Working Papers

CENTRO EURO-MEDITERRANEO
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CIP – Climate Impacts and Policy Division

The Impact of Climate Change on Energy Demand: a Dynamic Panel Analysis

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Centro Euro-Mediterraneo
per i Cambiamenti Climatici
www.cmcc.it

2007 ■ WP 10

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Summary
This paper presents an empirical study of energy demand in which demand for a series of energy goods (Gas, Oil Products, Coal, Electricity) is expressed as a function of various factors, including temperature. Parameter values are estimated econometrically, using a dynamic panel data approach. Unlike previous studies in this field, the data sample has a global coverage, and special emphasis is given to sensitivity to temperature variations. These features make the model results especially valuable in the analysis of climate change impacts. Results are interpreted in terms of derived demand for heating and cooling. Nonlinearities and discontinuities emerge, making necessary to distinguish between different regions, seasons, and energy sources. Short and long run temperature elasticities of demand are estimated.
Climate change impacts on human life have well defined and different origins, nevertheless in the determination of their final effects, especially those involving socialeconomic responses, interactions among impacts are likely to play an important role.

Keywords: Energy demand, cooling effect, heating effect, temperature, dynamic panel

JEL Classification: C3, Q41, Q54

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1 Introduction

There is an obvious link between climate change and energy demand. Climate change is related to the concentration of greenhouse gases in the atmosphere. Most of the emissions of greenhouse gases are due to the consumption of fossil fuels for energy production. Consequently, climate change policies aim at reducing energy demand, improving energy efficiency, switching to carbon-free technologies. However, there is also a distinct, direct impact of climate change on energy demand due to variations in the regional and temporal distribution of temperatures.

One particular issue in this context is how the increase of global temperature is changing the residential demand for energy. Two opposing effects are at work: the *heating effect*, which is the decrease in the use of energy for heating purposes, and the *cooling effect*, which is the increase in energy demand for cooling purposes.

The issue of residential energy demand and its relationships with temperatures has received a lot of attention. The existing literature on the impact of weather on energy demand is mostly characterized by fuel- and country-specific studies. Henley and Perison (1998) analyzed the effect of temperature on the British residential electricity demand, Vaage (2000) considers different technologies for residential heating in Norway, Asadoorian et al. (2006) addressed the impact of temperature on Chinese provinces, while Mansur et al. (2004) studied the effect on the US electricity market. These are microeconometric studies, estimating, first, the demand for energy-utilizing appliances and, subsequently, the conditional demand for energy. They rely on detailed, disaggregated, data that are not always available for all regions in the world. Other country-specific analysis have been performed with non-parametric estimation techniques, such as Hanley and Peirson (1996, 1997 and 1998), who study the relationship between energy demand for heating purposes and temperature in the UK, and Zarnikau (2003), who analyzes consumption expenditures in the US.

An alternative approach is to model energy demand as a cointegrating process. Cointegration has been used to study the relationship between energy demand and GDP growth in works such as Stern (2000), addressing this issues for the US, and Masish and Masish (1996), focusing on South-East Asia. Beenstock et al. (1999) also apply cointegration to study industrial and residential energy demand in Israel, considering cooling and heating degree days, among other variables.

Another approach involves modeling energy demand as a dynamic process, depending on a set of covariates and the lagged value of the dependent variable. Pioneered by Balestra and Nerlove (1966), this method is better suited when dealing with many countries and aggregate data. Another study taking an international perspective is Bigano et al. (2006), in which both residential and industrial demand for energy are studied for five types of energy sources (coal, gas, oil, oil products and electricity) by means of a dynamic panel analysis.

The present work builds upon Bigano et al. (2006) and follows on Balestra and Nerlove (1996) in modeling energy demand as a dynamic process. The demand for four different types of fuel, namely gas, oil products, electricity and coal, is analyzed using a world panel of 31 countries. Emphasis is given on modeling non-linearities and the possible presence of region heterogeneity. Clustering techniques are used to detect non-linearities and to understand how regions can be classified according to climate characteristics. This allows to create "temperature clusters" in which regions have similar distributions of temperatures, between seasons and across time. Country heterogeneity can therefore be addressed not just by using different constant terms in the regression equation, but by specifying cluster-specific relationships. Panel data estimation techniques are used to allow for the presence of other latent heterogeneities.

The rest of the paper is organized as follows. Section 2 analyzes the non-linearities involved in the energy demand and temperature relationship. Section 3 presents the dataset and addresses the issue of clustering and partial pooling of the panel. Section 4 illustrates the model, the estimation method and the results obtained. Finally, Section 5 summarizes our findings.

2 Climate Change and the Demand for Energy

Household demand for gas, electricity, oil products and coal is a derived demand for energy services and it is related to the stock of energy-utilizing appliances and equipments in place. Therefore, any attempt at modeling energy demand should account for such stock effect. In these markets, variations in prices, income and/or temperature induce a gradual adjustment in energy demand.

A dynamic model of the household demand for electricity, gas, coal and oil products is specified here. Energy demand is modeled as an autoregressive process in which energy demand depends on its own lagged values, as well as a set of independent variables, such as energy prices, temperatures and per capita GDP.

For N number of countries and T years:

$$y_{it} = c + \gamma y_{it-1} + \beta x_{it} + u_{it} \qquad \text{for } i = 1, ..., N \text{ and } t = 1, ..., T \tag{1}$$

where:

- y_{it} is the natural logarithm of household demand for respectively electricity, gas, oil products and coal;
- y_{it-1} is the natural logarithm of the lagged dependent variable;
- x_{it} is the vector of covariates, including natural logarithm of own and alternative energy good prices, average seasonal temperature levels, real per capita gross domestic product (GDP);
- u_{it} is the disturbance term.

Since all variables are in logarithmic form, the coefficients can be directly interpreted as elasticities. Whereas β represents the adjustment in the short run, long run elasticities are defined for a stable value of energy demand, $y_{it} = y_{it-1}$, that is $\frac{\beta}{1-\gamma}$.

The energy demand and climate relationship involves a number of non-linearities, as well as different specifications, depending on fuel use. The cooling effect refers to the increase in energy demand, due to the use of cooling devices, such as air conditioners. As these appliances are fueled by electricity, it is expected that the demand for this type of fuel will be positively associated with higher temperatures. The heating effect, instead, refers to the reduction in fuel demand for heating purposes. Gas and oil products are mostly used for heating and, therefore, they can be expected to display a negative relationship with temperature. Thus, different types of fuels are expected to relate differently to an increase in temperature. In order to account for this, equations have been run separately for each fuel type.

Secondly, the relationship between energy demand and temperature depends on the season. Indeed, the same temperature increase typically has different impacts in winter, spring, summer or autumn. For example, an increase in winter temperatures will cause a decrease in energy for heating, whereas an increase in summer temperatures will cause an increase in energy for cooling. To identify in which seasons there is a cooling or heating effect, and its magnitude, seasonal temperatures are included in the regressions for each fuel type.

Thirdly, geographic variability is taken into account. In warm regions, higher temperatures have a greater impact in the summer, because of the use of more air conditioning. In colder regions, instead, energy demand could be almost unaffected by higher summer temperatures, but will typically be more responsive to winter, fall or spring temperature.[1]

[1] Note that the distinction between colder and warmer climates can only partially account for the geographic variabilities between and within regions. In fact, variables other than average temperatures may be relevant, such as the presence of mountains, coastal areas, lakes, precipitations or monsoons.

Finally, energy demand is also influenced by income levels, as wealth and income affect the capability to adapt to climate change. For example, richer countries can spend more in cooling devices (which are superior goods), whereas poorer countries devote much of their expenditure on subsistence goods. For this reason, per capita income is included as a separate regressor in the estimated equations.

3 Data Analysis

3.1 Description of the Data

The dataset employed for the estimation of the demand equations outlined in section 2 consists of time series observations, spanning from 1978 to 2000, for 31 countries.[2] The variables of interests that need to be measured are energy prices, quantities, income and temperature. As mentioned above, the focus is on the residential sector, as industrial demand for energy does not seem to respond significantly to price (Liu, 2002) and temperature changes (Bigano et al. 2006; Asadoorian et al., 2006).

Data on real per capita GDP and energy residential demand are from the International Energy Agency (IEA) - Energy Balances and Statistics. Demanded quantities are expressed in thousand tonnes of oil equivalent (Ktoe). Household fuel prices, measured in US$/toe, are from IEA-Energy Prices and Taxes. GDP is measured in Purchasing Power Parity (PPP) and prices are expressed in 1995 US$. Temperature data have been obtained from the High Resolution Gridded Dataset of the Climate Research Unit University of East Anglia and from the Tyndall Center from Climate Change Research. [3]

The panel is characterized by a relatively large time dimension. In this context, the temporal persistence of the series may be an issue and therefore their stationarity is evaluated performing some unit root tests for panel data. The the Null Hypothesis of non-stationarity is rejected by all tests[4] performed for all variables, but electricity demand.[5] Given these results, the dynamic model for energy demand is estimated without employing cointegration techniques and using heteroskedasticity robust variance-covariance matrix.

3.2 Partial Pooling of the Panel and Clustering

When dealing with country panels, the standard estimator is the fixed effect estimator. This method would estimate a coefficient for temperature common to all countries, with only country specific constant terms. This approach is unsatisfactory here, because the effect of temperature is expected to vary, especially between warm and cold countries.

Since the time dimension is sufficiently high, the poolability hypothesis can be tested, using a Wald test.[6] The panel can be considered as N pooled time-series observations of length T,

[2]The dataset was provided by Andrea Bigano, Francesco Bosello and Giuseppe Marano, who are gratefully acknowledged.

[3]The present work deals with a panel of countries that belong to different hemispheres. In this context simply using seasonal averages for all countries would have created a bias in the different behavior between northern- and southern-hemisphere countries. Consequently, seasonal temperatures were calculated as the average temperature in the months related to a certain season. For example, winter temperature in France is the average between the temperatures of December, January and February, whereas in Australia it is the average between the temperatures of June, July and August.

[4]The Fisher test (Maddala and WU, 1999), the Levin and Lin Chu test (Levin and Lin Chu, 1992) and the Im-Pesaran-Shin test (Im et al. 2003) were perforemed.

[5]These findings are in line with previous studies using similar data, e.g.Al-Rabbaie and Hunt, 2005).

[6]Recent econometric literature on panel data have compared the validity of homogeneous versus heterogeneous estimators, to obtain energy demand elasticities with respect to price and income. Whereas some authors favor the pool estimator despite the rejection of the poolability assumption (Baltagi and Griffin, 1997), Pesaran and Smith (1995) favor an estimator based on the individual time series.

grouped in M pools. For each of these time series, it is possible to consider the autoregressive model:

$$\begin{aligned} y_{it} &= c + \gamma y_{it-1} + \beta x_{it} + u_{it} \\ u_{it} &= \rho_i + \nu_{it} \end{aligned} \tag{2}$$

Note that with this formulation the constant term becomes country-specific and the model can be rewritten as a fixed effect model by naming $\alpha_i = \rho_i + c$:

$$y_{it} = \alpha_i + \gamma y_{it-1} + \beta x_{it} + \nu_{it} \tag{3}$$

This model allows for correlation between the country-specific constant term and the regressors, $Cov(\alpha_i, x_{it}) \neq 0$.

Assuming a homogeneous panel implies that the pool-specific vectors $\theta_j = (\beta_j, \gamma_j)$ for $j = 1, ..., M$ are the same for all pools. This can be tested with a usual parameter restriction test in which the Null Hypothesis is the homogeneity of the panel:

$$\begin{aligned} &\mathrm{H}_0 = \theta_1 = \theta_2 = ... = \theta_M \\ &\mathrm{H}_1 = \text{at least one of the above does not hold} \end{aligned}$$

This test is strongly and significantly rejected for all four types of fuel, when each pool contains only one region. The next step involves the identification of characteristics for which countries are similar enough to be grouped into the same pool. In particular, the aim is to diversify the regions according to their temperature characteristics, into cold and warm regions.

Different studies have addressed this problem. For instance, Lehmijoki and *Pääkkönen* (2006) consider demographic pools, to study convergence and divergence between the groups, Durlauf and Johnson (1995) also consider multiple regimes, in which different economies follow different linear models, whereas Vahid (2000) considers clustering of regions, to study the gasoline demand functions of OECD countries.

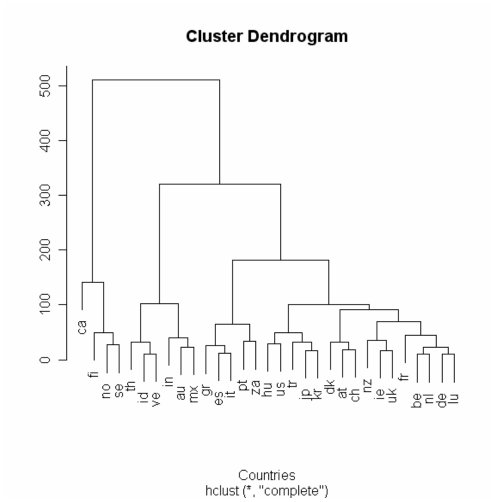
In order to group the countries in our data set, a clustering algorithm has been used. Following Kaufman and Rousseeuw (2005), Hartigan (1975) and Everitt (1974), hierarchical cluster analysis has been chosen to split the sample, in terms of average temperature characteristics. This clustering technique splits the sample into partitions, which become finer and finer. Hierarchic cluster analysis is based on the concept of distance. The metric that is used here is the Euclidean distance, though the results are robust to different types of distances. The cluster variables, that is, the characteristics to define a distance between observations, are the annual average, maximum and minimum temperature.

The clustering algorithm produces the following partition tree (cluster dendrogram):

It is then necessary to decide how many clusters to use (this is usually referred to as "pruning" the dendrogram). As the dendrogram shows three main clusters, it was decided to group the countries into three clusters:

- **Group 1**: Austria, Belgium, Denmark, France, Germany, Ireland, Luxembourg, Netherlands, New Zealand, Switzerland, Greece, Hungary, Italy, Japan, Korea, Portugal, South Africa, Spain, Turkey, United Kingdom, United States.
- **Group 2**: Australia, India, Indonesia, Mexico, Thailand, Venezuela.
- **Group 3**: Canada, Finland, Norway, Sweden.

The high correlation among average, maximum and minimum temperature (around 0.8) signals the existence of some redundancy, and suggests that it could be sufficient to use one of these three variables to identify the clusters. Indeed, using just one of the three variables leads to the same grouping, except when the maximum temperature was used, in which case two



groups were produced. Descriptive statistics of the temperature variables are summarized in Appendix A. As emerging from the mean, maximum and minimum temperature values, Group 1 constitutes the group of mild-temperature countries, Group 2 includes the hottest countries and Group 3 represents the coldest countries.

4 Estimation of Temperature Elasticities

4.1 Model Specification

A linear or log-linear model specification may not be able to capture all the nonlinearities involved in the energy demand and temperature relationship. A simple way to model non-linear effects is using interactive variables, where the impact of a variable depends on the level of another variable. More sophisticated techniques rely on non-parametric estimation methods (Zarnikau, 2003; Henley and Peirson, 1997).

The starting model for energy demand described by equation (3) is modified so as to reflect the hypothesis that the relationship between energy demand and all covariates is different across the three groups.

In order to capture this feature group dummies have been generated for the different temperature groups. The first, second and third group are related to unit values respectively of the dummies d_1, d_2 and d_0. Group 3 is the reference group, whose dummy-related variables will not be included in the regressions. The use of the dummies in level allows to capture the different effects of temperature increases between groups on the intercept. Interacting all the covariates with the two dummies capture the different effects on the slope. With these additional variables, the model reads as follow:

$$y_{it} = \alpha_{0i} + \alpha_{1i}d_1 + \alpha_{2i}d_2 + \gamma_0 y_{it-1} + \gamma_1 y_{it-1}d_1 + \gamma_2 y_{it-1}d_2 + \beta_0 x_{it} + \beta_1 x_{it}d_1 + \beta_2 x_{it}d_2 + \nu_{it} \quad (4)$$

The effect of each regressor now depends on the value of the dummy which identifies the group considered. This aspect becomes more clear if the model is formalized as follows:

$$\begin{array}{ll} y_{it} = \alpha_{0i} + \gamma_0 y_{it-1} + \beta_0 x_{it} + \nu_{it} & \text{if } d_0 = 1 \\ y_{it} = (\alpha_{0i} + \alpha_{1i}) + (\gamma_0 + \gamma_1) y_{it-1} + (\beta_0 + \beta_1) x_{it} + \nu_{it} & \text{if } d_1 = 1 \\ y_{it} = (\alpha_{0i} + \alpha_{2i}) + (\gamma_0 + \gamma_2) y_{it-1} + (\beta_0 + \beta_2) x_{it} + \nu_{it} & \text{if } d_2 = 1 \end{array}$$

The marginal effect of x on Group 1 countries, $\frac{\partial y_{it}}{\partial x_{it}} = \beta_0 + \beta_1$, is different than the marginal effect on countries belonging either to Group 2, $\frac{\partial y_{it}}{\partial x_{it}} = \beta_0 + \beta_2$, or to Group 3, $\frac{\partial y_{it}}{\partial x_{it}} = \beta_0$. Moreover, the relationship has a different intercept for each group: $\alpha_{0i} + \alpha_{1i}$ for Group 1, $\alpha_{0i} + \alpha_{2i}$ for Group 2 and α_{0i} for Group 3.

The overall significance of the dummy-interacted variables was tested using a Wald test for all four equations, with the the null hypothesis :

$$H_0 = (\alpha_1 + \gamma_1 + \beta_1)d_1 = (\alpha_2 + \gamma_2 + \beta_2)d_2 = 0$$

The test was rejected at 10% significance level for all four equations. Overall, the introduction of dummy-interacted variables increases the goodness of fit. The error terms were found not to be correlated.

4.2 Estimation Method

The inclusion of the lagged value of the dependent variable among the regressors leads to a violation of the exogeneity assumption which is required for the consistency of the fixed effect estimator. In these types of models the country specific effect, α_i is always fixed as it is always correlated with y_{it-1}. The permanent effect α_i can be eliminated using the within transformation. Ordinary least square (OLS) on the transformed model yields an estimator that is biased even for large N when T is small because $(y_{it-1} - \overline{y_{i}}_{-1})$ remains correlated with the new error term and thus it is endogenous. In the case of small T, Arellano and Bond (1991) have proposed an generalized method of moment estimator that controls for the small sample bias using past levels of the lagged dependent variable as instruments . This estimator has been proved to be efficient for small T and big N (Kiviet, 2005). Instead, when T is sufficiently large the within estimator is straightforward. As shown in Nickell (1981), the bias generated by the correlation between $(y_{it-1} - \overline{y_{i}}_{-1})$ and $(\nu_{it} - \overline{\nu_i})$ is of order $\frac{1}{T}$ and thus it goes to zero when T is sufficiently high. Both the instrumental variable approach suggested by Arellano and Bond and the fixed effect estimator proposed by Nickell have been used. Results were very similar and the fixed effect estimate of the lagged dependent variable does not appear significantly biased with respect to the Arellano Bond values.[7]

First, all seasonal temperatures have been introduced. Subsequently, the best model is identified on the base of the Akaike information criterion (AIC) for different model specifications, varying on the basis of which temperature variables are taken into account.[8]

[7]The paper reports the results obtained with the fixed effect estimator. Arellano Bond results are available upon request.

[8]The Aikaike information criterion is a criterion used to perform model selection. It is based on the R^2 adjusted for the loss of freedom occurring with the expansion of the model.

4.3 Results

Table 2 reports the estimation of the full model, where all temperatures have been included.[9] These results already reveal the presence of a cooling and heating effect. Summer temperature leads to higher annual electricity demand to feed a higher usage of air conditioners; the other fuels instead tend to respond negatively to temperature increases, especially when occurring in fall, spring or winter.

For each fuel type, the model can be simplified by removing those temperature variables that are not statistically relevant, using the Aikaike information criterion for all possible combinations of variables. The selected models, whose estimation results are reported on Table 3, strengthen the different effect seasonal temperatures have on each type of fuel demand. Summer temperature is relevant only in the model for electricity demand, whereas gas, oil products and coal respond significantly only to temperature variations that take place in winter, fall or spring.

Within each model specification a further distinction between cold, hot and mild countries emerges. Consider for example the demand for electricity. The effect of summer temperature is significant in all groups, but with a different sign. In very cold countries (Group 3, $d_0 = 1$) an increase in summer temperature of 1% reduces annual demand by 0.508%. In very hot countries (Group 2, $d_2 = 1$) it increases electricity demand by 1.659 %. In mild countries (Group 1, $d_1 = 1$), which is the largest group, the increase in electricity demand is lower and it equals 0.542 %.
Table 1 reports the temperature elasticities for the three groups of countries, for each type of fuel. The demand for gas and oil products, mostly used for heating, is particularly sensitive to changes in winter and spring temperatures. An increase in temperature in these seasons reduces the demand for these type of energy vector, but only in mild-climate regions. Cold regions probably have a baseline temperature so low that they are left unaffected. Only in the summer cold countries seem to use less electricity, probably for heating needs. The stronger effect of spring temperature compared to winter temperatures is probably related to the fact that the the dependent variable is the annual, and not the seasonal, demand for energy. Therefore, annual demand is expected to be affected more by the overall length of the cold season rather than a by a lower average temperatures in winter. Finally, coal also shows a negative relationship with winter temperatures, but a positive one with spring variations. Such result should be interpreted taking into account the fact that coal is used mostly in poorer countries, which coincide with the warmer ones, as it emerges from the average per capital GDP in Appendix A. A substitution effect between the cheaper coal and more expensive energy sources might be the explanation for an apparently unexpected positive sign.

Table 1: Temperature elasticities

	Electricity	Gas	Oil Products	Coal
$\frac{\partial y_{it}}{\partial Summer}$	$-0.523 + 0.544d_1 + 1.661d_2$			
$\frac{\partial y_{it}}{\partial Winter}$			$-0.571d_1$	$-1.063d_1$
$\frac{\partial y_{it}}{\partial Spring}$	$0.935d_2$	$-1.285d_1$		$2.16d_2$

[9] Estimating one model using the full sample and regional dummies should be almost equivalent to the estimation of the three models separately. Appendix B reports the results for the three groups of countries. Results are qualitatively similar to the full sample results. It emerges perhaps more clearly that the cooling effect is stronger in the hottest countries. In fact, in group one it is positively signed, but it is not significant. Instead, the heating effect prevails in Group 1, where the fuels to be reduced the most are gas and oil products. The effect on electricity is nearly zero. No cooling effect at is to be found in the group cold countries, where only electricity in the summer and oil products in winter are reduced when temperatures increase.

Table 2: Full sample regression, Within Estimator

Dependent variable:y_{it}	Electricity	Gas	Oil Products	Coal
		Coefficient (t-statistic)		
y_{it-1}	0.885 (28.420)***	0.704 (4.830)***	0.857 (10.820)***	
gdp_{pc}	0.050 (1.180)	-0.189 (-0.670)	-0.291 (0.318)	
p_i	-0.059 (-1.600)	-0.302 (-2.110)**	-0.224 (-1.730)*	
p_j		-0.314 (-1.320)	-0.001 (-0.020)	
$Summer$	-0.523 (-2.450)**	-0.054 (-0.060)	0.180(0.210)	
$Winter$	-0.022 (-0.510)	-0.240 (-1.110)	0.082 (0.850)	
$Fall$	-0.114 (-0.720)	-0.090 (-0.140)	-0.880 (-1.720)**	
$Spring$	-0.175 (-1.130)	0.272 (0.510)	-0.238 (0.534)	
$y_{it-1}d_1$	0.022 (0.600)	0.238 (1.620)	0.049 (0.540)	0.959 (15.46)*
$gdp_{pc}d_1$	0.035 (0.840)	0.323 (1.380)	0.416 (1.690)	-0.448 (-1.7)
p_id_1	0.043 (1.190)	0.166 (1.150)	0.184 (1.3)	0.074 (1)
p_jd_1		0.376 (1.570)	-0.022 (-0.250)	
$Summerd_1$	0.544 (2.330)**	-0.784 (-0.800)	-0.349 (-0.33)	-0.666 (-0.48)
$Winterd_1$	-0.068 (-1.030)	-0.067 (-0.270)	-0.568 (-2.640)***	-1.053(-2.12)*
$Falld_1$	0.122 (0.770)	0.099 (0.150)	0.808 (1.56)	1.625 (1.60)*
$Springd_1$	-0.169 (-0.860)	-1.161 (-1.990)**	-0.894 (-1.730)*	2.276 (2.72)*
$y_{it-1}d_2$	-0.071 (-1.090)	-0.894 (-1.73)*	-0.354 (1.240)	
$gdp_{pc}d_2$	0.106 (2.030)**	0.295 (1.38)	0.264(1.400)*	
p_id_2	0.040 (1.080)	0.09 (0.450)	-0.204 (2.590)	
p_jd_2		0.545 (2.010)**	-0.458(-2.18)**	
$Summerd_2$	1.661 (3.990)***	2.725(2.020)**	4.32(2.7)***	
$Winterd_2$	0.438 (1.260)	1.195 (1.840)*	1.550(1.54)	
$Falld_2$	0.111 (0.700)	0.085 (0.130)	0.839 (1.63)	
$Springd_2$	0.939 (2.110)**	-1.109 (-1.110)	-2.120(-1.510)	
OBS	550	418	418	154
T	22	19	19	22
N	25	22	22	7
R-sq	0.9876	0.9369	0.8751	0.9372
AIC	-2216.176	-696.117	-372.91	-26.24

*** signicant at 1%
** signicant at 5%
* signicant at 10%

Table 3: Full sample regression - selected models - Within Estimator

Dependent variable: y_{it}	Electricity	Gas	Oil Products	Coal
	Coefficient (t-statistic)			
y_{it-1}	0.892 (32.22)***	0.705 (5)***	0.854 (10.75)***	
gdp_{pc}	0.034 (0.91)	-0.199 (-0.85)	-0.292 (-1.01	
p_i	-0.052 (-1.57)	-0.306 (-2.34)**	-0.218 (-1.67)*	
p_j		-0.310 (-1.36)	-0.004 (-0.05)	
$y_{it-1}d_1$	0.013 (0.41)	0.233 (1.63)	0.052 (0.57)	0.959 (15.6)****
$gdp_{pc}d_1$	0.049 (1.3)	0.324 (1.66)*	0.414 (1.69)*	-0.458 (-1.75)*
$p_i d_1$	0.037 (1.1)	0.172 (1.28)	0.179 (1.25)	0.079 (1.08)
$p_j d_1$		0.370 (1.6)	-0.019 (-0.22)	
$y_{it-1}d_2$	-0.079 (-1.25)	-0.094 (-0.38)	0.145 (0.89)	
$gdp_{pc}d_2$	0.117 (2.31)**	0.637 (1.87)**	0.230 (1.01)	
$p_i d_2$	0.034 (0.99)	0.019 (0.08)	0.073 (0.3)	
$p_j d_2$		0.550 (2.05)**	-0.309 (-1.23)	
$Summer$	-0.508 (-2.36)**			
$Summerd_1$	0.542 (2.31)**			
$Summerd_2$	1.659 (3.89)***			
$Winter$	-0.029 (-0.69)	-0.243 (-1.15)	0.080 (0.84)	
$Winterd_1$	-0.060 (-0.91)	-0.082 (-0.33)	-0.571 (-2.61)***	-1.063 (-2.16)**
$Winterd_2$	0.406 (1.26	0.370 (0.5)	0.511 (0.45)	
$Spring$	-0.172 (-1.11)	0.256 (0.49)	-0.223 (-0.63)	
$Springd_1$	-0.169 (-0.86)	-1.285 (-2.24)**	-0.938 (-1.88)*	2.163 (2.78)**
$Springd_2$	0.935 (2.1)**	-0.558 (-0.54)	-1.276 (-0.75)	
$Fall$			-0.858 (-1.56)	
$Falld_1$			0.784 (1.41)	1.463 (1.5)
$Falld_2$			0.821 (1.49)	
OBS	550	418	418	154
T	22	19	19	22
N	25	22	22	7
R-sq	0.9875	0.936	0.8748	0.937
AIC	-2219.949	-702.2341	-378.0887	-27.88955

*** signicant at 1%
** signicant at 5%
* signicant at 10%

Table 4 reports the own-price and income elasticities based on the selected models estimation. This table also compares the results from the present study with the values of thee exiting literature. It can be seen that price and income elasticities are within the ranges estimated by other authors. When significant, income elasticity is always less than one and positive, signaling the tendency for richer people to increase energy consumption. Only coal, which is more widespread among poor, is characterized by a negative sign reflecting its nature as an inferior good. Significant price elasticities are always negative, pointing at the substitution possibilities among fuels.

In the long run, when the stock of equipment and appliances can also be adjusted, the effect of price, income and temperature is larger. Table 5 and 6 reports these long run elasticities. The pattern is the same as in the short run, but of bigger magnitude.

Table 4: Income and own price elasticities

	Price elasticities	Income elasticities
Current study		
Electricity	$-0.052 + 0.037d_1 + 0.034d_2$	$0.034 + 0.049d_1 + 0.117d_2$
Gas	$-0.306^{**} + 0.172d_1 + 0.019d_2$	$-0.199 + 0.324d_1^* + 0.637^{**}d_2$
Oil Products	$-0.218 * +0.179d_1 + 0.073d_2$	$-0.292 + 0.414^*d_1 + 0.230d_2$
Coal	$0.079d_1$	$-0.458d_1^*$
Other studies		
Liu (2002)	[-0.039;0.191]	[-1.148;0.058]
Nordhaus (1977)	[-0.68;-0.03]	[0.29;1.11]
Bigano et al. (2006)	[-0.321;- 0.165]	[-0.76;0.317]
Fiebig (1987)		[1.24;1.64]

*** signicant at 1%
** signicant at 5%
* signicant at 10%

Table 5: Income and own price long run elasticities

	Income	Own price
Electricity	$0.108 + 0.454d_1 + 1.083d_2^{**}$	$-0.481 + 0.343d_1 + 0.315d_2$
Gas	$-0.675 + 1.098d_1^* + 2.159d_2^{**}$	$-1.037^* + 0.583d_1 + 0.064d_2$
Oil products	$5.849 + 2.836d_1^* + 1.575d2$	$-1.493^* + 1.226d_1 + 0.5d_2$
Coal	$-11.170d_1^*$	$-0.007d_1$

Table 6: Temperature long run elasticities

	Summer Temp.	Winter Temp.	Spring Temp.
Electricity	$-4.704^{**} + 5.019d_1^{**} + 15.361d_2^{***}$		$8.657d_2$
Gas		$-0.824 - 0.278d_1 + 1.254d_2$	$0.868 - 4.356d_1^* - 1.892d_2$
Oil products		$0.548 - 3.911d_1^* + 0.087d_2$	$-1.527 - 6.425d_1 - 8.740d_2$
Coal		$-25.927d_1^{**}$	$52.756d_1^{**}$

5 Conclusions and Extensions

Climate change has caused variations in average seasonal temperatures that are likely to affect the patterns of residential demand for energy for heating and cooling purposes. This paper constitutes an attempt at identifying and quantifying these heating and cooling effects.

The present paper contributes to the existing empirical literature on energy demand under several aspects. The data coverage is broader than in earlier studies, in terms of geographical coverage and fuel types considered. From the methodological point of view, the model accounts for non-linearities characterizing the relationship between energy demand and temperature.

The results can be interpreted in terms of derived demand for heating and cooling. Cluster analysis reveals the presence of three major groups of countries responding similarly to temperature variations. The cooling effect can be seen through the increase in electricity demand caused by an increase in summer or spring temperatures. Such effect is present in mild and warm regions, whereas it turns out to be negative in countries such as Canada, Norway, Sweden and Finland. The heating effect can be seen through a demand reduction for those fuels that are typically used for heating purposes: gas, oil products and coal.

The global effect of higher temperatures on annual energy demand depends on the region. Cold countries such as Canada or Norway are the only countries where the net effect of temperature increases on total energy demand is negative. In mild countries, like Italy, the higher demand for electricity during the summer is compensated by lower demand for gas, oil products and coal in winter and spring. In warm countries, such as Mexico, the cooling effect increases energy demand not only in the summer, but also in the spring.

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A Data statistics summary

Table 7: Summary statistics for the three temperature groups

	Group 1			Group 2			Group 3		
	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.	Obs	Mean	Std.dev.
Gas	368	12223	26162	23	1798	510	46	5687	5874
Electricity	483	6693	16694	138	1739	1334	92	4204	3525
Coal	483	1366	2398	138	1248	2788	92	31.22	31.54
Oil pr.	483	5706	8986	138	4312	4824	92	2775	2450
Gdp PC	483	16874	6368	138	6617	6044	92	20142	2855
T ann	483	73	5.450	138	97	3.688	92	54	5.712
T max	483	89	6.313	138	103	2.614	92	78	2.946
T min	483	57.053	8.0712	138	90	8.148	92	30.093	11.534

B Sub-sample regressions: results

Table 8: Sub sample regression, Within Estimator (t-statistic in brackets): Group 1

Dependent variable: y_{it}	Electricity	Gas	Oil Products
y_{it-1}	0.906 (54.770)***	0.936 (29.450)***	0.907 (20.770)***
gdp_{pc}	0.091 (3.920)***	0.217 (4.700)***	0.200 (3.90)***
p_i	-0.017 (-4.870)*	-0.125 (-3.570)***	-0.051 (-0.88)
p_j		0.053 (1.580)	-0.008(-0.160)
$Summer$	0.021 (0.230)	-0.834 (-2.860)***	-0.150 (-0.250)
$Winter$	-0.091 (-1.810)*	-0.308 (-2.380)**	-0.484 (-2.540)**
$Fall$	0.008 (2.310)**	0.010 (0.930)	-0.071 (-1.240)
$Spring$	-0.345 (-2.850)	-0.915 (-4.060)***	-1.122 (-3.3)***
OBS	440	352	352
T	22	22	22
N	20	26	16
R-sq	0.9876	0.955	0.8687

*** signicant at 1%
** signicant at 5%
* signicant at 10%

Table 9: Sub sample regression, Within Estimator (t-statistic in brackets): Group 2

Dependent variable: y_{it}	Electricity	Gas	Oil Products
y_{it-1}	0.835 (17.420)***	0.796 (5.960)***	0.997 (8.6)***
gdp_{pc}	0.196 (3.270)***	0.421 (1.260)	0.074 (0.240)
p_i	-0.021 (-2.510)*	-0.262 (-1.520)	-0.175 (-0.7)**
p_j		0.172 (1.130)	-0.38(-1.09)
$Summer$	1.136 (3.000)**	2.644 (1.920)*	4.49 (1.92)*
$Winter$	0.436 (1.200)	0.753 (0.720)	1.86 (1.110)
$Fall$	-0.002 (-0.420)	-0.006 (-0.500)	-0.041(-2.110)***
$Spring$	0.720 (1.600)	-0.822 (-0.700)	-2.381 (-0.790)
OBS	44	22	22
T	22	22	22
N	2	1	1
R-sq	0.996	0.9818	0.9527

***signicant at 1%
** signicant at 5%
* signicant at 10%

Table 10: Sub sample regression, Within Estimator (t-statistic in brackets): Group 3

Dependent variable: y_{it}	Electricity	Gas	Oil Products
y_{it-1}	0.895 (22.260)***	0.694 (4.730)***	0.956 (11.05)***
gdp_{pc}	0.029 (0.470)	-0.481 (-1.030)	0.131 (0.340)
p_i	-0.057 (-1.410)	-0.359 (-2.170)**	-0.272 (-1.9)*
p_j		-0.319 (-1.190)	0.053 (0.54)
$tsummer$	-0.512 (-2.300)**	0.283 (0.270)	0.090 (0.1)
$twinter$	-0.023 (-0.520)	-0.221 (-0.940	0.052 (0.520)
$tfall$	-0.085 (-0.470)	0.098 (0.130)	-1.14 (-1.95)*
$tspring$	-0.172 (-1.060)	0.302 (0.510)	-0.279 (-0.73)
OBS	66	44	44
T	22	22	22
N	3	2	2
R-sq	0.975	0.6674	0.9257

*** signicant at 1%
** signicant at 5%
* signicant at 10%