Abstract

This paper presents an empirical analysis on residential demand for electricity considering the existence of possible spatial effects. This analysis has been performed using aggregate panel data at the province level for 46 Spanish provinces for the period from 2001 to 2009. For this purpose, we estimated a log-log demand equation for electricity consumption using a spatial autoregressive model with autoregressive disturbances (SARAR). The purpose of this empirical analysis is to determine the influence of price, income, and spatial spillovers on residential electricity demand in Spain. We are particularly interested in analyzing the impact of the heterogeneous disposable income variations across provinces observed during the crisis period 2008-2009 on electricity demand. The estimated income elasticity is high although lower than 1 and the demand is very inelastic to prices. We have found that spatial effects characterize the residential electricity consumption in Spain significantly.

JEL: D, D2, Q, Q4, R2.

Keywords: residential electricity demand, aggregate panel data, spatial economic effect, economic crisis.
Economic Crisis and the Residential Electricity Consumption of Spanish Provinces: A Spatial Econometric Analysis

1. Introduction

Since the beginning of the new century, Spanish economy has experienced a period of rapid growth between 2000 and 2007 followed by a period of recession, as other European countries, after 2008. During the period of economic prosperity, the cumulative annual growth rate of the Spanish households’ disposable income was 6.8% (in nominal terms), whereas in 2009, last year with statistical information on this data, the growth rate was only 0.94%. The despair regional socio-economic structures make the growth rates of the disposable income show a relatively high heterogeneity across regions and provinces. Indeed, we can find territories during the economic crisis that still experience a positive growth rate of the disposable income while there are provinces characterized by a significant decrease in the same.

Changes in the growth rate of the regional household disposable income have, of course, an impact on the residential electricity consumption. This impact is expected to be different across provinces for several reasons. First, as already mentioned, the growth rate of the household disposable income shows a relatively high heterogeneity across provinces. Second, due to the socioeconomic relations between the provinces, we can hypothesize the presence of spatial spillovers and spatial clusters in the consumption of electricity. For instance, the electricity consumption in one region can be influenced by the lifestyle of the households in neighbourhood provinces. We could think of a mimicking phenomenon of neighbours that can produce “spillovers” in the adoption of more electrical appliances or in the adoption of new energy efficient appliances. This behaviour can create spatial clusters in the adoption and use of electrical appliances, and therefore, in the consumption of electricity. Furthermore, we could also observe learning experiences from neighbours in the energy consultant sector. In this case, the same energy consultant company is operating in several provinces or one energy consultant company operating in one province learn from the companies operating in the neighbours provinces. Another spatial economic effect could arise from the presence of workers living in one region but working in adjacent or close provinces or, even without working there, having a strong economic dependence on what happen in bordering territories. In this case, the change of the economic situation in one province would also have an impact on the socioeconomic situation in the neighbourhood provinces and, therefore, on the electricity consumption. Finally, since the majority of energy policies are
implemented in Spain at regional level, one could suppose that it could be certain imitation or influence of the measurement taken in one province on the surrounding territories.

Therefore, in this paper we argue that the existence of possible spillover effects makes consumption of electricity cannot be regarded as independently generated within provinces. Unobservable variables may be spatially correlated and observed consumption patterns in neighbouring provinces may also be correlated with the local consumption. As a consequence, standard estimation procedures like Ordinary Least Squares (OLS) can lead to bias and inefficiency in the estimates. From the energy economics point of view, the presence of possible spatial effects in the consumption of electricity has been so far neglected. Since the pioneer work of Houthakker (1951), vast literature on modelling the residential demand for electricity and examining its determinants has been published. Most of the published works focus on calculating short and long-run price and income elasticities. Many of these estimations used nationwide data based on panel data, aggregated at the state level (e.g., Houthakker, 1980; Hsing (1994); Maddala et al., 1997; Bernstein and Griffin, 2006; Paul et al., 2009 and Alberini and Filippini, 2011). These studies have the advantage of being able to provide regional elasticities, both long-run and short-run, across the nation. Log-log static model and simultaneous equations have been the most widely used methodology with aggregate data (e.g. Beierlein et al., 1981; Lin et al., 1987 and Espey and Espey, 2004) although the dynamic approach is also fairly extended (e.g. Paul et al., 2009 and Alberini and Filippini, 2011). Most of these studies are for USA and many researchers have found significant difference between responses to price changes in different regions within the country (Bernstein and Griffin, 2006). For Spain, the only study estimating the residential electricity demand using aggregate panel data is by Blázquez et al. (2012). These authors have estimated a demand model using aggregate panel data at the province level for 47 Spanish provinces for the period from 2001 to 2008. For this purpose, they estimated a log-log demand equation for electricity consumption using a dynamic partial adjustment approach and using a two-steps system GMM estimator proposed by Blundell and Bond (1998). None of these studies take into account possible spatial effects that could characterize the consumption of electricity. In this respect, this paper wants to explore the use of spatial econometric methods in the estimation of energy demand models. One of the scarce works including the spatial effect in the analysis of electricity residential demand is the one by Noonan et al. (forthcoming), who, by using household data, study the adoption of energy-efficient residential and air conditioning systems in the Greater Chicago area from 1992 to 2004. They

\[ \text{1 For a systematic review of these papers see Heshmati (2012).} \]
apply a spatial lag model (without considering the spatial error effect) and find a significant spatial multiplier effect that magnifies the effect of other factors affecting adoption rates.

The aim of this paper is to estimate price and income elasticity for Spanish residential electricity demand by considering the presence of spatial effects. Additionally, we intend to analyze the impact of the change of the disposable income observed during the crisis period 2008-2009 on the electricity consumption in the Spanish provinces. We are particularly interested in estimating the effects for each province by considering spatial spillover effects. In order to do this, we will use a spatial autoregressive model with autoregressive disturbances (SARAR) using a panel data set on the 46 mainland Spanish provinces for the period 2001 to 2009.

The paper is organized as follows: Section 2 presents the empirical model. In section 3, the econometric approach and the empirical results are discussed. Some concluding remarks appear in section 4 of the paper.

2. Model specification and data

Residential electricity demand can be specified using the basic framework of household production theory (Flaig, 1990; Filippini and Pachauri 2004; and Alberini and Filippini, 2011). According to this theory, households purchase inputs to produce "commodities" that appear as arguments in the household's utility function. In our specific case, a household combines electricity with electrical appliances to produce energy services such as heated rooms, lighting and hot water. Following this theoretical framework, the electricity demand function, as formally derived in Filippini and Pachauri (2004), should include as explanatory variables, the price of electricity, the price of substitutes, the capital price (electrical appliances), income and some socioeconomic variables. Usually, in the studies on the econometric estimation of the electricity demand using aggregate data, the explanatory variables considered are the real disposable income of the household sector, the real price of electricity, the household size, the gas price and some climate variables. The capital price is usually absent because of missing information. Therefore, based on previous studies and on the availability of the data, we specified the following static residential electricity demand model:

\[ el_{it} = f(y_{it}, pel_{it}, pengas_{it}, hss_{it}, hdd_{it}, cdd_{it}, time) \] (1)

where \( el_{it} \) is aggregate electricity consumption; \( y_{it} \) is the net real disposable income of the household sector in Euros (Base: 2006=100); \( pel_{it} \) is the real average price of electricity in
Euros (Base: 2006=100); \( hss_{it} \) is household size (total population/number of principal houses); \( pengas_{it} \) is the percentage of households that have access to gas and that is used as a proxy for the unavailable gas price and considered as endogenous; \( hdd_{it} \) and \( cdd_{it} \) are, respectively, the heating degree days and the cooling degree days all for province \( i \) in year \( t \) with 15°C as the threshold for heating and 22°C for cooling; and \( time \) is a time trend to capture a time specific effect.

For the estimation of equation (1) we use a log-log functional form and, as mentioned previously, a spatial econometric specification which consider a SARAR model, i.e. a combination of a spatial lag and a spatial error model for panel data as proposed by Kelejian and Prucha (1998) and Kapoor et al. (2007). In this model, the spatially lagged dependent variable captures the spatial dependence between provinces, whereas the spatial autocorrelation term captures the spatial dependence. Therefore, the spatial econometric specification of equation (1) is the following:

\[
\ln e_{it} = \alpha_0 + \lambda \sum_{j=2}^{NT} (w_{ij} \cdot \ln e_{jt}) + \alpha_1 \ln(y_{it}) + \alpha_2 \ln(pel_{it}) + \alpha_3 \ln(pengas_{it}) + \alpha_4 \ln(hss_{it}) + \alpha_5 \ln(hdd_{15it}) + \alpha_6 \ln(cdd_{22it}) + \alpha_7 \times \text{time} + u_{it}
\]

\[
u_{it} = \rho \sum_{i=1}^{NT} w_{it} \cdot u_{it} + \epsilon_{it}
\]

\[
\epsilon_{it} = \mu_i + \nu_{it}
\]

where \( w_{ij} \cdot \ln e_{jt} \) is the weighted average of residential electricity consumption of the neighbouring provinces, \( \lambda \) is the spatial autoregressive parameter and the term \( u_{it} \) defined as the \( NT \times 1 \) vector of spatially lagged residuals. Let it be noted that, since electricity consumption and the regressors are in logarithms, the coefficients are directly interpretable as demand elasticities. Table 1 gives some details on the explanatory variables employed in the analysis.

[Insert Table 1 about here]

The price is measured as average price. The income variable is measured as the disposable income available for the sector “households”, expressed in real terms. The variable population stands for the total population in each province \( i \) in year \( t \). Household size is included in the model to capture the impact of the number of members per household on the demand for electricity. This size has been calculated as the ratio between the population and the number of principal houses and a negative sign is expected for its coefficient. To account
for the impact of natural gas on electricity demand, we introduce the penetration rate of gas into the equation (1), measured as the number of gas consumers divided by number of houses. The number of heating degree days and cooling degree days are used to measure the effect of climate on electricity demand.

3. Econometric analysis

As anticipated previously, for the estimation of Spanish domestic electricity demand equation (2) we will use a SARAR model for panel data proposed by Kapoor et al. (2007). It has to be noted that the estimation of a SARAR model with panel data that consider the unobserved heterogeneity through a fixed effect or random effect model can be performed using a General Methods of Moments (GMM) approach or a Maximum Likelihood (ML) approach. Generally, the ML approach is more often utilized when it comes to the estimation of spatial models. To our knowledge, one of the very few studies which applied a GMM estimator to a SARAR model with panel data was the one by Egger et al., 2005, where the focus was laid on the analysis on unbalanced panel data. The GMM estimator has several advantages over the ML estimator. First, no a priori assumption about on distribution of the residuals has to be made. Second, additional endogenous variables can be used on the right-hand side of the model, which is more cumbersome in the ML setting. For this reason, in this paper we have decided to performance the empirical analysis by using a GMM approach. The general econometric model can be formulated in matrix notation as

\[
y = \lambda \times (W \otimes I_T)y + X \beta + u
\]

\[
u = \rho \times (W \otimes I_T)u + \varepsilon
\]

\[
\varepsilon = \mu \otimes e_T + v
\]

(3)

with \( N \times 1 \) vector of the dependent variable, being the term \( \lambda \) is the spatial-auto-correlation coefficient (of coefficient of the spatially lagged dependent variable); \( W \) is a \( N \times N \) spatial weighting matrix with all diagonal elements equal to zero; \( \beta \) is the \( K \times 1 \) vector of coefficients of the exogenous regressors and \( u \) is the \( NT \times 1 \) vector of spatially lagged residuals. In the definition of \( u \), \( \rho \) is the spatial auto-regressive coefficient (or coefficient of the spatially lagged residuals); \( I_T \) is a \( TT \times I \) identity matrix; \( \mu \) is the \( NT \times 1 \) vector of individual effects which might be fixed or random, \( \varepsilon \) is the \( NT \times 1 \) vector of i.i.d. residuals; and \( e_T \) is a \( TX \times 1 \) vector of ones. It should be noted, that in the spatial weighting matrix we have two possibilities of normalization: either all row sums are normalized to one or at least the maximum row sum is equalized to one ( e.g. LeSage and Pace, 2009). In this analysis we have decided to normalize
the matrix by the maximum row-sum. In this setting, spatial weight entries in the matrix are decreasing with increasing distance. Figure 1 shows the resulting contiguous spatial matrix.

[Insert Figure 1 about here]

Further, the following assumptions are made in the estimation:

\[
\begin{align*}
E(\mu) &= 0 \\
E(\mu \cdot \mu') &= \sigma^2_{\mu} \cdot I_N \\
E(\nu) &= 0 \\
E(\nu \cdot \nu') &= \sigma^2_{\nu} \cdot I_{NT} \\
E(\nu' \cdot (\mu \otimes e_T)) &= 0 \text{ (for random effects)}
\end{align*}
\] (4)

According to Kapoor et al. (2007), we estimate the model in three steps. Firstly, we need to obtain consistent estimates for the residuals: \( u \). When we do not have a spatially lagged dependent variable, this would be estimated by OLS. With a spatially lagged dependent variable, the estimation is carried out using two-stages-least-squares, using \( X, (W^I \otimes I_T), (W^2 \otimes I_T) \) as instruments for the (endogenous) spatially lagged dependent variable: \( (W \otimes I_T)y \). Secondly, we would find a consistent estimate for the coefficient of the spatially lagged residuals: \( \rho \). In order to do this, one possibility is to apply the respective moment conditions for the panel case using equation (3) (e.g. Kelejian and Prucha, 1998, 1999; Kapoor et al., 2007). Finally, by applying a Cochrane-Orcutt transformation to the model in equation (2) we would obtain Feasible Generalized Least Squares (FGLS) estimators. Of course, before estimating the equation (2) using this spatial econometric approach, we use several Lagrange multiplier tests proposed by Baltagi et al. (2003) and Baltagi and Long (2008) in order to verify the presence of either a spatially lagged dependent variable and/or spatially lagged residuals. The results of these tests confirm the presence of both of them.

4. Estimation Results.

The results of the three estimation stages of the SARAR model are shown in Table 2. Although we consider the high order process that combine the spatial lag with spatial error dependency the best approach, we present individual estimation results both for the spatial lag model and for the spatial lag error model for comparison purposes. The coefficients for the three estimation are shown with the standard errors. Additionally, the standard deviation of \( u \)
and \( e \), as well as the portion of variance due to \( u \), are presented. Moreover, in Table 2 we also show the number of instruments used in the estimation and the R-squared values.

[Insert Table 2 about here]

These results are satisfactory insofar as the coefficients of the price, income and spatially lagged dependent variables are significant and carry the expected signs. In particular, it is noteworthy the significance of disposable income and its corresponding elasticity that is, with a value of 0.64, rather high. And also the high and clearly significant coefficient of the spatial lag variable. These results show, therefore, that spatial effects characterize the residential electricity consumption in Spain. The estimated price elasticity is approximately 0.06, very much in line with the results obtained by Blázquez et al. (2012) applying a dynamic partial adjustment model to Spanish aggregate panel data, and lower that the ones obtained also for Spain in Labandeira et al. (2006) and Labandeira et al. (2011) using household disaggregate data. They are also much more inferior than the ones obtained in the literature for other countries. Moreover, we observe that this extreme price inelasticity is present across all the three models.

The demand for electricity is responsive to the level of income \((y)\) with an elasticity of 0.64 (an intermediate value between 0.53 obtained in the spatial lag model and 0.71 in the spatial error model); again very similar to the coefficient obtained in Blázquez et al. (2012). Since these values are well below unity, income increase (decrease) apparently results in a less than proportional growth (reduction) in electricity demand. While these results are again lower than the ones found in Labandeira et al. (2006) –they found a elasticity of 0.70— they are in consonance with numerous studies for other countries (e.g. Houthakker et al. (1974) for USA, Baker et al. (1989) for UK, Garcia-Cerruti (2000) for California, Leth-Petersen (2002) for Denmark, Hondroyiannis (2004) for Greece, Holtedahl and Joutz (2004) for Taiwan, or Kamerschen and Porter (2004) for USA). They also suggest that improvement in Spanish households' income will not be translated into proportional increases in electrical equipment and, in turn, into proportional electricity consumption, although there still is certain margin for Spanish households to acquire better equipment as they increase their income. Similarly, as typical for necessity goods, decreases in their income will be only partially translated into reductions in electricity demand at home. Nevertheless the coefficients are high enough to indicate a significant effect of possible drops in the households' income on electricity consumption, which could imply, especially for low-income household, important losses of welfare.
We also observe a significant and high spatial contagion effect of the variation in the residential electricity consumption between provinces. And this result is explicit and significant both in spatial lag model and in the high order model, with quite similar coefficients: around 0.7. This coefficient means that, holding all the other variables constant, if the households in the neighbouring provinces increase, on average, by one percent their electricity consumption, we would expect the consumption of residential electricity in the province considered to increase in 0.7 percent. In other words, around 70% of the variation in electricity consumption of one province's neighbours spills over to its own consumption.

4. The impact of the economic crisis on the residential electricity consumption

The results reported in Table 2 can be used to compute the direct impact on electricity consumption of a change in an explanatory variable as well as the spatial impacts of this change. Since in the SARAR model the dependent variable is spatially lagged, it is therefore possible to estimate the direct effect of a change in the disposable income on the electricity consumption of that province as well as, through the coefficient of the spatial lag variable, the indirect effects arising from the change that affect other provinces. The sum of both effects gives the total effect of changes in disposable income on electricity consumption in one province.

Formally, the effects are calculated as follows. We rearrange the econometric model described in equation (2) to:

\[ y = [(I_N - \lambda W)]^{-1}(X \cdot \beta + u) \]  

(5)

From this expression, we can calculate the direct effect of a change in an independent variable occurred in a location on the dependent variable of the same location:

\[ \frac{\partial y_j}{\partial x_{jk}} = [(I_N - \lambda W)]^{-1}_{j,j} \cdot \beta_k \]  

(6)

This expression equals the \( j,j \)-element of the inverse matrix times the respective coefficient.

The total effect can be calculated then as the impact that is produced on a location's dependent variable when an independent variable is simultaneously altered in all locations. This is:

\[ \frac{\partial y_j}{\partial x_k} = [(I_N - \lambda W)]^{-1} \cdot e_N \cdot \beta_k \]  

(7)
which is equal the row-sum of the inverse matrix times the estimated coefficient. The indirect effect then is equal to the difference between the total effect and the direct effect. In table 3 the average values of direct and total effect for the whole country are presented.

[Insert Table 3 about here]

In Table 3 we can observe how this neighbouring factor substantially multiply the direct effect that the own-price and income variations have in the residential electricity consumption. We observe that the income elasticity, on average, almost twofold its impact when spatial contagion is taken into account. When spatial effect considered in the analysis, the response of electricity demand to changes in the disposable income is more than proportional. This means that variations in the households' income occurring in the whole country affects largely to the residential electricity consumption of each of its provinces. In this way, the own-income effect is reinforced by the neighbouring income-effect. And the same comes about with price elasticity, although the demand remains highly inelastic even taking into account the spatial effect. This is logical if we keep in mind that the electricity price variation between Spanish provinces is fairly low.

We can come down one step in our analysis and study the direct effects and the total effects for each of the Spanish provinces in a certain period of time. In particular, in this paper we are interested in analyzing the impact of the change in the disposable income due to the economic crisis on the residential electricity consumption. We are mainly concerned with studying how the regional differentiated growth rate of the disposable income from 2008 to 2009, the first two years of the economic crisis, influenced the electricity consumption across Spanish provinces. Figure 2.1 represents the percentage change in households' disposable income from 2008 to 2009 in the Spanish provinces. The average percentage change in income was -1.8% for all provinces, ranging widely from -18.3% to +11.8%. This variation is represented by the different colour shades in the map. We observe that the provinces most adversely affected by the crisis are located mostly in the North of Spain. Some of them are provinces sparsely populated, with a low disposable income per capita (e.g. Soria, Segovia, Orense, Lugo and Teruel). Asturias, also in the North of the country, suffered a significant fall in its income as well. We can also note that the three Basque provinces (Álava, Vizcaya and Guipúzcoa) and Navarra have seen their income decreases albeit not significantly. These provinces are traditionally among the wealthiest in Spain. On the other side, even in the middle of the crisis, some provinces still maintained positive increases in their households' income. For instance, Madrid and some of their adjacent (and poorer) provinces: Guadalajara,
Toledo and Cuenca; the three of them belonging to the same region. A fourth province from the same region, Albacete, registered also positive figures. The four Catalanian provinces (Barcelona, Tarragona, Lleida and Girona) increased their residential income between 2008-2009, too. Some of Andalusian provinces, especially those sited in the South Western (Seville and Málaga) improved their income as well. And other provinces like Zaragoza, León, Salamanca and La Coruña augmented their income in more than 1%.

Figure 2.2 represents for each of the provinces the total effect of the change in the disposable income on residential electricity consumption (sum of direct and indirect effect). The figures 2.3 and 2.4 decompose this total effect into two other effects: a direct effect, showed in Figure 2.3., i.e. the change in a province's electricity consumption resulting from changes in its own income; and an indirect effect, represented in Figure 2.4, i.e., the change in residential electricity consumption resulting from changes in the income of the considered province's neighbours.

Firstly, we observe in Figure 2.2 that, similarly to the growth rate of disposable income, the sensitivity of the residential electricity consumption to the changes in the households’ disposable income is quite heterogeneous across Spanish territory: from -6.0 per cent of Soria to +3.0 of Málaga. We note for the majority of provinces a positive relation between the growth rate of the disposable income and the effect of this on the residential electricity consumption. The coloured map in Figures 2.1 and 2.2. are quite similar. Additionally, we can see that, in general and with the exception of Soria, in those provinces that have suffered a higher contraction of their disposable income the effect on their residential electricity consumption has been lower than the positive reaction that electricity consumption has had in those provinces where disposable income has grown.

We can also see in Figures 2.3 and 2.4 that in the majority of cases, independently on the direction of the change in disposable income, in those provinces that have been the most or the least adversely affected by the crisis the indirect effect has reinforced the direct effect; and in most cases the direct effect is superior to the indirect effect. In the intermediate cases, both effects frequently compensate to each other. We also observe that the positive spatial effect is more intense in the Central and Southern provinces of Spain. In the North, the indirect effect is only significantly positive in the Eastern provinces. In the rest of the Northern provinces the spatial effect has been mainly negative, although less intense than spatial effect registered in the those provinces with positive indirect effect.
Going further into details, it is noteworthy the positive spatial effect that display the majority of the provinces around Madrid, especially those located in the South of the capital. The increase in the growth rate of disposable income in Madrid has positively influenced the electricity consumption in these provinces bordering this province (and vice versa). Many people who live in these surrounding provinces work (or used to work) in the capital, especially in the construction sector or in industries with strong linkages to this sector, and, therefore, the economic activity is these provinces is very much affected by the performance of Madrid. This seems to be also the case of other provinces bordering other main Spanish cities like Barcelona or Seville. On the other extreme, we also note the significant negative spatial effect among the three provinces of the Basque Country and others surrounding this region like La Rioja, Navarra, Burgos and Cantabria, where the contagion effect has compensated their own positive direct effect. All these provinces have very intense economic linkages between them and especially with the industrial centres of the Basque Country.

Additionally, the configuration of the map in Figure 2.4 could be conditioned by the spatial distribution of the electricity companies in Spain. For example in the whole Andalusian territory, Badajoz, and Catalonia the main distribution company is Endesa. In those three areas we observe an intense positive spatial effect. Also, an important portion of the South of Madrid and other bordering provinces of the capital like Toledo, Cuenca, Guadalajara and Segovia share the same distribution company: Gas Natural. Therefore, the policy applied by these common operator could also influence on the behaviour of household. Nevertheless, there should be kept in mind that most of the Spanish households still remain contracting massively the same regulated tariff, and therefore the action of companies is not very much active.

5. Concluding Remarks

In this paper we have estimated the price and income elasticity for Spanish residential electricity demand, considering the presence of spatial effects. In order to do this, we have applied spatial econometric methods in the estimation of energy demand; in particular a spatial autoregressive model with autoregressive disturbances (SARAR). We have used an aggregate panel data set on the 46 mainland Spanish provinces for the period 2001 to 2009. Additionally, we have analyzed the impact of the change of the disposable income observed during the crisis period 2008-2009 on the electricity consumption in the Spanish provinces, distinguishing a direct and an indirect (spatial) effect.
The empirical results show a high, although less than one, income elasticity and a relative low own-price elasticity. This would indicate a very modest impact of electricity price variation on the residential electricity demand and a significant effect of possible variations in the households' income on it. We have also found the prevalence of a high spatial contagion effect of the variation in the residential electricity consumption between neighbouring provinces. In particular, the own-income effect is strongly reinforced by the neighbouring income-effect. This result is especially relevant during periods of economic crisis such as the one Spain is undergoing in recent years.

The average percentage change in income was very despair across Spanish provinces during the first two year of the economic crisis (2008-2009), with provinces located mostly in the North of Spain suffering the most significant drops while other provinces still enjoyed positive growth rates. As expected, in those provinces that have suffered a higher contraction of their disposable income the effect on their residential electricity consumption has been lower than the positive reaction that electricity consumption has had in those provinces where disposable income has grown. In any case, in those provinces that have been the most or the least adversely affected by the crisis the spatial effect has reinforced the direct effect. We have also found an significant spatial effect, both positive and negative, exerted by principal Spanish provinces in terms of population and/or economic activity in those provinces bordering them.
References


Table 1: Definition of variables and descriptive statistics (2000-2009)

<table>
<thead>
<tr>
<th>Variables</th>
<th>1. Quartile</th>
<th>2. Median</th>
<th>3. Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity consumption (kWh)</td>
<td>451,834,000</td>
<td>788,745,000</td>
<td>1,384,952,000</td>
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<tr>
<td>Electricity Price (€/kWh)</td>
<td>0.081</td>
<td>0.101</td>
<td>0.111</td>
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<td>Disposable Household Income (thousand 2006 €)</td>
<td>4,126,600</td>
<td>6,744,543</td>
<td>12,300,000</td>
</tr>
<tr>
<td>Population</td>
<td>356,437</td>
<td>580,077</td>
<td>955,045</td>
</tr>
<tr>
<td>Household size (HS)</td>
<td>2.633</td>
<td>2.732</td>
<td>2.856</td>
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<td>Penetration Gas (%)</td>
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<td>0.115</td>
<td>0.263</td>
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<td>Heating degree days (HDD) 15</td>
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<td>969</td>
<td>1,486</td>
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<td>Heating degree days (HDD) 18</td>
<td>1,167</td>
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<tr>
<td>Cooling degree days (CDD) 22</td>
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<td>191</td>
<td>356</td>
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<tr>
<td>Cooling degree days (CDD) 18</td>
<td>311</td>
<td>587</td>
<td>920</td>
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Table 2. Estimation Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Spatial Lag Model</th>
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<th>Spatial Error Model</th>
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<th>Total Spatial Regression</th>
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<td></td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>p-value</td>
<td>Coefficient</td>
<td>Std. Error</td>
<td>p-value</td>
</tr>
<tr>
<td>Constant ($\alpha_0$)</td>
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<td>3.172</td>
<td>-0.460</td>
<td>1.890</td>
<td>1.396</td>
<td>1.350</td>
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<tr>
<td>W1_lnel ($\lambda$)</td>
<td>0.744</td>
<td>0.127</td>
<td>5.850</td>
<td>0.713</td>
<td>0.120</td>
<td>5.930</td>
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<td>Lny ($\alpha_1$)</td>
<td>0.530</td>
<td>0.126</td>
<td>4.210</td>
<td>-0.081</td>
<td>0.031</td>
<td>-2.590</td>
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<tr>
<td>Lnpel ($\alpha_2$)</td>
<td>-0.055</td>
<td>0.025</td>
<td>-2.160</td>
<td>-0.512</td>
<td>0.277</td>
<td>-1.850</td>
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<td>pengas ($\alpha_3$)</td>
<td>-0.374</td>
<td>0.283</td>
<td>-1.320</td>
<td>-0.493</td>
<td>0.291</td>
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<tr>
<td>Lnhs ($\alpha_4$)</td>
<td>0.032</td>
<td>0.048</td>
<td>0.670</td>
<td>0.020</td>
<td>0.048</td>
<td>0.420</td>
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<tr>
<td>Lnhd ($\alpha_5$)</td>
<td>0.072</td>
<td>0.030</td>
<td>2.410</td>
<td>0.059</td>
<td>0.036</td>
<td>1.660</td>
</tr>
<tr>
<td>Lnhd2 ($\alpha_6$)</td>
<td>0.013</td>
<td>0.007</td>
<td>1.790</td>
<td>0.018</td>
<td>0.010</td>
<td>1.830</td>
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<tr>
<td>time ($\alpha_7$)</td>
<td>0.012</td>
<td>0.006</td>
<td>2.020</td>
<td>0.017</td>
<td>0.004</td>
<td>3.990</td>
</tr>
<tr>
<td>Spatially lagged residuals ($\rho$)</td>
<td></td>
<td></td>
<td>0.796</td>
<td>0.028</td>
<td>0.281</td>
<td>0.007</td>
</tr>
<tr>
<td>$\sigma_u$</td>
<td>2.935</td>
<td></td>
<td>0.655</td>
<td></td>
<td>2.482</td>
<td></td>
</tr>
<tr>
<td>$\sigma_e$</td>
<td>0.069</td>
<td></td>
<td>0.071</td>
<td></td>
<td>0.071</td>
<td></td>
</tr>
<tr>
<td>Fraction of variance due to $u$</td>
<td>0.999</td>
<td></td>
<td>0.988</td>
<td></td>
<td>0.999</td>
<td></td>
</tr>
<tr>
<td>$R^2$  within</td>
<td>0.739</td>
<td></td>
<td>0.386</td>
<td></td>
<td>0.634</td>
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<tr>
<td>$R^2$ between</td>
<td>0.025</td>
<td></td>
<td>0.997</td>
<td></td>
<td>0.274</td>
<td></td>
</tr>
<tr>
<td>$R^2$ overall</td>
<td>0.023</td>
<td></td>
<td>0.997</td>
<td></td>
<td>0.267</td>
<td></td>
</tr>
<tr>
<td>Number of instruments</td>
<td>32</td>
<td></td>
<td>32</td>
<td></td>
<td>32</td>
<td></td>
</tr>
</tbody>
</table>

* $W1_{lnel}$ is the weighted average of residential electricity consumption of the neighboring provinces; $y$ is real disposable income of the household sector; $pel$ is the price of electricity; $hss$ is household size; $pengas$ is the gas penetration rate; $hdd$ and $cdd$ are, respectively, the heating degree days and the cooling degree days; $time$ is the time trend.
Table 3. Direct Effect and Total Effect. Average Values\textsuperscript{a}

<table>
<thead>
<tr>
<th>Income elasticity</th>
<th>Direct Effect</th>
<th>Total Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Spatial lag Model</td>
<td>Total Spatial Regression</td>
</tr>
<tr>
<td>Income elasticity</td>
<td>0.530</td>
<td>0.639</td>
</tr>
<tr>
<td>Price elasticity</td>
<td>-0.055</td>
<td>-0.061</td>
</tr>
</tbody>
</table>

\textsuperscript{a} Income and price elasticities are calculated according to expressions (6) and (7).
Figure 2.1. Percent Change in Spanish Households' Disposable Income (2008-2009)

Figure 2.2. Total Effect of Change in Household Disposable Income on Residential Electricity Consumption. (2008-2009). Percentage Points.
Figure 2.3. Direct Effect of Change in Household Disposable Income on Residential Electricity Consumption. (2008-2009). Percentage Points.

Figure 2.4. Indirect Effect of Change in Household Disposable Income on Residential Electricity Consumption. (2008-2009). Percentage Points.