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ORIGINAL ARTICLE

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

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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

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-run 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

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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 & 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-run 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-run 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 & Abdessalem, 2018; Wang et al., 2014; Zhang & Peng, 2017) were higher than those estimated for Catalonia (Spain) and Beijing (China) (Freire-González,

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 and Peng (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

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-run 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.

Methodology and data

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 & 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 & Dimitropoulos, 2008). This implies 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 & 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:

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

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 & 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 $\left(\eta_{P_E}(E)\right)$.

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

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 & 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, 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 et al., 2009; Sorrell & Dimitropoulos, 2008).

We estimate the DRE through Eq. 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 (Eq. 1). Sorrell (2007) clarified that Eq. 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, Eq. 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" section 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 entail 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 & 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 on 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 & 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.

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).[1] These prices do not vary between provinces, but they do over time. We gathered the information about heating oil prices from the Eurostat (2016).[2] 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 Table 6 and 7. In

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

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

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 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),[3] 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).[4] The base temperature chosen to calculate the heating and the cooling degree days are 21°C and 22°C respectively; Appendix Table 8 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).[5]

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 & 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.

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:

$$\ln\left(E_{it}/hh_{it}\right) = \alpha + \beta_1 \ln P_{E_{it}} + \beta_2 \ln P_{X_{it}} + \beta_3 \ln Y_{it} + \beta_4 \ln CDD_{it} + \beta_5 \ln HDD_{it} + \beta_6 \ln\left(E_{it-1}/hh_{it-1}\right) \tag{4}$$

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

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

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

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

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 a 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 Fig. 1 and Table 9 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.

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 1 year in our model (Sorrell & Dimitropoulos, 2007). On the contrary, in the short run, households' energy demand has fewer adjustment possibilities. Therefore, to estimate both short-run 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, 2010). An ECM is an econometric model that deals with the cointegration of variables to obtain both short-run 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:

$$\ln\left(E_{it}/hh_{it}\right) = \alpha + \mu_i + \beta_1 \ln P_{E_{it}} + \beta_2 \ln P_{X_{it}} + \beta_3 \ln Y_{it} + \beta_4 \ln CDD_{it} + \beta_5 \ln HDD_{it} + \mathrm{u}_{it} \quad (5)$$

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-sectional weights. This model provides long-run elasticities. Second, the predicted residuals from estimating Eq. 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:

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-sectional random effects			
Test summary	**Chi-Sq. statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-sectional random	66.046	6	0.000

$$\begin{aligned}\Delta\ln\left(E_{it}/hh_{it}\right) &= \propto +\delta_1\Delta\ln P_{E_{it}} + \delta_2\Delta\ln P_{X_{it}} \\ &+\delta_3\Delta\ln Y_{it} + \delta_4\Delta\ln CDD_{it} + \delta_5\Delta\ln HDD_{it} \\ &+\delta\Delta_6\ln\left(E_{it-1}/hh_{it-1}\right) + \vartheta_{it}u_{it-1} + \varepsilon_{it}\end{aligned} \tag{6}$$

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-sectional 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 Table 10.

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-step 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-sectional effects are significant. Moreover, the cross-sectional fixed effects test equation is relevant for all the variables.

Table 4 Redundant fixed effects tests

Test cross-sectional fixed effects				
Effects test	**Statistic**	**d.f.**	***p*-value**	
Cross-sectional F	49.126	(51.462)	0.000	
Cross-sectional fixed effects test equation				
Variable	**Coefficient**	**Std. error**	**t-statistic**	***p*-value**
C	*−2.303*	*0.410*	*−5.611*	*0.000*
$\ln P_{E_{it}}$	−0.811	0.056	−14.388	0.000
$\ln P_{G_{it}}$	0.064	0.033	1.938	0.053
$\ln P_{HO_{it}}$	−0.331	0.051	−6.401	0.000
$\ln CDD_{it}$	0.159	0.011	13.978	0.000
$\ln HDD_{it}$	−0.219	0.019	−11.424	0.000
$\ln Y_{it}$	0.405	0.040	10.097	0.000

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 & Bond, 1991; Arellano & Bover, 1995; Blundell & 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 & Bover, 1995; Baltagi, 2008; Blundell & Bond, 1998; Roodman, 2009a). See Roodman (2009a) for further details regarding the difference and system GMM:

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

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 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 Eq. 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, 2009b).

Arellano and Bover (1995) presented an alternative transformation of Eq. 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 & Bover, 1995; Blundell & 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):

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

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).

Results

In this section, we show the obtained results, the first three columns of Table 5 provide the results of this article, and 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 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.

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)
$\ln P_{E_{it}}$	**−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)
$\ln P_{G_{it}}$	**−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)
$\ln P_{HO_{it}}$	**−0.104** **	**−0.121** **			
	0.013	0.006			
	(0.042)	(0.044)			
$\ln CDD_{it}$	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)
$\ln HDD_{it}$	0.067*				
	0.034				
	(0.031)				
$\ln Y_{it}$	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: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

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 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, and 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 moment 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, and 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 Table 11 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 Table 11 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 & 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 $\left(\eta_{P_E}(E)\right)$ (Sorrell & 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 & 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.

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 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. 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 relationships 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 & Sancho, 2010). Using recent data from all the 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 positive DRE with energy savings. We also provide the individual short-run 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 & 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 emission 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 & Puig-Ventosa, 2014).

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Appendix 1 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 < 15,000 kWh
DE	Consumption > 15,000 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

Appendix 2 Calculation method of the climatic variables

Table 8 Calculation of heating and cooling degree days

Condition	Heating degree days formula
$T_{min} > T_{base}$	$HDD = 0$
$(T_{max} + T_{min})/2 > T_{base}$	$HDD = (T_{base} - T_{min})/4$
$T_{max} \geq T_{base}$	$HDD = (T_{base} - T_{min})/2 - (T_{max} - T_{base})/4$
$T_{max} < T_{base}$	$HDD = T_{base} - (T_{max} + T_{min})/2$
Condition	**Cooling degree days formula**
$T_{max} < T_{base}$	$CDD = 0$
$(T_{max} + T_{min})/2 < \mathrm{T}_{base}$	$CDD = (T_{max} - T_{base})/4$
$T_{min} \leq T_{base}$	$CDD = (T_{max} - T_{base})/2 - (T_{base} - T_{min})/4$
$T_{min} > T_{base}$	$CDD = (T_{max} + T_{min})/2 - T_{base}$

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

Appendix 3 Data on final energy consumption of Spanish households

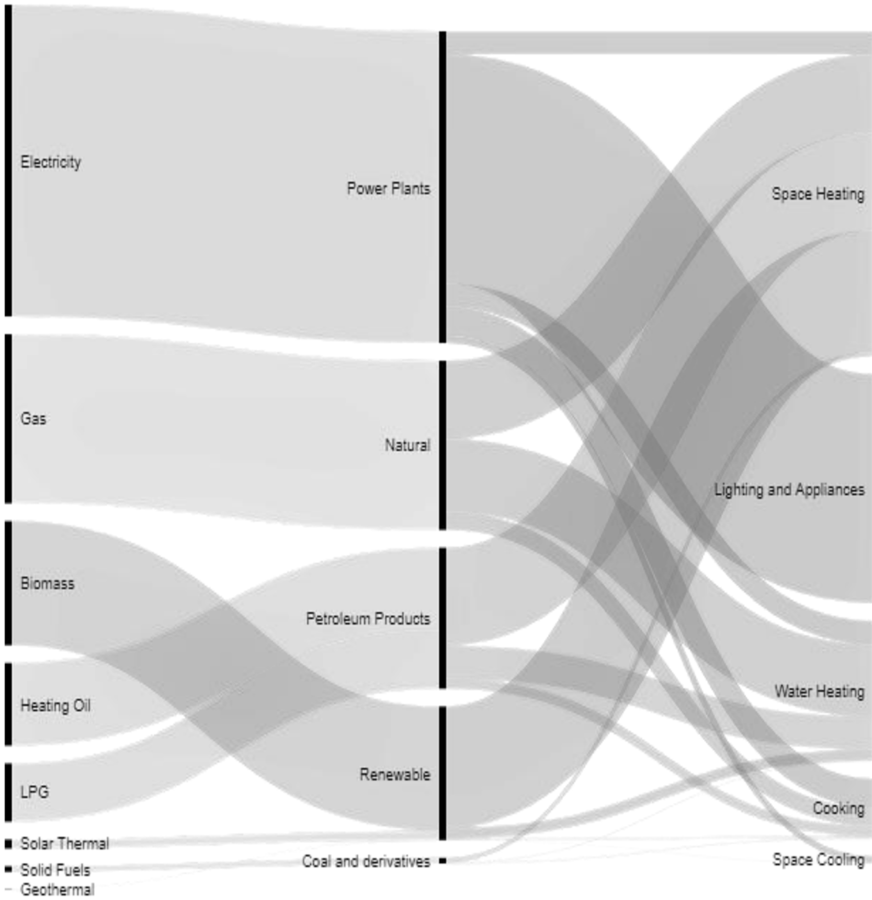

Fig. 1 Sources of energy for final energy consumption in Spanish households (Ktep) (2010-2015). Source: IDAE (2015)

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

Energy source	Space heating	Space cooling	Water heating	Cooking	Lighting and appliances	TOTAL
2015						
Electricity	444	141	450	560	4431	*6025*
Heat	0	0	0	0	0	*0*
Gas	1398	0	1291	329	0	*3017*
Solid fuels	72	0	6	11	0	*89*
Petroleum products	2174	0	625	187	0	*2985*
LPG	*393*	*0*	*465*	*187*	*0*	*1045*
Other kerosene	*0*	*0*	*0*	*0*	*0*	*0*
Diesel oil	*1781*	*0*	*160*	*0*	*0*	*1941*
Renewable energy	2460	2	259	27	0	*2749*
Solar thermal	*16*	*0*	*205*	*0*	*0*	*221*
Biomass	*2439*	*0*	*52*	*27*	*0*	*2517*
Geothermal	*5*	*2*	*3*	*0*	*0*	*11*
TOTAL	*6548*	*143*	*2631*	*1113*	*4431*	*14,865*
2014						
Electricity	448	142	454	565	4472	6081
Heat	0	0	0	0	0	0
Gas	1433	0	1324	337	0	3094
Solid fuels	75	0	6	11	0	92
Petroleum products	1876	0	607	191	0	2674
LPG	401	0	474	191	0	1066
Other kerosene	0	0	0	0	0	0
Diesel oil	1476	0	133	0	0	1608
Renewable energy	2479	2	243	27	0	2751
Solar thermal	15	0	188	0	0	203
Biomass	2459	0	52	27	0	2537
Geothermal	5	2	3	0	0	11
TOTAL	*6311*	*144*	*2634*	*1131*	*4472*	*14,691*
2013						
Electricity	450	143	456	568	4494	6111
Heat	0	0	0	0	0	0
Gas	1479	0	1366	348	0	3193
Solid fuels	77	0	6	11	0	95
Petroleum products	1858	0	636	204	0	2698
LPG	429	0	507	204	0	1140
Other kerosene	0	0	0	0	0	0
Diesel oil	1429	0	128	0	0	1558
Renewable energy	2462	2	231	27	0	2722
Solar thermal	14	0	176	0	0	190
Biomass	2443	0	52	27	0	2521
Geothermal	5	2	3	0	0	10
TOTAL	*6327*	*145*	*2695*	*1158*	*4494*	*14,819*
2012						
Electricity	476	151	482	600	4749	*6458*
Heat	0	0	0	0	0	*0*

Table 9 (continued)

Energy source	Space heating	Space cooling	Water heating	Cooking	Lighting and appliances	TOTAL
Gas	1625	0	1501	382	0	*3509*
Solid fuels	89	0	7	13	0	*110*
Petroleum products	1784	0	653	214	0	*2651*
LPG	*451*	*0*	*533*	*214*	*0*	*1198*
Other kerosene	*0*	*0*	*0*	*0*	*0*	*0*
Diesel oil	*1333*	*0*	*120*	*0*	*0*	*1453*
Renewable energy	2452	2	220	26	0	*2700*
Solar thermal	*13*	*0*	*165*	*0*	*0*	*178*
Biomass	*2434*	*0*	*51*	*26*	*0*	*2512*
Geothermal	*5*	*2*	*3*	*0*	*0*	*10*
TOTAL	*6426*	*153*	*2863*	*1236*	*4749*	*15,428*
2011						
Electricity	482	153	489	608	4814	*6545*
Heat	0	0	0	0	0	*0*
Gas	1580	0	1460	372	0	*3411*
Solid fuels	100	0	8	15	0	*122*
Petroleum products	1913	0	677	220	0	*2809*
LPG	*462*	*0*	*546*	*220*	*0*	*1228*
Other kerosene	*0*	*0*	*0*	*0*	*0*	*0*
Diesel oil	*1451*	*0*	*130*	*0*	*0*	*1581*
Renewable energy	2413	2	206	26	0	*2647*
Solar thermal	*12*	*0*	*152*	*0*	*0*	*164*
Biomass	*2396*	*0*	*51*	*26*	*0*	*2473*
Geothermal	*5*	*2*	*3*	*0*	*0*	*10*
TOTAL	*6488*	*155*	*2839*	*1240*	*4814*	*15,535*
2010						
Electricity	479	152	486	605	4786	*6508*
Heat	0	0	0	0	0	*0*
Gas	1972	0	1821	464	0	*4257*
Solid fuels	141	0	11	21	0	*173*
Petroleum products	2238	0	771	248	0	*3257*
LPG	*521*	*0*	*617*	*248*	*0*	*1386*
Other kerosene	*0*	*0*	*0*	*0*	*0*	*0*
Diesel oil	*1717*	*0*	*154*	*0*	*0*	*1871*
Renewable energy	2403	2	186	26	0	*2617*
Solar thermal	*11*	*0*	*133*	*0*	*0*	*144*
Biomass	*2388*	*0*	*51*	*26*	*0*	*2464*
Geothermal	*5*	*2*	*3*	*0*	*0*	*9*
TOTAL	*7233*	*154*	*3275*	*1363*	*4786*	*16,812*

Source: IDAE (2015)

Appendix 4. Fixed effects of each Spanish province

Table 10 Cross-sectional 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

Appendix 5. 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)
$\ln P_{E_{it}}$	−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)
$\ln P_{G_{it}}$	−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)
$\ln P_{HO_{it}}$	Without	Without	−0.104**	−0.121**			
			0.013	0.006			
			(0.042)	(0.044)			
$\ln CDD_{it}$	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)
$\ln HDD_{it}$	Without	Without	0.067*				
			0.034				
			(0.031)				
$\ln Y_{it}$	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: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

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