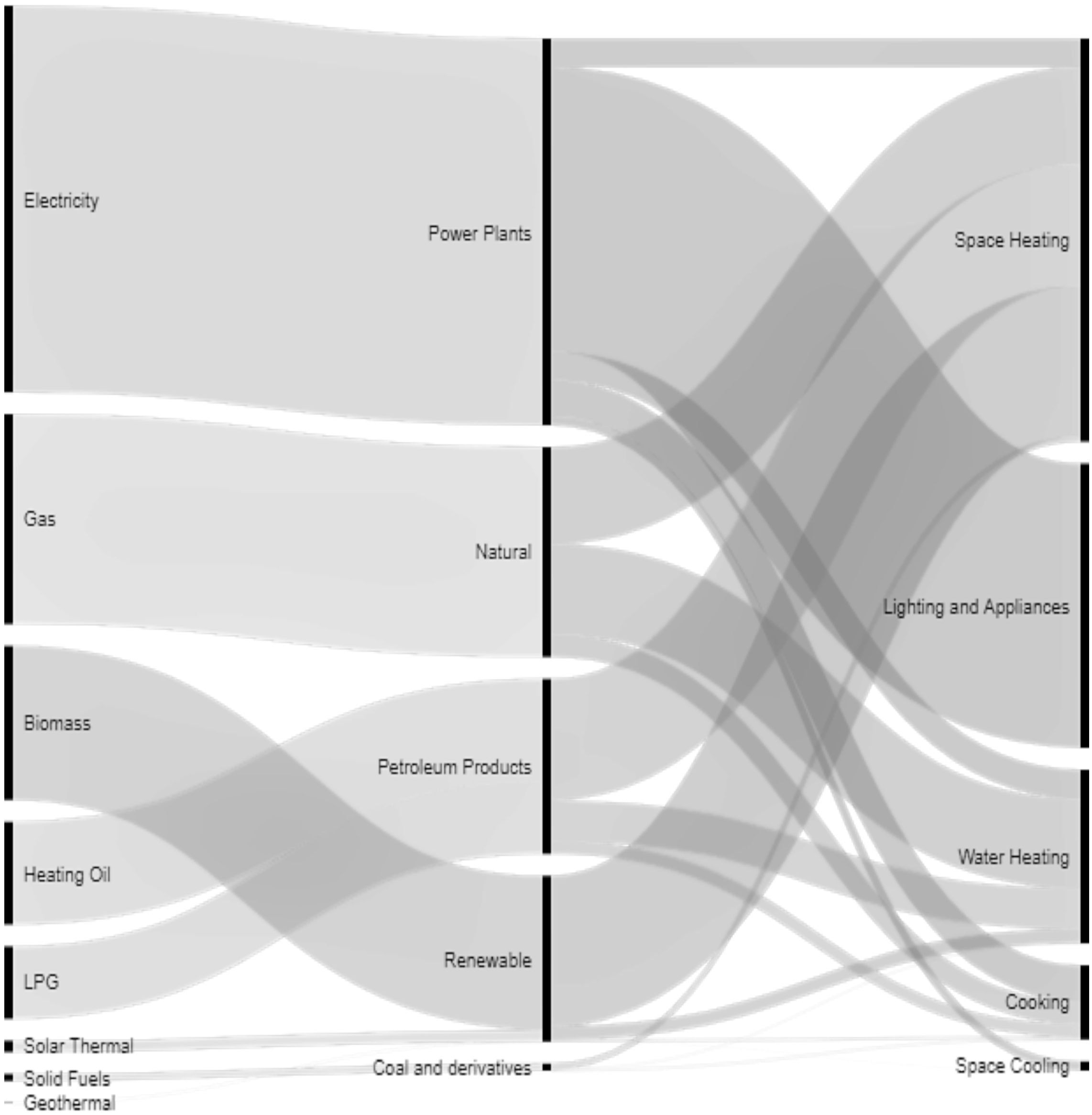


Table 9. Final energy consumption by uses of residential sector (ktep). Period 2010–2015.

2015								
Energy source		**Space Heating**	**Space Cooling**	**Water Heating**	**Cooking**	**Lighting and Appliances**		**TOTAL**
Electricity		444	141	450	560	4,431		*6,025*
Heat		0	0	0	0	0		*0*
Gas		1,398	0	1,291	329	0		*3,017*
Solid Fuels		72	0	6	11	0		*89*
Petroleum Products		2,174	0	625	187	0		*2,985*
	LPG	*393*	*0*	*465*	*187*	*0*		*1,045*
	Other Kerosene	*0*	*0*	*0*	*0*	*0*		*0*
	Diesel Oil	*1,781*	*0*	*160*	*0*	*0*		*1,941*
Renewable Energy		2,460	2	259	27	0		*2,749*
	Solar Thermal	*16*	*0*	*205*	*0*	*0*		*221*
	Biomass	*2,439*	*0*	*52*	*27*	*0*		*2,517*
	Geothermal	*5*	*2*	*3*	*0*	*0*		*11*
TOTAL		**6,548**	**143**	**2,631**	**1,113**	**4,431**		**14,865**

2014								
Energy Source		**Space Heating**	**Space Cooling**	**Water Heating**	**Cooking**	**Lighting and Appliances**		**TOTAL**
Electricity		448	142	454	565	4,472		6,081
Heat		0	0	0	0	0		0
Gas		1,433	0	1,324	337	0		3,094
Solid Fuels		75	0	6	11	0		92
Petroleum Products		1,876	0	607	191	0		2,674
	LPG	401	0	474	191	0		1,066
	Other Kerosene	0	0	0	0	0		0
	Diesel Oil	1,476	0	133	0	0		1,608
Renewable Energy		2,479	2	243	27	0		2,751
	Solar Thermal	15	0	188	0	0		203
	Biomass	2,459	0	52	27	0		2,537
	Geothermal	5	2	3	0	0		11
TOTAL		**6,311**	**144**	**2,634**	**1,131**	**4,472**		**14,691**

2013							
Energy Source	**Space Heating**	**Space Cooling**	**Water Heating**	**Cooking**	**Lighting and Appliances**		**TOTAL**
Electricity	450	143	456	568	4,494		6,111
Heat	0	0	0	0	0		0
Gas	1,479	0	1,366	348	0		3,193
Solid Fuels	77	0	6	11	0		95
Petroleum Products	1,858	0	636	204	0		2,698
LPG	429	0	507	204	0		1,140
Other Kerosene	0	0	0	0	0		0
Diesel Oil	1,429	0	128	0	0		1,558
Renewable Energy	2,462	2	231	27	0		2,722
Solar Thermal	14	0	176	0	0		190
Biomass	2,443	0	52	27	0		2,521
Geothermal	5	2	3	0	0		10
TOTAL	**6,327**	**145**	**2,695**	**1,158**	**4,494**		**14,819**

2012							
Energy source	**Space Heating**	**Space Cooling**	**Water Heating**	**Cooking**	**Lighting and Appliances**		**TOTAL**
Electricity	476	151	482	600	4,749		*6,458*
Heat	0	0	0	0	0		*0*
Gas	1,625	0	1,501	382	0		*3,509*
Solid Fuels	89	0	7	13	0		*110*
Petroleum Products	1,784	0	653	214	0		*2,651*
LPG	*451*	*0*	*533*	*214*	*0*		*1,198*
Other Kerosene	*0*	*0*	*0*	*0*	*0*		*0*
Diesel Oil	*1,333*	*0*	*120*	*0*	*0*		*1,453*
Renewable Energy	2,452	2	220	26	0		*2,700*
Solar Thermal	*13*	*0*	*165*	*0*	*0*		*178*
Biomass	*2,434*	*0*	*51*	*26*	*0*		*2,512*
Geothermal	*5*	*2*	*3*	*0*	*0*		*10*
TOTAL	**6,426**	**153**	**2,863**	**1,236**	**4,749**		**15,428**

2011

Energy source	Space Heating	Space Cooling	Water Heating	Cooking	Lighting and Appliances		TOTAL
Electricity	482	153	489	608	4,814		6,545
Heat	0	0	0	0	0		0
Gas	1,580	0	1,460	372	0		3,411
Solid Fuels	100	0	8	15	0		122
Petroleum Products	1,913	0	677	220	0		2,809
LPG	462	0	546	220	0		1,228
Other Kerosene	0	0	0	0	0		0
Diesel Oil	1,451	0	130	0	0		1,581
Renewable Energy	2,413	2	206	26	0		2,647
Solar Thermal	12	0	152	0	0		164
Biomass	2,396	0	51	26	0		2,473
Geothermal	5	2	3	0	0		10
TOTAL	**6,488**	**155**	**2,839**	**1,240**	**4,814**		**15,535**

2010

Energy source	Space Heating	Space Cooling	Water Heating	Cooking	Lighting and Appliances		TOTAL
Electricity	479	152	486	605	4,786		6,508
Heat	0	0	0	0	0		0
Gas	1,972	0	1,821	464	0		4,257
Solid Fuels	141	0	11	21	0		173
Petroleum Products	2,238	0	771	248	0		3,257
LPG	521	0	617	248	0		1,386
Other Kerosene	0	0	0	0	0		0
Diesel Oil	1,717	0	154	0	0		1,871
Renewable Energy	2,403	2	186	26	0		2,617
Solar Thermal	11	0	133	0	0		144
Biomass	2,388	0	51	26	0		2,464
Geothermal	5	2	3	0	0		9
TOTAL	**7,233**	**154**	**3,275**	**1,363**	**4,786**		**16,812**

Source: IDAE (2015)

2.8. Appendix IV. Fixed Effects of each Spanish Province

Table 10: Cross-Section Fixed Effects

Provinces	**Long-run Fixed Effect** (μ_i)	**Short-run Fixed Effect** (μ_i)
1. Alava	-0.070	0.008
2. Albacete	0.002	-0.000
3. Alicante	0.030	-0.014
4. Almeria	0.029	-0.003
5. Avila	-0.412	-0.018
6. Badajoz	-0.034	0.002
7. Barcelona	0.116	0.010
8. Bizkaia	0.027	0.001
9. Burgos	-0.084	0.036
10. Caceres	-0.151	-0.014
11. Cadiz	0.081	-0.010
12. Cantabria	-0.008	0.010
13. Castellon	-0.009	0.006
14. Ceuta	0.140	0.015
15. Ciudad Real	0.060	-0.001
16. Cordoba	0.227	0.006
17. Coruna A	0.083	-0.006
18. Cuenca	-0.178	-0.007
19. Gipuzkoa	0.045	0.008
20. Girona	0.006	0.004
21. Granada	0.014	-0.011
22. Guadalajara	0.003	0.013
23. Huelva	0.001	0.006
24. Huesca	-0.075	-0.000
25. Baleares	0.380	0.002
26. Jaen	0.150	0.001
27. La Rioja	-0.143	0.002
28. Las Palmas	0.297	-0.009
29. Leon	-0.187	0.007
30. Lleida	0.079	0.011
31. Lugo	-0.079	0.008
32. Madrid	0.120	-0.004
33. Malaga	0.188	-0.007
34. Melilla	0.092	-0.010
35. Murcia	0.206	0.001
36. Navarra	-0.001	-0.002
37. Ourense	-0.208	-0.002
38. Palencia	-0.245	0.011
39. Pontevedra	0.094	-0.001
40. Asturias	-0.050	-0.016

41. Tenerife	0.170	-0.011
42. Salamanca	-0.198	-0.007
43. Segovia	-0.093	0.005
44. Sevilla	0.262	-0.004
45. Soria	-0.317	0.011
46. Tarragona	-0.036	0.001
47. Teruel	-0.200	-0.008
48. Toledo	0.132	-0.008
49. Valencia	0.073	-0.006
50. Valladolid	-0.058	0.005
51. Zamora	-0.289	-0.009
52. Zaragoza	0.014	-0.000

Source: Own elaboration

2.9. Appendix V. Robustness Checks

Table 11. Robustness checks

Dependent Variable: $ln(E_{it}/hh_{it})$	ECM		ECM		System GMM	System GMM (OM)	Fixed Effects
	Long-Run	Short-Run (Δln)	Long-Run (OM)	Short-Run (Δln) (OM)			
α	−0.520**	0.003	−1.923***	−0.001	−0.937***	−0.578***	−0.520**
	0.001	0.091	0.000	0.618	0.000	0.000	0.001
	(0.162)	(0.002)	(0.498)	(0.003)	(0.241)	(0.134)	(0.162)
$lnP_{E_{it}}$	−0.408***	−0.409***	−0.358***	−0.348***	−0.567***	−0.261***	−0.408***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.033)	(0.036)	(0.039)	(0.045)	(0.065)	(0.049)	(0.033)
$lnP_{G_{it}}$	−0.159***	−0.137***	−0.142***	−0.129***	−0.049	−0.079**	−0.159
	0.000	0.000	0.000	0.000	0.358	0.008	0.000
	0.015	(0.014)	(0.016)	(0.015)	(0.053)	(0.028)	(0.015)
$lnP_{HO_{it}}$	Without	Without	−0.104**	−0.121**			
			0.013	0.006			
			(0.042)	(0.044)			
$lnCDD_{it}$	0.063***	0.061***	0.061**	0.062***	0.120***	0.048**	0.063
	0.000	0.000	0.001	0.000	0.000	0.004	0.000
	0.0169	(0.012)	(0.018)	(0.013)	(0.240)	(0.015)	(0.016)
$lnHDD_{it}$	Without	Without	0.067*				
			0.034				
			(0.031)				

lnY_{it}	Without	Without	0.111*				
			0.042				
			(0.055)				
$\Delta ln(E_{it} - 1/hh_{it} - 1)$		0.132**		0.092*	Without	0.596***	Without
		0.001		0.044		0.000	
		(0.041)		(0.046)		(0.099)	
$u_{it} - 1$		−0.813***		−0.790***			
		0.000		0.000			
		(0.058)		(0.061)			
R-squared	0.945	0.559	0.945	0.560			0.945
Prob (F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin-Watson stat.	1.445	2.062	1.470	2.048			1.445
Number of Instruments					34	48	Without
Number of Groups	52	52	52	52	52	52	52
$AR(1)$ test ($p -$ value)					0.037	0.012	
$AR(2)$test ($p -$ value)					0.103	0.642	
Hansen Test of over-identification ($p -$ value)					0.059	0.183	
Diff-in-Hansen tests of exogeneity ($p -$ value)					0.543	0.766	
IV (lnCDD) Hansen Test excluding group					0.056	0.157	

Source: own elaboration
(OM) stands for Original Model
We use stars alongside each coefficient to denote its significance:
* p<0.05 ** p<0.01 ***p<0.001

3. Chapter 2

The direct rebound effect for two income groups: The case of Paraguay[7]

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. We derive from our findings some policy measures to improve the situation.

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

[7] This paper has been published in the journal *Energy for Sustainable Development* on 26 August 2022. Bordón-Lesme, M., Freire-González, J. and Padilla Rosa, E. (2022b). The direct rebound effect for two income groups: The case of Paraguay. *Energy for Sustainable Development*, 70, 430-441

3.1. 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.

3.2. 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. 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, 2020) 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, 2020). 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, 2020).

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%).[8] 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.[9] 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

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

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

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 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.

3.3. 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[10] 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:

$$\eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1 \tag{10}$$

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.

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

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

$$ln\left(\frac{E_{it}}{hh_{it}}\right) = \alpha + \beta_1 ln(P_{E_{it-1}}) + \beta_2 lnP_{LPG_{it}} + \beta_3 lnCDD_{it} + \beta_4 lnHDD_{it} + \beta_5 lnY_{it} + \beta_6 ln(\frac{E_{it-1}}{hh_{it-1}}) + \varepsilon_{it} \tag{11}$$

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; $P_{LPG_{it}}$ 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.[11] 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.

[11] 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 12. 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, 2020)	Positive for the lagged dependent variable $\left(\frac{E_{it-1}}{hh_{it-1}}\right)$
$(P_{E_{it}-1})$	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, 2020)	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 (2020)	Negative
CDD_{it}	Cooling degree days. A base temperature of 22 degrees Celsius (see Appendix 3 for further details about the calculation) (www.degreedays.com/calculation)	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 (2020)	Positive
HDD_{it}	Heating degree days. A base temperature of 21 degrees Celsius (see Appendix 3 for further details about its calculation) (www.degreedays.com/calculation)	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 (2020)	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)	DGEEC - Dirección General de Estadística, Encuestas y Censos (2020)	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 (BCP, 2020). 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, 2020).

3.4. Econometric Model Estimation

Following equation (11), 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 13). 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 14. 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 13. 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 14. 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.

3.4.1. Results

Table 15 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 15. 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.[12] 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.

[12] 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.

3.4.2. 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[13], 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 2 shows, electricity accounts for only 16% of total residential energy input consumption[14] 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 69% 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).

[13] 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.

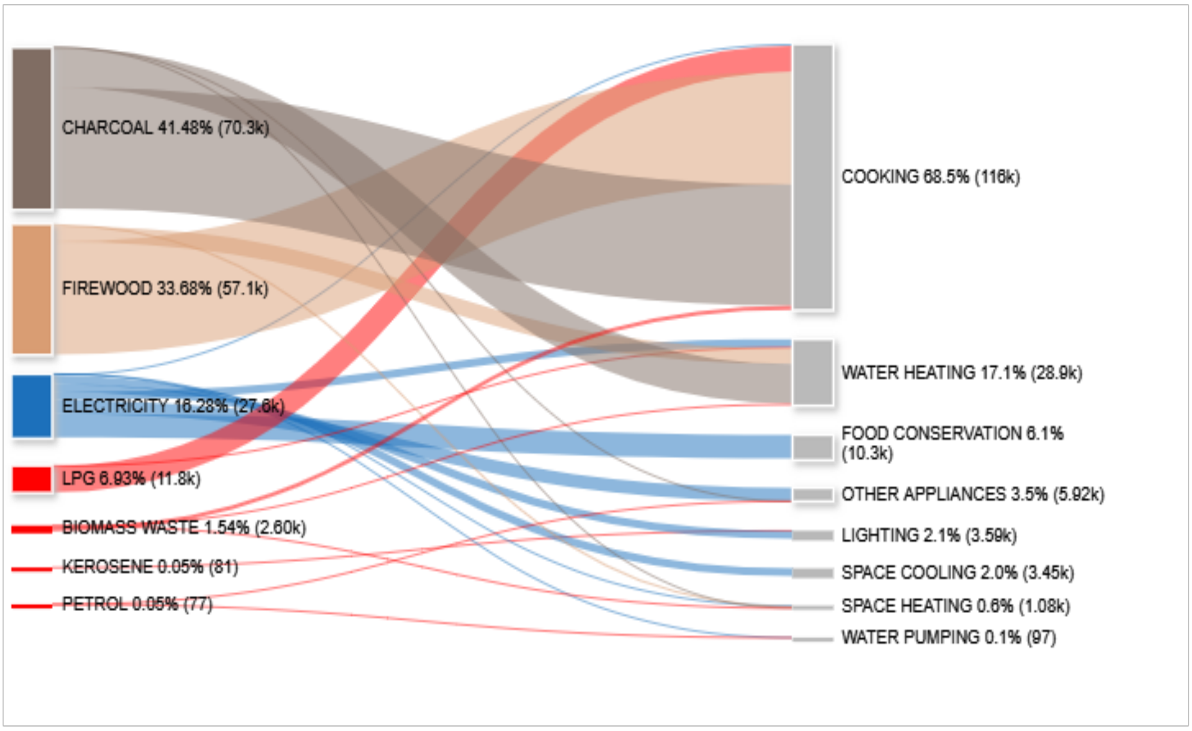
[14] Energy input is the energy before its transformation into useful energy.

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 Yacyreta in Argentina (Blanco et al., 2017).[15] However, this electricity supply does not match electricity consumption, especially in low-income households (Figure 2). Furthermore, according to the (IEA , 2020), 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, 2020), 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.

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).

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

Figure 2. The share of energy input, in kiloton of oil equivalent (KTOE), per energy service in Paraguayan low-income households of 2011. Source: Personal elaboration from BNEU (2020).



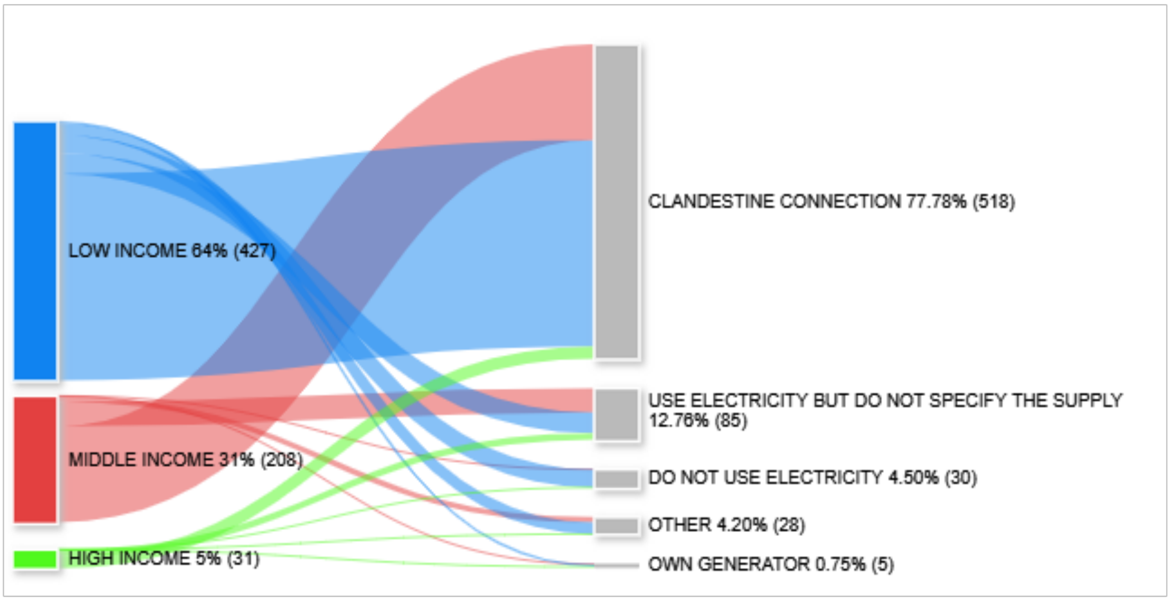
ii. Clandestine electricity connections:

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)[16]; 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 3) 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, 2020). 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.

[16] The energy ledder and energy stacking are models analyzed in the energy poverty literature.

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.

Figure 3. Clandestine electricity connection per income level. Source: Personal elaboration from BNEU (2020).



3.5. Policy Implications

The two factors we identify in the above section would be a consequence of electricity consumption barriers affecting only the poverty-stricken group. The higher capital cost of the energy conversion devices run by electricity could explain why low-income households are not affected by electricity prices or electricity improvements in home appliances and so, they rely on energy conversion devices that require charcoal or firewood.

Given the income constraint of Paraguayan low-income households, they might be focused on just consuming the energy services for basic living, such as cooking and water heating. These energy services can also be provided more or less effectively without electricity, using biomass. On the other hand, non-low-income households might decide their energy services requirements according to their comfort needs. Thus, space cooling has a greater share of the total energy consumption for this type of households. More advanced energy carriers, such as electricity, provide the possibility to access modern energy services, such as space cooling, lighting, and more efficient cooking.

Another type of electricity consumption barrier could be the incompatible periodicity between irregular informal incomes and electricity bills. The results of a survey to low-income households in a Paraguayan poverty-stricken settlement suggest that, on average, those households spend on charcoal and firewood as much as they do on electricity, and show a lack of energy conversion devices run by electricity, especially for cooking and space cooling (Llamosas et al., 2018). Therefore, in the short run, it is less risky to buy a bag of charcoal daily or to collect firewood whenever necessary than paying the monthly electricity bill; regardless of whether they are registered in the social electricity tariff program and regardless of the charcoal and firewood effectiveness versus electricity effectiveness in providing energy services. Because the electricity bill is charged after consumption, low-income households might not know for sure what will be their discount percentage or what range of consumption they will have. Moreover, if they have an irregular income, they might not know if they would be able to pay the electricity bill at the end of the month.

Hence, given these electricity consumption barriers, such as the capital cost of energy conversion devices run by electricity, the income constraint of the Paraguayan low-income households, and the available energy carrier per energy service, it would be desirable to develop policies promoting the increase of the stock of energy conversion devices run by electricity in low-income households. If this is implemented, the social tariff discount would provide a real benefit to low-income households, as they would be able to consume electricity more effectively. Then, the transition from charcoal and firewood to electricity would be easier for low-income households and so their consumption of energy services would be more effective.

The incompatibility between irregular informal incomes and electricity bills could be tackled introducing an alternative payment option for the electricity bill. This can be the pay-as-you-go prepayment of energy, which is implemented by several energy companies in the UK, such as British Gas, E.ON, SSE, and Ecotricity, among others. Those companies provide a pay-as-you-go meter which allows households to pay a certain amount of money for electricity before using it. This payment method would allow low-income households to budget their expenditure on electricity consumption as the timespan of their income will match the electricity bill. Then, they might be able to spend less of their income in energy because electricity is more effective in providing the energy services of cooking and water heating than charcoal and firewood.

Roy (2000) studied the case of rural lighting where The Ministry of New Renewable Energy Sources replaced kerosene lamps with solar lanterns. She estimated a DRE between 50 and 80%. That is, up to 50 to 80% of the potential kerosene savings were reduced. However, she also mentioned that if the energy service of cooking was included, the DRE would have been as much as 200%. This is because the efficiency improvement did not only cause more lighting in households, but also the kerosene saved from the more efficient lighting was used for cooking and, in some cases, the saved kerosene was even sold by some households to their neighbors (Roy, 2000). Hence, if the low-income households get a real benefit from the social tariff discount, given additional and complementary policies, the Paraguayan policymakers should expect a greater DRE for electricity for this type of household and, consequently, an increase in total electricity consumption.

The Vice Ministry of Mines and Energy estimates that, by the year 2040, it would be necessary to incorporate new hydroelectric plants to match the internal demand for electricity. If the DRE for low-income households is considered in a scenario where the social tariff discount has a real benefit for this type of households (if the alternative and complementary policies suggested were applied), the internal demand for electricity in Paraguay might exceed the supply before 2040. Currently, the Paraguayan senate is passing a bill that fosters the production of electricity from non-conventional non-hydraulic renewable energy sources in order to diversify the production of energy (Florentín, 2021). Thus, if there is a positive appraisal of the Paraguayan government towards increasing levels of the DRE in low-income households, given their low levels of electricity consumption, production of energy through non-conventional renewable energy sources should be considered.

An energy efficiency improvement of an energy service can come in a variety of technical changes, such as more efficient conversion devices (energy system), more efficient energy sources (energy transition) or investments in more efficient infrastructure, such as proper household insulation (energy system). Most of the rebound effect studies focus on measuring the consumption of energy and/or its related greenhouse gas emissions after an energy efficiency improvement. The findings of Roy (2000) are an example of it, because she measured the consumption of kerosene for lighting after it was improved by solar lanterns, which is explained above. However, the increase in welfare in these Indian households after improving their energy service of lighting was not entirely measured.

The energy poverty literature provides us with several concepts and measurements for it. The energy ladder model suggests that households will change their energy sources for more advanced ones as their income increases, while according to the energy stacking model a household use a bundle of multiple energy sources (Van der Kroon et al., 2013). In Paraguay, there might be a mix between the two models. First, because in both extremes of the Paraguayan social levels, high-income and low-income households, there is a use of multiple energy sources to satisfy their households' energy service needs. Second, because in the energy sources bundle of high-income households there is a higher share of advanced energy sources (electricity and LPG) than in the one of low-income households. Moreover, a concept of energy poverty is the absence of choice in accessing energy services that are affordable, of high-quality, environmentally benign, adequate and reliable (Reddy et al., 2000). González-Eguino (2015) clarifies this issue by stating that the households' needs are not energy consumption, but the provision of energy services (cooking, space heating, lighting, etc.). However, as we explained at the beginning of this section, it is the difficulty in accessing advanced energy sources what might define the consumption of each energy service. For example, in Paraguay, space cooling, an energy service that is provided by an advanced energy source, such as electricity, does not have the same share of energy consumption in high-income and low-income households. Nevertheless, the rebound effect literature acknowledge increasing magnitudes of rebound effect as a potential increase in social welfare because of the increase in energy consumption (Sorrell, 2018).

Therefore, energy policymakers in developing countries should consider linking the lessons of the energy poverty literature with those of the rebound effect literature because the former would determine to which energy source households should transition whereas the latter would provide information about how these households are responding to the energy source change. For climate change mitigation purposes, it is more effective to switch to non-conventional renewable energy sources than encourage energy efficiency, since CO_2 emissions are not reduced as expected (Chen et al., 2021; Chitnis & Sorrell, 2015; Druckman et al., 2011).

With these policy recommendations and as explained in section 4.2., Paraguayan low-income households would be able to improve their current situation in a sustainable manner by transitioning from charcoal and firewood to electricity, which is a cleaner energy source. First, electricity requires less energy input per energy service; therefore, low-income households would spend less on energy consumption. 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).

3.6. Conclusions

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.

3.7. 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.

3.8. 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.

3.9. Appendix 3. Calculation Methods for the Climatic Variables

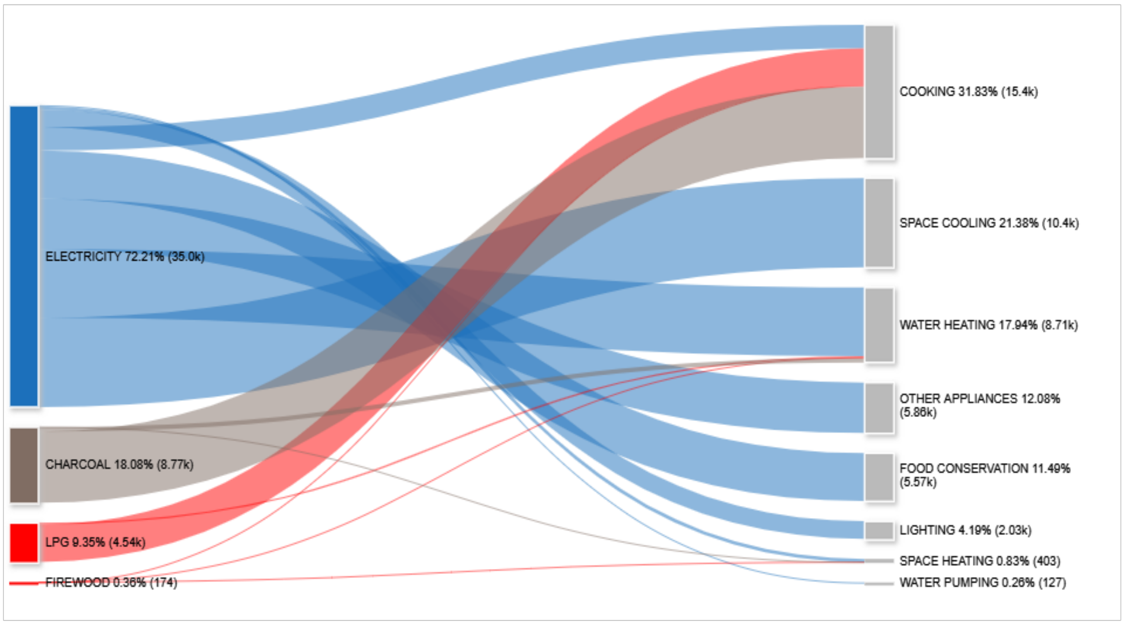
Condition	**Heating Degree Days Formula**
$T_{min}>T_{base}$	HDD = 0
$(T_{max}+T_{min})/2>T_{base}$	HDD = $(T_{base}-T_{min})/4$
$T_{max}>=T_{base}$	HDD = $(T_{base}-T_{min})/2-(T_{max}-T_{base})/4$
$T_{max}<T_{base}$	HDD = $T_{base}-(T_{max}+T_{min})/2$

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

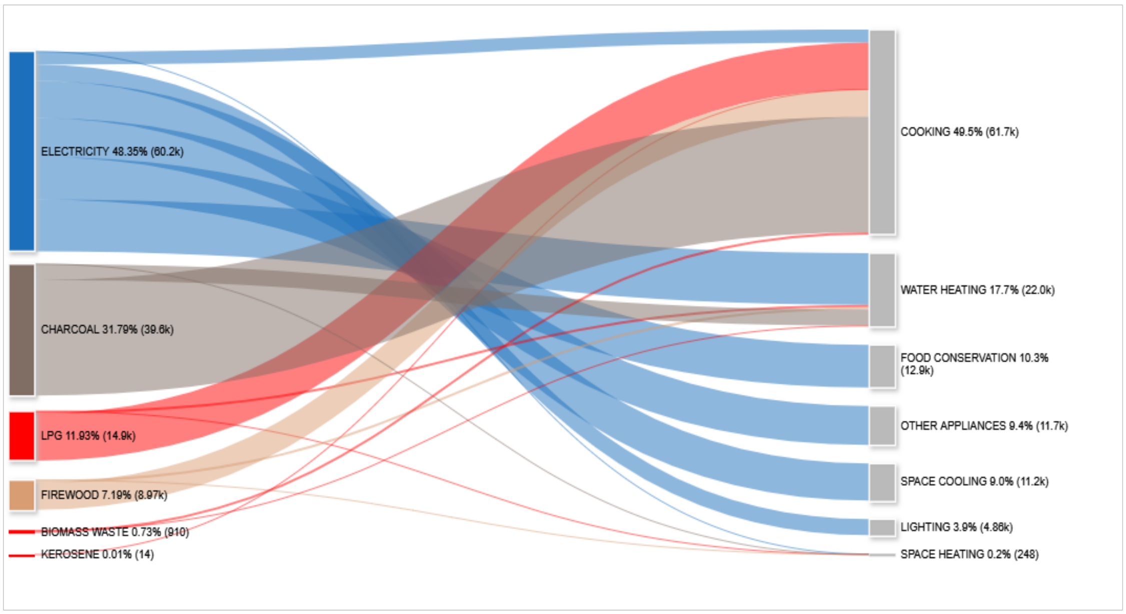
Source: (*Calculating Degree Days*, n.d.).

3.10. Appendix 4. Share of Energy Sources' Input (KTOE) per Energy Services in Paraguayan High-Income Households of 2011



Source: Personal elaboration with BNEU data.

3.11. Appendix 5. Share of Energy Sources' Input (KTOE) per Energy Services in Paraguayan Middle-Income Households of 2011



Source: Personal elaboration with BNEU data.

3.12. 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.

3.13. Appendix 7. Robustness Checks

		Municipality Fixed Effects		Province Fixed Effects		
Dependent Variable: $ln(E_{it}/hh_{it})$		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: $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

4. Chapter 3

The direct rebound effect for natural gas in Spain, considering the influence of electricity and diesel oil

Abstract

We estimate the magnitude of the direct rebound effect of improving the efficiency of the household energy services that are provided by natural gas in Spain. In addition, we consider the influence of other energy services that are provided by electricity and diesel oil. The results indicate a direct rebound effect for natural gas between 42% and 64% in the long-run and 79% and 89% in the short-run. Moreover, we find that increasing the efficiency of the energy services that are provided by electricity and diesel oil would be more effective than increasing the efficiency of the energy services that are provided by natural gas to reduce natural gas consumption in Spain.

Keywords: Direct rebound effect; electricity; energy services; diesel oil; natural gas.

3.2. Introduction

The sources of rebound that are usually mentioned in the literature of the rebound effect are the direct rebound effect, the indirect rebound effect, and the economy-wide rebound effect. The direct rebound effect emerges after an energy service becomes more efficient causing a change in its own consumption. The most known sources of the indirect rebound effect are: (1) the secondary effects, which are the re-spending of the monetary savings in energy cost, caused by the energy efficiency improvement of the energy service considered, and (2) the embodied energy, which are the energy requirement actions to obtain an energy efficiency improvement (Sorrell, 2007). Chan and Gillingham (2015) and Chitnis et al. (2020) define the secondary effects as the change in the consumption of other energy services due to an energy efficiency improvement of the energy service considered. For example: energy efficiency improvements of lighting may affect the consumption of heating and vice-versa (Chitnis et al., 2020). Moreover, Chitnis et al. (2020) and Greening et al (2000) included in their definition of the secondary effects the change in the quantity demanded of other non-energy goods and services that require energy for their production and distribution, caused by an energy efficiency improvement of the energy service considered. Freire-González (2011) establishes the link between the direct and the secondary effects through a re-spending framework. That is, the monetary savings in energy cost caused by energy efficiency improvements, after estimating the direct rebound effect, can be re-spent in other goods and services that need energy to be obtained. To do so, he combines econometric estimations of energy demand functions (direct rebound effect) with re-spending modeling and generalized input–output of energy modeling for different economic sectors that require energy (secondary effects). This estimation methodology assumes that the monetary savings in energy cost caused by the energy efficiency improvement minus the direct rebound effect are re-spent in different economic sectors that require energy.

The focus of this paper is to estimate the direct rebound effect for natural gas in Spain and to test if energy services that are provided by electricity and diesel oil affect the consumption of the energy services provided by natural gas. Thus, following Bordón-Lesme et al. (2022a; 2022b) we include the price of electricity and diesel oil in the econometric estimation method to estimate the direct rebound effect for natural gas. We estimate the direct rebound effect through price elasticities, and we provide the shares of the energy services per energy source to see which energy services would be more affected by our estimation of the direct rebound for natural gas.

Most empirical evidence of the direct rebound effect for households focuses on electricity consumption, which is also the case for Spain. Thus, to our knowledge, this is the first empirical evidence of the direct rebound effect for residential natural gas consumption in Spain. For the case of France, there is empirical evidence of the direct rebound effect of natural gas which is 60% in the short-run and 63% in the long-run (Beläid et al. 2018).

There are studies about the price elasticity demand of natural gas in European households, which can be a suitable proxy for the direct rebound effect for natural gas if certain assumptions are met. In this sense, for the period 1960 to 2002, Asche et al. (2008) find an own-price elasticity of natural gas demand using a fixed effects estimator, considering the countries of Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland, and the UK, of −0.242 in the short-run and −1.541 in the long-run. They also find very low but significant cross-price elasticity between natural gas and light fuel oil and no significant cross-price elasticity between natural gas and electricity. Another suitable proxy for the direct rebound effect for natural gas in Spain can be the estimates of Labandeira et al. (2006), who find an own-price elasticity for natural gas between −0.047 and −0.445. In their results, urban households are more affected by natural gas prices, and given their cross-price elasticity estimates, there is a limited substitution between electricity and natural gas, and a substitution relationship between LPG and electricity.

Blázquez et al. (2013) also provide empirical evidence of energy demand in Spain. In their estimation of the residential electricity demand, they introduce the gas penetration rate, which is the number of gas consumers divided by the number of houses, to test if natural gas affects electricity consumption. They find the greater the penetration rate, the less the electricity consumption. However, their penetration rate variable may not capture how energy services affect each other, whether it is through the efficiency of their energy source conversion devices or through the prices of the energy sources. Moreover, in Spain, most households have installed a set of energy carriers to supply the energy services they demand. Thus, household occupants would tend to consume less electricity in a household with electricity and natural gas energy carriers than in a household with just the energy carrier of electricity.

There is also empirical evidence of the direct rebound effect for a specific energy service that is provided by natural gas. Thus, for the case of Canada, Dolthitt (1986) finds a direct rebound effect between 10% and 17% in the short-run and between 35% and 60% in the long-run for the residential demand of the natural gas used in space heating and water heating. For the United States, Hsueh and Gerner (1993) estimate a short-run direct rebound effect of space heating of 58% for natural gas and 35% for electricity.

Most of the empirical evidence of the direct rebound effect —whether they are estimates of the energy services provided by an energy source, such as electricity and natural gas or they are for a specific energy service— does not consider how the efficiency of an alternative (substitute or complementary) energy source–service affects the consumption of the energy source–service analyzed (Bordón-Lesme et al. 2022a; 2022b). Nevertheless, Asche et al. (2008) and Labandeira et al. (2006) consider the price of alternative energy sources to estimate the own-price elasticity of natural gas, which is a suitable proxy for the direct rebound effect for natural gas.
Moreover, Freire-González (2010) include in their estimation of the direct rebound effect of electricity for Catalonia the price of natural gas, but it was not significant. He finds a magnitude of the direct rebound effect of 35% in the short-run and 49% in the long-run.
The results of this paper would deepen the understanding of how energy services affect each other in Spain and would complement the paper by Bordón-Lesme et al. (2022a), who focused on the rebound effect of electricity consumption and on the influence of natural gas and diesel oil on electricity consumption. A significant relationship between energy services that are provided by different energy sources could entail a new source of secondary effects.

The efficiency of an energy source conversion device that provides an energy service could affect the consumption of another energy source conversion device that provides another energy service. Thus, if the energy services are substitutes, policymakers could reduce the consumption of the second energy source–service by increasing the efficiency of the first energy source conversion device and vice versa. In the same way, if energy services are complementary, policymakers could increase the consumption of the second energy source–service by increasing the efficiency of the first energy source conversion device and vice versa.
The rest of the paper is structured as follows. Section 2 succinctly provides the methodological background of the direct rebound effect estimation method. Section 3 presents the data sources and the econometric approach for the estimation of the direct rebound effect. Section 4 shows our results. Finally, in Section 5, we conclude and discuss the policy implications.

3.3. Direct rebound effect estimation method

The direct rebound effect is usually estimated as follows (Berkhout et al., 2000; Sorrell, 2007; Sorrell and Dimitropoulos, 2008):

$$\varepsilon = {}^{S}/_{E} \tag{12}$$

Where ε is the energy efficiency of an energy service, which measures the inverse of the amount of energy input required (E) to provide a unit of energy service's useful work (S). One definition for useful work or useful output is what consumers require in terms of an end-use service from an energy conversion device (Patterson, 1996). Thus, an energy efficiency improvement of an energy service can affect its own demand for useful work (Sorrell and Dimitropoulos, 2008):

$$\eta_{\varepsilon}(S) = \frac{\partial S}{\partial \varepsilon}\frac{\varepsilon}{S} \tag{13}$$

Likewise, an energy efficiency improvement in an energy service can affect its own demand for energy (Sorrell and Dimitropoulos, 2008):

$$\eta_{\varepsilon}(E) = \frac{\partial E}{\partial \varepsilon}\frac{\varepsilon}{E} \tag{14}$$

The relationship between equation 2, which is the efficiency elasticity of the demand for useful work and equation 3, which is the efficiency elasticity of the demand for energy, is the primary definition for estimating the direct rebound effect (Sorrell and Dimitropoulos, 2008):

$$\eta_{\varepsilon}(E) = \eta_{\varepsilon}(S) - 1 \tag{15}$$

Under certain assumptions, the efficiency elasticity of useful work (equation 4) which is the primary definition of the direct rebound effect, can be measured indirectly, without data on energy efficiency improvement, through the own-price elasticity of energy demand as follows (Sorrell and Dimitropoulos, 2008):

$$\eta_{\varepsilon}(E) = -\eta_{P_E}(E) - 1 \tag{16}$$

The assumptions required for equation 5 are, first, symmetry, that is, it is expected that consumers would react the same to a decrease in energy prices as to an increase in energy efficiency. Second, exogeneity, that is, energy prices do not foster energy efficiency, to fulfill this assumption the period analyzed must be on stability or decrease in energy prices because the increase in energy prices could prompt improvements in energy efficiency. Third, constant energy efficiency, that is, the energy service has the same level of efficiency regardless of the amount of useful work it provides.

Thus, in the econometric estimation method, the coefficient of the own-price elasticity of natural gas demand would represent equation 5. Moreover, to account for how the energy services provided by electricity and diesel oil affect the energy services provided by natural gas we add into the econometric estimation method the price of electricity and diesel oil (Bordón-Lesme et al. 2022a). See the next section for further details. Therefore, the assumptions required to estimate the direct rebound effect through price elasticities considering the relationship between energy services provided by different energy sources are:

1. Consumers would react the same whether energy services affect each other through their energy prices or their energy efficiency.
2. The increase in the energy source price of an energy service would not affect the efficiency of another energy service.
3. The energy services analyzed have a constant energy efficiency.
4. Energy services provided by a different energy source which provide the same useful work are considered as different energy services. For example: heating (useful work) run by natural gas is different than heating (useful work) run by electricity.

4.3. Empirical strategy

According to the Spanish Institute for the diversification and saving of Energy in Spain, electricity and natural gas provide energy services of different useful work. The energy service of lighting is solely provided by electricity, whereas the energy service of space cooling is provided in a 99% by electricity. On the other hand, for the energy services of space heating and water heating, natural gas has a greater share than electricity in providing them. For space heating, natural gas has a share of around 21%, diesel oil has a share of 27% and electricity has a share of 7%, while for water heating natural gas has a share of 49%, diesel oil of 6% and electricity has a share of 17%. For the energy service of cooking, there seems to be a substitution relationship between energy sources because the shares are more balanced: for cooking the shares of energy sources are electricity 50%, natural gas 30% and diesel oil 17%. Nevertheless, cooking has only an 8% share of total residential energy consumption, whereas space heating, lighting and other household's appliances have a share of 74%. Therefore, because electricity provides the energy services of lighting and space cooling, the energy sources of natural gas and diesel oil do not provide them and space heating and water heating are mostly provided by natural gas and diesel oil, we expect a complementary relationship between the energy services that require electricity and natural gas and a potential substitution relationship between the energy services provided by diesel oil and natural gas. On top of that, most Spanish households just have one type of installation to provide these energy services. Moreover, Bordón-Lesme et al. (2022a) found that, for Spain, natural gas has an influence on electricity consumption (a complementarity relationship). See Appendix 1 for further details regarding the residential energy sources consumption in Spain and the useful work each of them provides.

Nevertheless, as we can see in Appendix 1, electricity can provide all the energy services that are provided by natural gas and diesel oil, having a 40% share of total energy consumption in households. Therefore, in the long run there might be a substitution relationship between electricity and natural gas. In this sense, Bordón-Lesme et al. (2022b) find that, in Paraguay, for middle and high income households liquefied petroleum gas has a substitution relationship with electricity consumption.

Given the explanation above, we assume a significant relationship between the energy services that are provided by electricity and natural gas, and between the energy services provided by diesel oil and natural gas. Hence, we estimate the following econometric model.

$$ln\left(\frac{G_{it}}{hh_{it}}\right) = \alpha + \beta_1 lnP_{G_{it}} + \beta_2 lnP_{E_{it}} + \beta_3 lnP_{DO_{it}} + \beta_4 lnY_{it} + \beta_5 lnHDD_{it} + \beta_6 ln\left(G_{it-1}/hh_{it-1}\right) + u_{it} \quad (17)$$

$\frac{G_{it}}{hh_{it}}$ denotes the average natural gas consumption according to the subscribers[17]. $P_{G_{it}}$ is the real natural gas price charged to the subscribers, if the assumptions of Section 2 are met the coefficient associated to this variable (β_1) represents a suitable proxy of the direct rebound effect for natural gas because we estimate it through its own-price elasticity. $P_{E_{it}}$ is the real electricity price charged to the subscribers, the coefficient of this variable (β_2) captures how electricity affects natural gas consumption. $P_{DO_{it}}$ denotes the real diesel oil price charged to the subscribers, the coefficient of this variable (β_3) indicates how diesel oil affects natural gas consumption. Y_{it} is the average disposable income, its coefficient (β_4) indicates how income would affect natural gas consumption. HDD_{it} are the heating degree-days, the coefficient associated to this variable (β_5) indicates how cold days would affect natural gas consumption. $\left(\frac{G_{it-1}}{hh_{it-1}}\right)$ is the average natural gas consumption in period $t-1$, its coefficient (β_6) captures the long-run effects and it stands for the data of province i in period t. We estimate an error correction model (ECM) with fixed effects and cross-section weights to deal with cointegration of variables to obtain both short- and long-run estimates and to solve spurious relationship between the variables. The ECM with lagged variables is also an appropriate model that address potential endogeneity issues providing consistent estimates (Greene, 2003).

In this case, to estimate the fixed effects and the cross-section weights in both steps of the ECM we exclude the provinces of Ceuta, Baleares, Las Palmas, Melilla and Tenerife because they have only one or two entries for the dependent variable (natural gas consumption), thus, given their predicted residual were equal to zero it was not possible to do both the fixed effects with the cross-section weights in the second step of the ECM. Moreover, without these provinces the panel is balanced.

The second step of the ECM is performed using the predicted residual of the first step as exogenous variable in a regression containing the variables in differences plus the lagged error term. We did not add into the model the cooling degree-days variable because, as we can see in Appendix 1, natural gas is not used for the energy service of space cooling.

Our variables of interest are the price of natural gas (P_G), the price of electricity (P_E) and the price of diesel oil (P_{DO}), whereas heating degree-days (HDD) and income (Y) are the control variables. The lagged dependent variable $(G_{it}-1/hh_{it}-1)$ and the error correction term are

[17] The subscribers are the households who request the energy carrier of natural gas for the year

only used in the second step of the ECM $(u_{it} - 1)$, which provides the coefficients in the short-run.

The ECM1 is the estimation method with all the variables included, ECM2 provides the coefficients using only the variables of interest, and ECM3 and ECM4 provides the coefficients with each control variable respectively. These last two models are included in Appendix 2 as robustness checks.

4.3.1. Data

We obtain information on natural gas price, electricity, and diesel oil price from the Statistical office of the European Union (Eurostat). We take household disposable income data per each Spanish region as a proxy for each province from the Spanish statistical office (INE). Information of the climatic variables have been obtained from the State Meteorological Agency of Spain (AEMET). We use data on natural gas consumption per province from the Ministry of Industry, Commerce and Tourism of Spain. We also use the consumer price index per province from the INE.

4.4. Results

Table 16 shows the estimations of the model specified in sections 2 and 3. The coefficient of each variable is in the first row with its corresponding asterisks denoting its significance, the p-values are below, and the standard errors are in the last row in parenthesis.
For the long-run estimates, the estimation methods ECM1 to ECM4 provide an own-price elasticity of natural gas demand with a negative sign of 64%, 42%, 43% and 63%, respectively, which means that a 100% energy efficiency improvement of energy services run by natural gas would lead to less than 100% reduction of natural gas consumption. In the short-run the own-price elasticity demand for natural gas we obtain are 88%, 80%, 79% and 89%. That is, in the long-run, there would be a reduction of natural gas consumption between 58% and 36% and in the short-run between 11% and 21%.

Regarding the relationship between energy services, we find that electricity price influences natural gas consumption. In the short-run there is a complementary relationship whereas in the long-run the coefficient has a positive sign indicating a potential substitution relationship. Moreover, diesel oil price also influences the consumption of natural gas, with a substitution relationship in both the short- and long-run. Thus, when there is an increase in natural gas price its consumption decreases, in the short- and long-run. If the electricity price increases the consumption of natural gas would decrease in the short-run and it would increase in the long-run, and if the price of diesel oil increases the consumption of natural gas would increase in the short- and long-run.

Regarding the control variables, we find a positive relationship between heating degree-days (HDD) and the consumption of natural gas but only in the short-run, whereas income has a negative relationship with natural gas consumption both in the short- and long-run. Thus, as HDD increases the consumption of natural gas increases in the short-run and in the long-run HDD has no effect on natural gas consumption, and as income increases the consumption of natural gas decreases both in the short- and long-run.

Table 16. Empirical estimates of the residential natural gas demand in Spain

Dependent Variable: $ln(G_{it}/hh_{it})$	ECM1		ECM2	
	Long-Run	Short-Run	Long-Run	Short-Run
α	11.5832***	0.0957***	1.4582***	0.1053***
	0.0000	0.0000	0.0000	0.0000
	(2.3845)	(0.0143)	(0.3170)	(0.0139)
$lnP_{G_{it}}$	−0.6444***	−0.8795***	−0.4196***	−0.8020***
	0.0000	0.0000	0.0000	0.0000
	(0.0801)	(0.0659)	(0.0727)	(0.0633)
$lnP_{E_{it}}$	1.0488***	−0.2821	1.2535***	−0.4863**
	0.0000	0.1019	0.0000	0.0068
	(0.1449)	(0.1720)	(0.1289)	(0.1786)
$lnP_{DO_{it}}$	1.4153***	2.1355***	0.4384***	1.8356***
	0.0000	0.0000	0.0000	0.0000
	(0.1913)	(0.2091)	(0.092)	(0.1697)
$lnHDD_{it}$	0.2315	0.8747***		
	0.1579	0.0000		
	(0.1637)	(0.1144)		
lnY_{it}	−1.5800***	−0.9271**		
	0.0000	0.0014		
	(0.2607)	(0.2872)		
$\Delta ln(E_{it} - 1/hh_{it} - 1)$		−0.1571**		−0.2168***
		0.0083		0.0007
		(0.0591)		(0.0630)
$u_{it} - 1$		−0.4720***		−0.4999***
		0.0000		0.0000

		(0.0757)		(0.0837)
Weighted Statistics				
R-squared	0.8639	0.6053	0.8540	0.5740
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000
Unweighted Statistics				
R-squared	0.6695	0.4378	0.6531	0.3734

$*$ $p<0.05$ $**$ $p<0.01$ $***p<0.001$

4.5. Discussion of results

The magnitude of the direct rebound effect for natural gas estimated through its own-price elasticity of natural gas demand (42–64%) falls in the higher range (or a bit above, depending on the estimated model) of the expected values for developed countries which is 30% and 50% (Greening et al., 2000; Sorrel et al., 2009; Freire-González, 2017). These potential range of values of the direct rebound effect are for specific energy services such as space heating, space cooling, and personal automotive transport, which are provided by different energy sources. However, in the short-run the magnitude of the direct rebound effect for natural gas greatly exceeds that limit of 50%, reaching a value of 79% to 89%. Thus, the resulting energy savings of natural gas consumption from a 100% improvement in energy efficiency of the energy services provided by it would reach energy savings of 58% in the long-run and 11% in the short-run. Belaïd et al. (2018) also estimate high values for the direct rebound effect for natural gas in French households of 60% and 63% in the short and long-run, respectively.

The sign of the coefficients of the climatic variable HDD shows a positive relationship with natural gas consumption, as expected. However, the income variable has a negative relationship with natural gas consumption, that is, as income increases the natural gas consumption decreases. Moreover, electricity has a complementarity relationship in the short-run and a substitution relationship in the long-run. A possible explanation for these two results can be that natural gas consumption is an inferior good in relation to electricity consumption. Thus, as income increases households change their energy carrier from natural gas to electricity. This is also in line with the energy ladder theory because transitioning to electricity consumption is seen as a decrease in energy poverty (Sovacool, 2014). Appendix 1 shows that Spanish households can obtain all the necessary residential energy services through the electricity energy carrier. Moreover, Masera et al. (2000) find empirical evidence suggesting that households move up the energy ladder not only to increase the efficiency of their energy consumption but also to demonstrate an increase in socioeconomic status. Furthermore, Chan and Gillingham (2015) also highlight a potential energy source-switching behavior of households in developed countries. The HDD coefficient also suggests this change of energy carrier from natural gas to electricity as in the long-run it has no effect on natural gas consumption.

Hence, more efficient energy services run by electricity would increase the consumption of energy services run by natural gas in the short-run but it would be reduced in the long-run. Moreover, given the magnitude of the coefficients of the cross-efficiency elasticity of demand, a 1% energy efficiency improvement of energy services run by electricity would lead to more than 1% reduction in natural gas consumption, which is known in the literature as super-conservation rebound effect (Wei, 2010).

For the case of the cross-efficiency elasticity of demand between energy services of natural gas and diesel oil there is also a substitution relationship with a super-conservation rebound effect in both short- and long-run as the efficiency of energy services run by diesel oil increases.

Respecting the estimation of the direct rebound effect through price elasticities, Hunt and Ryan (2014, p. 24) stated: “price elasticities will still provide information about combinations of rebound effects, and if these elasticity estimates can be supplemented with information about the shares of an energy source that are used for different purposes, it may be possible to provide some conditional information about specific rebound effects”. Therefore, as Appendix 1 and Table 2 show, the direct rebound effect of natural gas would have a greater effect on the energy services of space heating and water heating.

In the same way, given our approach through price elasticities, the cross-efficiency elasticity of demand between natural gas and diesel oil would have a greater effect on the energy services that provide space heating through these two energy sources. For the case between natural gas and electricity, the greater effect would be on space heating and water heating run by natural gas because in the short-run more efficient energy services run by electricity would increase its consumption. However, in the long-run the consumption of these energy services provided by natural gas would be reduced.

Thus, our results suggest that electricity and diesel oil affect natural gas consumption which is empirical evidence for the potential substitution and complementarity relationship between energy services. In this sense, Chan and Gillingham (2015, p.29) stated: “Despite the demonstrated importance of complement and substitute relationship between energy services, there is extremely limited empirical evidence on such relationships. Economic logic suggests that similar complementarity and substitution relationships are also critical for determining the magnitude of the macroeconomic rebound effect, yet we have not seen any research exploring this path". However, the magnitudes of the coefficients should be taken with caution because the proxy of the direct rebound effect using price elasticities of an energy source could be overestimated or underestimated depending on the substitution or complementarity relationship between the energy services that are provided by the same energy source (Chan and Gillingham, 2015). Furthermore, another limitation of estimating the direct rebound effect through price elasticities is that energy prices are more salient for consumers than energy efficiency improvements. In contrast, data on energy efficiency is usually unavailable, inaccurate and provide limited variation in energy efficiency providing results with large variance (Sorrel, 2007).

4.6. Conclusion and policy implications

The purpose of this article is to estimate the direct rebound effect for natural gas, and to test if electricity and diesel oil affect natural gas consumption, and whether their relationship is of substitution or complementarity, as previous evidence suggested that energy services may affect each other (Bordón-Lesme et al., 2022a; 2022b; Chan and Gillingham, 2015).

Because we estimate the direct rebound effect for natural gas through price elasticities, we add to the econometric estimation method the price of electricity and diesel oil. We find a positive direct rebound effect for natural gas which is between 79% and 89% in the short-run and between 42% and 64% in the long-run. That is, the resulting energy savings of natural gas consumption from improvement in the energy services provided by it would be between 21% and 11% in the short-run and between 58% and 36% in the long-run.

These decreasing magnitudes of the direct rebound effect for natural gas in the long-run can be due to the cross-efficiency elasticity of demand with electricity because, according to our results, in the long-run there is a substitution relationship between the two whereas in the short-run they are complementary services. Moreover, according to the sign and significance of the income variable, natural gas consumption may be an inferior good. Thus, in the long-run, households in Spain may change their energy carrier consumption from natural gas to electricity.

We also find a substitution relationship between natural gas and diesel oil, both in the short- and long-run. This is as expected because both energy carriers are mostly used for the energy services of space heating. That is, more efficient energy services run by diesel oil would decrease the consumption of energy services run by natural gas.

Hence, policymakers in Spain should consider the cross-efficiency elasticity between energy services to accurately reduce energy consumption. In this manner, given our results, if the goal is to reduce natural gas consumption in Spain, it would be more effective to increase the efficiency of energy services run by electricity and diesel oil than to increase the efficiency of energy services run by natural gas.

Given the empirical evidence provided in this paper, in further research, it would be relevant to deepen the understanding of how the efficiencies of energy source conversion devices of the energy services affect each other.

4.7. Appendix 1. Data on final energy consumption in Spanish households.

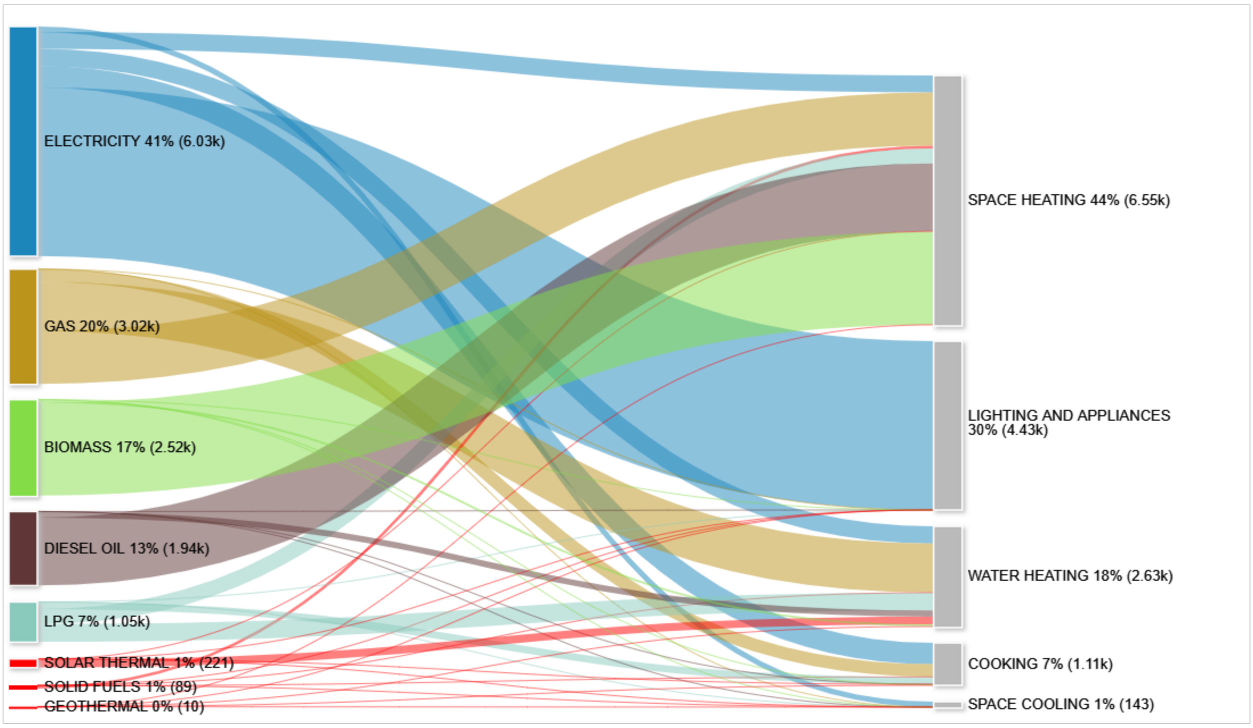


Figure 4. Source of energy for final energy consumption in Spanish households (ktep) (2010 – 2015). Source IDAE.

Table 16. Final energy consumption by useful work of residential sector (ktep). Period 2015

2015							
Energy source	**Space Heating**	**Space Cooling**	**Water Heating**	**Cooking**	**Lighting and Appliances**		**TOTAL**
Electricity	444	141	450	560	4.431		*6.025*
Heat	0	0	0	0	0		*0*
Gas	1.398	0	1.291	329	0		*3.017*
Solid Fuels	72	0	6	11	0		*89*
Petroleum Products	2.174	0	625	187	0		*2.985*
LPG	*393*	*0*	*465*	*187*	*0*		*1.045*
Other Kerosene	*0*	*0*	*0*	*0*	*0*		*0*
Diesel Oil	*1.781*	*0*	*160*	*0*	*0*		*1.941*
Renewable Energy	2.460	2	259	27	0		*2.749*
Solar Thermal	*16*	*0*	*205*	*0*	*0*		*221*
Biomass	*2.439*	*0*	*52*	*27*	*0*		*2.517*
Geothermal	*5*	*2*	*3*	*0*	*0*		*11*
TOTAL	**6.548**	**143**	**2.631**	**1.113**	**4.431**		**14.865**

4.8. Appendix 2. Robustness checks

Dependent Variable: $ln(G_{it}/hh_{it})$	ECM3		ECM4	
	Long-Run	Short-Run	Long-Run	Short-Run
α	0.7311	0.1076***	13.3854***	0.0919***
	0.6517	0.0000	0.0000	0.0000
	(1.6184)	(0.0139)	(2.0099)	(0.0148)
$lnP_{G_{it}}$	−0.4320***	−0.7915***	−0.6319***	−0.8913***
	0.0000	0.0000	0.0000	0.0000
	(0.073)	(0.0658)	(0.0794)	(0.0663)
$lnP_{E_{it}}$	1.3109***	−0.3174*	0.9675***	−0.4504**
	0.0000	0.0657	0.0000	0.0134
	(0.1412)	(0.1719)	(0.1366)	(0.1812)
$lnP_{HO_{it}}$	0.4315***	1.7972***	1.4011***	2.1766***
	0.0000	0.0000	0.0000	0.0000
	(0.0953)	(0.1656)	(0.1901)	(0.2188)
$lnHDD_{it}$	0.0781	0.8397***		
	0.6413	0.0000		
	(0.1675)	(0.1149)		
lnY_{it}			−1.5287***	−1.0009***
			0.0000	0.0007
			(0.2573)	(0.2926)

$\Delta ln(E_{it}-1/hh_{it}-1)$		−0.1592**		−0.2234***
		0.0125		0.0002
		(0.0634)		(0.0599)
$u_{it}-1$		−0.4786***		−0.4902***
		0.0000		0.0000
		(0.0824)		(0.0794)
Weighted Statistics				
R-squared	0.8521	0.6011	0.8648	0.5629
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000
Unweighted Statistics				
R-squared	0.6541	0.4292	0.6697	0.3823

5. Conclusion

The purpose of this thesis is to provide three essays on the direct rebound effect, through its magnitude estimation. In the three essays of this thesis, we test if the efficiency of an energy source conversion device affects the consumption of an energy service which is provided by an alternative energy source conversion device. Thus, we provide three empirical essays about the estimation of the direct rebound effect considering the influence of energy services that are provided by an alternative energy source. In this thesis, we also provide an updated magnitude of the direct rebound effect for electricity for households in Spain, the first empirical evidence of the direct rebound effect for Paraguay for two income groups, an updated study of the residential electricity demand for Paraguay, and an updated magnitude of the direct rebound effect for natural gas for households in Spain.

In the first chapter, our results suggest the first significant relationship between energy services through the efficiency of their energy source conversion devices. We find a direct rebound effect between 26% and 35% in the short-run and 36% in the long-run, which are in line with the literature on the direct rebound effect.

In the second chapter, we also find results suggesting a significant relationship between energy services through the efficiency of their energy source conversion devices. Here, we find lower magnitudes of the direct rebound effect for low-income households. Hence, we highlight the existence of electricity consumption barriers that only affect the poverty-stricken group, such as the higher capital cost of the energy source conversion devices run by electricity and the incompatible periodicity between irregular informal incomes and electricity bills. This could explain why low-income households do not consume electricity as much as non-low-income households.

The results of this chapter would broader the connection of the lessons provided by the energy poverty literature with those of the direct rebound effect literature because the former would determine to which energy source households should transition whereas the latter would provide information about how these households are responding to the energy source change.

In the third chapter, we find again empirical evidence suggesting a relationship between energy services through the efficiency of their energy source conversion devices. However, in this case, we estimate the direct rebound effect for natural gas consumption instead of electricity for households in Spain. Here, we provide an updated set of assumptions for estimating the direct rebound effect through price elasticities considering the relationship between energy services. In this chapter, our results suggest a decreasing magnitude of the direct rebound effect, the explanation for this can be the cross-efficiency elasticity of demand between the energy services provided by natural gas, electricity, and diesel oil. Thus, in the long-run, electricity can substitute natural gas by providing its energy services and diesel oil can substitute natural gas both in the short- and long-run.

Given the results of the three empirical essays we provide in this thesis, there seems to be a relationship between energy services through the cross-efficiency elasticity between their energy source conversion devices. Hence, policymakers should consider this cross-efficiency elasticity between energy services to accurately estimate the direct rebound effect. Moreover, this thesis opens a new line of research by deepen the understanding of how conversion devices that require a specific energy source may affect the consumption of the energy services they provide through their respective efficiencies. The study of the cross-efficiency elasticity of demand for energy services could also benefit the estimation of the indirect and the economy-wide rebound effect.

The results of this thesis are meaningful for policymakers whether their goal is to maximize energy and environmental policy effectiveness, which could be the case for developed countries such as Spain or if it is the increase in social welfare by increasing the consumption of energy which could be the case for developing countries such as Paraguay.

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