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Provinces: A Spatial Econometric Analysis

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The Economic Crisis and Residential Electricity Consumption in Spanish Provinces: A Spatial Econometric Analysis

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Abstract

This paper presents an empirical analysis of residential electricity demand considering the existence of 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 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 household disposable income variation across provinces observed during the economic crisis period from 2008-2009. The estimation results show relatively high income elasticity and relatively low price elasticity. Furthermore, the results show the presence of spatial effects in Spanish residential electricity consumption.

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The Economic Crisis and Residential Electricity Consumption in Spanish Provinces: A Spatial Econometric Analysis

1. Introduction

Since the turn of the century, the Spanish economy has experienced a period of rapid growth followed in 2008, as in other European countries, by a period of recession. During the period of economic prosperity leading up to the crisis, the annual growth rate of Spanish household disposable income was approximately 6-7% (in nominal terms), whereas in 2009 the growth rate was only 0.94%. It should be noted that due to relatively different regional socioeconomic structures, disposable income growth rates are heterogeneous across Spanish regions and provinces. Indeed, during the economic crisis we can find provinces that still experience a positive growth rate of household disposable income while others are characterized by a significant decrease of disposable income (Ortega and Peñalosa, 2012; INE, 2012). These changes in the growth rates of regional household disposable income naturally have an impact on energy consumption and, therefore, on electricity consumption. In some cases, the decrease of disposable income determined serious effects on the welfare of a household. For instance, during the years of economic crisis, an increase in the number of households facing serious difficulties to adequately satisfy their energy necessities has been observed (Tirado et al., 2012).[1]

The impact of the change in the growth rate of regional household disposable income on residential electricity consumption is also expected to be different across provinces. The reasons for this spatial differentiation are the following. First, as already mentioned, the growth rate of household disposable income shows a relatively high heterogeneity across provinces. Second, due to the socioeconomic relations between provinces, we can hypothesize the presence of spatial spillovers and spatial clusters in electricity consumption. For instance, electricity consumption in one region can be influenced by the lifestyle of the households in neighbouring provinces. One might imagine a phenomenon of imitating neighbours that can produce "spillovers" in electricity consumption behaviour as well as in the adoption of more electrical appliances or of new energy-efficient appliances. This behaviour can create spatial clusters in the adoption and use of electrical appliances, and therefore, in electricity consumption. From a theoretical point of view, these types of behaviours assume that

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[1] This percentage is estimated to be around 10%. Moreover, during recent years the share of energy expenditure in total household expenditure has increased steadily (Ministry of Agriculture, Food and Environment, 2012).

consumption preferences are not separable across households.[2] Another spatial economic effect could arise from the presence of workers living in one region but working in adjacent or nearby provinces. This effect could also develop from those who have a strong economic dependence on what occurs in bordering territories, even though they do not work there. In this case, a change of the economic situation in one province would also have an impact on the socioeconomic situation in neighbouring provinces and, therefore, on electricity consumption. Finally, since the majority of energy policies are implemented in Spain at the regional level, one could suppose that policy measures taken in one province have certain influence in the surrounding territories.[3]

In this paper we argue that due to the presence of spillover effects in electricity consumption it is important to use a spatial econometric approach in the empirical analysis. In fact, unobservable variables may be spatially correlated and consumption patterns observed in neighbouring provinces may also be correlated with local consumption. As a consequence, standard estimation procedures like Ordinary Least Squares (OLS) can lead to bias and inefficiency in the estimates (e.g. Anselin et al., 2008; LeSage and Pace 2009; and Anselin, 2010).

From an energy economics point of view, the presence of possible spatial effects in electricity consumption has been so far neglected. Since the pioneer work of Houthakker (1951), a relatively high number of studies on estimating residential demand for electricity have been published.[4] Most of the published works focus on calculating short and long-run price and income elasticities. Many of these estimations use aggregate regional panel data sets and static as well as dynamic specifications of the electricity demand model (e.g., Houthakker, 1980; Hsing 1994; Maddala et al., 1997; Bernstein and Griffin, 2006; Paul et al., 2009 and Alberini and Filippini, 2011). Most of these studies are for the US and provide an estimation of the price and income elasticities that do not vary across regions. One exception is the study by Bernstein and Griffin (2006), who found significant regional differences in price elasticity values. For Spain, the only study estimating residential electricity demand using aggregate panel data is the one 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

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[2] For a discussion and review of the literature on the separability and non-separability assumption of the preferences across households see Varian (1974), Ravina (2008) and Alvarez-Cuadrado et al. (2012). Ravina (2008) and Alvarez-Cuadrado et al. (2012), using micro-data, based the construction of their reference group on a purely geographical criterion as long as the reference group of any given household is compared with the other households that live in the same census tract. Both works find that households derive around one fourth of their consumption services from comparison between their consumption and that of their neighbours.
[3] See LeSage and Pace (2009) for a detailed overview on the different types of spatial effects (spillovers).
[4] For a systematic review of these papers see Heshmati (2012).

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 the two-steps system GMM estimator proposed by Blundell and Bond (1998).

To our knowledge, none of the studies published on residential electricity demand using aggregate regional data has taken into account spatial effects. One exception is the study 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 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. In this respect, this paper seeks to explore the use of spatial econometric methods in the estimation of static electricity demand models estimated using aggregate regional data. Therefore, the main difference of this paper with respect to the one by Blázquez et. al. (2012) is the use of a static and spatial econometric approach.

The aim of this paper is, therefore, to estimate price and income elasticities for Spanish residential electricity demand by considering the presence of spatial effects. Additionally, we intend to analyze the impact of the change in household disposable income observed during the economic crisis period (2008-2009) on electricity consumption in 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) and we will employ a panel data set that considers 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 is explained. In section 4 the empirical results are discussed. Some concluding remarks appear in section 5 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 should include the following explanatory variables: the price of electricity, the price of substitutes, the capital price (electrical appliances), income and some

socioeconomic and climate variables. It should be highlighted that due to missing information, only a few studies consider the capital price as an explanatory variable.[5]

Based on previous studies and on the available data, we specified the following static residential electricity demand model:[6]

$$el_{it} = f(y_{it}, pel_{it}, pengas_{it}, pop_{it}, hdd_{it}, cdd_{it}, time) \tag{1}$$

where el_{it} is aggregate electricity consumption for province i in period t; 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[7] in Euros (Base: 2006=100); pop_{it} is population; and $pengas_{it}$ is the percentage of households that have access to gas. This variable is used as a proxy for the unavailable price of gas. Of course, one could expect that an increase in electricity consumption could have a negative impact on the number of households interested in gas consumption. In this case, this variable would become endogenous. As we will discuss later, this problem has been taken into account in the econometric analysis. Additionally, to measure the effects of climate on electricity demand, the heating degree days (hdd_{it}) and the cooling degree days (cdd_{it}) for province i in year t are considered, with 15°C as the threshold for heating and 22°C for cooling. Finally, $time$ is a time trend to capture a time specific effect. We expect a negative sign for the coefficients of the electricity price and gas penetration rate, and a positive sign for the coefficients of disposable income, population and climate variables.

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

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[5] It should be noted that generally, the regional variation of the capital price is relatively homogenous. Therefore, the impact of this variable should be captured by the constant term. Furthermore, the price of electrical appliances does not generally vary across regions.

[6] For a more detailed discussion of the model specification and variables see also Bláquez et al. (2012).

[7] The Spanish tariff scheme for domestic electricity consumption is a two-part tariff system, regulated in the majority of cases. This tariff is composed of two elements: a fixed monthly charge (or power term), which is based on the level of contracted power and the (regulated) price per kWh. In this case, the level of the average electricity price depends both on the amount of electricity consumed and on the level of power contracted and this could create an endogenous problem. Nevertheless, Bernstein and Griffin (2005); Paul et al. (2009); Filippini and Alberini (2011); and Bláquez et. al. (2012) argue that, at the aggregate level, the potential for the price to be endogenous with consumption is mitigated by the presence of many different regulated block pricing levels, in our case many power block pricing levels. In order to verify the endogeneity of price, we performed the Davidson-MacKinnon test. The result of this test indicates that this variable should be considered exogenous (p-value=0.16).

and Prucha (1998) and Kapoor et al. (2007). Furthermore, the empirical analysis has been performed using panel data for 46 Spanish provinces for the period from 2001 to 2009.[8]

In this model, the spatially lagged dependent variable and the spatial autocorrelation term capture the spatial dependence between provinces. Therefore, the spatial econometric specification of equation (1) is the following:

$$\ln el_{it} = \alpha_0 + \lambda \sum_{i=1}^{NT}(w_{ij} \cdot lnel_{it}) + \alpha_1 \ln(y_{it}) + \alpha_2 \ln(pel_{it}) + \alpha_3 \ln(pengas_{it}) +$$

$$\alpha_4 \ln(pop_{it}) + \alpha_5 \ln(hdd_{15_{it}}) + \alpha_6 \ln(cdd_{22_{it}}) + \alpha_7 time + u_{it}$$

$$u_{it} = \rho \sum_{i=1}^{NT} w_{it} \cdot u_{it} + \varepsilon_{it}$$

$$\varepsilon_{it} = \mu_i + v_{it} \tag{2}$$

where $w_i \cdot lnel_{it}$ is the weighted average of residential electricity consumption of each of i's neighbouring provinces, λ is the spatial autoregressive parameter and the term u_{it} is defined as the $NT \times 1$ vector of spatially lagged residuals.

The decision to estimate equation (1) using a spatial econometric approach is supported by the results of several statistical tests on the presence of either a spatially lagged dependent variable and/or spatially lagged residuals. For instance, we used several Lagrange multiplier tests proposed by Baltagi et al. (2003) and Baltagi and Long (2008). The results of these tests confirm the presence of both spatial effects.[9]

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]

3. Econometric analysis

As previously anticipated, for the estimation of Spanish domestic electricity demand equation (2) we will use the SARAR model for panel data proposed by Kelejian and Prucha

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[8] Due to missing information on climate variables, the province of Palencia has not been considered in the analysis.
[9] The Moran I test as described in Kelejian and Prucha (2001) rejects the null hypothesis of no spatial autocorrelation below the 1% level (p-value: 0.0000). Additionally, the conditional Lagrange multiplier test (Baltagi et al., 2003) rejects the same null hypothesis below the 1% level (p-value: 0.0062). And, finally, the conditional Lagrange multiplier test (Baltagi and Long, 2008) rejects the null hypothesis of no spatial lag dependence below the 1% level (p-value: 0.0032).

(1998) and Kapoor et al. (2007). It should be noted that the estimation of a SARAR model with panel data that considers the unobserved heterogeneity through a fixed or random effect model can be performed using a General Methods of Moments (GMM) approach and a Maximum Likelihood (ML) approach. Generally, most of the studies utilize the ML approach. To our knowledge, one of the very few studies which applied a GMM estimator to a SARAR model with panel data is the one by Egger et al. (2005). In our view, the GMM estimator has several advantages over the ML estimator. First, no a priori assumption on the distribution of the residuals has to be made. And second, in a GMM framework the treatment of several endogenous variables is less problematic than in the ML setting. As mentioned before, in our model the variable related to gas penetration is considered, as in Blázquez et al. (2012), as endogenous. For this reason, in this paper we decided to use a GMM approach.[10] The general econometric model can be formulated in matrix notation as follows:

$$y = \lambda \cdot (W \otimes I_T)y + X \cdot \beta + u$$

$$u = \rho \cdot (W \otimes I_T)u + \varepsilon$$

$$\varepsilon = \mu \otimes e_T + v \tag{3}$$

with N cross-sectional units observed over T periods of time. In expression (3) y is the $NT \times 1$ vector of the dependent variable, with the term λ being the spatial-auto-correlation coefficient (or coefficient of the spatially lagged dependent variable); W is a $N \times N$ spatial weighting matrix with all diagonal elements equal to zero; β is the $K \times 1$ vector of coefficients of the exogenous regressors, X; and u is the $NT \times 1$ vector of spatially lagged residuals. In the definition of u, ρ is the spatial auto-regressive coefficient (or coefficient of the spatially lagged residuals); I_T is a $T \times T$ identity matrix; μ is the $N \times 1$ vector of individual effects which might be fixed or random; v is the $NT \times 1$ vector of i.i.d. residuals; and e_T is a $T \times 1$ vector of ones. In order to choose between the random and the fixed effects model, we performed the Hausman test. The result of this test confirms the superiority of the fixed effects model.[11] Therefore, we decided to estimate the SARAR model using a fixed effects approach.

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

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[10] It should be noted that STATA does not contain a code for the estimation of the SARAR model using GMM. For this reason a special STATA code has been developed.
[11] p-value = 0.0000.

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]

Furthermore, for the estimation of the general model (3), the following assumptions are made:

$$E(\mu) \qquad = 0$$

$$E(\mu \cdot \mu') \qquad = \sigma_\mu^2 \cdot I_N$$

$$E(v) \qquad = 0$$

$$E(v \cdot v') \qquad = \sigma_v^2 \cdot I_{NT}$$

$$E\big(v' \cdot (\mu \otimes e_T)\big) = 0 \text{ (for random effects)} \qquad (4)$$

According to Kapoor et al. (2007), we can estimate the model in three steps. Firstly, we need to obtain consistent estimates for the residuals: u. If we did not have a spatially lagged dependent variable, this could be estimated by OLS. With a spatially lagged dependent variable, the estimation is carried out using two-stages-least-squares, using X, $X(W^1 \otimes I_T)$ and $X(W^2 \otimes I_T)$ as instruments for the (endogenous) spatially lagged dependent variable: $(W \otimes I_T)y$. These instruments are also used for the second endogenous variable, i.e. gas penetration.[12] Secondly, we need to find a consistent estimate for the coefficient of the spatially lagged residuals: ρ. In order to do this, we used a GMM approach as proposed by Kapoor et al., 2007. Finally, λ and β in equation (3) are estimated using a Feasible Generalized Least Squares (FGLS) estimator.

4. Estimation results

The estimation results of the SARAR model are shown in the third column of Table 2. For comparison purposes, in this table we also report the estimation results obtained using fixed effects spatial lag model and a fixed effects spatial lag error model. The coefficients of the three econometric specifications are showed with the standard errors. Additionally, in the same table we report the standard deviation of u and e, the portion of variance due to u, the number of instruments used in the estimation and the R-squared values.

[Insert Table 2 about here]

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[12] In order to verify the endogeneity of this variable, we performed the Davidson-MacKinnon test. The result of this test indicates that this variable should be considered endogenous (p-value=0.0000).

The results are satisfactory insofar as most of the coefficients are significant and carry the expected signs. In all models the coefficients of the price and income variables as well as the coefficients of the spatially lagged dependent variables and of the spatial error term are significant. These latter results show, therefore, that spatial effects characterize residential electricity consumption in Spain. Furthermore, in all models the values of the R^2 are relatively high.

The values of the coefficients of the three models are generally similar. As already discussed, from the econometric point of view the SARAR model is superior to the other two models because it considers the presence of spatial effects through both the spatial lag and the spatial error. Therefore, all further analysis focuses on the results obtained using the SARAR model.

Electricity demand is responsive to income level (y) with an elasticity of 0.66. The value of this elasticity is similar to the values obtained for Spain by Blázquez et al. (2012) and Labandeira et al. (2006), and for other countries such as the US by Kamerschen and Porter (2004) and Greece by Hondroyiannis (2004). The value of this coefficient shows that a variation in disposable income—for instance, a decrease in disposable income due to the economic crisis—will have a relatively substantial effect on electricity consumption. As we will show later, this effect is heterogeneous across Spanish provinces.

The estimated price elasticity is relatively small (0.06). This value is in line with the value 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. This value indicates that residential electricity demand is extremely price inelastic. There are two possible reasons for this low price elasticity value. First, residential electricity prices in Spain are fairly low and stable for the period analysed. And second, due to the tariff structure applied in Spain, the within and between variation of the average electricity price is relatively low. As discussed in Clark and Linzer (2012), this low variation could create some problems in the estimation of the price coefficient value. In particular, a low within variation of a variable might render the estimate of the respective coefficient to be highly imprecise. Theoretically, the coefficient will be unbiased but exhibit a relatively high variance.

Finally, we also observe a significant and relatively high coefficient value of the spatial lag variable. The coefficient value of this variable implies that, holding all the other variables constant, if household electricity consumption in neighbouring provinces increases

by one percent, then the consumption of residential electricity in the province considered will increase by 0.65 percent.

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

The results reported in Table 2 can be used to compute the direct impact of a variation in an explanatory variable on electricity consumption as well as, by using the coefficient of the spatial lag variable, the indirect impact of this change. In this paper we are particularly interested in analysing the direct and indirect impact of disposable income variation determined by the economic crisis during the first two years of the economic crisis (2008-2009) on residential electricity demand. The sum of both impacts gives the total impact of a change in disposable income on electricity consumption in each province.

In most Spanish regions the economic crisis has resulted in a decrease of household disposable income from 2008 to 2009. However, in some regions household disposable income increased. Similarly, we will show that the impact of the economic crisis on regional residential electricity demand has also been heterogeneous. As we will discuss in more detail later, most of the regions that experienced a decrease of disposable income during the crisis also showed a decrease of electricity demand and most of the regions that experienced an increase in disposable income during the crisis also showed an increase in electricity demand. However, we also identified regions characterized by a decrease of disposable income and an increase in electricity demand. These counterintuitive effects can be explained, at least partially, by the presence of important positive consumption spatial effects.

Formally, the direct, indirect and total effects are calculated as follows. We rearrange the econometric model described in equation (3) to:

$$y = [(I_N - \lambda W)]^{-1}(X \cdot \beta + u) \tag{5}$$

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

$$\frac{\partial y_j}{\partial x_{jk}} = [(I_N - \lambda W)]^{-1}_{j,j} \cdot \beta_k \tag{6}$$

This expression equals the *j,j*-element of the inverse matrix multiplied by 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:

$$\frac{\partial y_j}{\partial x_k} = [(I_N - \lambda W)]^{-1} \cdot e_N \cdot \beta_k \tag{7}$$

which is equal to 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 the following, we used equations (6) and (7) to compute the direct, indirect and total effects of the change of the disposable income from 2008 to 2009 on electricity consumption for each Spanish province.

Figure 2 represents the percentage change in household disposable income from 2008 to 2009 in the Spanish provinces. The average percentage change in income was 0.4% for all provinces, ranging widely from -9.2% to 4.6%. 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 sparsely populated provinces, 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 decline in its income as well. We can also note that three Basque provinces (Álava, Vizcaya and Guipúzcoa) and Navarra have seen their income decrease albeit not significantly. These four provinces are traditionally among the wealthiest in Spain. On the other hand, even in the middle of the crisis, some provinces such as Madrid, Guadalajara, Toledo and Cuenca or the four Catalonian provinces of Barcelona, Tarragona, Lleida and Girona continued to maintain positive increases in household income

[Insert Figure 2 and 3 about here]

Figure 3 represents the total effect of disposable income variation on residential electricity consumption (sum of direct and indirect effect) for each of the provinces. Figures 4 and 5 show the decomposition of this total effect into two other effects: a direct effect, i.e. the change in a province's electricity consumption resulting from changes in its own income; and an indirect effect, i.e. the change in residential electricity consumption resulting from changes in the income of the considered neighbours' provinces.

Firstly, we observe in Figure 3 that, similarly to the growth rate of disposable income, the sensitivity of residential electricity consumption to changes in household disposable

income is quite heterogeneous across Spanish territory: from -5.4% in Soria to +2.6% in Málaga. For the majority of the provinces we observe a relationship between the growth rate of disposable income and the effect of this on residential electricity consumption moving in the same direction. The coloured maps in figures 2 and 3 are quite similar, which means that, in general, those provinces more severely affected by the crisis are the provinces that have reduced their electricity consumption to a higher extent. Furthermore, the provinces with a positive disposable income growth rate are the provinces that have increased their electricity consumption to a higher extent.

[Insert Figures 4 and 5 about here]

We can also see in figures 4 and 5 that in the majority of cases and independently from 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. Furthermore, in most of these cases the direct effect is superior to the indirect effect. Finally, we can also observe a group of provinces with a direct effect that is compensated by the indirect effect.

The map depicted in figure 6 shows the change in disposable income for each province as well the direct, indirect and total effects. The provinces shaded in green are those that experienced an increase in disposable income from 2008-2009 and the blue-shaded ones are provinces that had a decrease in disposable income. The bars and the respective numbers display the total, direct and indirect effects of the change in disposable income on electricity consumption. We can observe some provinces that experienced an increase in disposable income but a decrease in electricity consumption due to the total effect of income. This is the case for provinces like La Rioja, which actually experienced an increase in disposable income which is offset by a negative indirect effect arising from the surrounding provinces and which is insufficient to compensate a timid positive direct effect. It can be seen in figure 6 that the surrounding provinces of La Rioja mainly experienced a decrease in disposable income and only a few had a slight increase in disposable income. This leads to an indirect effect of -0.6% which adds up to a total effect of -0.5%. The same holds true for the provinces of Cantabria and Valladolid, although with a less significant indirect effect and total effect.

[Insert Figure 6 about here]

We also observe provinces that experienced a decrease in disposable income (blue-shaded) but an increase in electricity consumption. For instance, let´s consider the province of Granada in the South. According to figure 2, it experienced a decrease in disposable income

by -0.5%. This leads to a direct effect on consumption of -0.3% [0.57·(-0.5%) ≈ -0.3%] where 0.57 is the income elasticity. However, Granada is surrounded by 4 provinces which experienced an increase in disposable income and only by two which had a decrease in income. Therefore, the indirect effect on Granada's electricity consumption is +0.5%, which leads to a total effect of +0.2%. The same mechanism applies for the provinces of Ciudad Real and Córdoba.

The above examples show the importance of considering spatial effects in the estimation of an electricity demand model using aggregate panel data. Concerning these contagion effects, we 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 the spatial effect registered in those provinces with a positive indirect effect. This result could be mainly a reflection of the labour mobility patterns in Spain. During the analysed period, around 12% of contracts were signed by workers whose residence was located in a different province than their workplace. There are three main characteristics of these flows: contiguity character, belonging to the same region and the importance of Madrid as both a sourcing and destination province. Additionally, a general movement between all provinces is observed. It should be noted that in 2009 the sharp decrease in employment especially affected contracts with displacement between provinces (Ministry of Labour and Immigration, 2010 and 2011).

According to these figures, the positive spatial effect that displays the majority of the provinces around Madrid, especially those located to the South of the capital, and the province of Madrid itself is noteworthy. It seems that the increase in the growth rate of disposable income in Madrid has positively influenced the electricity consumption in three of their bordering provinces (Toledo, Cuenca and Ávila) and negatively in Segovia and Guadalajara, although the spatial effect of other neighbouring provinces should also be considered. But it also seems that the provinces surrounding Madrid have positively influenced the electricity consumption of Madrid. It is not a surprise that Guadalajara, Cuenca and Toledo display the highest rate of labour mobility in Spain. This positive spatial effect related to labour mobility is also observed for the case of other provinces bordering other major Spanish cities like Barcelona in the East (all of the Catalonian provinces are very connected among themselves and with other bordering provinces) or Seville and Málaga in the South.

To 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 and Cantabria, where the contagion effect has compensated their own positive direct effect. All of these provinces have very intense economic linkages between them and especially with the industrial centres of the Basque Country.

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 to 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 from 2001 to 2009. Additionally, we have analyzed the impact of household disposable income variation observed during the economic crisis period from 2008-2009 on electricity consumption in 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 residential electricity demand and a significant effect of possible variations in household 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 the one Spain has been undergoing in recent years.

The average percentage change in income during the first two year of the economic crisis (2008-2009) was very despair across Spanish provinces, with provinces located mostly in the north of Spain suffering the most significant drops while other provinces still enjoyed positive growth rates.

The empirical analysis shows that the impact of the change of household disposable income due to the economic crisis on residential electricity demand is quite heterogeneous across the Spanish territory. For the majority of the provinces we observe a positive relation between the growth rate of disposable income and residential electricity consumption. Moreover, the indirect effects, i.e. the spatial effects, seem to be important in explaining the impact of the economic crisis on the residential electricity consumption of some provinces.

Furthermore, the empirical results show that the economic crisis is more severely affecting some regions characterized by a relatively low disposable income per capita and located in relatively cold regions which are precisely the regions that seem to experience the

highest impact on electricity consumption. These regions may be at risk of suffering fuel poverty, a phenomenon that has been increasing in recent years in Spain. Therefore, the results of this paper could be helpful to the authorities in order to design regional differentiated social and energy policy instruments to prevent fuel poverty. So far, there is not a specific strategy in Spain aimed to combat fuel poverty, as there is in other countries like the United Kingdom.

Finally, the regional differentiated income elasticity obtained in this study could be used by electricity companies to forecast the development of electricity demand, and , therefore, to plan investment in production as well as distribution capacity.

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

Variables	1. Quartile	2. Median	3. Quartile
Electricity consumption (kWh)	451,834,000	788,745,000	1,384,952,000
Electricity price (€/kWh)	0.081	0.101	0.111
Household disposable income (thousand 2006 €)	4,126,600	6,744,543	12,300,000
Population	356,437	580,077	955,045
Gas penetration (%)	0.057	0.115	0.263
Heating degree days (HDD) 15	626	969	1,486
Heating degree days (HDD) 18	1,167	1,623	2,217
Cooling degree days (CDD) 22	59	191	356
Cooling degree days (CDD) 18	311	587	920

Table 2. Estimation Results[a,b]

Variables	Spatial Lag Model			Spatial Error Model			SARAR Model		
	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value	Coefficient	Std. Error	p-value
Constant (α_0)	-0.977	3.079	0.751	6.863**	2.920	0.019	-2.054	2.859	0.472
W1_lnel (λ)	0.700***	0.112	0.000				0.650***	0.147	0.000
Lny (α_1)	0.464***	0.126	0.000	0.451***	0.133	0.001	0.575***	0.129	0.000
Lnpel (α_2)	-0.060**	0.025	0.017	-0.094**	0.026	0.000	-0.065**	0.028	0.018
pengas (α_3)	-0.351	0.266	0.186	-0.196	0.278	0.482	-0.440	0.270	0.104
Lnpop (α_4)	0.120***	0.044	0.007	0.168***	0.046	0.000	0.107	0.049	0.40
Lnhdd$_{15}$ (α_5)	0.071**	0.0288	0.014	0.112**	0.115	0.029	0.059**	0.045	0.019
Lncdd$_{22}$ (α_6)	0.014*	0.007	0.053	0.020***	0.007	0.006	0.015*	0.008	0.069
time (α_7)	0.013**	0.006	0.023	0.017***	0.027	0.005	0.012**	0.006	0.036
Spatially lagged residuals (ρ)				0.777**	0.027	0.022	0.275**	0.014	0.032
σ_u	2.750			0.393			2.292		
σ_e	0.068			0.072			0.070		
Fraction of variance due to u	0.999			0.967			0.999		
R^2 within	0.746			0.717			0.652		
R^2 between	0.017			0.958			0.198		
R^2 overall	0.015			0.945			0.191		
Number of instruments	32			32			32		

[a] One, two and three stars indicate statistical significance at 10%, 5% and 1% levels, respectively.
[b] **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.

Figure 1. The Spatial Weighting Matrix
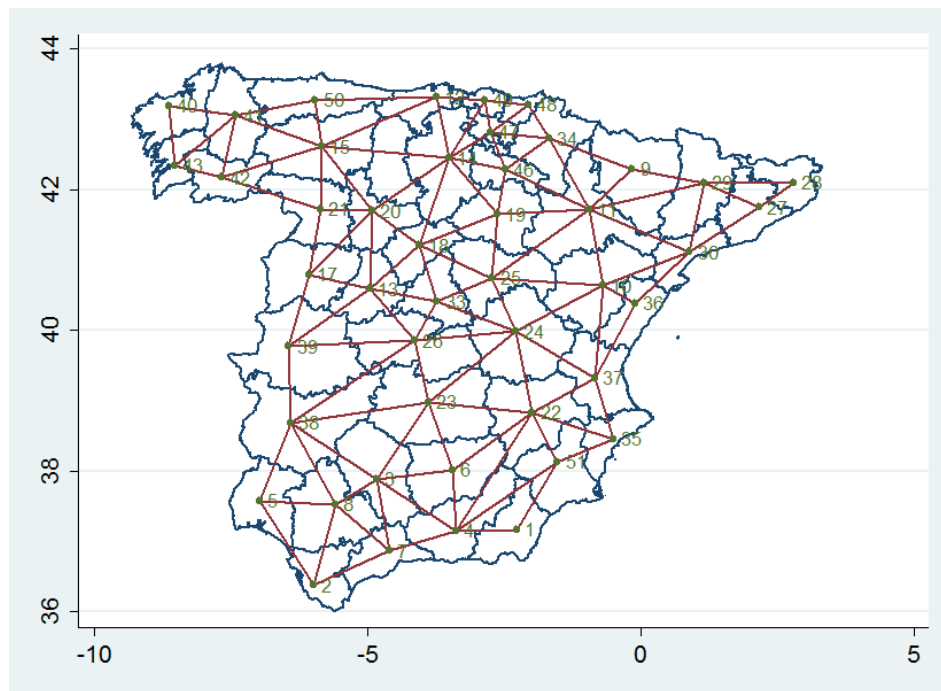
Figure 2. House Disposable Income Variation in Spain from 2008-2009 (%)
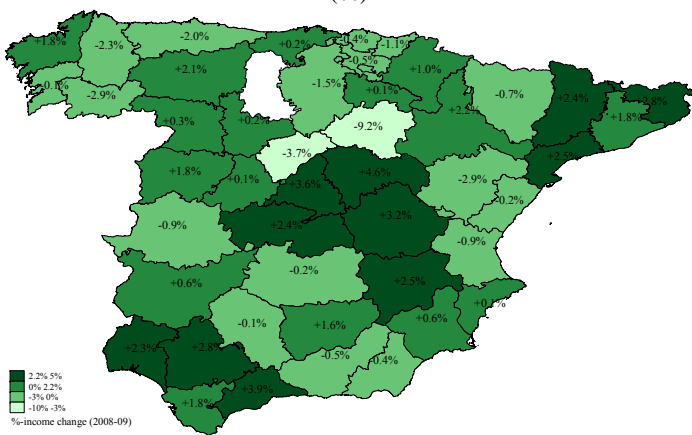
Figure 3. Total Effect of Household Disposable Income Variation on Residential Electricity Consumption from 2008-2009 (%)
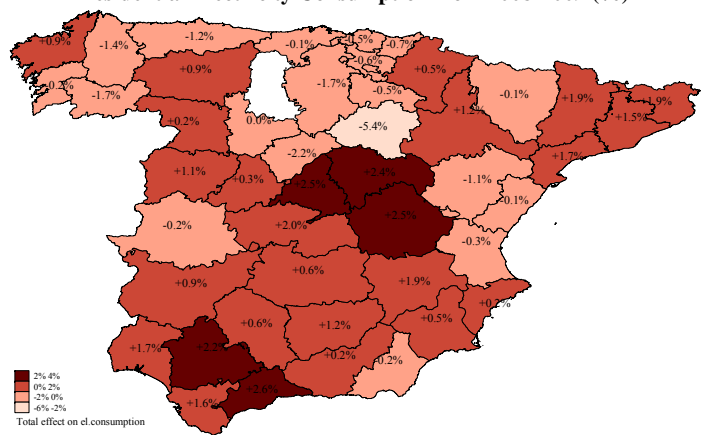
Figure 4. Direct Effect of Household Disposable Income Variation on Residential Electricity Consumption from 2008-2009 (%)
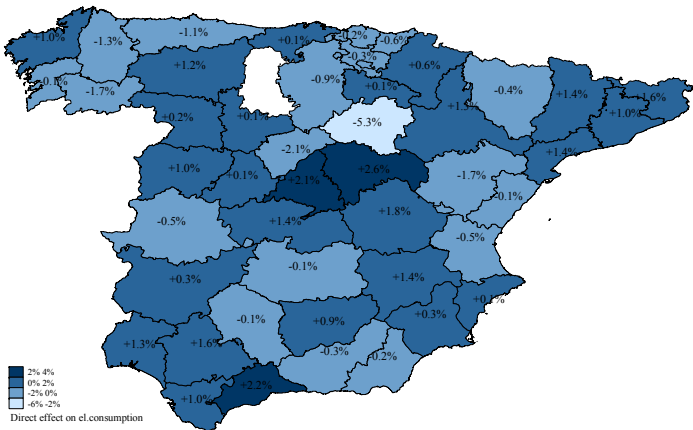
Figure 5. Indirect Effect of Household Disposable Income Variation on Residential Electricity Consumption from 2008-2009 (%)
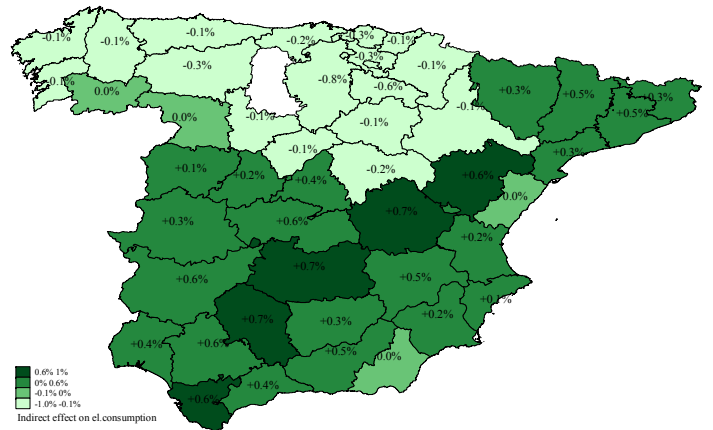
Figure 6. Total, Direct and Indirect Effects of Household Disposable Income Variation on Residential Electricity Consumption from 2008-2009 (%)
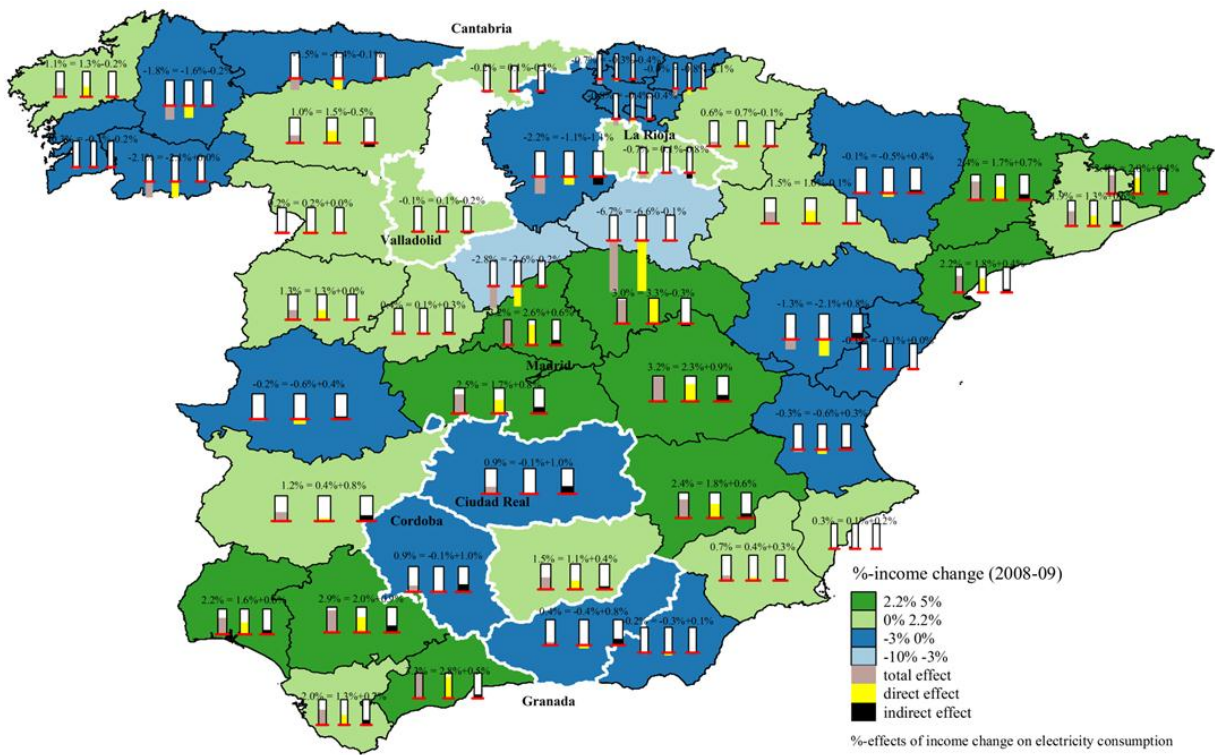
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