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20.02

Aquest document pertany al Departament d´Economia Aplicada

Data de publicació: **Maig 2020**

Departament d´Economia Aplicada

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The Direct Rebound Effect of Electricity Energy Services in Spanish Households: Evidence from Error Correction Model and System GMM estimates

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Abstract

We review the empirical literature concerning the magnitude of the direct rebound effect in households, focusing on econometric studies, and analyze the theoretical and methodological aspects for the estimation of the direct rebound effect. We then estimate the magnitude of the direct rebound effect of households' electricity consumption in Spain. Using panel data from 2007 to 2016 for all the Spanish provinces, we estimate the short- and long-run direct rebound effects. In order to deal with cointegration of variables and to solve potential spurious relationships between them, we use a two-step Error Correction Model. We also estimate the dynamic model through a GMM system. The results indicate a direct rebound effect between 26% and 35% in the short-run and around 36% in the long-run. These findings suggest that, in Spain, energy efficiency policies with the aim of saving electricity consumption are significantly less effective without complementary measures to tackle the direct rebound effect. Moreover, one can expect a greater electricity savings response from households to price changes than to income or weather changes. We find a significant influence of other energy sources that appear to be complementary to electricity consumption according to our estimation.

Keywords: Energy efficiency; direct rebound effect; households' electricity consumption; dynamic panel data model.

1. Introduction

Most governments are promoting improvements in energy efficiency to reduce energy consumption and associated pollutant emissions (Gillingham et al., 2006; Grubb et al., 1991; Hoeller and Coppel, 1992; Park et al., 2009; Sorrell, 2007). These improvements aim at providing the same amount of energy service to the consumer using less energy. 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." By driving improved fuel-efficient vehicles less fuel is used. However, by using less energy, the energy service becomes cheaper for the user than before the energy efficiency improvement. This decrease in the cost of the energy service causes behavioral responses from consumers that can be translated into different outcomes: driving further, new trips, more vehicle owners, less vehicle sharing, etc., causing what is known in the literature as the (direct) "rebound effect." Hence, the direct rebound effect 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 identification of the sources of the rebound helps to assess its magnitude (Greening et al., 2000). One of the most common classifications in the economic literature regarding the rebound effect is the following (Freire-González & Font Vivanco, 2017; Greening et al., 2000; Sorrell, 2007):

(i) Direct rebound effect, which was first defined by Daniel Khazzoom as the increase in the demand of an energy service caused by improvements in the efficiency of that particular energy service (Khazzoom, 1980).

(ii) Indirect rebound effect, which can originate from three sources: (1) embodied energy, that is, the energy needed to implement the measure that leads to the technical change; (2) secondary effect, that is, when the demand for other goods and services that also require energy for their production and

distribution are affected by the reduction in the effective cost of the energy service considered (Sorrell, 2007); (3) cross effect, which is a new additional source of rebound that has been recently labeled by Freire-Gonzalez and Font Vivanco (2017) as "cross rebound effect," consisting in the variation in the use of other natural resources following an energy efficiency improvement. This source of rebound comes from extending the concept of the classical rebound effect to broader perspectives considering multiple environmental pressures (Font Vivanco et al., 2016), and can be classified as a subtype of the indirect rebound effect.

(iii) Economy-wide rebound effect are the adjustments of prices and quantities of goods and services on the whole economy after an energy efficiency improvement (Sorrell, 2007).

There is open discussion regarding the magnitude of the rebound effect, whether it is lower than 100%, which implies that there are energy savings after an improvement in efficiency, or greater than 100%, which means that there is a greater consumption of energy after an efficiency improvement, causing what is known as "backfire." The core of this discussion lies in the magnitude of the economy-wide rebound effect.[1] Nonetheless, the direct and the indirect rebound effects are the most important sources of rebound at the microeconomic level.

The purpose of this article is to obtain empirical evidence of the direct rebound effect for all the energy services that require electricity for their provision in Spanish households. Using recent data, this paper delivers an estimated magnitude of the direct rebound effect 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 direct rebound effect in a developed country of a collection of energy services provided by electricity in households. We will provide new evidence for

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[1] The magnitude of the economy-wide rebound effect can be estimated by the use of Computable General Equilibrium (CGE) models or macro-econometric models (see Sorrel, 2007).

the case of Spain, as there is a lack of empirical evidence of the direct rebound in this area (except for the region of Catalonia, Freire-González, 2010). 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 direct rebound effect literature, but it will also provide updated and useful information to policymakers. Furthermore, a methodological contribution of our paper is that we test the impact of the prices of other energy sources, which may be substitutes or complementary goods.

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).

The paper is structured as follows: Section 2 contains a short updated review of the empirical literature related to the direct rebound effect; Section 3 explains the theoretical and methodological developments for estimating the direct rebound effect and the sources of data employed; Section 4 shows the results obtained; and finally, Section 5 presents the main conclusions.

2. Literature review of the direct rebound effect in households

The empirical literature shows different magnitudes concerning the rebound effect, which stimulates the debate on whether improvements in energy efficiency will reduce energy consumption and save energy or whether they will increase energy use instead (Saunders, 1992). This heterogeneity depends on the kind of rebound effect analyzed, but can also be due to factors like the different structural components of economies (Freire-González, 2017a), or the level of industrialization of the analyzed region.[2] The

[2] Freire-González (2017a) developed indicators to assess the rebound vulnerability for a specific economic structure after an energy efficiency improvement in households. Rebound vulnerability is the propensity of an economy to experience direct and indirect rebound effects given its economic structure.

rebound effect in developing countries tends to be greater than in developed countries. Possible explanations for this are:

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

(ii) They experience a rapid accumulation of energy-using technologies as well as more energy-intensive consumption, due to their high rate of growth (Van den Bergh, 2011).

(iii) The energy cost is relatively more expensive given their low wages. Hence, energy conservation may induce a larger re-spending effect (Van den Bergh, 2011).

In order to put our analysis into context, this section reviews the literature on the direct rebound effect in households. There are several ways to measure the direct rebound effect (Sorrell, 2007, 2009; Sorrell et al., 2009). Nevertheless, our focus is on the direct rebound effect estimation through econometric estimates for energy services supplied by electricity and natural gas in households.

2.1. Space Cooling

Space cooling has not been analyzed as much as space heating. Nonetheless, Hausman (1979) and Dubin et al. (1986) estimated its direct rebound effect. They found a direct rebound effect of less than 30%. This magnitude is greater in the long- than in the short-run (see Table 2). Given the period analyzed by these studies (1979 and 1981), their results may not reflect the current magnitude of the rebound effect for this particular energy service.

2.2. Space Heating

Studies associated with the estimation of the direct rebound effect for space heating in households are mostly conducted for developed countries. In the first studies, all estimates found a magnitude of the direct rebound effect lower than 100% (Douthitt, 1986; Dubin and McFadden, 1984; Haas et al., 1998; Hsueh and Gerner, 1993; Klein, 1988, 1987; Nesbakken, 2001; Schwarz and Taylor, 1995). These studies found a short-run upper bound of the direct rebound effect of around 30% and a long-run direct rebound effect between 40% and 60%. More recently, Gram-Hanssen et al. (2012) combined survey results with electricity consumption data in 185 households in Denmark to estimate the direct rebound effect after the replacement of direct electric heating with air-to-air heat pumps. They contributed to the literature by finding no energy savings for summer houses, that is, a direct rebound effect of 100%. Regarding the permanently occupied dwellings, the direct rebound effect fell into the expected magnitude considering the previous studies on space heating, a 20% reduction on the achievable energy savings (see Table 1).

2.3. Other energy services in households

The empirical evidence for other household energy services is even more limited than for space cooling. Guertin et al. (2003) measured the long-run estimate regarding water heating. They found this rebound to be between 34% and 38%. For appliances and lighting, the direct rebound effect was found to be between 32% and 49%. Davis (2007) found that for clothes washing the direct rebound was relatively small, less than 5%. Table 3 summarizes these two studies.

2.4. Sets of energy services in households

Under certain assumptions, the estimation of the own-price elasticity of domestic electricity demand would reveal the direct rebound effect. In this approach, the estimation is based upon an overall improvement in electricity efficiency used by households (Sorrell, 2007). Hence, the direct rebound effect refers to all energy services run by electricity.

Table 4 summarizes some empirical evidence of the direct rebound for households' electricity and gas consumption. One of the first studies to analyze the direct rebound effect 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 direct rebound effect 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 direct rebound effect is expected to be greater in developing regions (Sorrell, 2007); since the direct rebound effects 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)[3] (Freire-González, 2010; Wang et al., 2016). Another recent measure of the direct rebound effect for domestic energy services was conducted by Belaïd et al. (2018). They found short- and long-run direct rebound effects of 60% and 63% respectively, for all energy services supplied by gas in France. The size of both effects may seem large for a developed country considering the economic literature on the direct rebound effect. 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 5 indicates the findings of these studies.

Table 1. Econometric estimates of the direct rebound effect for household heating.

Author/year	**Country**	**Short-run RE**	**Long-run RE**	**Data**	**Estimation technique**
Dubin and McFadden (1984)	US	25–31%	-	Cross-section 1975 Sample size: 313	Logit (discrete) and instrumental variables (utilization)
Douthitt (1986)	Canada	10–17%	35–60%	Cross-section 1980-1981 Sample size: 370	OLS
Klein (1987, 1988)	US	25–29%	-	Pooled cross-section: 1973–1981 Sample size: 2,157	3SLS
Hsueh and Gerner (1993)	US	35%	-	Cross-section 1980-1981 Sample Size: 253 Electricity	OLS

[3] 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).

Schwarz and Taylor (1995)	US	-	1.4–3.4%	Cross-section 1984-1985 Sample Size: 1,188	OLS
Haas et al. (1998)	Austria	-	15–48%	Cross-section Sample size: 400	OLS
Nesbakken (2001)	Norway	15–55% (average 21%)	-	Cross-section 1990 Sample size: 551	Logit (discrete) and instrumental variables (utilization)
Guertin et al. (2003)	Canada	-	29–47%	Cross-section 1993 Sample size: (188 gas; 252 electric)	OLS
Gram-Hanssen et al. (2012)	Denmark	-	Space heating: 20% Permanently occupied dwellings. 100% Summerhouses	Panel: 1990–2009. Sample size: 180	OLS

Source: own elaboration based on Sorrell et al. (2009).

Table 2. Econometric estimates of direct rebound effect for space cooling.

Author/year	**Country**	**Short-run RE**	**Long-run RE**	**Data**	**Estimation technique**
Hausman (1979)	US	4%	26.5%	Cross-section 1978 Sample size: 46	Nested logit (discrete) and instrumental variables (utilization)
Dubin et al. (1986)	Florida (US)	1–26%		Cross-section 1981 Sample size: 241–396	Nested logit (discrete) and instrumental variables (utilization)

Source: own elaboration based on Sorrell et al. (2009).

Table 3. Econometric estimates of direct rebound effect for other household energy services.

Author/year	**Country**	**Short-run RE**	**Long-run RE**	**Data**	**Estimation technique**
Guertin et al. (2003)	Canada	-	34–38% (water) 32–49% (appliances/lighting)	Cross-section 1993 Sample size: 440	OLS

Davis (2008)	US	< 5.6 clothes washing		Panel 142 days of 1997 Sample size: 98	Fixed effects

Source: own elaboration based on Sorrell et al. (2009).

Table 4. Econometric estimates of direct rebound of all energy services in households that use electricity or gas.

Author/year	**Country**	**Short-run RE**	**Long-run RE**	**Data**	**Estimation technique**
Freire-Gonzalez (2010)	Catalonia (Spain)	35%	49%	Panel: 1991–2002 Sample size: 43	Fixed effects and Error Correction Model
Wang et al. (2014)	China	72%	74%	Panel: 1996–2010 Sample size: 30	Fixed effects and Error Correction Model
Wang et al. (2016)	Beijing (China)	16%	40%	Time series: 1990–2013	Fixed effects and Error Correction Model
Zhang et al. (2017)	China		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
Alvi et al. (2018)	Pakistan	42.9%	69.5%	Panel: 1973–2016 Sample size: not specified	Fixed effects and Error Correction Model
Labidi and Abdessalem (2018)	Tunisia		81.7%	Panel: 1995, 2000, 2005 and 2010 Sample size: 21	Fixed Effect
Belaïd et al. (2018)	France	60% (gas)	63% (gas)	Time series: 1983–2014	OLS and ARDL

Source: own elaboration.

3. Methodology and Data

This section details the theoretical and methodological developments for the estimation of the direct rebound effect using econometric approaches. The theoretical developments followed in this section can be found in Berkhout et al. (2000), Sorrell

(2007), and Sorrell and Dimitropoulos (2008). This section also shows the proposed formal specifications and the estimated models.

3.1. Methodological developments on the estimation of the direct rebound

There is a consensus in the economic literature regarding the measurement of the direct rebound effect through the efficiency elasticity of the demand for useful work (Berkhout et al., 2000). This is the primary definition of the direct rebound effect:

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

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).

The most common outcomes found in the literature when estimating the direct rebound effect are the following:

(i) A zero direct rebound effect, 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 the final energy saving would achieve its maximum.

(ii) A positive direct rebound effect with energy savings, when the efficiency elasticity of the demand for useful work is positive ($\eta_{\varepsilon}(S) > 0$) and the efficiency elasticity of the demand for energy is less than 1 ($\eta_{\varepsilon}(E) < 1$) (Sorrell and Dimitropoulos, 2008). This would imply that there will be a reduction in the achievable energy savings. This is the most common outcome in the literature.

(iii) A positive direct rebound effect causing an increase in energy consumption, when the demand for useful work is elastic ($\eta_{\varepsilon}(S) > 1$). Thus, an improvement in energy efficiency will actually increase energy consumption (backfire) (Saunders, 1992).

Under certain assumptions, the direct rebound effect can be measured indirectly, without data on energy improvements, through price elasticities. This approach is based upon two assumptions in order to be analogous to the estimation of the direct rebound effect (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 direct rebound effect can be expressed as:

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

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 direct rebound effect, through the estimation of the own-price elasticity of energy demand $(\eta_{P_E}(E))$.

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

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 relations between variables (Freire-González, 2010). 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).

Most of the empirical evidence briefly reviewed in Section 2 suggests that the direct rebound effect 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 direct rebound effect 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 direct rebound effect give rise to the possibility that the indirect rebound effect reaches a wider range of values; likewise, high estimations of the direct rebound effect 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 direct rebound effect is measured.[4] 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 that is not always 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 direct rebound effect lies between 30% and 50% (Freire-González, 2017; 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 direct rebound effect (Sorrell, 2007; Sorrell et al., 2009). Under the assumptions explained above, both approaches are accepted in the direct rebound effect literature (Freire-González, 2017b; Sorrell and Dimitropoulos, 2007).

[4] 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.

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).

3.2. 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 European Commission Database of Energy Statistics.[5] These prices do not vary between provinces, but they do over time. We gathered the information about heating oil prices from the European Commission’s *Oil Bulletin*.[6] We could not find data for renewable energy prices, which is mainly biomass.[7] 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 Alava, 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 Avila and Caceres (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

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

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

[7] According to IDAE the renewable energy sources used by Spanish households are the following: Biomass (96.6%), Solar Thermal (0.03%), and Geothermal (0.002%).

average household consumption per province per year to be the 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),[8] 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).[9] 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 direct rebound effect 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 Ministry of Industry, Commerce, and Tourism.[10]

3.3. Econometric models estimated

This subsection shows the econometric models estimated to measure the direct rebound effect. Following the proposal of Freire-González (2010), the estimation of the direct rebound effect 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:

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

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

[10] Ministerio de Industria, Comercio y Turismo, https://energia.gob.es/balances/Publicaciones/.

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

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, 2010-2015). For space cooling services, electricity is the main energy source with a 99% share (IDAE, 2010-2015). Therefore, families do not have much 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, 2010-2015); 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, 2010-2015) (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 direct rebound effect 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.

3.3.1. 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 direct rebound effect (Alvi et al., 2018; Freire-

González, 2010). 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 5 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 6). Hence, the fixed effects estimator is more suitable than the random effects to estimate the two steps ECM. Table 6 output rejects the null hypothesis of no correlation between the unique errors and the regressors. Likewise, Table 7 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.

3.3.2. 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 Methods 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)[11]:

$$y_{it} = \alpha y_{i,t-1} + \beta x'_{it} + \varepsilon_{it} \tag{7}$$
$$\varepsilon_{it} = \mu_i + \upsilon_{it}$$
$$E(\mu_i) = E(\upsilon_{it}) = E(\mu_i \upsilon_{it}) = 0$$

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":

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

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 $\nu_{i,t-1}$ in $\Delta \nu_{it} = \nu_{it} - \nu_{i,t-1}$. Additionally, predetermined variables in x' could also add another endogeneity problem; as they might also be correlated with $\nu_{i,t-1}$ (Roodman, 2009c).

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

[11] See Roodman (2009a) for further details regarding the difference and system GMM. This article also provides instructions about how to apply the GMM estimators in Stata through the xtabond2 command

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):

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

The *xtabond2* command in the software Stata, developed by Roodman (2009b), provides the estimates of the system GMM, which was fully developed by Blundell and Bond (1998). They contributed to the method by eliminating the fixed effect not through instrumenting differences with levels but instrumenting levels with differences (Roodman, 2009c). 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, 2009c).

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).[12]

[12] The syntax used in Stata was the following: gmmstyle(($ln(E_{it-1}/hh_{it-1})$ $lnP_{E_{it}}; lnP_{G_{it}}$, laglimits(2 2)) ivstyle ($lnCDD$).

Table 5. 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 6. 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 7. 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

4. Results

Table 8 shows the estimations of the model specified in the previous sections. 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.

Table 8. 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		

We use asterisks alongside each coefficient to denote its significance:

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

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 are 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.[13]

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.

[13] 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.

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. On the other hand, there is no evidence of a significant second order serial correlation $AR(2)$, as we failed to reject the null hypothesis. 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 direct rebound effect in households' electricity consumption, with a slightly higher direct rebound effect in the long-run than in the short-run. Our estimated direct rebound effect 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 direct rebound effect 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 direct rebound effect (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.[14]

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, 2017). Nevertheless, the models presented differently in Appendix V could overestimate the magnitude of our variable of interest, as they estimated a greater magnitude than our original model.

[14] We use the same lag limits as the original model.

5. Conclusions

The aim of this research was to obtain empirical evidence of the direct rebound effect for all energy services that require electricity for their provision in Spanish households.

If there are no measures to tackle the direct rebound effect in Spain, our results indicate that electricity savings would be between 26% and 35% lower in a situation without direct rebound in the short-run and 36% lower in the long-run.

According to the literature, the estimation of the direct rebound effect 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 direct rebound effect 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 direct rebound effect may be underestimated (Sorrell, 2007; Sorrell and Dimitropoulos, 2008).

Regarding the symmetry assumption, Schimek (1996) found approximately equal magnitudes when estimating the direct rebound effect 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). In this case the energy service considered was transportation. On the other hand, Wheaton (1982) found a significant larger magnitude of the direct rebound effect 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 for consumers energy prices are more salient than energy efficiency. Hence, the symmetry assumption, when estimating the direct rebound effect 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.

Since we estimated the direct rebound effect of a collection of energy services, the magnitude of the direct rebound effect 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 with a 73.54% share.

One substantial novelty of this paper is that we find a significant influence of other energy sources, which in the case analyzed are complementary to electricity (the energy source considered), in the estimation of the direct rebound effect. This newness in the estimation of the direct rebound effect opens up 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.

Another contribution of this paper is that this research is the first empirical analysis of this type for Spain. Using recent data from the 52 provinces of Spain, a time frame of 10 years, and controlling the weather variables by using information on all provinces' weather stations, we found a significant direct rebound effect of less than 100% in all estimates. 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.

The reduction in electricity savings caused by the direct rebound effect estimated in this research is relevant for energy and environmental policies in Spain. 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 the direct rebound effect to increase the effectiveness of the measures to produce electricity savings and reduce the associated pollutant emissions (Freire-González and Puig-Ventosa, 2014). Our findings suggest that, given the value of price elasticities coefficients, if the authorities want to maximize the electricity savings associated to efficiency improvements in Spain, an electricity pricing policy could be implemented.

Acknowledgments

This research was funded by Becas Don Carlos Antonio López (BECAL), grant agreement number 106/2017 between the Treasury of Paraguay and Martín Adolfo Bordón Lesme.

We also acknowledge support from project RTI2018-095484-B-I00 (Spanish Ministry of Economy and Competitiveness and ERDF).

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Appendix I Energy carrier price categories

Table A3: 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 the European Commission Database of Energy Statistics.

Table A4: 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 the European Commission Database of Energy Statistics.

Appendix II Calculation method of the climatic variables

Table A5. 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

Appendix III. Data on final energy consumption of Spanish households

Figure A1. Sources of energy for final energy consumption in Spanish households (Ktep) (2010-2015). Source: IDAE 2010

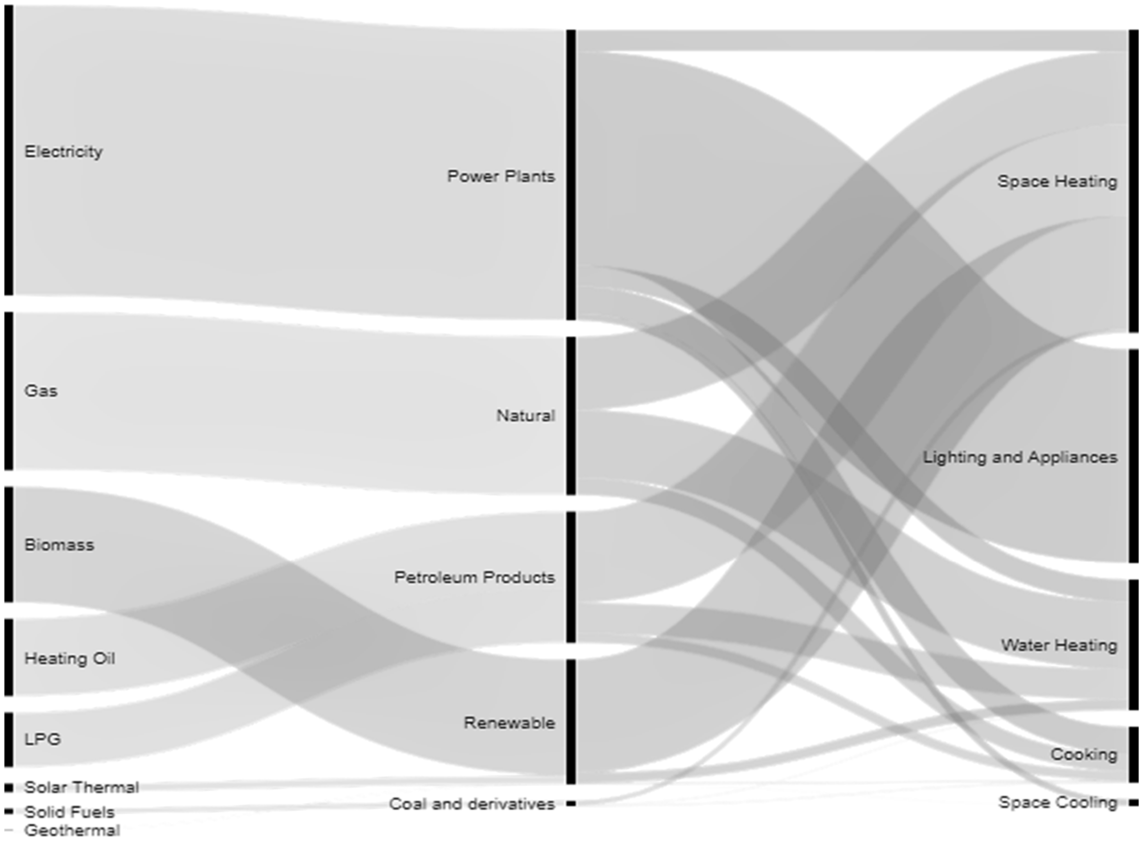

Table A1. Final energy consumption by uses of residential sector (ktep). Period 2010–2015.

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**

Source: IDAE 2010.

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**

Source: IDAE 2010.

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**

Source: IDAE 2010.

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**

Source: IDAE 2010.

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**

Source: IDAE 2010.

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 2010.

Appendix IV. Fixed Effects of each Spanish Province

Table A2: Cross-Section Fixed Effects

Provinces	**Fixed Effect** (μ_i) Table 11	**Fixed Effect** (μ_i) Table 12
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.

Appendix V. 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	

(OM) stands for Original Model

We use stars alongside each coefficient to denote its significance:

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

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