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The role of space in the energy-environment nexus: a policy-making perspective

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Introduction

Energy and Environment are two very complex and interconnected systems. Both are extremely important for economic development and for societies' quality of life. The natural environment favours and supports the production of energy resources. Non-renewable primary energy sources, such as oil, coal and natural gas are the results of long natural processes which take millions of years before the resources can be extracted and used. These resources have been and they are still fundamental drivers of economic process and progress, however their production and consumption pose highly costs to natural environment and ultimately on human beings. Oil and coal are the world's leading fuels: oil accounts for a third of global energy consumption and coal equals to 28.1 % (BP report, 2017) but they are also the main responsible for climate change (COP21). Renewable energies are clean resources which are naturally produced such as sunlight, wind, geothermal heat, etc., they represent an important opportunity for energy-shifting, fundamental for the mitigation of climate change. Renewable resources contribution to world energy production is growing, but it is still negligible with respect to the traditional resources.

This thesis aims at contributing to the debate on the link of energy and environment from a political economy point of view. From one perspective, energy production and consumption are dangerous for the environment and policy decision makers need to incentivise internalization of energy externalities. On the other hand, the transition towards renewable resources need to be facilitated by appropriate policy instruments promoting sustainable energy paths. Conventional resources represent a threat for the environment, renewables energies are a concrete clean alternative. On the fossil fuel side, policy interventions are designed to address environmental damages; on the renewable energies side policy makers need to incentivize the development and diffusion of clean technologies. The thesis is structured in three different chapters representing three independent essays. On one hand the three chapters share the same topics of interest and they are linked to one another; on the other hand, they could be singularly read, as autonomous papers. The common topic shared by the three chapters is the analysis of the relationship between energy technologies and environmental aspects, for which this research would like to support the policy decision makers in designing the appropriate policy instruments. Further, the three chapters present empirical techniques adequate to answer the case-to-case research questions.

The **first chapter** is dedicated to fossil fuels energy sources, in particular to environmental damages of coal mining and extraction process. The aim is to empirically assess the effectiveness, efficiency and distributional effects of policies aiming at internalizing coal mining externalities by means of a systematic literature review, which would offer several insights on the right mix of policy instruments to apply for a sustainable path. Whereas some coal combustion externalities are largely addressed, policies for mining and extraction externalities appear less regulated. The coal extraction history evolved rapidly in the last decades. European countries had subsidised the coal extraction to encourage the coal industries production since the second half of last century. Only in the mid-1990s the growing concern for coal environmental effects forced European decision-makers to implement a mixture of reforms to minimize external impacts and stop subsidizing coal prodcution (Steenblik & Coroyannakis, 1995). As a consequence of subsidies stop, some EU countries closed their mines in mid-1990s and started importing coal from abroad. The reduction of subsidies to coal industries in Europe was a sure benefit for the environment but around the world coal industries continued to develop. As a consequence, in the last decade the coal global use seems to experience an inverse tendency. Coal can still offer many advantages for newly industrialized countries: it can be extracted without new technology efforts; it is relatively cheap; and is often locally available. The awareness of external impacts of coal extraction, transport and use is growing but economic forces are still promoting its demand. Forecast increase of world coal demand suggests that externalities might need to be tackled and a systematic literature review of current findings on coal externalities and policy instruments can support policy decision making. The chapter aims to review policy options for coal mining in several countries and provides empirical findings on policy instruments performance. The chapter shows that there is an important proportion of mining externalities which are still partially researched and further that some environmental externalities are neglected by policy makers. The second and third chapter, instead, deal with renewable energy sources, in particular with the photovoltaic technology use in microgeneration electricity production.

The **second chapter** contributes to the emerging stream of research applying spatial econometrics techniques in order to model microgeneration technology adoption among households, in particular domestic Photovoltaic (PV) systems. PV technology represents an important opportunity for the electricity supply side, making electricity consumers also electricity producers guarantees the security and affordability of the energy supply. Renewable energy diversifies the electricity production mix and contributes to the sustainable development of energy systems. The main goal of the second chapter is analysing the drivers of PV systems adoption among households focusing on characteristics of adopters (sociodemographic factors as age, education, income etc.), settlement structures (the housing pattern distribution and infrastructure in a specific area) and spatial dependence. The empirical analysis is conducted on aggregated cross-sectional data of 746,639 residential photovoltaic systems across 163 NUTS3 regions in Great Britain. In contrast with the previous literature, the main contribution of the paper is twofold: proposing innovative spatial weighting techniques to capture the interaction degree between regions, and comparing different kind of spatial models, in order to capture the spatial global and local spillovers of technology diffusion. The overall research question is providing evidence on main drivers of PV systems diffusion among households. Results suggest that some socio-economic characteristics and settlement variables play a key role in explaining the spatial diffusion of photovoltaic systems. Population density, household size, the share of houses occupied by renters, the number of detached dwellings and the amount of domestic electricity consumption are the main drivers of technology adaption.

The **third chapter** is linked to chapter two but it represents a completer approach to integrate and extend the second chapter findings. The main objective of the third chapter is still analysing the drivers of spatial diffusion of domestic photovoltaic systems installation in Great Britain but testing the robustness of chapter 2 findings using data at different granularities: NUTS3, Local Authorities and Wards. As spatial resolution of data can impact on results findings the chapter tests stability of findings. Further, as spatial econometrics is a new growing filed, the chapter aims to contrast spatial econometric results with more traditional multi-level models. The two methodologies (spatial econometrics techniques and multi-level models) are applied at three different spatial resolution zones to verify whether drivers of PV installations could play a different role at alternative regional scales. The spatial econometrics models control for spatial spillovers and potential technology diffusion patterns, multilevel technique integrates the results simultaneously controlling for different levels of variables aggregation, each for a particular regional scale. From the policy maker point of view, these findings could be useful in order to understand whether the same phenomenon assumes different characteristics depending on the scale of adoption, suggesting a differentiated policy intervention on macro and micro regions. The empirical analysis is conducted on aggregated cross-sectional data on 746,639 residential photovoltaic systems across 163 NUTS3, 374 Local Authorities, 8591 wards in Great Britain. Results suggest that spatial econometrics findings might be sensitive for some variable to data granularities. For example, some variables as household size, education variables, income variables and share of 'green parties' become significant and with expected sign at finer granularities. Other factors have instead constant effects across spatial units, as population density, share of rent houses, share of detached dwellings, consumption of domestic electricity, few variables show an opposite effect, in terms of sign, at different geographies. Multilevel models employ the hierarchical spatial structure of data, controlling for two different levels, in particular the Local Authority and Ward level. Results support and integrate the spatial econometric findings, confirming those obtained for ward data granularity, both in terms of direct and spillover effects.

CHAPTER 1

Is the case of coal mining externalities appropriately addressed? A Literature Review

[1]

1.1 Introduction

The coal extraction history evolved rapidly in the last decades. European countries had subsidised the coal extraction to encourage the coal industries production since the second half of last century. Only in the mid-1990s the growing concern for the environmental effects of coal forced European decision-makers to implement a mixture of reforms to minimize external impacts and stop coal subsidizing measures (Steenblik & Coroyannakis, 1995). As a consequence of subsidies stop, some EU countries closed their mines in mid-1990s and started importing coal from abroad. The reduction of subsidies to coal industries in Europe was a sure benefit for the environment but around the world coal industries continued to develop. As a consequence,

[1] The first chapter of my thesis is an evolution with new original contents of a previous working paper published as *Di Matteo, M., Ferrini, S., Talia, V., et al. (2015). An analysis of the effects of policies; the case of coal. Technical report.*

in the last decade an inverse tendency seemed to happen. Coal shows again many advantages for newly industrialized countries: it can be extracted without new technology efforts; it is relatively cheap; and is often locally available. This implies that while in Europe and US policy instruments (i.e. tax, tax-incentive, etc.) are mainly used to reduce coal mining externalities in other places they can be used to promote coal industries. Indeed, despite the findings of the last fifteen years on its social costs, the demand for coal remains significantly high and projections on future coal demand are even less reassuring: recently the US Government has announced the coal mines restoration. According to the U.S Energy Information Administration, coal will continue to play an important role in meeting global energy demand with the expectations/projections that the world coal consumption will increase by 56% in 2035 (w.r.t. 2007 consumption).

The awareness of external impacts of coal extraction, transport and use is growing but with an increase in the forecast of world coal demand a systematic revision of current findings on coal externalities and policy instruments applied seems to be useful.

The research questions that the paper sets out to answer are the following:

- Q0. Are coal mining externalities appropriately addressed by policy instruments?
- Q1. What is the empirical assessment of policy instruments accordingly to the common criteria effectiveness, efficiency and distributional effects?
- Q2. Which are the most effective instruments for internalizing coal mining externalities?
- Q3. Are different countries treating coal mining externalities similarly?

The paper aims to review policy options for coal mining in several countries and provides empirical findings on policy instruments performance.

This research is not intended to give a univocal conclusion about the best policy option. The definition of "best" can be controversial and is highly influenced by socio-economic, political and country-specific characteristics. However, the systematic literature review of coal mining policy instruments aims at summarizing years of coal mining regulations to draw conclusion for the expected future of coal mining. The paper is organized as follows. Section 2, after a brief background of coal externalities history, recalls the coal mining externalities analysed in recent papers and shortly reviews the main policy instruments available for addressing externalities coupled with a description of assessment criteria. Section 3 describes the research method: literature review collection, classification of externalities and policy evaluation strategy. Section 4 introduces the cluster analysis used to summarize our findings. Results are discussed in section 5 and conclusion and suggestions are reported in the last section.

1.2 Background

In 1995, the International Conference, held at Ladenburg (Germany) on "Social Costs and Sustainability" discussed fossil fuel externalities, energy and transport costs with a review of the results reported in EU ExternE report (1995). The ExternE project was the first comprehensive attempt to use a consistent "bottom-up" approach to evaluate the external costs of different fossil fuels production chains. The project also analysed the impacts of coal production chain, concluding that external costs of EU coal energy plants were roughly Euro 1.5 million, but further research was needed to assess the full impacts of coal, including its extraction, transport and production. The ExternE steering group did not identify possible actions for internalizing the coal external costs but Hohmeyer et al. (1991, 1997) filled this gap and discussed the main policy options for doing so. Recently several authors focus on coal externalities, categorizing them by environmental, social and economic impacts (e.g. Goulder and Parry, 2008). Our work aims to contribute to the mentioned research context by analysing the coal mining external costs on environment and society and focusing on the performance of policy instruments. In what follows we concentrate our attention on coal mining externalities as better explained bellow.

1.2.1 Coal Mining external costs

The coal extraction follows two main techniques: underground and surface mining. In past decades, the underground mining was the most used technique with huge environmental and social consequences, nowadays technological improvements have increased the extraction efficiency in surface[2] and underground mines but external costs remain sizeable.

Epstein et al. (2011) present the most comprehensive life cycle analysis of US coal production systems and estimate the major elements of external costs. Figure 1.1 shows that main external costs occur in combustion (blue rectangle) but extraction costs (red rectangle) are worth to be considered.

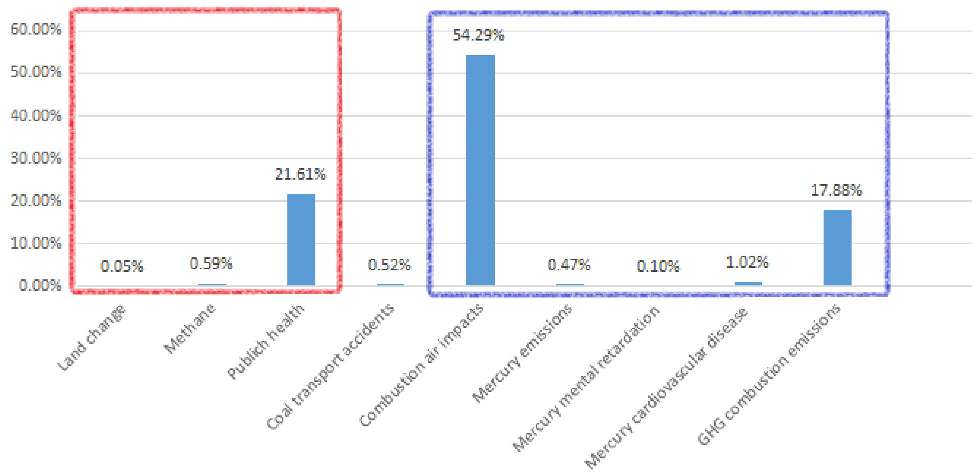

Figure 1.1: Principal coal external impacts from mining (red) to consumption (blue). Source: (45)

[2]The surface mining offers higher rate of extraction efficiency, one of the technique is for example the mountaintop removal technique, it uses explosives to break up rocks and access buried coal; it requires fewer workers but it is a main driver of land-use changes in several regions; this technique is now the major form of mining in the US.

Consistently with Epstein et al. (2011) findings, Table 1.1 firstly reports the underground and surface externalities analysed in the present study, divided according to the classification between social and environmental externalities. The objective of this study is to classify and assess the performance of policy instruments in internalizing coal mining externalities around the world.

Table 1.1: Main Coal Mining Externalities Classification and related impacts. Source: Epstein et al. (2011)

Mining	**Social externalities**	**Environmental externalities**
Underground	Mortality and morbility in coal communities	Methane emissions
	Health risks due to abandoned mines	Abandoned mines
Surface Mining	Mortality and morbidity in coal communities	Biodiversity lost
	Health risks due to water and air contamination	Rivers, stream, ponds water contamination
	Coal miners/workers health risks[3]	Air contamination
		Methane Emissions
		Acid Rain
	Health risks due to abandoned mines	Landscape effects due to abandoned mines

As reported in the Table 1.1 environmental external effects are several and related to different dimensions of environmental damages: air, water, land and biodiversity. All impacts could be defined multidimensional, because the same impact involves several effects, for example abandoned mines represent a huge damage in terms of soil contamination and landscape change, and at the same time they continue to produce methane emissions.

The public health impacts of coal mining operations are quite substantial and it can be claimed that they are related to health and safety of coal communities and coal miners. This latter dimension has been widely researched

[3]For our research purposes the miners safety risks have been eliminated from the dataset. The main reason is that this external effect is different with respect to the other, in particular because of the way policy makers address it. Risks occurring in mining environment for workers are likely treated with other instruments different of macro policy interventions, for example wage premium in miners wages could be classified as an *ad hoc* micro intervention. Given this feature of workers safety externalities we have excluded this externality from our analysis.

and partially addressed by successful regulations (Boden1977, Lewis-Beck and Alford 1980, Darmstadter 1997, Lofaso2011), this paper focuses only on the health impact on communities[4]. In the next session a range of applicable policy options is analysed by means of a theoretical framework.

1.2.2 Theoretical Context

Multiple solutions have been proposed to minimize externalities. Three macro-categories can summarize the policy instruments set 1.2 : i) traditional instruments, ii) market-based instruments, iii) innovative instruments.

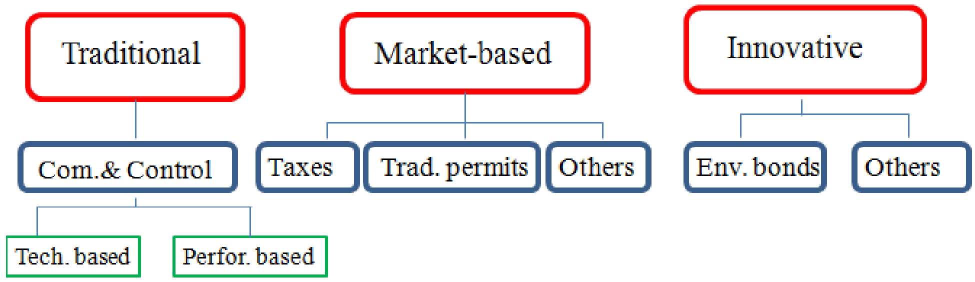

Figure 1.2: Policy Options Classification

The "command-and-control" is a traditional method to internalize externalities that set uniform standards irrespectively of different firms' production costs. The standard can be technology or performance based. The former dictates the method or the equipment that firms must use to reduce the environmental impacts. The latter defines a target that firms can achieve using different strategy technology.

[4]The choice of overlooking the external effect on coalminers is dictated by the salary system for risky jobs. In case of health risks, the workers receive a wage premium which should equalize the marginal health risk of the job. Although the efficacy of the job market in fully internalizing coal miners' health risks is doubtful, as several policy instruments are constantly designed to minimize workers' risks (Di Matteo et al 2015), the literature review presented here will overlook this effect.

The market-based instruments were initially formalized in the early 20th century by Pigou but only widely introduced in the 1980s. It is claimed that market-based instruments encourage environmental friendly behaviour through market signals such as tradable permits or pollution charges (OECD, 2010). If these instruments are well designed and implemented (e.g. tradable permits are well distributed), they encourage firms (and/or individuals) to undertake pollution control efforts which satisfy their own interests along with collective interests set by the government.

In the early 1990s several countries implemented the "green tax reform". On this context, innovative policy options such voluntary agreements or environmental bonds were introduced. Since then a variety of instruments, belonging either to the market based or innovative group, has been proposed (OECD 2001) and their aim is to be focused on specific sectors or to capture complex environmental issue (OECD, 2012). This progression in designing new policy instruments suggests that "no a single instrument is clearly superior along all the dimensions relevant to policy choice; even the ranking along a single dimension often depends on the circumstances involved" (Goulder and Parry, 2008). Common measures to assess policy instruments are the effectiveness, efficiency and distributional effects (Perman et al., 2003). A measure of effectiveness says to what degree the achieved outcome corresponds to the intended goals of a policy instrument.

The efficiency criterion has two key dimensions: (i) balancing marginal benefits and costs in achieving environmental objectives; and (ii) whatever environmental goal is set, that goal should be achieved at the least possible economic cost, i.e. cost-effectiveness should be pursued (OECD, 2008). Efficiency could be also read in static and dynamic terms. The static efficiency refers to the current costs of implementing the environmental friendly behaviour. The dynamic refers to the future cost of achieving the environmental friendly behaviour.

The distributive dimension of a policy instrument concerns distributional impacts on society across numerous dimensions such as income classes, regions, ethnic groups and generations. Chichilnisky and Heal (1994, 2000) show that implementing a policy that aims at restoring efficiency due to an externality is very similar to the public good case; it is impossible to avoid considerations about income distribution. Indeed, as the correction of an externality requires a different product mix and therefore different relative prices, this in turn involves change in the distribution of income. This will make someone better off and someone else worse off. In this paper we aim to investigate whether distributional effects are formally assessed in revising the effect of implemented policy instruments.

1.3 Data and descriptive statistics

The literature review collection was conducted through a web search routine. All details of the web search routine, the collection of information and evaluation criteria are explained in Appendix A.1. Roughly sixty studies were extracted and main information used in order to populate the final dataset. As an example, few lines of the dataset are reported in Figure 1.3.

paper	id	categ	year	countryr	countrya	life_stage	externalit	policy	year	effective	efficient	policy_assessment
Document-01	1	Paper	2009	France	Europe	undergrou	air	reg_policy	1995	na	na	na
Document-01	2	Paper	2009	France	Europe	undergrou	air	reg_policy	1996	na	na	na
Document-01	3	Paper	2009	France	Europe	undergrou	air	reg_policy	1997	na	na	na
Document-01	4	Paper	2009	France	Europe	undergrou	air	reg_policy	2003	na	na	na
Document-01	5	Paper	2009	France	Europe	undergrou	air	reg_policy	2003	na	na	na
Document-01	6	Paper	2009	France	Europe	undergrou	air	reg_policy	2006	na	na	na
Document-01	7	Paper	2009	France	Australia	undergrou	air	reg_policy	2002	yes	yes	both
Document-01	8	Paper	2009	France	Australia	undergrou	air	reg_policy	2008	yes	yes	both
Document-20	70	Brochure	2008	USA	USA	undergrou	air	volunt_po	1994	yes	yes	both
Document-39	109	Report	2010	USA	USA	surface	water	reg_policy	1972	no	no	failure

Figure 1.3: Example rows of the constructed dataset

More than 160 externality/policy cases (included in roughly 60 papers) are included in the dataset. Data includes information on the type of article, year of publication, country, coal mining technique, classification of externality, policy instruments, application year of policy instruments, effectiveness and efficiency of policy instruments. Surprisingly none of the study revised consider the distributional effects of the policy instrument.

Policies analysed in the dataset were divided in policies applied before and after 1990, the latter is considered as a threshold year for the environmental policy awareness. The nineties represent indeed, years of important political initiatives as Kyoto Protocol, which put the political and public attention on environmental consequences of industrialization, in particular on GHG emissions and the resulting climate alteration.

1.4 and 1.5 summarize the main externalities and policy instruments represented in the dataset. Air emission is the most studied external effect (in particular methane emissions, whereas regulatory instruments are the most used for coal mining policies.

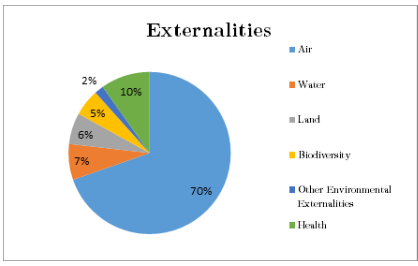

Figure 1.4: Externalities Cases within dataset

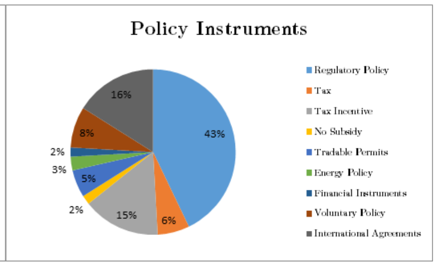

Figure 1.5: Policy Option within the dataset

1.4 Methodology: the Cluster Analysis Technique

For the methodological analysis we followed the approach presented by Norusis, (2009) (SPSS 16.0 Statistical Procedures Companion).

The Cluster Analysis is a classification method which does not need any initial assumptions about the distribution of data. It is useful in order to identify groups of observations that are similar to each other from some aspects/factors/characteristics and different from the others. There are different methods, which can be used to divide cases into groups, depending on the size of dataset and the nature of variables. In the present paper we use a two-step process, applying firstly a hierarchical clustering and then a partitioning clustering.

The underlying idea of clustering data according a hierarchical method is that at the beginning every point in the data set represents a unique group/cluster. The algorithm then successively merge clusters, by measuring the "distance"/"proximity" or the "dissimilarity"/"similarity" between data points, until there is one big cluster containing all of the data.

The similarities between elements is computed for all attributes classified in the dataset. In our dataset variables are all categorical variables, such that computing distances between dataset's rows means taking into account similarities for all characteristics, i.e. two elements are close one to each other, so more similar if they are classified with the same level or close levels for the same characteristic (e.g. two papers published the same year, analysing the same characteristic are more similar than two papers published the same year analysing two different characteristics). All the pairwise dissimilarities distances between observations for each characteristic in the data set are reported in a dissimilarity matrix. After the dissimilarity matrix is computed, a criterion is chosen in order to compute the total distance between elements. In our case the general dissimilarity coefficient of Gower is used. The Gower Distance measures the distance between element i and j, using distance measures between 0 and 1 for each variable d_{ij}. When the Gower Metric is used, the dissimilarity between two rows is the weighted mean of the contributions of each variable. Specifically:

$$d_{ij} = d(i,j) = \frac{\sum_{k=1}^{p} w_k \delta(ij,k) d(ij,k)}{\sum_{k=1}^{p} w_k \delta(ij;k)}$$

Where:

d_{ij} is a weighted mean of $d(ij,k)$ with weights $w_k(ij;k)$;

$w_k = \text{weight}[k]$;

$(ij;k)$ is 0 or 1;

$d(ij,k)$, the k-th variable contribution to the total distance, is a distance between $x[i,k]$ and $x[j,k]$

The 0-1 weight $\delta(ij,k)$ becomes zero when the variable $x[\ ,k]$ is missing in either or both rows (i and j), or when the variable is asymmetric binary and both values are zero. In all other situations it is 1.

The contribution $d(ij, k)$ of a nominal or binary variable to the total dissimilarity is 0 if both values are equal, 1 otherwise. The contribution of other variables is the absolute differences of both values, divided by the total range of that variable.

As the individual contributions $d(ij, k)$ are in $[0, 1]$, the dissimilarity d_{ij} will remain in this range. If all weights $w_k \delta(ij; k)$ are zero, the dissimilarity cannot be calculated.

Accounting for all Gower measures between elements means that the algorithm merge more similar and close elements until one unique cluster is formed. The process goes ahead merging point by point, then cluster by cluster. Distance between clusters is then calculated according to the method average, in other words the distance between two clusters is the average of the Gower measures between the points in one cluster and the points in the other cluster. The results of this process are plotted in a dendogram, which is a tree diagram, where results arranged from hierarchical clusters are represented. It graphically plots the results from different groups sharing similar characteristics in one big group of elements. At this point a partitioning clustering is applied, because the dendogram helps the researcher to see how many groups of element he can considered in order to partition his data. In our case we run two general cluster analysis (before and after the 1990), and two cluster analysis dividing the results by countries (before and after 1990). Results obtained from each cluster analysis are plotted in different dendogram, which show how many groups could be used in order to represent the most recurring characteristics of membership of each group. In our analysis we cut each dendogram in twenty groups representing the most typical characteristics of observations in our dataset.

1.5 Results: General Cluster Analysis

In this section results are presented. The classification of policy instruments accordingly to their ability to internalize coal mining externalities is obtained using the hierarchical cluster analysis, described above.

First, results are discussed dividing them in environmental and social externalities according to the findings of a general cluster analysis (Figure 1.6). Then the cluster analysis is run country by country, and results are commented for each country (Figure 1.7).

The cluster analysis is run considering policies applied before and after 1990, using the latter as a threshold year, as mentioned above.

1.5.1 General Cluster Analysis

Figures 1.6 compares the two general cluster analysis before and after 1990. Air emissions and health are the most researched externalities, both before and after 1990, however we observe an increase of policy instruments for air emission after 1990, as a consequence of newer attention to climate change.

Local externalities as biodiversity, land use change and water imply high costs on society (e.g. surface mining are responsible for millions of hectares of forest loss) but government interventions appear to be rather minimal in this literature review. For example, the biodiversity protection is recognized as an important element of sustainable development, however in more than 100 years of coal mining our systematic review retrieved only six cases were biodiversity was broadly addressed. After 1990 three of these studies found that the tax-incentive mechanism aimed at minimizing the biodiversity loss failed to reach this goal, the other three studies were dated before 1990 and they miss to report any assessment of the policy instruments. It is also important to observe that two of these policy instruments belong to the innovative group of instruments which use financial or voluntary initiative to internalize environmental externalities (e.g. financial assurance for cleaning up costs).

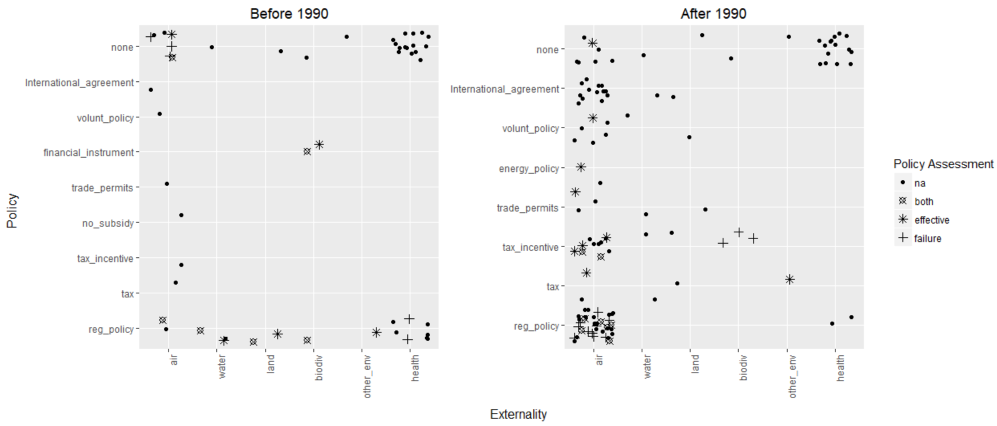

Figure 1.6: Classification of studies according to externality/policy instrument and success criteria before 1990 and after 1990

1.5.2 General Cluster Analysis: Environmental Externalities

Among air emissions, Methane (CH4) is the main source of surface and underground mines pollution. Methane emissions from surface mines are usually ten times less than those from underground mines. The emission potential for each type of mine is determined by the coal's gas content. Some of the gases can remain in the coal but roughly 70% is released during extraction. Methane is a highly potent/reactive greenhouse gas with a much higher radioactive potential than CO2. According to several authors the methane from mines is responsible for 8-12% of global methane emissions (Cheng et al 2011, Bracmort et al 2011, Dessus et al 2009, Badarch et al 2009, IEA 2009, WB Group 2007, Zhi et al 2006, OECD & IEA 2008, US EPA 1999). Underground mines contribute around 90% of the coal methane emissions (OECD & IEA, 2008). Abandoned mines are also responsible for methane emissions and they can contribute for nearly 5% of the total US methane emissions (EPA 2004).

Beyond its contribution to climate change, methane has always been considered as a danger for underground coal mining. It can create serious threats to workers' health and productivity. Methane concentration in the coal mines air between 5-15% represents an explosion hazard. For this reason, governments initially regulated the methane concentration for health reasons and only recently the regulation tackles environmental consequences. As these impacts have global consequences, a wide range of policy instruments have been used for this externality.

Before 1990, a variety of policy instruments were used and their performance was rarely assessed. Contrary, after 1990 two clusters of policies are identified. The major cluster refers to regulatory policies and the other to innovative voluntary agreements. A less dense cluster refers to market-instruments but the majority of these studies reports positive assessment (mainly effectiveness). Two examples of tax-incentive instruments are reported to be effective and efficient in abating methane emissions (one designed by Australian government in 2000 and the other one designed by US Government in 2000). In particular, tax-incentive, mixed ad-hoc energy policies, voluntary policies and international agreement are mainly commented as effective instruments. On the contrary, several of the regulatory policies have been assessed as unsatisfactory. Understandably, the majority of innovative instruments which are the most recent among all other policies lacks any form of assessment.

1.5.3 General Cluster Analysis: Social Externalities

The main social effects retrieved in the review refer to morbidity and mortality in coal mine communities. Colagiuri et al. (2012) list that the main risks for communities are:

- Higher rates of mortality from lung cancer, chronic heart, respiratory and kidney diseases;
- Higher rates of cardiopulmonary disease, chronic obstructive pulmonary disease and other lung diseases; hypertension, kidney disease, heart attack and stroke, and asthma;

- Increased probability of a hospitalisation for chronic obstructive pulmonary disease (by 1% for each 1,462 tons of coal mined), and for hypertension (by 1% for each 1,873 tons of coal mined);
- Poorer self-rated health and reduced quality of life;
- Increased respiratory symptoms especially in children including wheeze, cough and absence from school;
- High blood levels of heavy metals such as lead and cadmium;
- Higher incidence of neural tube deficits, a high prevalence rate of any birth defect, and a greater chance of being of low birth weight (a risk factor for future obesity, diabetes and heart disease).

Before 1990, the regulatory approach appeared the most common for health externalities although these instruments were mainly included in coal regulations to minimize miners' health effect, but not communities' health threats. Few attempts exist to use market or innovative instruments to regulate coal mining social effects and their performance was assessed as unsatisfactory.

The general analysis just presented shows the set of instruments used for coal mining externalities and their performance, it can help answering the first three key research questions.

Q0: Are coal mining externalities addressed by policy instruments?

The literature review shows that globally important externalities have been widely regulated with a mixture of policy instruments. Contrary, local externalities which can potentially impact biodiversity loss, water quality, land use changes and communities' health problems need to be more considered by policy-maker and better addressed. It would be globally relevant to incorporate these externalities in the global price of carbon to support emerging economies to sustainably manage their natural capital. The global market for coal is mainly concerned by GHG emissions abatement, but other externalities need to be internalized. CO2 abatement might be technically feasible through innovative technologies such as CO2 capture and storage. There are similar technologies which could be used as, for example methane emissions could be reused, making coal mining a long-term viable source of fossil fuel.

Q1: What is the empirical assessment of policy instruments accordingly to the common criteria effectiveness, efficiency and distributional effects?

The review shows how the assessment of policy instruments is still quite inadequate. The majority of studies (in particular those treating more recent policy instruments) does not provide any measure of assessment. This does not necessary mean a failure in reducing the external impacts of coal mining but the lack of quantitative assessment of the policy effects. This lack of information a large extent prevents the transferability of successful policies from developed economies to emerging ones.

Q2: Which are the most successful instruments for internalizing coal mining externalities?

Figure 1.6 shows that market based instruments have been mainly assessed positively and this finding echoes theoretical results by, for example, Goulder and Parry (2008).

1.6 Results: Cluster analysis by country

Finally, to investigate whether the attitude towards policy instruments and coal externalities is similar across countries (Q3) we split the cluster results of Figure 1.6 into four main coal producers treated in our literature review: Europe, USA, Australia and China (Fig. 1.7) OECD is kept as a fifth group to represent the overall tendencies in several other countries after 1990. Since 1990 many of the OECD countries have reduced or eliminated direct coal subsidies and lifted price controls, this process produced constant and significant decline in coal production favouring natural gas or less polluting fuels (OECD, 2001). In the last decade of 20 th century, UK, Belgium and Portugal removed all coal production support (IEA, 1999) and the EU introduced new and more stringent environmental regulations. This tendency is confirmed by the substantial increased regulation after the 1990. Health effects on coal miners' communities appear less regulated than environmental issues and this tendency seems constant before and after 1990 (Fig. 1.7). In term of policy instruments, several policies have been found unsatisfactory to internalize air emission, land use changes and biodiversity although a wide variety of policy instruments is well represented at the OECD level.

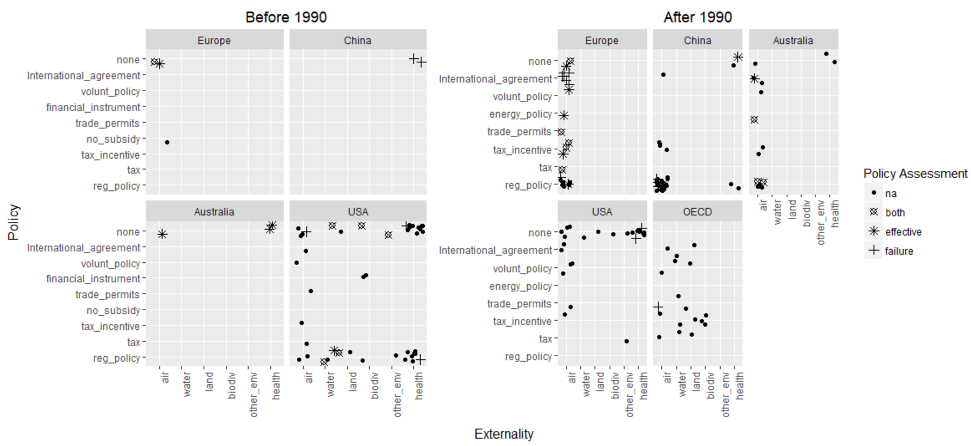

Figure 1.7: Classification of studies according to externality/policy instrument and success criteria by country before 1990 and after 1990 by country

1.6.1 Australia

Inspecting more closely the governmental attitudes towards coal mining externalities we observe some similarities between Australia and Europe both before and after 1990. Air emissions have been widely addressed in Australia as between 1990 and 2011 methane emissions were significantly increased. The Australian government reports that fossil fuel methane emissions are responsible for 30% of all methane emissions and coal mining is responsible for 83% of these emissions (Department of Industry, Innovation, Climate Change, Science, Research and Tertiary Education, 2013). A successful initiative in Australia is the '13% Queensland Gas Scheme' launched in 2005 and valid for 15 years. This scheme forces energy producers to source 13% of electricity from emitted gases. For example, the scheme promotes CMM (Coal Mine Methane)[5] paying higher prices. This has produced successful results in term of methane captured and the current percentage of electricity from gas is 18% that is 5% more than the set target. Another initiative is the 'Coal Sector Assistance Package'. This program encourages innovation in coal production to explore opportunities for reducing methane emissions. Government supports the scheme with around $38.5 million to fund innovative projects. Australia seems in favour of innovation policy options which rely on industry initiative to mitigate externalities. Several of the Australian initiatives to internalize air emission have been found successful and they can represent good examples for other coal producer countries.

[5]The coal mine methane (CMM) is the gas extracted with coal while the coal bed methane (CBM) is associated with pre-mine drainage activity and if it is not exploited is no longer available so it is disregarded in this paper.

The CMM can be emitted from abandoned or active mines. In the past, abandoned mines were not specifically regulated and if the mine top of the shaft was sealed for safety reason and the gas built up, there was a serious risk of gas escape or explosion. Nowadays, active and abandoned mines are regulated for safety reasons. In the active mines the CMM needs to be treated before the mines can operate.

The main systems are:

- Large-scale ventilation system, which aims at diluting the gas with massive quantities of air and release the mixture in the atmosphere
- Degasification or Pre-drainage system, which absorbs methane from mine before coal mine activities start.

Innovative technologies can support both systems in capturing and using methane for energy production or local energy uses (Banks, 2012). Banks (2012) reports that the majority of the methane currently extracted with coal is not economically used and represents an externality. For this reason appropriate policy instruments are still needed to minimize this coal mining externality.

1.6.2 Europe

In Europe, after 1990 air emissions are the main externality addressed with a variety of policy instruments. CMM represents 5% of the total EU methane emissions but, in absolute terms, is declining with the downward trend of coal mining. According to AEAT (1998), Germany produces 42% of the EU total methane, Spain 27%, UK 17% and France 11%. EU tackles methane emissions in the so called 'Climate and Energy Package' (2007) together with other GHG emissions. The EU regulation does not tackle CMM directly and national legislations can independently promote the reduction of fugitive methane losses. Since 90s UK and Germany have started capturing methane from coal mining but currently Germany captures more than 70% of the methane whereas the UK only 30%. Germany presents a high rate of capture via the feed-in-tariff which promotes the use of renewable energy. This policy was introduced in the 1990 and reviewed in 2004 and 2006. CMM is considered a renewable energy and the goal of the feed-in tariff is to offer cost-based compensation to CMM producers at the expense of the energy consumer. This could be considered a distributive effect. The feed-in-tariff turns on a mechanism where CMM producers are compensated from electricity consumers to offer clean energy from methane emissions, so the cost of negative externalities is internalized in electricity price. The policy provides long-term price deal and promotes investments in CMM capture and use projects. In the UK, the emphasis is on methane control and flaring rather than energy recovery. Whilst this regulatory policy is successful in reducing methane emissions in a cost-effective way, it does not promote the economic incentive to capture and use methane. The UK has also activated the methane Emission Trading Scheme from active coal mines but the scheme excludes abandoned mines which might represent a significant source of pollution. Since April 2002, the electricity generated from CMM has been exempted from the Climate Change Levy (CCL) but this is not a sufficient economic driver for investment in electricity generation technologies.

1.6.3 USA

The US methane emissions were initially regulated only for health and safety reasons. Since 1994 the US has started regulating CMM for environmental reasons. In 1994 the US Environmental Protection Agency (US EPA) promoted the 'Coalbed Methane Outreach Program'. This voluntary program was signed by mining companies to reduce methane emissions. State administrations could also offer tax incentives (shifting the burden on the general taxpayer) to attract investment and stimulate the recovery and use of CMM. Again, the CMM recovery give us an example of distributive effect, where electricity producers are incentivized to invest in technology innovations by means of compensation from electricity producers. US EPA (2011) established that coal mining industry in the period 1994-2009 was able to capture and use 81% of methane emissions. This success meant \$150-350 million as direct revenues without accounting for the environmental benefits of greenhouses gases reduction. Despite this individual policy has been assessed positively, the results of the cluster analysis in Figure 1.7 suggests that overall the success of air emission policy instruments is still unknown. In 2004 the U.S. EPA launched and started administering the 'Methane-to-Markets Partnership' or 'Global Methane Initiative'. The program is an internationally voluntary initiative which sets guidelines for CMM. It also supports innovative technologies and projects that promote to capture and reuse methane around the world. Currently 41 countries plus the European Commission contribute to the 'Global Methane Initiative'. Unfortunately, the benefits of this long-lasting initiatives haven't been measured yet.

In general US, contrary to Europe and Australia, has also dedicated attention to other coal mining externalities such as social health impacts, water, land use changes and biodiversity. Social and health consequences are particularly relevant in US policy intervention as coal miner communities are experiencing several health side effects (Hendryx and Ahern 2008; Ahern and Hendryx 2009, Ahern et al. 2011; Hendryx et al 2007, Ahern and Hendryx, 2009, Hendryx et al. 2011, Hendryx 2012). The most common policy instrument is the regulatory policy with four federal acts, issued already before 1990, which enforce standards to improve mining techniques with benefits for the surrounding communities:

- the SMCRA regulation issued in 1977 for all coal mining process;
- the Clean Water Act;
- the National Environmental Policy Act;
- and the Administrative Procedure Act.

  The first two regulations provide substantive standards for regulating surface mining, whereas the last two acts are procedural statutes that guide enforcement of the laws. Kaneva (2011) reviews in details these regulations but her main conclusion is that there is a lack of stringent enforcement. Kaneva (2011) also reports that in 1997 75% of the active surface mines in West Virginia were being operated in violation of state and federal laws.

1.6.4 China

China is an emerging economy and is increasingly addressing many of the common externalities of coal mining. Indeed, before 1990 no Chinese policies are reported. The CMM is regulated by several laws mainly for safety reasons but China is seriously committed to recover and use CMM in the short-run for environmental and energy reasons. Currently, China is the largest emitter of CMM. The 'Mineral Resource Law' (revised in 1996) has made important changes in the management of coal resources mainly to monitor coal supply. In the past, several small mines were operating in China under standard safety and environmental conditions and they distorted the coal market and exploited coal reserves. These inefficiencies prompted the attention of the Chinese government which has issued several regulations. In China CMM is considered an associated mineral of coal and financial incentives promote its recovery and use. In 2005 the 'Five year Plan 2006-2010' aimed at draining 5 billion of cubic meters of methane (draining efficiency of 40%) and utilizing 3 billion of cubic meter (efficiency of 60%) by 2010. Cheng et al. (2011) present the results of the program and report that the drained CMM successfully reached the target but the utilization rate has not significantly increased compared to previous years. To address coal mine methane emissions, in June 2006, the State Council issued 'Opinions on Speeding up CBM/CMM Extraction and Utilization' which clarified the guiding principle of gas extraction prior to coal mining. Key aspects of this policy are: CMM draining is compulsory for coal mining activity;

CMM measurement and monitoring activities must be implemented;

The coal production is not allowed without a CMM drainage system and in case of significant problems mining activity must be suspended;

Coal mine owners and operators have legal responsibilities to ensure that the standards are met.

This regulation has been successful and several mines have installed draining systems (IEA 2009, Info). In support of the 'Five year Plan 2006-2010' initiative, the Chinese government issued, in 2007, the 'Notice on CBM/CMM Price Management' in which it is established that the price of CMM can be freely negotiated. At the same time, the Ministry of Finance issued the 'Executing Opinions on Subsidizing CBM/CMM Development and Utilization Enterprises' whereby any enterprise engaged in CBM/CMM extraction within China is entitled to financial subsidies, if it is used on site or marketed for residential use or as a chemical feedstock. In 2008, the Ministry of Environmental Protection issued an 'Emission Standard of CBM/CMM'. This new standard dictated rules for CMM draining systems, methane dilution and transport of lower concentration. Details about the effects of the recent Chinese regulations are still missing but Cheng et al (2010)'s results suggest potential effective results in the CMM recovery.

The successful attention of Chinese government towards health impacts on coal miner communities appears surprising compared to developed economies such as Europe and Australia. We acknowledge that this might be just a time effect, as Chinese interventions are recent and possibly better reported.

In responding to Q3 (Are different countries treating coal mining externalities similarly?) we observe a diversity of behaviour and attention to coal mining externalities and policies among countries. Europe can provide example of satisfactory and unsatisfactory air emission policies. Australia can present successful results in tackling air emissions via voluntary agreement and China seems to be extremely focused in regulatory instruments. Although the governmental feasibility of policy instruments reflects cultural and institutional traditions this review seems to suggest that new coal countries producers as China can gain effective and efficient reduction in coal mining externalities using market-based or innovative instruments as experienced by developed economies.

1.7 Discussion and conclusions

The sustainable pathway of energy production requires broader awareness of fossil fuel external impacts. The history of coal extraction, transport and use is very long and many government interventions have been realized to reduce the social and environmental impacts. The attention to coal is motivated by its great importance as future source of fossil fuels for many developed and emerging economies. This paper poses questions on the ability of policy instruments to guarantee a sustainable consumption of coal resources which can guarantee long term cheap fossil fuel at minimal social and environmental costs. Here we concentrated our attention, through a systematic literature review and an appropriate statistical analysis, both on coal mining externalities and policy instruments implemented to deal with them, with the hope that countries that today rely heavily on coal can learn a useful lesson.

The main conclusions to the research question are:

the coal mining externalities (Q0) are still partially researched and we observe a number of “neglected” externalities, namely those externalities that have not been considered by policy makers important enough to deserve policy measures, with the exception of the USA. We refer in particular to local impacts as forest and biodiversity loss, water contamination, and changes in land use.

The current assessment of policy instrument performances (Q1) is still inadequate. In particular, a proper quantitative evaluation of policy actions is missing, thus making extremely difficult to transfer supposedly good practices to other contexts. This is particularly worrying for emerging countries that would greatly benefit from the possibility to implement successful measures and avoid unsatisfactory policies.

The literature review confirms theoretical expectation (Q2) and on average market based instruments and innovative instruments have been found to exhibit a high degree of efficacy. Market based instruments (i.e. feed-in tariff in UK) and innovative instruments (i.e. voluntary programs in US) show also examples of distributional effects: in both cases the CMM emissions impact are internalized in the price of electricity consumption, a compensation for producers who invest in the capture and utilizations of methane.

For other policies the distributional issues are still ignored, it represents a serious defect for the enactment of policy instruments even if they are efficacious and efficient, indeed, their adoption can be seriously hampered by adverse distributional effects across groups and regions.

It is worth noting that the distributional effects considered one of the most important policy dimension by traditional economic theory, in the analysed empirical cases, is almost missing. Whereas the technology innovation, missing in traditional economic theory as a policy evaluation dimension, plays an important role in applied cases. It is the case of CMM capture and use as a renewable resource: in most cases, policies are evaluated by means of the innovation technology initiatives of energy producers, and in some cases these initiatives are compensated in a distributional process between electricity producers and consumers.

Summarizing similarities and differences among countries (Q3) is the most difficult result to draw.

Methane is the main external effects tackled in all countries and we claim that this follows the international attention on greenhouse gas which promotes/forces countries to control this externality. Whereas in the UK emphasis has been mainly on controlling methane emissions, Germany has been exploiting the possibility that methane can be used as an energy source by subsidizing producers. Australia has been even bolder by encouraging in various ways innovative policy options that rely on industry initiatives. Finally, the US had relied on a mix of voluntary agreements and tax incentives to attract investment in the recovery and use of methane. China, not surprisingly has extensively used regulations to impose standards and thus controlling methane emissions. More recently even China has moved towards market oriented policies for promoting methane use although a proper assessment of such policies is still to be done.

Social health effects on coal mining communities have been less interested by policy actions. Most of the studies present regulations for communities and workers and it is impossible to disentangle the direct effect on communities. USA, Australia and China present few examples of policy interventions for coal mining communities. USA and Australia mainly rely on regulations whereas China has successfully implemented market-based and innovative instruments to secure a safer environment to communities and miners.

Whereas the governmental feasibility of policy instruments reflects cultural and institutional traditions this review seems to suggest that new coal countries producers can gain effective and efficient reduction in coal mining externalities using market-based instruments for environmental externalities and regulation policies for social and health externalities.

A.1 Appendix A.1

A.1.1 Literature Review Collection

The literature review was conducted through a web search routine. Both advanced Google and Google Scholar search interface were used to gather published and grey literature on coal mining externalities and policy instruments. A set of rules were introduced to systematically interrogate the world wide web. The search rules were the following:

- Keywords driven search: the search string jointly included externalities (@) and Policy options (*);
- Search and results in English;
- Different web page domains: multiple domains were chosen to collect information from the most relevant organizations including World Bank, U.S. Environmental Protection Agency, U.S. Energy Information Administration, etc.

Details of the web search are reported in Table 2: the first column indicates the general string used in order to run the web search routine, the second column contains the set of policy options alternatively considered in the search string, the third column summarizes the analysed externalites taken into account, the last column shows different used web domains.

The objective was to identify studies which assess coal mining (social and environmental) externalities and policy instruments. The final dataset aims at including coal mining externalities addressed with one or more policy instruments and an assessment of the efficiency, effectiveness and distributional effect of the policy. Ideally the assessment methods of policy instruments should be based on quantitative transparent approached (such as cost-benefit analysis, cost effectiveness analysis, impact evaluation etc.), however the literature review shows that qualitative assessment is more likely than the quantitative. As a consequence, the assessment of policy instruments for coal mining externalities is based on mainly qualitative information derived by each study.

A.1.2 Policy evaluation criteria

In this section the policy evaluation criterion used to collect data is reported. As already mentioned in the core of the paper, even if quantitative measures of policy strategies are ideally the best, qualitative assessment of policy instruments is the most used among researchers and so the most present within the literature review. An example of qualitative information researched in the documents is the following:

since its launch in 1994 through 2009, CMOP (coalbed methane outreach program) has assisted the coal mining industry in successfully increasing its methane recovery by 50 percent. These emissions reductions are due to active underground mines recovering and utilizing drained gas. In 2009, the U.S. coal mining industry recovered and used about 81 percent of all drained CMM. Between 1994 and 2009, U.S. CMM emissions reductions have effectively removed the equivalent of more than 263 million metric tons of carbon dioxide from the atmosphere. These avoided emissions are equivalent to 654 billion cubic feet of methane-588 from active underground mines and the remaining 66 from abandoned underground mines. These emissions reductions have had an important economic impact as well. CMM gas sales nationally generated between $150 million and $350 million in revenue in recent years, depending on natural gas prices (EPA, Coalbed Methane Outreach PrograM, 2011)

This policy was classified in the dataset as effective for the reached goal of increasing the methane recovery by 50 percent and efficient for its important economic impact in terms of revenue effects. A contrary example is represented by Cathie Bird and Landon Medley for Strip-mine Issues Committee of Statewide Organizing for Community eMpowerment (formerly, Save Our Cumberland Mountains) (2010) where we can read that:

various analysts, pundits and stakeholders agree only on two things: the future of the Clean Water Act is uncertain, and it's going to take a long time to clear the muddy waters of small stream protection. [...] continuing challenges to the reach of federal jurisdiction until citizen's rights to a clean and healthy environment are amended to the U.S. Constitution.

In this case the policy instrument is commented as uncertain and away from effectiveness or efficiency. Many other studies failed to report any measure of performance. Surprisingly, none of the revised studies assess the distributional effect of the policy instruments. Multiple studies provided only information about qualitative or quantitative assessment of coal mining impacts on local, regional and global economy, without mention internalizing policy instruments. Table 2 provides an overview of these impacts.

CHAPTER 2

Innovation and Technology Diffusion for green energy pathways: GB domestic photovoltaic (PV) systems

2.1 Introduction

Innovation and technology diffusion is a hot topic in many sectors of applied economics. This paper contributes to the emerging stream of research covering the quantitative applied innovation diffusion spatial econometrics models in the analysis of microgeneration technology adoption among households, in particular on domestic Photovoltaic (PV) systems. PV technology represents an important opportunity for the electricity supply side, in order to meet the European policy goals relating to the decarbonisation of energy systems; the UK Climate Change Act (CCA, 2008), for example, legislates an 80% emissions reduction target from 1990 levels by 2050. The diffusion of microgeneration electricity systems, making electricity consumers also electricity producers, guarantees the security and affordability of the energy supply, diversifies the electricity production and contributes to sustainable growth of European countries. The study focuses on the key drivers for adopting PV systems among households. Characteristics of adopters (sociodemographic factors as age, education, income etc.) and settlement structure (the housing pattern distribution and infrastructure in a specific area) are the variables under investigation whereas the spatial dependence, due to the closeness of regions, contributes to understand the presence of "solar clusters" (Schaffer and Brun, 2015). Among others, the main purpose of this study consists in capturing the spatial dynamic of technology diffusion, modelling the spillover effects in the adoption of PV technologies by means of spatial econometric models. The empirical analysis is conducted on aggregated cross-sectional data on 746,639 residential photovoltaic systems across 163 NUTS level 3 regions in Great Britain. Previous studies addressed the spatial pattern on household adoption of PV systems employing standard and basic spatial econometrics models, which do not capture key geographical feature of innovations diffusion i.e. differences in global vs. local spillovers. In contrast with the previous literature, the key contribution of the present paper is twofold. Firstly, it proposes innovative weighting techniques which capture the spatial relationship among adopters, within different regions. Indeed, previous literature employs exogenous and pre-specified spatial weights but in our analysis we propose endogenously generated weights, estimated by econometric parameterization techniques. Along with the newer weighting techniques, the second goal of the paper is to compare different spatial specification models which take into account the global, but also the local dimension of spillover dynamics. Previous studies completely overlooked these components and just assume global spillovers which might be inappropriate for PV technology diffusion. Our paper aims to cover this gap, showing the advantages to parameterize spatial weights, taking the local spillover econometric specification as a reference framework to model the innovation diffusion of photovoltaic systems. The research questions our paper set out to answer are the following:

Q1. Which, and in which measure, adopters' characteristics influence the probability to uptake a domestic photovoltaic system?

Q2. Which is the role of settlement structure in the technology diffusion mechanism of residential photovoltaic systems?

Q3. Assuming the local nature of spatial spillover, which is the better spatial econometric specification to apply for describing the technology diffusion of residential photovoltaic systems?

2.2 Literature Review

Quantitative literature on the innovation and technology diffusion is important in promoting the shift towards microgeneration technology systems among households, and in particular for domestic Photovoltaic (PV) systems. Lately, Dharshing (2016) considers four main factors in assessing PV technology diffusion such as:

- characteristics of adopters;
- settlement structure;
- spatial dependence by means of regional spillovers in technology diffusion dynamic;
- economic profitability of PV systems;

These factors can play a crucial role along with the energy policy framework within which PV systems have being adopted by households. Specific governmental programs which support the adoption of renewable resources such as microgeneration technologies among households, exists and they aim at reducing greenhouse gases emissions and mitigating climate changes. The following literature review takes into account the first three streams of literature and the energy policy framework, focusing on quantitative studies which has inspired the present research.

2.2.1 Characteristics of adopters

Specific characteristics of adopters are expected to influence the probability of the uptake of a PV system. Dharshing (2016) divide these characteristics in two categories: sociodemographic characteristics and attitudinal factors, with the first category referring to the traditional socio demographic attributes of a household such as income, age, education, etc. and the latter, mainly adopted by psycho-sociological works, focusing on households' environmental concern. The role played by households' socio-demographic characteristics as income, age, education is considered a key-driver of PV adoption, although its effect is unclear. Households' income has a controversial role in literature. It seems plausible that households with higher incomes would be able to invest in microgeneration techonology for their houses, however some studies confirm this intuition, others provide opposite conclusions. Rode and Weber (2012); Sardinaou and Genoudi (2013); Dharshing (2016), indeed, stress the positive role played by household wealth and/or income as an important determinant of the PV system installation, others studies (e.g. Zhang et al. 2011 and Balta-Ozkan et al. 2015) suggest that households' income has not a significant impact on PV uptake. The education level has usually a positive impact on the likelihood of a PV uptake (e.g. Sardinau and Genoudi, 2013; Davidson et al., 2014; Ritcher,2014; Balta-Ozkan et al., 2015; Dharshing, 2016), while the role of age seems more uncertain with some researchers finding a negative relationship with age and PV adoption (Islam, 2014), while others suggest no significant effect (Graziano and Gillingham, 2014). With regard to environmental awareness[1] of adopters, Jager (2006), Zhang at al. (2011) and Dharshing (2016) confirm the significant positive impact on the decision of adoption. Other studies, instead, report an unclear relationship between people environmental commitment[2] and the microgeneration technology adoption (Bamberg, 2003).

[1]Some studies measure the environmental concern with the regional participation to intermediary organizations, such as governmental and non-governmental agencies, energy service companies (Schaffer and Brun, 2015)

[2]"A mixture of self-interest (e.g., to pursue a strategy that minimises one' s own health risk) and of concern for other people, the next generation, other species, or whole ecosystems (e.g., preventing air pollution that may cause risks for others' health and/or the global climate" (Bamberg, 2003)

2.2.2 Settlement Structure

The settlement structure, which is defined as "the quantitative and qualitative pattern of distribution of housing, places of work and infrastructure within a certain are" (European Commission, INTERREG III B project COMMIN, 2007) also has an important impact on the likelihood of adopting roof-based PVs. Some studies find a positive relationship between PV adoption and density of urbanized geographical areas (Wallace and Wang, 2006; Rode and Weber, 2012), a relationship which could be explained by the presence of social networks contributing to transmission of information among citizens (Lutzenhiser, 1993) or the higher building density, which increases the number of potential adopters in an area. On the other hand, other studies find that small and mid-sized communities, or less densely populated areas, have higher PV adoption rates than cities (Muller and Rode, 2013; Graziano and Gillingham, 2014, Balta-Ozkan et al., 2015). This might be in rural areas, where it is more common to find detached single-family houses. Detached single family houses encounter no shadowing, have larger roofs and easier access to solar radiation than multi-family dwellings. In addition, multi-family dwellings and homes occupied by renters are more common in urban areas. Furthermore, property houses rarely suffer of coordination problem typical of rented properties. Indeed, if share-property inhabitants expect others to free-ride in the use of a shared PV, they are less incentivized to invest in PV technology.

2.2.3 Spatial dependence

One of the main beliefs in regional science is based on the first law of geography "everything is related to everything else, but near things are more related than distant thing" (Tobler, 1970, p. 236), so spatial closeness is related to the co-development of neighbouring regions. In the specific case of PV system adoption, researchers suggest that geographical similarities due to the closeness of regions contribute to the presence of "solar cluster" (Schaffer and Brun,2015). As PV systems are visible to the public, adoption can be affected by peer effect. Although there is some debate in the literature with regard to the definition of peer effect, Manski (1993) relates it to "imitatio","herd behaviou","social interactio" occurring when the behaviour of an individual is influenced by the behaviour of a social reference group. In the geography and spatial econometric literature, it is normally postulated that the peer effect is related to social interaction, occurring at a very fine scale of geography resulting in spatial correlation. On the contrary, spillover effects, involving a less local dimension, tend to occur between spatially adjacent regions, so that social interactions occur across regional borders. Previous studies suggest that the spatial cluster tendency of PV uptake is due to the presence in the same area of technical expertise (Shaffer and Brun, 2015), while, regional spillover effects could be due to the pro-solar local movements, as these initiatives tend to generate knowledge externalities, which help to develop similar initiatives in neighbour regions (Dewald and Truffer, 2012). Given the presence of spatial dynamics in the technology diffusion, previous studies have modelled the presence of spatial spillovers in the adoption of PV systems with specific applied techniques such as the spatial econometrics models (e.g. Balta-Ozkan et al., 2015, Schaffer and Brun, 2015, Dharshing, 2016).

2.2.4 Energy Policy Framework

The challenge of greenhouse gases emissions reduction to mitigate climate change is a recgnised driver of the environmental and energy policy goals of the European Union. Several Member States have embraced this challenge: launching and promoting programs which support the adoption of renewable energy sources as the feed-in-tariff scheme (FiT). In the UK, Climate Change Act (CCA, 2008) legislates an 80% emissions reduction target from 1990 levels by 2050. In addition, the UK goal is to meet 15% of all energy consumption from renewable energy sources by 2020 (EC, 2009), a commitment reaffirmed in various UK policy documents. The UK FiT Scheme, which was introduced in April 2010, is applicable to a number of technologies (PV, wind, hydroelectric and anaerobic digestion) up to a maximum of 5 MW (Cherrington et al., 2012). The scheme provides three financial incentives:

i. Generation tariff: energy suppliers pay a set rate for each unit (kWh) of electricity generated, with the level of tariff depending on the technology and size of installation;

ii. Export tariff: all technologies receive a further fixed rate for each unit of electricity supplied to the grid;

iii. Electricity bill savings: electricity generated on-site reduces the amount of electricity required from the grid resulting in lower electricity bills for the households. There are some examples in scientific literature in addressing renewable energy programs: two recent studies prove the effectiveness of the feed-in-tariff in Germany. As Schaffer and Brun (2015) state "there is no doubt the FiT proved to be effective in recent year" (p. 226). The same result is reported by Dharshing (2016), according to his research the FiT has a significantly positive impact on PV deployment. Results from key quantitative studies are summarised in A.2.1 in the Appendix A.2.

2.3 The spatial dimension: the Spillover Effects

According to LeSage (2014, p. 14) "a spatial spillover arises when a causal relationship between the r^{th} characteristic/action of the i^{th} entity/agent ($X_t h^r$) located at position i in space exerts a significant influence on the outcomes/decisions/actions (y_j) of an agent/entity located at position j, where X is a matrix of k characteristics/actions of all n regions/entities/agents. A spatial spillover therefore implies $\partial y_j / \partial X_i^R \neq 0$, i.e. an impact from the $r_t h$ characteristic/action of region/agent/enitity i to the outcome/decision/action in region".

It is necessary to make a distinction between local and global spatial impacts, both in conceptual and econometric terms. A local impact happens when a change in some characteristic/variable in one region has an impact just on its neighbours, not involving other regions. As LeSage (2014) also explains, from an econometric point of view, this effect is represented by the non-zero cross-partial derivative: if it has an impact on neighbouring locations/regions that do not involve endogenous feedback effects, then we have a local spatial spillover, this is the most appropriate specification in most applied modelling situations (LeSage, 2014) . The main attribute of local spillovers, as already stated, is that endogenous interaction feedback effects do not exist, which are effects involving a loop process according to if observation i affects observation j, as a feedback effect also observation j affects observation i. This happens only in global spillover setting as follows. If the nonzero cross-partial derivative implies an impact on neighbouring regions which propagates itself on to the neighbours of the neighbours regions and so on, then we have a global spatial spillover effect. The main feature of this situation is that endogenous interaction and feedback effects are present, so that changes in one region/agent/entity set in motion a sequence of adjustments in all regions. According to the analysis conducted by LeSage (2014) global spillover phenomena should be rarer than local spillovers although in applied regional science they are popular, e.g. in the case of common resources shared by numerous states as congestion in a highway or pollution in a river. These impacts could produce situations of feedback and endogenous interaction effects because commuters might react to congestions, regional authorities could respond to pollution, and so on.

2.4 Methodology: Spatial Econometrics Modelling

According to Anselin (2001) spatial econometrics is a subfield of econometrics that deals with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression model, for cross-sectional and panel data. The spatial heterogeneity produces structural instability which could assume the form of non-constant error variances in a regression model (heteroschedasticity). If the stochastic disturbances are "affected" by spatial autocorrelation, some of all the off-diagonal elements of the variance-covariance matrix are non-zero. In this situation, OLS is BLUE and a feasible GLS (Generalized Least Squares) can be implemented if a plausible form of autocorrelation is specified. Following the approach of Arbia (2014), we can consider various alternatives to model non-diagonal variance-covariance matrices where data are observed in spatial units (e.g. countries, regions) which rely on various concepts of closeness and distance, leading to a specification of weights matrix (or connectivity matrix), which specifies whether each location is connected with the others. The simplest of all definitions of a weight matrix is the following:

$$W_{nn} = \begin{bmatrix} w_{11} & \dots & w_{1n} \\ \dots & w_{ij} & \dots \\ w_{n1} & \dots & w_{nn} \end{bmatrix}$$

in which each generic element is defined as:

$$w_{ij} = \begin{cases} 1 \; if \; j \in N(i) \\ 0 \; otherwise \end{cases}$$

where N(i) being the set of neighbours of location i, it means that location j is a neighbour of location j if it belongs to N(i). By definition we have that $w_i i = 0$. Different concepts of neighbouring set N(i) for each element i are possible, ranging from the one based on mere adjacency between the two territorial units, to those based on maximum distance (that is $j \in (i)$ if $d_(ij) < d_{max}$, with d_{ij} being the distance between location i and location j), or based on nearest neighbour criterion. More general W matrices can also be specified by considering entries as geographical functions of geographical, economic or social distances between areas rather than dichotomous entries. In line with the classification between local and global spillovers suggested by LeSage (2009), we specify the spatial econometric models in local and global spatial spillover specification.

2.4.1 Local Spillover Specification

Following the LeSage approach, the two most common local spatial spillover models are the Spatial Lag in X Model (SLX) in (2.1) and the Spatial Durbin Error Model (SDEM) in (2.2).

$$y = \alpha i_n + \beta_1 X + \beta_2 WX + \varepsilon \qquad (SLX) \tag{2.1}$$

$$y = \alpha i_n + X + \beta_2 WX + u \qquad (SDEM) \tag{2.2}$$

$$\text{where } u = \lambda W_u + \varepsilon$$
$$\text{and } \varepsilon \sim N(0, \sigma_\varepsilon^2 I_N)$$

where local spillovers to neighbouring observations are modelled through spatial lag terms for the explanatory variables: WX. A spatial lag consists of a matrix product such as WX, with X a matrix of regressors and W the weight matrix. The matrix product (WX) forms a linear combination of values from the matrix X or vector of the dependent variable y. As mentioned above W is of dimension $n * n$, where n is the number of observations, and each observation represents a region (or location). Non-zero elements in the i, j row and column positions of the matrix W indicate that region/observation j is a neighbour to i. Main diagonal elements are zero, and rows are normalized so that elements of each row sum to unity. Following the distinction between local and global spatial impacts presented above, we could consider the partial derivatives, own-region partial derivatives are $(\partial y_i)/(\partial X_i^K) = \beta_1$, while cross-partial derivatives that reflect the local nature of spatial spillovers to only neighbouring regions are $(\partial y_i)/(\partial X_J^K) = W\beta_2$. Since the main diagonal elements of W are zero and the row-sums are unity, we can interpret the coefficient β_2 as the cumulative partial cross-partial derivative or indirect effect. Cumulative means that the coefficient β_2 denotes the sum of spillovers on all neighbours. Like all regression coefficients, β_2 reflects average or typical spillovers, where averaging takes place over all observations. This makes these models easy to interpret relative to the global spillover category. For the specific case of SLX model, least-squares coefficient estimates for β_1 and β_2 with measures of dispersion such as t-statistics can be used to produce inferences regarding the magnitude and significance of direct (own-region, β_1) and indirect (other-region, spillover, β_2) impacts, so standard regression techniques such as linear models can be used to estimate the SLX model. Lesage and Pace (2009) argue that cross-sectional versions of these local spillover models have received too little attention in applied work by regional scientists. The SDEM allows disturbances to capture the global diffusion of shocks in the error component terms. To avoid confusion of terminology, we do not call these shocks spillovers. To see that we have global impacts arising from shocks to disturbances, it needs to note that from equation (2.2) we can derive:

$$u = (I_n - \lambda W)^{-1}\varepsilon$$

which can be expressed as:

$$u = (I_n + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + ...)\varepsilon$$

A change in the disturbance of a single region can produce impacts on disturbances on neighbouring regions $\lambda W\varepsilon$, neighbours to the neigbouring regions, $\lambda^2 W^2\varepsilon$, and so on. As the scalar parameter λ is < 1, impacts decrease with order of neighbours, so higher-order neighbours (i.e. neighbours to neighbours) receive less impact. An econometric observation is that regression estimates of β_1 and β_2 from SLX model should be unbiased even when the true model is SDEM, since spatial dependence in the disturbances represents only an efficiency problem. A related point is that the partial derivatives with respect to the explanatory variables are the same for both models. It is worth noting that neighbouring regions/observations might be defined as those located far away of geographical space, in other words although the term local spillovers could be used to characterize a local model, it does not mean that neighbours regions are necessarily and effectively close in the space. It is worth mentioning that LeSage (2009) recommends practitioners of spatial regression models to spend value time in thinking about whether the phenomena they study are likely to produce local or global spillovers. A change in the disturbance of a single region can produce impacts on disturbances on neighbouring regions $\lambda W\varepsilon$, neighbours to the neigbouring regions, $\lambda^2 W^2\varepsilon$, and so on. As the scalar parameter ε is < 1, impacts deccrease with order of neighbours, so higher-order neighbours (i.e. neighbours to neighbours) receive less impact. An econometric observation is that regression estimates of β_1 and β_2 from SLX model should be unbiased even when the true model is SDEM, since spatial dependence in the disturbances represents only an efficiency problem. A related point is that the partial derivatives with respect to the explanatory variables are the same for both models. It is worth noting that neighbouring regions/observations might be defined as those located far away of geographical space, in other words although the term local spillovers could be used to characterize a local model, it does not mean that neighbours regions are necessarily and effectively close in the space. It is worth mentioning that LeSage (2009) recommends practitioners of spatial regression models to spend value time in thinking about whether the phenomena they study are likely to produce local or global spillovers.

2.5 Global Spillover Specification

The spatial Durbin model (SDM) is a global spillover specification, taking the following form in equation (2.3):

$$y = \rho W y + \alpha i_n + \beta_1 X + \beta_2 W X + \varepsilon \ (SDM) \tag{2.3}$$

This model includes a spatial lag vector Wy representing a linear combination of values of the dependent variable vector from neighbouring observations, as well as a matrix of own-region characteristics X, and a matrix of characteristics of neighbouring regions (WX) as additional explanatory variables, αi_n represents the model intercept . Direct and indirect effects for the SDM model shown in (2.3) for the r^{th} explanatory variable in the matrix X, are given by the matrix cross-partial derivative expression in (2.4):

$$\frac{\partial y}{\partial X'_R} = (I_n - \lambda W)^{-1}(I_n \beta_1^r + W \beta_2^r) \tag{2.4}$$

The presence of global spillovers can be seen developing the following equation:

$$(I_n - \lambda W)^{-1} = I_n + \rho W + \rho^2 W^2 + ... \tag{2.5}$$

It means that there is a spatial multiplier effect: the outcome in a location i will not only be affected by the exogenous characteristics of I, but also by those in all other locations through the term $(I_n - \lambda W)^{-1}$

It is worth noting that a plausible interpretation of the partial derivatives from a cross-sectional model such as the SDM would be that the cross-partial derivative impacts on neighbouring regions (indirect effects or spillovers) arise simultaneously. Intuitively, such impact should take time, in our methodological setting there is no explicit role for time adjustments.

According to LeSage (2014) one obstacle in confronting regional scientists who attempt to use the spatial econometric methods is the huge amount of model options in the literature. For the cases where a global spillover specification is theoretical appropriate, LeSage suggests that the only relevant specification is the SDM. The SDM subsumes the Spatial Autoregressive Model (SAR), it is a global spillover specification and it is nested in SDM, it accounts only for the spatial lag of dependent variable as in equation (2.6):

$$y = \rho W y + \alpha i_n + X\beta_1 + \varepsilon (SAR) \tag{2.6}$$

Whether $\beta_2 = 0$ the SDEM collapses to the SEM specification and there are spatial shocks just in the disturbances such as eq. 2.7: The SDEM specification subsumes the SLX, but also the SEM specifications as special cases. In fact, when $\lambda = 0$ the SDEM collapses into the SLX and there is no spatial dependence in the disturbances. Whether $\beta_2 = 0$ the SDEM collapses to the SEM specification and there are spatial shocks just in the disturbances such as equation (2.7):

$$\begin{aligned} y &= X\beta_1 + u \\ u &= \lambda W u + \varepsilon \end{aligned} \tag{2.7}$$

A popular model since Anselin (1988) is the SAC, the Spatial Autoregressive Combination model in equation (2.8):

$$\begin{aligned} y &= \rho W y + \alpha i_n + X\beta + u (SAC) \\ u &= \lambda W u + \varepsilon \end{aligned} \tag{2.8}$$

This model is challenging from an estimation point of view. The researcher faces two spatial dependence parameters to estimate ρ and λ. The additional spatial dependence parameter adds to the costs and complexity of model estimation. According to LeSage the marginal cost of applying this model exceed marginal benefits.

2.5.1 Focus on the SLX model and parameterizing W

Even if there are theoretical reasons indicating that spatial interaction effects are related to distance, as to say there is a distance-effect to be investigated, economic theory is silent about the precise nature of distance effect. For this reason, the common practice is to adopt convenient spatial weight matrices and contrast alternative specifications of the W matrix as a test of robustness. Vega and Elhorst (2015) explore the literature and identify different approaches to specify the W matrix. As they state, the most common approach is using pre-specified W with fixed weights within a linear regression framework. Although units' interaction can be independent from geographical proximity, for those cases in which researchers can place more weight on closer observations, Vega and Elhorst (2015) demonstrate the flexibility that occurs if they take one step forward by using a simple parametric approach applied to the elements of an inverse distance matrix:

$$w_{ij} = 1/d_{ij}^{\gamma} \tag{2.9}$$

Where d_{ij} denotes the distance between observations i and j, and γ is the distance decay parameter to be estimated. The estimation of γ provides more information on spatial interactions in the sample. If the estimate of γ is small this is an indication that the commonly applied binary contiguity principle is not an accurate representation of the spatial dependence. This is because contiguity can be thought as a restrictive distance measure where units' interaction is confined only to those units that share borders.

2.5.2 Interpretation and comparison between different spatial models

In spatial models, the traditional least-squares interpretation of the coefficients of independent variables is not valid, because changes in independent variables include all changes in the neighbouring regions, and these changes differ over all regions. A summary measure of these varying impacts is needed. This summary measures are represented by marginal effects. In a linear regression model a marginal effect is represented by equation (9):

$$\partial E[y_i]/\partial X_{ik} = \beta_k \tag{2.10}$$

$$\partial E[y_i]/\partial X_{jk} = 0 \tag{2.11}$$

In SAR, SDM and SAC, a change in a single observation (region) associated with any given explanatory variable, xk, will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect effect) through the spatial multiplier mechanism. According to the classification of Page and LeSage (2006), we report the definition of these summary measures used to average the impacts across all regions. The Average Direct Effect is the effect averaged over all n regions/observations, which is a summary measure of the impact arising from changes in the i_{th} observation of variable r. An exemple for our case study: if there is an increasing of environmental awareness campaigns in region i, which is the average impact on the number of domestic systems in region i. It is espressed as:

$$\partial E[y_i]/\partial x_{ik} \tag{2.12}$$

It includes the effect of feedback mechanism where observation i affects j and observation j also affects i.

The Average Indirect effect measures the impact on one regions of changes arising in all other regions. For example: what happens to the number of domestic PV systems in one region if all other region raise their environmental awareness campaign?. In formal terms it could be expressed as:

$$\partial E[y_i]/\partial x_j k \neq \partial E[y_j]/\partial x_i k \tag{2.13}$$

The Average Total effect is the sum of the average direct effect and average indirect effect. This total effect will include both the average direct impact plus the average indirect impact. This measure has two interpretations, the first interpretation is the following: if there is a raise of income, what will be the average total impact on the number of domestic PV systems of typical region? The second interpretation is the following: it is a measure of the increasing/decreasing of income on the number of PV systems in region j (on average).

2.6 Data and Model Specification

Data on domestic photovoltaic system installations come from the Ofgem's E-serve Database which provides a breakdown of accredited installations under the UK Feed-in-Tariff scheme from 1 April 2010 to 31 March 2017. The database contains installed and declared capacity of 797,320 microgeneration systems for five different technologies, i.e. anaerobic digestion, hydro, micro CHP, photovoltaic, wind and four different installations type, i.e. community, domestic, commercial and industrial. With 99% and 80% of installations and installed capacity, respectively, photovoltaic systems are the most commonly adopted technology (2.1 and 2.2).

Table 2.1: Percentage distribution of the number of Microgeneration Systems by technology and installation type. Own elaboration of Ofgem FiT database, as 31/03/2017

	Domestic (%)	Commercial (%)	Industrial (%)	Community (%)
Anaerobic digestion	0	1	4,7	0
Hydro	0	1,9	2,3	1,4
Micro CHP	0,1	0,1	0	0
Photovoltaic	99,3	87,1	86,6	93
Wind	0,6	9,9	6,3	5,5

Table 2.2: Percentage Distribution of installed capacity by technology type. Own elaboraton of Ofgem FiT database, as 31/03/201

Technology Type (%)	Installed Capacity (%)
Anaerobic digestion	4,4
Hydro	3,1
Micro CHP	0,0
Photovoltaic	80,4
Wind	12,1

In the Ofgem database there is no a specific definition of characteristics which are necessary for an installation system to belong to the domestic category, indeed installations which are categorized as domestic cover a large range of installation capacity from a minimum of 0,020 kW to a maximum of 3,38 MW. Following the approach of Balta-Ozkan et al. (2015) all systems equals or less than 10 Kw are classified as domestic and are included in this analysis. We use the third level of the European NUTS (Nomenclature of territorial units for statistics) [3]. There are a total of 174 NUTS3 regions in the UK based on the 2015 classification. In this analysis we consider 746.639 photovoltaic systems distributed within the 163 NUTS 3 regions in Great Britain, excluding Northern Ireland and the major islands[4]. The spatial concentration of PV is shown in 2.1. The value of the Moran Index computed by using a binary contiguity matrix and the queen method for both the number of PV installation and installed capacity is positive and statistically significant, see 2.2 and 2.3. The Moran Index is a measure of spatial autocorrelation between a region and its neighbours. It is calculated as a ratio of the product of the variable of interest and its spatial lag, with the cross-product of the variable of interest, and adjusted for the spatial weights used. A positive value of Moran Index is a signal of the presence of autocorrelation.

[3]According to the Eurostat definition the NUTS classification is a hierarchical system for dividing up the economic territory of the EU for the purpose of collection, development and harmonization of European Regional statistics, socio-economic analysis of the regions, framing of EU regional policies.

[4]Excluded islands are the Isle of White, Isle of Anglesey, Shetland Islands, Orkney Islands.

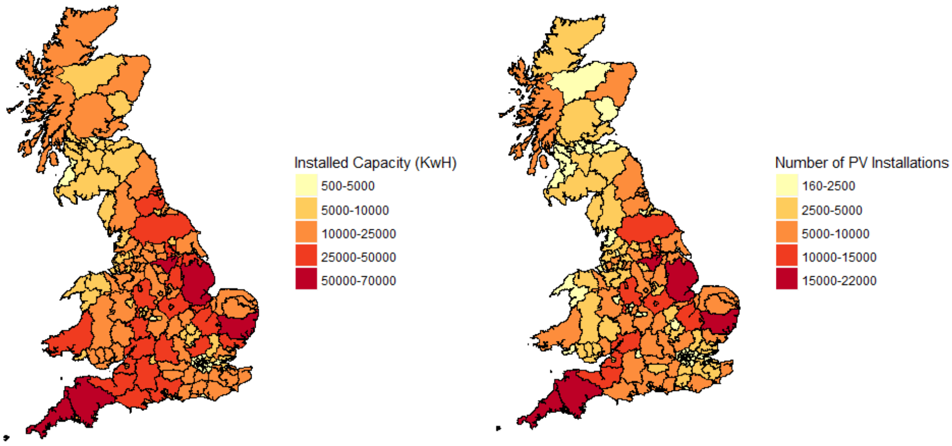

Figure 2.1: Distribution of residential PV systems in Great Britain. Installed capacity in kWH (left) and number of installations (right).

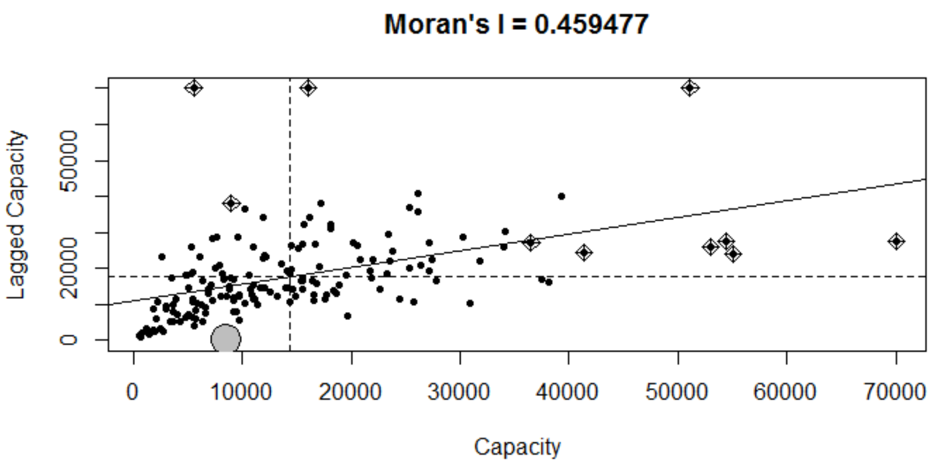

Figure 2.2: Moran's Index Scatterplot for installed capacity

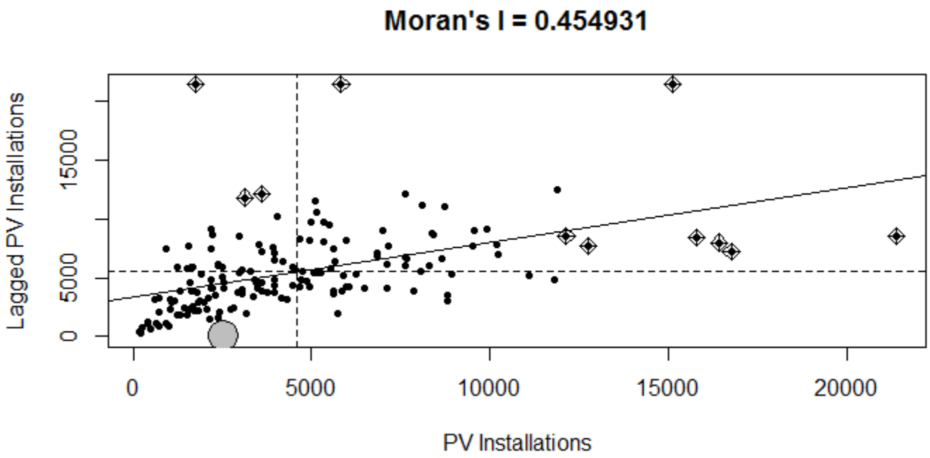

Figure 2.3: Moran's Index Scatterplot for number of PV installations systems

2.6.1 Explanatory Variables

2.3 reports all variables collected in our dataframe, which are meant to influence the uptake of PV systems. Following the classification conducted in the literature review, the main explanatory variables are divided in characteristics of adopters and settlement structure[5]. For the sake of completeness there is also an additional category regarding the solar radiation data under meteorological data category. Following Balta-Ozkan et al. (2015), 2.3 reports data source and availability, geographical scale and data processing.

[5]At the present stage of our analysis there are no independent variables capturing the effect of environmental policy frame.

Table 2.3: List of collected variables

	Variable	Geographical Availability	Data Source	Granularity of Data
Characteristics of adopters	Population Density	England and Wales (LSOA[6])	ONS[7]	Aggregated to NUTS3
		Scotland (Datazone)[8]	NRS[9]	
	Household Size	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS[10]	
	Low Income (Dummy variable = 1 for income in first quartile)	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS	
	High Income (Dummy variable = 1 for income in last quartile)	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS	
	Median Age	England and Wales (LSOA)	NOMIS[11] (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Edu 1 Share (Share of people with education level = 1)[12]	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Edu 4 Share (Share of people with education level = 4)[13]	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Costituency)	NRS	
	Green Electoral Data	England and Wales (Costituency)	The electoral Commission	Aggregated to NUTS3
		Scotland (Costituency)		
	Domestic Electricity Consumption	England and Wales (LSOA)	DECC[14]	Aggregated to NUTS3
		Scotland (DataZone)		
Settlement Structure	Accomodation/Dwelling Type (Number of detached dwellings)	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Rented Houses (Number of owned houses)	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland	NRS	
Metereological Data	Solar Radiation	England and Wales (LSOA)	JRC	Aggregated to NUTS3
		Scotland (Datazone)		

[6]A (LSOA) is a geographic area, designed to improve the reporting small area statistics in England and Wales. Lower Layer Super Output Areas are built from groups of contiguous Output Areas and have been automatically generated to be as consistent in population size as possible, typically the mean population is 1500.

[7]Office of National Statistics

[8]The data-zone geography covers the whole of Scotland and nests within local authority boundaries. A datazone has a population of between 500 and 1,000 household residents

[9]National Records for Scotland

2.6.2 Model Specification

The model specification we implement is:

$$
\begin{aligned}
log(nPV_i) =&\beta_0 + \beta_1 density_i + \beta_2 hh\ size_i + \beta_3 low\ income_i + \\
&+ \beta_4 high\ income_i + \beta_5 median\ age_i + \\
&+ \beta_6 edu\ 1\ share_i + \beta_7 edu\ 4\ share_i + +\beta_8 rent_i + \\
&+ \beta_9 detached_i + \beta_{10} electricity\ consumption_i + \\
&+ \beta_{11} green\ electorate_i + \beta_{12} solar\ radiation_i \qquad (2.14)
\end{aligned}
$$

In the equation 2.14 the dependent variable i denotes regions and u is an independently and identically distributed error term with zero mean and variance σ^2. The dependent variable is the logarithm of number of all regional domestic photovoltaic systems under an installed capacity of 10 kWH. The explanatory variables include: 1) density, the regional population density; 2) hhsize, the regional average size of households; 3) low income and high income, two dummy variables for income[15]; 4) median age, the regional median age; 5) edu 1 share and edu 4 share, two dummy variables for ed-

[10]Scottish Neighbourhood Statistics

[11]Official Labour Market Statistics

[12]Level 1: 1-4 O Levels/CSE/GCSEs (any grades), Entry Level, Foundation Diploma, NVQ Level 1, Foundation GNVQ, Basic/Essential Skills. Source: Nomis: Official Labour Market Statistics

[13]Degree (for example BA, BSc), Higher Degree (for example MA, PhD, PGCE), NVQ Level 4-5, HNC, HND, RSA Higher Diploma, BTEC Higher level, Foundation degree (NI), Professional qualifications (for example teaching, nursing, accountancy)

[14]Department of Energy and Climate Change

[15]Low income is a dummy variable equal to one if the regional income is in the first quartile, High income is a dummy variable equal to one if the regional income is in the fourth quartile

ucation level[16]; 6) rent, the regional number of rented houses; 7) detached, the regional number of detached dwellings; 8) electricity consumption, the regional domestic electricity consumption; 9) green electorate, the regional electoral data[17]; 10) solar radiation, the regional average of solar irradiation.

2.7 Results and Discussion

2.7.1 OLS regression

Despite the Moran test shows a positive spatial pattern, as a first step an OLS regression was run. In 2.4 results are reported. The R2 indicates the coefficient of determination, AIC is the Akaike Information Criterion and BIC is the Bayesian Information Criterion.

[16] Edu 1 share is the share of population with education level equal to one; Edu 4 share is the share of population with education level equal to three

[17] Electoral data report the regional votes in favour of the six principles party in UK. The variable green electorate indicates the number of regional votes in favour of the labourist party, liberal democrats party, the Scottish National Party and the green party. The other two categories in electoral data are represented of CON category indicating the regional votes in favour of the conservative party and UKIP party, while OTHER indicates all other votes.

Table 2.4: OLS estimation results

Variables	Coefficient Value (p-values)
Constant	7.378 ** (0.001)
Density	-0.021*** (0.000)
Hh Size	-0.759 ** (0.007)
Low Income	0.007 (0.933)
High Income	-0.286** (0.001)
Median Age	-0.059*** (0.000)
Edu 1 Share	-0.510 (0.724)
Edu 4 Share	-1.281. (0.085)
Rented Houses	0.048* (0.011)
Detached Dwellings	0.108*** (0.000)
Electricity Consumption	2.908* (0.012)
Green Electorate	0.119 (0.674)
Solar Irradiation	0.114 (0.150)
R2	0.88
AIC	107.718
BIC	151.030
Number of observations	163

Estimation results in 2.4 reveal that the diffusion of PV correlates negatively with population density, household size and the median age. On the other hand, a higher number of rented houses, detached dwellings and higher levels of domestic electricity consumption in a region seem to incentivize the diffusion of PV systems. The share of high educated people seems to have a negative impact, slightly significant. It would be premature to draw conclusion from the results in the 2.4 due to the various alternatives presented above. In order to check for spatial auto-correlation we run a Moran's I statistics and a Lagrange multiplier (LM) tests. The Moran's I statistics (2.5) show considerable evidence of spatial autocorrelation in the regression residuals. LM tests confirm the inadequacy of the OLS model. Both versions, testing for spatial correlation of the error terms and the spatial correlation of the lagged dependent variable term, are strongly significant, therefore making it difficult to choose between controlling for either of these issues.

Table 2.5: Tests for spatial dependence on the residuals in OLS regression

Test	
Moran's I	0.162***
	(0.000)
LM (error)	7.870**
	(0.005)
LM (error robust)	3.748.
	(0.052)
LM (lag)	9.883**
	(0.001)
LM (lag robust)	5.762*
	(0.016)

2.7.2 Spatial Econometric Analysis: A Standard Approach

Following the approach of Vega and Elhorst (2015), in this section we first develop a spatial econometric standard approach, focusing in particular on spillover implications. The model in equation 2.14 is analysed using different spatial econometric specifications to capture spillovers effects and testing different W matrixes. Firstly, we specify the common binary contiguity matrix with elements $w_ij = 1$, if two regions have a common border or a common edge[18] and zero otherwise. According to the classification reported in the literature we run the Spatial Durbin Model (SDM) as a global spillover specification, a Spatial Lag in X Model (SLX) as a local spillover specification, and other two intermediate models: the Spatial Autoregressive Model (nested in the SDM), and the Spatial Error Model, which accounts for the spatial lag in the error term. 2.6 reports the estimation results for different spatial econometric models. The spatial models are estimated by ML, the only exception is the SLX model, which is fitted using a linear model, augmented with the spatially lagged independent variables.

[18]This distance weights matrix is computed using the queen method. The queen method follows the mechanism already mentioned: it two regions share a border or an edge, then are considered neighbours.

Table 2.6: Spatial model estimation results

	SAR	SEM	SDM	SLX
Constant	5.095*	3.817	6.793*	9.587**
	(0.017)	(0.113)	(0.017)	(0.003)
Density	-0.018***	-0.018***	-0.016***	-0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Hh Size	-0.508.	-0.1697	-0.001	-0.132
	(0.057)	(0.511)	(0.994)	(0.670)
Low Income	0.070	0.115	0.073	0.043
	(0.369)	(0.127)	(0.314)	(0.602)
High Income	-0.260**	-0.150*	-0.126	-0.172.
	(0.001)	(0.047)	(0.103)	(0.055)
Median Age	-0.042*	-0.051**	-0.048**	-0.048*
	(0.012)	(0.001)	(0.003)	(0.012)
Edu 1 Share	0.718	1.027	3.862	3.653
	(0.604)	(0.579)	(0.157)	(0.246)
Edu 4 Share	-0.616	-0.497	0.616	0.499
	(0.388)	(0.525)	(0.521)	(0.652)
Rented Houses	0.051**	0.026	0.049**	0.060**
	(0.003)	(0.125)	(0.002)	(0.001)
Detached Dwellings	0.099***	0.083***	0.082***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Electricity Consumption	3.017**	4.504***	4.140***	3.565**
	(0.004)	(0.000)	(0.000)	(0.004)
Green Electorate	0.014	-0.035	-0.375	-0.387
	(0.954)	(0.895)	(0.156)	(0.205)
Solar Radiation	0.070	0.020	-0.391	-0.570.
	(0.342)	(0.885)	(0.158)	(0.073)
W*Density			0.004	-0.004
			(0.292)	(0.335)
W*Hh Size			-1.500**	-1.755**
			(0.008)	(0.008)
W*Low Income			-0.189	-0.282.
			(0.198)	(0.097)
W*High Income			-0.203	-0.274.
			(0.117)	(0.062)
W*Median Age			0.005	-0.003
			(0.840)	(0.916)
W*Edu 1 Share			-3.514	-4.207
			(0.312)	(0.294)
W*Edu 4 Share			-1.037	-1.458
			(0.456)	(0.363)
W*Rented Houses			0.032	0.062.
			(0.257)	(0.053)
W*Detached Dwellings			-0.018	0.006
			(0.492)	(0.821)
W*Electricity Consumption			-2.286	-0.946
			(0.114)	(0.559)
W*Green Electorate			-0.095	0.021
			(0.840)	(0.969)
W*Solar Radiation			0.477	0.730*
			(0.106)	(0.031)
ρ W*number PV	0.103**		0.381***	
	(0.001)		(0.000)	
λ W*error		0.617***		
		(0.000)		
AIC	99.395	91.657	73.258	83.576
BIC	145.800	138.063	156.789	164.013

Looking at point estimates (2.6), some results are in line with OLS results: population density and population median age have a significant and negative effect on PV diffusion, this result is robust in all models. On the other hand, a higher share of houses occupied by the renters as more detached dwellings, and a higher level of domestic electricity consumption have a significant and positive impact on PV diffusion according to all different model specifications. The dummy variable for high income is another robust result in all models, but in SDM: a higher share of population belonging to last quartile of income distribution seem to hinder PV diffusion. All spatially lagged component, the lag of dependent variable in the case of SAR and SDM, the lag of the error component in case of SEM have all positive and significant coefficients, revealing a spatial diffusion dynamic. In SAR and SDM, a higher number of domestic photovoltaic systems in one region results in more PV systems in neighbouring regions. On the other hand the SEM reveals a process according to a random shock in a specific location i (i.e. a shock in the error u at any location i) affects the outcome y in i, and also all other locations. In previous spatial econometric studies on photovoltaic systems diffusion, the analysis of different model specifications ended with results shown in 2.6, looking just at different point estimates. But the interpretation and the comparison between all models by means the only point estimates could be misleading, driving to wrong conclusions. Indeed, the model coefficients cannot be interpreted as partial derivatives as in standard regression models. In order to compare all different models, in particular the coefficient estimates of the global specification with each other and with the coefficient estimates of the local specifications, it is necessary look to the direct and indirect (or spillover) effects (2.7 and 2.8). If a model specification includes the spatial lag of the dependent variable (WY), this is the case of SAR and SDM, it does mean that endogenous interaction effects are present, in other words a change in a specific variable in one area has impacts on neighbouring states and comes back to the state where the change started: a change in a single observation (region) associated with any given explanatory variable, xk, will affect the region itself (a direct impact) and potentially affect all other regions indirectly (an indirect effect) through a spatial diffusion effect. It is the key component of global spatial spillover, whereas local spillover do not produce this kind of outcome. For this reason, there are slightly differences between direct effects estimates and point estimates in the explanatory variable coefficient estimates for the SAR and SDM, but not for the SLX and the SEM. Looking at direct impacts estimates (2.7), population density, dummy variable for high income and level of median population age in one region have all negative and statistically significant direct impacts on PV diffusion. The magnitude of coefficients allows us to discuss the dimension of feedback effect arising from impacts passing through neighbouring regions and back to the region itself. Indeed, the difference between the direct impact coefficient and the coefficient β_k of each variable give us the magnitude of feedback effect. In the case of population density and median age there are just slightly differences between direct impacts and point estimates coefficients, it does mean that the magnitude of feedback effects is so small to be negligible. In the case of high income coefficient, the point estimate in SDM and the estimated direct impact, we could discuss the following difference:

$$DirectImpact(HighIncome)_i - \beta(HighIncome)_i = Feedback\ Effect$$

Which is equal to:

-0.152 - (-0.126) = -0.026

It means that there is a negative feedback effect of high income equal to -0.026, confirming previous results, according to high income negatively correlates with the diffusion of photovoltaic system. The impacts of the number of houses occupied by the renters, as the number of detached dwellings, and domestic electricity consumption, are positive and statistically significant. Even in this case the dimension of feedback effects is negligible. The only case is worth noting is the magnitude of feedback effect domestic electricity consumption level estimated in SDM which is equal to -0.072.

Table 2.7: Spatial models direct effects

	SAR	SEM	SDM	SLX
Density	-0.018***	-0.018***	-0.017***	-0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Hh Size	-0.509.	-0.169	-0.154	-0.132
	(0.057)	(0.511)	(0.569)	(0.669)
Low Income	0.071	0.115	0.056	0.043
	(0.379)	(0.127)	(0.405)	(0.601)
High Income	-0.261***	-0.150*	-0.152*	-0.172.
	(0.000)	(0.047)	(0.038)	(0.053)
Median Age	-0.042**	-0.051**	-0.049**	-0.048*
	(0.008)	(0.001)	(0.003)	(0.011)
Edu 1 Share	0.719	1.027	3.653	3.653
	(0.477)	(0.579)	(0.163)	(0.244)
Edu 4 Share	-0.618	-0.497	0.534	0.499
	(0.351)	(0.525)	(0.583)	(0.651)
Rented Houses	0.051**	0.026	0.054***	0.060**
	(0.001)	(0.125)	(0.000)	(0.001)
Detached Dwellings	0.099***	0.083***	0.083***	0.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Electricity Consumption	3.025**	4.504***	4.068***	3.565**
	(0.004)	(0.000)	(0.000)	(0.003)
Green Electorate	0.015	-0.035	-0.399*	-0.387
	(0.881)	(0.895)	(0.044)	(0.203)
Solar Radiation	0.070	0.020	-0.357	-0.570.
	(0.264)	(0.885)	(0.161)	(0.071)

2.8 reports the estimation results for the indirect impacts. The SAR model shows the most significant indirect impacts on the dependent variable. The percentage of low educated people, number of houses occupied by the renters, number of detached houses, and the amount of domestic electricity consumption seem to have positive and significant direct impacts on the presence of PV systems. Whereas population density, dummy variable for high income, and population median age have a negative impact. SDM and SLX model show similar and comparable results, in particular the household size and dummy variable for high income have in both models negative and significant impact. The number of houses occupied by renters and the level of solar radiation have, instead, positive and significant indirect impacts

Table 2.8: Indirect effects estimation results

	SAR	SEM	SDM	SLX
Density	-0.002***		-0.003	-0.004
	(0.000)		(0.423)	(0.333)
Hh Size	-0.056.		-2.259**	-1.755**
	(0.095)		(0.004)	(0.007)
Low Income	0.007		-0.242	-0.282.
	(0.437)		(0.335)	(0.094)
High Income	-0.029*		-0.379*	-0.274*
	(0.015)		(0.031)	(0.060)
Median Age	-0.004*		-0.018	-0.003
	(0.031)		(0.475)	(0.916)
Edu 1 Share	0.080*		-3.071	-4.207
	(0.0486)		(0.647)	(0.292)
Edu 4 Share	-0.069		-1.207	-1.458
	(0.379)		(0.736)	(0.362)
Rented Houses	0.005*		0.077.	0.062.
	(0.029)		(0.065)	(0.051)
Detached Dwellings	0.011**		0.019	0.006
	(0.001)		(0.717)	(0.821)
Electricity Consumption	0.338*		-1.062	-0.946
	(0.023)		(0.639)	(0.558)
Green Electorate	0.001		-0.359	0.021
	(0.876)		(0.466)	(0.969)
Solar Radiation	0.007		0.493.	0.730*
	(0.292)		(0.079)	(0.029)

According to the common approach of using a binary contiguity matrix, results show minor differences between global and local spillovers models. Results are mutually comparable in terms of coefficient signs, significance and magnitude of coefficients. Whereas it seems that a less flexible models such as the SEM model it results in an oversimplification of the spatial dynamic involved in the diffusion of photovoltaic system. The main limitation of this approach is represented by the distance weight matrix. The matrix is based on ad-hoc assumptions which cannot explain the potential effect of distance. In many socio-economic contexts, similar to our case, we do not know at which degree closer regions are more similar than those located far away. The other problem is that different spatial models (local vs. global spillover) are difficult to distinguish. Even if the SDM and SLX model are comparable in terms of sign and significance of coefficients, the spatial dynamics they are designed for are very different, posing challenges in the interpretation of results. In SDM the spillovers include both endogenous and exogenous effects, the SLX model, instead, the interactions are just exogenous. Following Vega and Elhorst (2015), we propose an alternative approach, parameterizing the distance weight matrix and using the SLX model as a point of departure, starting from the assumption that we are modelling a local spillover dynamic. In other words, the economic model we are modelling is based on the dynamic according to if someone sees his neighbour installing a PV system, then he does the same thing.

2.7.3 An alternative approach: parameterized distance weight matrix and SLX model

In this section we propose an alternative approach in specifying the W matrix. This alternative setting is based on the assumption that the spatial dynamic of photovoltaic systems adaptation just includes local spillover effects. Indeed, if we imagine the diffusion dynamic underlying the installations of PV systems on houses roofs in a certain area, it is plausible that there could be an imitation effect between neighbours (*I see my neighbour installing a PV system, so I do the same*), but it is less plausible that there is an effect which come back to the neighbour who did the installation first (*I installed a PV system imitating my neighbour, who can't do the same because he already has* *a PV system*). For this reason, the reference model is the SLX model, which has advantages in this context. It allows to model local spillover dynamic by means of parameterized distance weight matrix which represents better the network structure of regions as follows. The estimation of the parameterized distance weight matrix is based on the concept of distance decay discussed in the methodology section. As already mentioned the equation (8) represents the elements within the matrix:

$$w_i j = 1/d_i j^{\gamma} \tag{2.15}$$

where $d_i j$ is the distance between region i and j, and γ is the distance decay parameter to be estimated. This methodology allows more flexibility and information on regionals dependencies. The estimation technique follows the mechanism suggested by Vega and Elhorst (2015) and the SLX models specified as in eq 2.16:

$$y = \alpha i_N + \beta_1 X + \beta_2 W X + \varepsilon \qquad (SLX) \tag{2.16}$$

the elements of W are specified as in equation (8), the parameters to be estimated, the scalar α and the vector of parameters β_1 and β_2, given γ, and γ given α, β_1 and β_2 were alternatively estimated in Log Likelihood function until convergence occurs. In other words, the routine alternatively sets one parameter, while others are estimated for all parameters. For this routine a mixed weight matrix approach is adopted, mixed because we used both the k-nearest neighbour criterion and also the parametrization of distance decay as follows: we first considered the nearest 8 neighbours regions[19] of each area, we inverted the distances and estimated the distance decay. The interpretation of the distance decay parameter is the following: if γ presents a small value[20],

[19]The choice of 8 regions is motivated by the fact that we include a number of neighbours which could potentially include all regions sharing a border or an edge with the reference region, as the queen method suggests, but modelling the distance instead of the contiguity.

[20]The estimation of the distance decay parameter is 1.35. Graphically it designs a function which assigns to the nearest neighbours of a region bigger interaction weights,

it could be interpreted as an indication that the binary contiguity principle is not an accurate representation of the interaction which occurs between regions. Contiguity, indeed, considers as neighbours just regions which share a border, cutting off all others. This could be seen in 2.4, which shows the difference between the degree of interaction, between different distances in a Binary Contiguity setting with respect to the parameterized distance decay matrix.

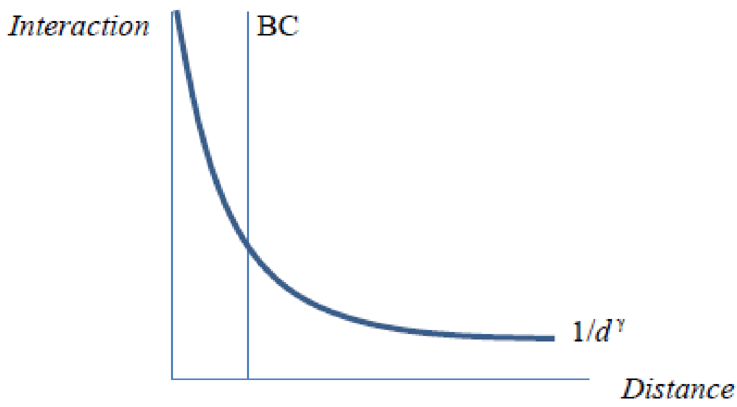

Figure 2.4: Binary Contiguity Matrix vs. Distance Decay Matrix. Source: Vega and Elhorst (2015).

2.9 repeats the results using the binary contiguity matrix for the SLX model, and shows the results for the SLX, using a parameterized inverse weight matrix.

The comparison between the two models (2.9) suggests that some results are robust under different W matrix specification strategies, in terms of significance and signs of coefficients. Although the AIC and BIC determination coefficients show a better fit of the parameterized model with respect to that one which applies a binary contiguity matrix. In terms of direct impacts

and for higher distances very small interaction distances; with respect to binary contiguity matrix, which employs a distance threshold to cut off regions which do not share a border

Table 2.9: SLX model estimation results with both binary contiguity matrix and parameterized matrix

	SLX(Binary Contiguity Matrix)	SLX(Parameterized Matrix)
Density	-0.017***	-0.018***
	(0.000)	(0.000)
Hh Size	-0.132	0.141
	(0.670)	(0.606)
Low Income	0.043	0.007
	(0.602)	(0.911)
High Income	-0.172.	-0.155.
	(0.055)	(0.063)
Median Age	-0.048*	-0.043**
	(0.012)	(0.012)
Edu 1 Share	3.653	0.622
	(0.246)	(0.807)
Edu 4 Share	0.499	-0.585
	(0.652)	(0.527)
Rent Houses	0.060**	0.063***
	(0.001)	(0.000)
Detached Dwellings	0.085***	0.069***
	(0.000)	(0.000)
Ln Electricity Consumption	3.565**	4.610***
	(0.004)	(0.000)
Green Electorate	-0.387	-0.481.
	(0.205)	(0.068)
Solar Irradiation	-0.570.	0.242
	(0.073)	(0.586)
W*Density	-0.004	-0.004
	(0.335)	(0.237)
W*Hh Size	-1.755**	-2.373***
	(0.008)	(0.000)
W*Low Income	-0.282.	-0.276
	(0.097)	(0.117)
W*High Income	-0.274.	-0.546**
	(0.062)	(0.003)
W*Median Age	-0.003	-0.033
	(0.916)	(0.339)
W*Edu 1 Share	-4.207	-0.155
	(0.294)	(0.967)
W*Edu 4 Share	-1.458	0.939
	(0.363)	(0.571)
W*Rent Houses	0.062.	0.135**
	(0.053)	(0.001)
W*Detached Dwellings	0.006	0.071*
	(0.821)	(0.042)
W*Ln Electricity Consumption	-0.946	-5.244*
	(0.559)	(0.021)
W*Green Electorate	0.021	-1.515*
	(0.969)	(0.010)
W*Solar Irradiation	0.730*	-0.186
	(0.031)	(0.702)
AIC	83.57	53.34
BIC	164.01	133.78

regional population density, high income, and median population age seem to hinder the diffusion of PV systems. Spillover effects of the two models differ both in significance than in magnitude of coefficients. It seems that the parametrization of distance decay allows to catch more indirect impact than the model estimated by means of the binary contiguity matrix. The spatially lag coefficients of household size and high income are negative and significant more in the model with the parameterized distance weights than in the other one. This implies that overall some areas experiences a minor diffusion of photovoltaic systems if in neighbourhood the size of household and the population with higher income increases. The opposite happens in the case of the rent houses and detached dwellings, which seem to have spillover effects between an area and its neighbourhood. The coefficients of domestic electricity consumption show opposite signs in direct and spillover effects. It means that a higher domestic electricity use within a region incentives PV system diffusion, whereas a higher domestic electricity consumption in the neighbours areas seem to hinder the PV systems diffusion. This is because having neighbours with high consumption of electricity could be synonymous of more populated areas so, areas sensible to density effects. The probability to install a PV system is higher in less populated areas, nearby cities, where there is more available space due to the presence of detached single-family houses and the access to well-developed network technologies from the cities is easier.

2.8 Discussion

From a policy point of view there are some key drivers a policy maker should take into account in order to design policy instruments to incentivize the uptake of PV systems. We refer to socio-economic variables and settlement structures, which show robust results in all specification models. As socio-economic characteristics, household income and population median age are significant in all models. As settlement structure variable we refer to population density, the number of houses occupied by renters, the type of dwellings, in particular whether they are detached or not, and the amount of domestic electricity consumption. The fact that the dummy variable for high income households has a significant and negative impact, with the number of houses occupied by renters which has, instead, a positive and significant impact suggests that the wealth is not an important determinant for the decision to install a photovoltaic system. High-income families who are house owners would see a minor incentive in investing in a PV technology given the current FiT settings, contrary low-income households are keener on PV technology. This result is opposite with Balta-Ozkan et al. (2015), Zhang et al. (2011), who did not find household wealth as an important determinant for the PV investment. Regarding the house ownership, instead, Balta-Ozkan et al. (2015), in particular, find that the share of home owners has negative effects of PV uptake, not in line with ours which find, instead, a positive impact of houses renters. The impact of population median age is statistically negative, in line with Islam (2014). It is plausible that younger families would invest in a technology with long-run benefits with respect to older people. Another result which is worth to mention is the negative relation between PV uptake and average household size, in particular in terms of spillover impacts, the evolution of families' size in the neighbourhood has a negative impact on PV uptake, which is in line with Balta-Ozkan at al. (2015) findings. The population density, as already stated, has a negative and statistically significant impact. This finding is in line with a part of previous literature (Muller and Rode, 2013; Graziano and Gillingham, 2014, Balta-Ozkan et al., 2015), the idea is that less-densely populated areas have more available space for installing PV systems, an idea coherent with the result of detached dwellings, which have a positive and statistically significant impact on PV uptake, as in Balta-Ozkan et al. (2015). Finally, the amount of domestic electricity consumption has a positive and statistically significant impact, meaning that families with higher consumption are more likely to uptake a PV. All these results allow to draw the socio-economic profile of families who should be the policy-maker goal in designing renewable technologies incentivizing instruments. Our finding, indeed, reveal that low-income, young households with high demand of electricity consumption are more likely to install a PV system, even if they do not dispose of a property-house. Settlement structure variables allows to identify the typical characteristics of areas which are more suited to host PV technologies, we refer to less-densely populated areas with a high share of detached single-family homes. With respect to previous literature, our analysis followed two lines of research. The first refers to the traditional way of modelling the spatial dynamic by means of global spillover specification. This analysis shows the similarities and differences of alternative spatial models commonly employed in the published literature. The second contribution of the paper is the modelling of spatial spillover effects by means of local spillover model using an endogenous parametrization of weight matrix. As econometric theory suggests, local spillover is the most appropriate specification in most of the applied modelling situations (LeSage, 2014). In our specific case, indeed, the endogenous interaction feedback effect do not exist, because the imitation effect in installing a PV is unidirectional (I could install a PV, after my neighbour, who can't do the same after me). This idea is confirmed by the magnitude in estimated coefficients in feedback effects, which are negligible. The reference model to take into account is the SLX, with an improved feature, represented by the parameterized weight matrix, which allows to capture more spillover impact with respect to SLX performed with traditional binary contiguity matrix, as the effects of high income, rent houses, detached dwellings and electricity consumption. In terms of policy implications, the findings of the paper are reassuring as most variables are robustly estimated in terms of signs and magnitude in all models (global and local specification) and with different weights matrix (binary contiguity and parameterized weights). These suggests that some socio-economic variables and settlement structure are fundamental for designing successful policies for micro-generation technology diffusion.

2.9 Conclusions

This paper analyses the main drivers governing the technology diffusion of photovoltaic systems in Great Britain, focusing on three particular categories of determinants: adopters' characteristics, regional settlement structure and the role of spatial spillover effects. The key contribution of this paper is the econometric approach of spatial dependence. With respect to the previous literature, the spatial weights, capturing the interaction degree between regions, are endogenously parameterized within the model specification, giving different spatial weights on distances of neighbouring regions. This technique, proposed by Vega and Elhorst (2015), is applied for the first time to photovoltaic systems diffusion. The parametrized weighting matrix represents a finer representation of the network interactions and suggests improvements toward the standard binary contiguity matrix. The second innovation element is represented by the developing of local spillover specification framework, which is almost ignored by the previous research. Results show some similarity with previous findings, but innovative findings on the spatial boundaries relevant for PV diffusion. From a policy point of view some results are worth to be mentioned: a policy maker who wants to improve instruments in order to incentivize the uptake of microgeneration technologies should take into account socio-economic characteristics as population median-age, household income, household average size, and settlement structure characteristics as population density, the share of rent houses, and the amount of domestic electricity consumption as key driver in the process of policy decision.

A.2 Appendix A.2

Table A.2.1: Schematic literature review on applied studies on Photovoltaic Systems Adoption

Authors	Data	Methodology	Results
Bollinger and Gillingham (2012)	85,046 residential PV installations in California (2001 – 2003)	Fixed Effects Panel Model	Strong causal peer effects within a zip code district Increasing peer effects in magnitude over time and greater for larger installations at a more localized street level
Ritcher (2014)	332,216 residential solar PV installation in England and Wales, UK (2010 – 2013)	Linear dynamic panel model	Small, but positive and significant social effects Social effects vary across months and overall diminish overtime Spillovers on the postcode district are stronger than on a higher geographical level Affluent neighbourhoods show less pronounced installed base effect Higher educated neighbourhoods show stronger installed base effects
Rode and Weber (2016)	576,000 household PV systems, Germany (2009)	Epidemic diffusion model with temporal and spatial fixed effects	Imitation in households PV adoption is highly localized Decreasing influence of distance
Muller and Rode (2013)	324 grid-connected PV system in the city of Wiesbaden, Germany (2009)	Binary Panel logit model	Positive impact of a previous installed PV system on the propensity of new adoption Early adopter belongs to a higher income level class
Graziano and Gillingham (2014)	3,833 PV systems in Connecticut (2005-2013)	Fixed effects Panel Model	Positive impacts of previous PV installations and built environment variables on new PV installations Small and midsized centres of housing density are important as larger centres as the main players for the diffusion of PV systems Important spatial neighbours effects
Balta-Ozkan et al. (2015)	374,445 PV installations in UK (2013)	Spatial econometrics cross-sectional models	PV adoption is positively influenced by the share of detached homes and education level, household electricity spending; and negatively influenced by the density and the number of households Significant spatial spillovers
Schaffer and Brun (2015)	820,000 small-scale PV installations (<= 16 kW), Germany (1991-2012	Spatial econometrics cross-sectional models	PV adoption is positively influenced by high house density, home ownership, population's ecological attitude, per capita income Significant cross-regional spatial spillovers
Dahrshing (2016)	807969 residential PV systems, Germany (2000-2013)	Spatial econometrics panel data models	Larger Population shares of individuals with high income and high education levels, as well as unemployment rates, lead to high numbers of residential PV installations Feed-in-tariff increase the financial attractiveness of residential PV installations The age of 20 is negatively correlated with regional PV adoption rates The impact of environmental attitude remains unclear Time-varying feed-in-tariffs, system prices and solar radiation, has a significantly positive impact on PV deployement. Significant spatial spillovers effects.

CHAPTER 3

PV technology diffusion at different regional scales: the spatial approach vs. the multilevel methodology

3.1 Introduction

The main objective of the present work is the deepened understanding of drivers of spatial diffusion of domestic photovoltaic systems installation in Great Britain. As spatial spillovers can play a key role in determining the up taking of renewable technologies (as per chapter 2), in this chapter we focus on the granularities of data considering three different geographical areas: NUTS3, Local Authorities and Wards. The analysis is carried out using two different methodologies: spatial econometrics and multilevel techniques. In the first one the spatial pattern of PV domestic systems is further investigated using spatial methods in three different regional specifications in order to understand whether the same phenomenon could assume a different profile considering different regional scales. The multilevel method aims at integrating the spatial models' results with a simultaneously controlling for different levels of variables aggregation, each for a particular regional scale.

From the policy maker point of view, our research could be useful in order to understand whether the same phenomenon assumes different characteristics depending on the geographical scale. Different drivers at finer regional scales might suggest tailored policy intervention which could maximize the chance of success.

From the econometric and statistical point of view different results would suggest that techniques are sensible to alternative data granularities. This issue is known in literature as the Modifiable Aeral Unit Problem, it pertains to the fact that there are differences in estimation results depending on considered regions.

The empirical analysis is conducted on aggregated cross-sectional data on 746,639 residential photovoltaic systems across 163 NUTS 3, 374 Local Authorities, 8591 wards in Great Britain. The first part of analysis models the spatial proximity of the regions by means of spatial econometrics, in particular local spillover specifications, estimated along an endogenous parameterized distance weight matrix, are used to model the spatial dynamic which assumes that there is a mimic effect in installing a rooftop PV system. Our results are supporting in reassuring that some variables present the same effect at all regional scales, however, other variables show opposite or at least different results depending on data granularities. The second part of analysis integrates the first, modelling the hierarchical structure of regions by means of multilevel modelling. We used the last two levels of regional aggregations: Local Authority and Ward level. Results confirm those obtained in spatial econometric models applied to ward data, both in terms of direct and spillover effects. From the policy making point of view some drivers are crucial in explaining the up taking of PV, other drivers, instead, would need more investigations and analysis in order to calibrate the policy interventions at local levels.

The applied multilevel technique is a preliminary attempt to integrate the spatial econometric analysis results with a further study on drivers of the spatial diffusion of PV systems. It confirms the results found on the smaller regions, giving to the policy maker a double useful instrument to design his own policy interventions to incentivize microgeneration electricity technology.

3.2 Literature Review

The problem of data granularities is explored in the literature through different approaches and research topics and in this section the discussion is focused on three of them. The first is dedicated to the so called Modifiable Aeral Unit Problem (MAUP), which is a necessary reference issue in order to set a spatial econometric analysis at different geographical scale, the second section presents the use of multilevel models in applied research fields, the last section introduces studies which compare multilevel and spatial econometrics models.

3.2.1 The Modifiable Aeral Unit Problem

In order to propose an integrated approach between spatial econometrics and multilevel methodology it is necessary to introduce the Modifiable Aeral Unit Problem. According to the definition of Arbia and Petrarca (2011), “the modifiable aeral unit problem refers to the modifications of any statistical analysis when changing the scale of observations (e.g. from region to countries) or aggregation criterion (e.g. different partitions of one country at a given scale)” (Arbia, G. and Petrarca, F., 2011). According to Anselin (1988), it pertains to the fact that statistical measures are sensitive to the way in which the spatial units are organized. Specifically, the level of aggregation and the spatial arrangement in zones affects the magnitude of various measures of association, such as spatial autocorrelation coefficients and parameters in a regression model. Indeed, in light of this double nature, the literature usually relates the MAUP to two different issues: aggregation and zone problem. The first is related to the sensitivity of statistical analysis when the level of aggregation changes. The zone problem is related to the variation in correlation statistics caused by the regrouping of data into different configuration in the same scale, which is related to the arbitrary nature of the boundary division. According to the analysis presented by Groenewegen et al., (1999), the zone problem represents not a real problem, if a variable is a real contextual variable instead of the aggregation of individual characteristics. Indeed, as Groenewegen et al. (1999) expalain: “the zone problem depends on whether level 2 variables are real characteristics of regions at level 2 or aggregation of individual characteristics. If the relation between a context variable and the dependent variable at the individual level is assumed to be linear, there is no modifiable aeral unit problem: if another zoning of the area is used, that would only mean that the neighbourhoods are somewhere else on the same underlying regression line”.

The scale problem is an open research question which attracts the attention of sensitive researchers who are aware that the spatial scales effects matter (Vanoutrive and Parenti, 2009). Vanoutrive and Parenti (2009) solve the scale issue integrating the spatial analysis with the hierarchical one. This approach provides the benefit of understanding the roots of spatial variation and to treat it accordingly. A difference in spatial variation might be caused by the “atomistic fallacy of individual-based studies”, i.e. the association between two variables at the individual level may differ from the association of analogous variables measured at the group level. Another source of variation is called the “ecological fallacy of aggregated research”. This issue arises as the association between two variables at the group level may differ from association between analogous variables measured at individual level (Roux, 2002). A similar approach to Vanoutrive and Parenti (2009) is proposed in this study.

The general intuition that we aim to assess is the following: a spatial pattern could originate from different dynamics, and a multilevel analysis could be useful, at least in a primary investigation, to start to treat all problems which arise in spatial analysis.

3.2.2 Multilevel Models Application

The multilevel methodology allows to control for nested data structure. Variables are specified at different levels, each for a different degree of data aggregation. Multilevel models are employed in a heterogeneous set of research fields as social, medical, biological, ecological sciences and in all those disciplines where hierarchical structures are used.

Referring to our specific case study of electricity technologies adoption and diffusion, multilevel modelling was not largely used in the literature, even if it seems to be a valid alternative considering the hierarchical structures of electricity chain (i.e. adopters, electricity suppliers, policy maker), but also the hierarchy of geographical locations of technologies, for example photovoltaic domestic systems clustered in a city, different cities grouped in a county, different counties in a region, and so on.

Bagherian and Lettice (2014), in their paper "A Multi-Level Perspective Towards Energy Regime Transitions: A Wind Energy Diffusion Case Study" propose a literature review to construct a framework for developing a theoretical multi-level approach to the transition from fossil fuel to wind energy, considering the case study of the region of Norfolk in UK. In presenting their multilevel theoretical model they want to explore the important actors and factors that affect the diffusion of wind energy at different levels.

Borchers et al. (2014) analyse the determinants of solar and wind technology adoption on US farms examining farmers, farm operations and state characteristics impacts on the probability of on-farm renewable energy generation, applying a multilevel logit model. The dependent variable is the binary $Adopt_{ij}$ variable, identifying the decision to adopt or not a wind or a solar energy system. The covariates are the characteristics of farms and farm operators (level 1 variables), which could increase or not the likelihood of adopting solar or wind generation technologies, and state characteristics (level 2 variables). As the authors state, the main motivation for employing this kind of model is that it allows different farms to be correlated within groups or areas. Results suggest that farm characteristics (i.e. livestock operations, owned acreage, operators with inherent access, organic operations, and new farmers) increase the propensity to adopt solar and wind generation. Also some level 2 variables have an impact on the adoption (i.e. solar resources, per capita income levels, and predominantly democratic voting).

3.2.3 Multilevel Models vs. Spatial Econometrics

The spatial econometric techniques and the multilevel methodology share an important feature. The spatial econometrics is used to model spatial patterns of correlated observations due to their spatial dynamics, the multilevel technique is employed in modelling the correlation of observation within and between different levels of areas.

The multilevel methodology, indeed, uses a “vertical” approach, incorporating the hierarchical structure of geographical units in the analysis: an underlying assumption of this technique is that it is more likely that two cities in the same county have common characteristics than two cities belonging to different counties.

The spatial econometrics, on the contrary, uses a “horizontal approach” based on the geographical proximity: it is more likely that two cities which are close one another are more similar than two cities which are located far away.

The critique moved to multilevel approaches is that, taking into account the administrative borders of spatial units, the actual spatial proximity is neglected: two cities located close to borders of two contiguous regions are maybe more similar due to for example geomorphological, meteorological or cultural reasons than two cities which belong to the same region, but at opposite sides. The critique moved to the spatial econometrics approaches is that, taking into account the spatial closeness of units, the common institutional features due to the belonging to the same higher institution/region might be overlooked.

The literature offers several attempts of contrasting the pros and cons of both approaches, and the common pragmatic solution is proposing an integration.

Chaix et al. (2005) examine whether spatial modelling approaches provide more relevant information with respect to multilevel techniques for the case study of healthcare utilization in France. In their study, the authors compare conceptually and empirically the two methodologies and they, conclude that, at least in the epidemiological field, the spatial techniques are the most appropriate. What they want to emphasize, in particular for epidemiological field, is that "even if appropriate size and shape are considered, the usual multilevel models, in neglecting spatial connection between areas, treat them as if they were disconnected entities. Assuming independence for persons from different areas even if the areas are adjacent or nearby, the multilevel analytical approach fundamentally assumes that all spatial correlation can be reduced to within area correlation. [...] However, people may be affected not only by the characteristics of their local administrative area of residence, but also by the context beyond these administrative boundaries, as their social activities may encompass a broader space" (Chaix et. al., 2005, p. 517). These considerations imply that as spatial econometric models can consider the space as a continuous dimension rather than fragmented administrative areas they are the favourite methodological approach.

In the empirical part of, Chaix at al. (2005)'s work, the authors use a multilevel analysis of healthcare utilization, examining the presence of unaccounted spatial autocorrelation; then they investigate whether spatial models are able to account for geographical variability to provide more accurate information on the spatial distribution of healthcare utilization; finally, they measure specific place characteristics across continuous space. The main multilevel model results show significant geographical variations in healthcare utilization, but Moran's I statistic suggests spatial autocorrelation unaccounted in multilevel. The spatial models, instead, take into account of the correlation between people as an inverse function of distance between them, giving information not only on the magnitude, but also on the scale of spatial variations.

Vanoutrive e Parenti (2009) reproduce the same analysis of Chaix at al. (2009) in contrasting the multilevel models and spatial econometrics techniques. Similarly they focus on the fact that multilevel models incorporate spatial units in a hierarchical structure, while spatial econometrics take into account neighbouring effect into the model design, and stress also the advantages of both methodologies: on one hand the multilevel models easily reflect the administrative structure and governmental levels, on the other hand spatial econometrics models take into account relationships between neighbours municipalities even if they are separated by a regional boundary.

In the first part of their case study, Vanoutrive e Parenti (2009) apply a spatial error model on labour productivity growth in 173 European regions. They find that spatial error model does not take into account the country level, and does not contain variables whose dimension is typically national, indeed they show that the 71% of the variance in the residuals can be attributed to the country level. In summary they assert that they can't ignore the hierarchical structure of the data, i.e. the nesting of region in countries. So they estimate a random intercept multilevel model and they obtain that at the lowest level of data specification the residual spatial pattern is largely reduced.

Finally, they discuss the pros and cons of both model, stressing how multilevel models "remain superior in modelling different scales simultaneously. Spatial econometrics on the other hand [...] preserves a relation between neighbouring regions separated by a national boundary" (Vanoutrive and Parenti, 2009). On the possibility of an integration between the two models, the authors warn about the risk of constructing too complex models, and suggest the general rule of model parsimony as a valid choice criterion.

De Aguiar et al. (2014) employ hedonic price hierarchical models, and a hierarchical-spatial approach to analyse the determinants of apartment prices in Belo Horizonte, MG, Brazil. They first apply hierarchical models to show that besides the first level characteristics (in particular apartments characteristics), the second level characteristics (the local variables), explained over the 75% of price remaining variability. Then, a hierarchical-spatial approach is used in order to analyse if there is some spatial correlation in price determination after controlling for price variability with the explanatory variables of both levels of the hierarchical models. The methodology applied is the following: the residues of the multilevel ANCOVA model are used as the dependent variable in the spatial models, using the set of variables of the second level as covariates. Results suggest the use of the hierarchical-spatial approach, which suggested that apartment houses were partially determined by some of the characteristics of the nearby areas.

Previous studies, which compared the two different methodologies have drawn different conclusions depending on specific case study. De Aguiar et al. (2014) paper represents, instead, a concrete attempt to integrate the two methodologies in a real multilevel spatial approach.

3.3 Materials and Methods

In this section we present a theoretical background of the material and methods used in our study, firstly analysing the adapted local spatial econometrics models and then the multilevel models. The broader theoretical background about the local spillover specification is the same as the second chapter of this thesis ("Innovation and Technology Diffusion for green energy pathways: GB domestic photovoltaic (PV) systems"), subsequently a formalization of models is presented. The multilevel model overview follows the analysis presented by Fiona Steele (Centre for Multilevel Modelling, University of Bristol, 2008).

3.3.1 Spatial Econometrics Thechnique: Local Spillover Specification

The taxonomy of spatial econometrics models follows the distinction between local and global impacts. A local impact happens when a change in some characteristics/variables in one region has an impact just on its neighbours, not involving other regions.

The two most common local spatial spillover models are the Spatial Lag in X Model (SLX) in (3.1) and the Spatial Durbin Error Model (SDEM) in (3.2)

$$y = \beta_1 X + \beta_2 WX + \varepsilon \qquad (SLX) \tag{3.1}$$

$$y = \beta_1 X + \beta_2 WX + u \qquad (SDEM) \tag{3.2}$$

$$\begin{aligned} &\text{where } u = \lambda W_u + \varepsilon \\ &\text{and } \varepsilon \sim N(0, \sigma_\varepsilon^2 I_N) \end{aligned}$$

Local spillovers to neighbouring observations are modelled through spatial lag terms for the explanatory variables: WX. A spatial lag consists of a matrix product such as WX, with X a matrix of regressors and W the weight matrix. The weight matrix or connectivity matrix specifies whether each location is connected with the others or not.

The matrix product (WX) forms a linear combination of values from the matrix X or vector of the dependent variable y. As mentioned above W is of dimension $n \times n$, where n is the number of observations, and each observation represents a region (or location). Non-zero elements in the i, j row and column positions of the matrix W indicate that region/observation j is a neighbour to i. Main diagonal elements are zero, and rows are normalized so that elements of each row sum to unity.

Following the distinction between local and global spatial impacts presented above, we could consider the partial derivatives, own-region partial derivatives are $\frac{\partial y_i}{\partial x_i^K} = \beta_1$, while cross-partial derivatives that reflect the local nature of spatial spillovers to only neighbouring regions are $\frac{\partial y_i}{\partial x_j^K} = W\beta_2$. Since the main diagonal elements of W are zero and the row-sums are unity, we can interpret the coefficient β_2 as the cumulative partial cross-partial derivative or indirect effect. Cumulative means that the coefficient β_2 denote the sum of spillovers on all neighbours. Like all regression coefficients, β_2 reflects average or typical spillovers, where averaging takes place over all observations. This makes these models easy to interpret relative to the global spillover category. For the specific case of SLX model, least-squares coefficient estimates for β_1 and β_2 along with measures of dispersion such as t-statistics can be used to produce inferences regarding the magnitude and significance of direct (own-region, β_1) and indirect (other-region, spillover, β_1) impacts, so standard regression techniques such as linear models can be used to estimate the SLX model. Lesage and Pace (2009) argue that cross-sectional versions of these local spillover models have received too little attention in applied work by regional scientists.

The SDEM allows disturbances to capture the global diffusion of shocks in the error component terms. To avoid confusion of terminology, we do not call these shocks spillovers. To see that we have global impacts arising from shocks to disturbances, it needs to note that from equation (3.2) we can derive:

$$u = (I_n - \lambda W)^{-1}\varepsilon, \text{ which can be expressed as:}$$

$$u = (I_n + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \cdots)\varepsilon$$

A change in the disturbance of a single region can produce impacts on disturbances on neighbouring regions $\lambda W \varepsilon$, neighbours to the neigbouring regions, $\lambda^2 W^2 \varepsilon$, and so on. As the scalar parameter (λ) is < 1, the impacts decrease with order of neighbours, so higher-order neighbours (i.e. neighbours to neighbours) receive less impact.

An econometric observation is that regression estimates of β_1 and β_2 from SLX model should be unbiased even when the true model is SDEM, since spatial dependence in the disturbances represents only an efficiency problem. A related point is that the partial derivatives with respect to the explanatory variables are the same for both models.

It is worth noting that neighbouring regions/observations might be defined as those located far away of geographical space, in other words although the term local spillovers could be used to characterize a local model, it does not mean that neighbours regions are necessarily close in the space. It is worth mentioning that LeSage (2009) recommends practitioners of spatial regression models to spend value time in thinking about whether the phenomena they study are likely to produce local or global spillovers.

3.3.2 Multilevel Modelling

Multilevel models, as already mentioned, are used in each discipline where hierarchical structure are common, i.e. individuals nested within geographical areas or institutions. When individuals are in the same group or cluster, it is likely that they are more similar rather than two individuals belonging to different groups, multilevel models can treat this kind of relationship.

One assumption of multiple regression model is that the residuals e_i are independent. So if data are grouped and the model setting does not take into account this feature, the independence assumption does not hold and the standard errors of the regression coefficients will generally be underestimated.

In order to introduce multilevel model, we first consider the simplest possible regression model: a model for the mean of the dependent variable y with no explanatory variables. It is called the null or empty model:

$$y_i = \beta_0 + e_i \tag{3.3}$$

Where y_i is the value of the variable y for the ith individual $(i = 1, ..., n)$, β_0 is the mean of y in the population, and e_i is the "residual" for the ith individual, i.e. the difference between an individual's y value and the population mean. It is assumed that the residuals follow a normal distribution with mean zero and variance σ^2, i.e. $e_i \sim N(o, \sigma^2)$.

The first form of multilevel model allows for group differences in the mean of y, data are organized in a hierarchical structure, with individuals $(i = 1, ..., n)$ at level 1 and groups $(j = 1, ..., N)$ at level 2.

In a multilevel model with 2 levels, residuals are divided into two components, corresponding to the two levels. The group-level residuals are called group random effects denoted by u_j, while the individual residuals are denoted by e_{ij}. So the extension of the model (3.3) is the following:

$$y_{ij} = \beta_0 + u_j + e_{ij} \tag{3.4}$$

Where β_0 is the overall mean of y (across all groups), u_j represents the group level residuals which is the difference between group and the overall mean, e_{ij} represents the individual level residual, which is the difference between the y value for the ith individual and the individual's group mean. Residuals at both levels are assumed to follow a normal distribution $u_j \sim N(0, \sigma_u^2)$ and $e_{ij} \sim N(0, \sigma_e^2)$.

The total variance is partitioned into two components: the one deriving from group variability and the one deriving from individuals variability within groups. The variance partition coefficient (VPC) analyses the variance composition measuring the proportion of total variance due to differences between groups:

$$VPC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2} \tag{3.5}$$

The VPC ranges from 0 to 1, where 0 represents all variance explained by the within variability, and 1 which represents all variance explained by the between variability.

3.3.3 Random Intercept Model

The equation (3.6) shows the simplest form of random intercept model, with one unique explanatory variable:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + u_j + e_{ij} \tag{3.6}$$

In the model (3.6), the between groups relationship between y and x is represented by a linear relation with the intercept β_0 and slope β_1.

The intercept for a given group j is given by $\beta_0 + u_j$ in other words the intercept for a given group could be higher or lower than the overall intercept β_0 by an amount u_j, which represents the group effect or residual with a normal distribution with a mean of zero and variance σ_u^2.

We can distinguish two parts in a multilevel model: a fixed part which is the relationship between the mean of y and explanatory variables, and a random part, containing level 1 and level 2 residuals. The fixed part is $\beta_0 + \beta_1 x_{ij}$ have fixed parameters β_0 and β_1, and the random part is $u_j + e_{ij}$, with random part parameters σ_u^2 and σ_e^2.

The name of the model (3.6) is random intercept model because the intercept is specific of a group and it is allowed to vary randomly across groups, indeed we could formalize the model (3.6) also in the form of two equations as:

$$\begin{aligned} y_{ij} &= \beta_{0j} + \beta_1 x_{ij} + e_{ij} \\ \beta_{0j} &= \beta_0 + u_j \end{aligned} \tag{3.7}$$

Where the intercept could vary from group to group, the slope is assumed to be the same for each group, so the effect of covariates is fixed.

The addition of a level 1 explanatory variable to the model will always reduce the variance, in particular the within variance at level 1 and the total variance. The between variance may stay the same, it could increase or decrease according to weather the distribution of x_{ij} differs across units.

3.3.4 Centring the variable: the Grand Mean Centring

In order to get a more intuitive interpretation of coefficients, it is a common practice centring the variable: in other words, subtracting the sample mean of x from the raw value, i.e. $x_{ij} - \bar{x}$. This centring is called grand mean centring.

In a random intercept model, after centring, the interpretation of the intercept is the predicted mean of y at the mean of x, for these kind of models the centring practice affects only the intercept.

3.3.5 Adding level 2 explanatory variable

As already stated, one of the main advantage of multilevel models is the possibility of adding level 2 explanatory variable, the so called contextual variables, while their effects on individual's y-value are called contextual effects.

In the case of the random intercept model, the model specification is the following:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij} \tag{3.8}$$

Contextual variables may come from different sources. Data may be collected at level 2 or derive from level 1 data that is aggregated to form level 2 variables.

Indeed, if the contextual variable is the level 2 mean of a level 1 variable that is also included in the model, the (3.8) becomes:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + \beta_2 \bar{x}_j + u_j + e_{ij} \tag{3.9}$$

Where $\bar{x_j}$ is the mean of x in group j. β_1 is the within-group effect of x and $\beta_1 + beta_2$ is the between-group effect of x. The within-group coefficients measure the relationship between an individual's x and y within a group. The between-group effect measures the relationship between x and y at the group level, the effect of the group mean of x on y. β_2 is the contextual effect of x, which is the effect of the group mean of x on an individual y.

We can rewrite the model (3.9) as following:

$$y_{ij} = \beta_0^* + \beta_1^*(x_{ij} - \bar{x}_j) + \beta_2^* \bar{x}_j + u_j + e_{ij} \tag{3.10}$$

Where $\beta^* = \beta_1$ is the within-group effect, and $\beta_2^* = \beta_1 + \beta_2$ is the between-group effect. The transformation in model (3.10) of x_{ij} to $(x_{ij} - \bar{x}_j)$ (the individual variables are centred around their respective group means) is called group-mean centring or the Cronbach Model, a practice similar to the one mentioned above which is the grand-mean centring.

3.4 Data, descriptive statistics and model specification

Data on domestic photovoltaic system installations come from the Ofgem's E-serve Database which provides a breakdown of accredited installations under the UK Feed-in-Tariff scheme from 1 April 2010 to 31 March 2017. The database contains installed and declared capacity of 797,320 microgeneration systems for five different technologies, i.e. anaerobic digestion, hydro, micro CHP, photovoltaic, wind and four different installations type, i.e. community, domestic, commercial and industrial. With 99% and 80% of installations and installed capacity, respectively, photovoltaic systems are the most commonly adopted technology[1]. Following the approach of Balta-Ozkan et al. (2015) all systems equals or less than 10 kW are classified as domestic and are included in this analysis.

We use three different geographical classifications: the third level of the European NUTS (Nomenclature of territorial units for statistics)[2], the Local Authorities and Wards classification.

There are a total of 174 NUTS3 regions in the UK based on the 2015 classification, 380 Local Authorities[3] (326 local authorities district in England,

[1]See the descriptive statistics of Chapter 2: *Innovation and Technology Diffusion for green energy pathways: GB domestic photovoltaic (PV) systems*, for distribution of different technologies in the data.

[2]According to the Eurostat definition the NUTS classification is a hierarchical system for dividing up the economic territory of the EU for the purpose of collection, development and harmonization of European Regional statistics, socio-economic analysis of the regions, framing of EU regional policies.

[3]The structure of local government in UK is complex and varies from area to area. Many parts of England, for example, have 2 tiers of local government: one is the county councils, the other one is district, borough or city councils; in some part of the country, there's just 1 (unitary) tier of local services. In the present analysis 326 local authorities in England, 32 unitary authorities in Scotland and 22 single-tier principal areas in Wales are considered, according to ONS data.

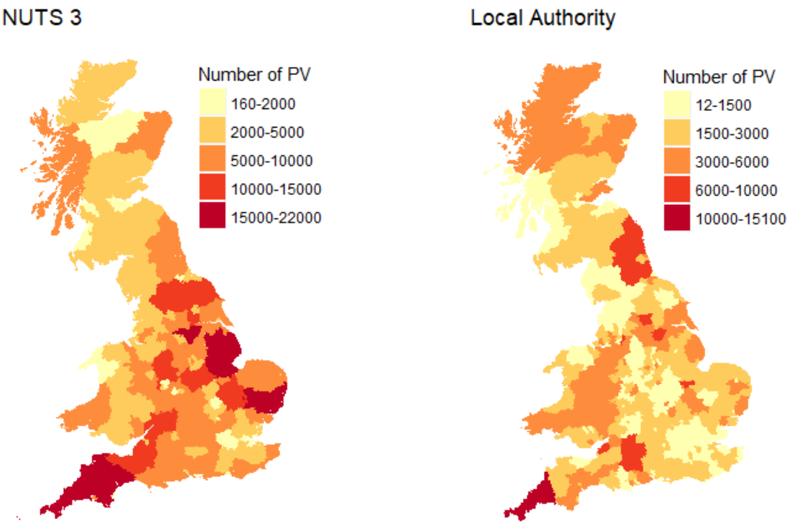

Figure 3.1: Distribution of residential PV systems in Great Britain. NUTS3 level (left) LA level (right)

single-tier principle areas in Wales and 32 unitary authorities in Scotland), and 8668 wards (7463 in England, 852 in Wales, 353 in Scotland). In this analysis we consider 163 NUTS 3 regions, 374 local authorities and 8591 wards, excluding Northern Ireland and the major islands[4].

The spatial concentration of the number of PV in NUTS3, Local Authorities and Wards is shown in Figures.

Figures 3.1 and 3.2 show a spatial pattern of the number of domestic photovoltaic installations and the finer spatial resolution show different spatial patterns. From the NUTS3 and Local Authority representations, it appears a more concentration of photovoltaic systems diffusions on south-west and north-east of England. Using, instead, a greater granularity, it appears that in Scotland there are less more concentrated PV installations.

To assess the spatial correlation of regional/subregional areas we employ the Moran Index. The Moran Index is a measure of spatial autocorrelation

[4]Excluded islands are the Isle of White, Isle of Anglesey, Isle of Schilly, Shetland Islands, Orkney Islands and Western Islands.

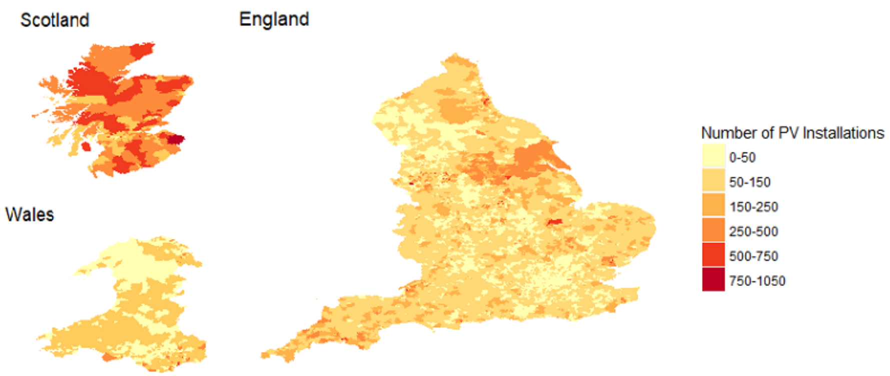

Figure 3.2: Distribution of residential PV systems in England, Scotland and Wales. Ward level

between a region and its neighbours. It is calculated as a ratio of the product of the variable of interest and its spatial lag, with the cross-product of the variable of interest, and adjusted for the used spatial weights. A Moran Index for the number of PV system installations is computed by using a binary contiguity matrix by means of the queen method[5] for all three granularity considered (Figure 3.3). A positive value of Moran Index is a signal of the presence of autocorrelation. Figure 3.3 reports that the value of the Moran Index is always positive and statistically significant for all the three granularity considered.

3.4.1 Explanatory Variables

Table A.3.1 in Appendix A.3 reports all variables collected in our dataframe, which are meant to influence the uptake of PV systems. Following the classification conducted in the literature review of the second chapter (*"Innovation and Technology Diffusion for green energy pathways: GB domestic photovoltaic (PV) systems"*), the main explanatory variables are divided in

[5]Two areas are considered neighbours if they share a common border or a common edge.

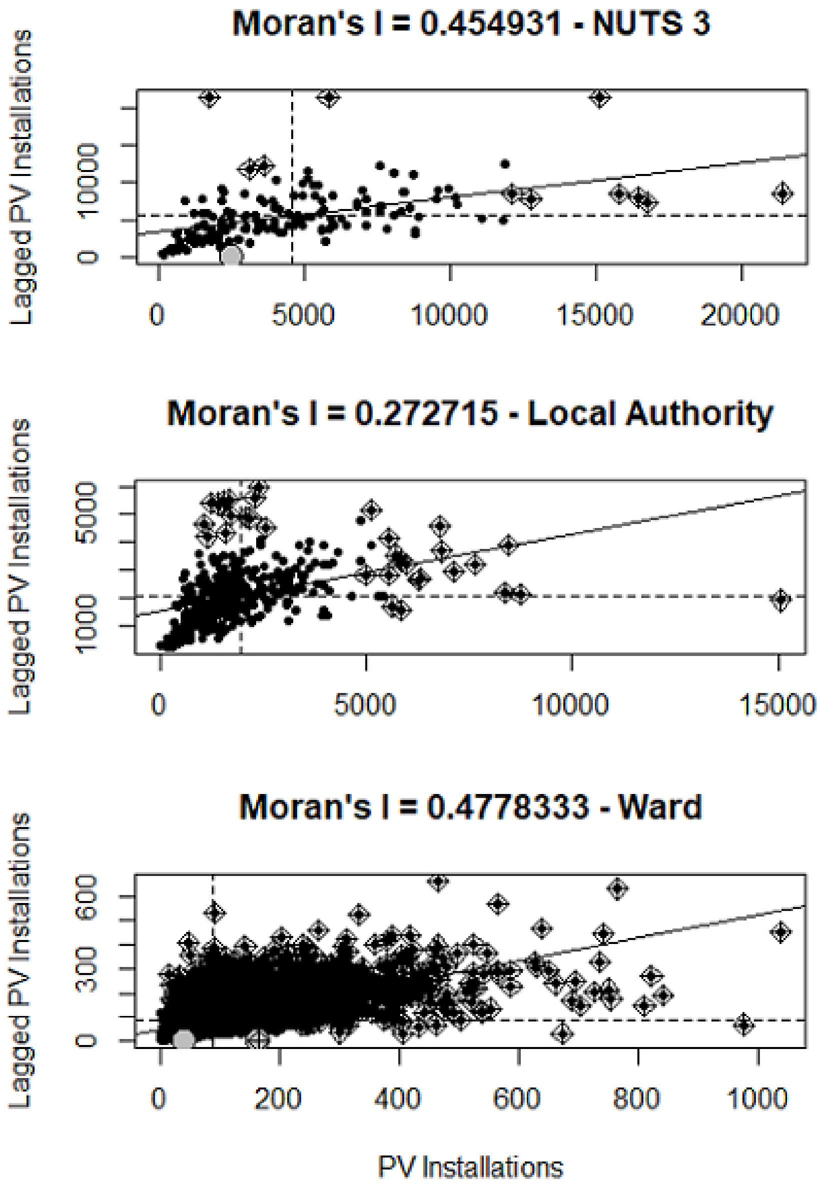

Figure 3.3: Moran's Index Scatterplot for number of PV installations systems at Nuts 3, Local Authority and Ward Level

characteristics of adopters and settlement structure[6]. For the sake of completeness there is also an additional category regarding the solar radiation data under meteorological data category. Appendix A.3 reports data source and availability, geographical scale and data processing.

3.4.2 Model Specification

Two slightly different model specifications are employed, one for the spatial econometrics methodology and the other one for the multilevel analysis. The model specification in equation (3.11) is used for the spatial econometric approach:

$$\begin{aligned} log(nPV)_i = &\beta_0 + \beta_1 density_i + \beta_2 hhsize_i + \beta_3 low\_income_i + \beta_4 high\_income_i + \\ &+ \beta_5 median\_age_i + \beta_6 edu\_1\_share_i + \beta_7 edu\_4\_share_i + \beta_8 rent_i + \\ &+ \beta_9 detached_i + \beta_{10} electricity\_consumption_i + \beta_{11} green\_electorate_i + \\ &+ \beta_{12} solar\_radiation_i + u_i \end{aligned} \tag{3.11}$$

where the index i represents the index of region (it indicates the NUTS 3, the Local Authority and the Ward index) and u is an independently and identically Normally distributed error term with zero mean and variance σ^2. The dependent variable is the logarithm of number of domestic photovoltaic systems registered in the tree zones under consideration (NUTS, LA, Wards). The explanatory variables are: 1) *density*, the zonal population density; 2) *hhsize*, the zonal average size of households; 3) *low_income* and *high_income*, two dummy variables for income[7]; 4) *median_age*, the zonal

[6] At the present stage of our analysis there are no independent variables capturing the effect of environmental policy frame.

[7] *low_income* is a dummy variable equal to one if the regional income is in the first quartile, *high_income* is a dummy variable equal to one if the regional income is in the fourth quartile.

median age; 5) *edu_1_share* and *edu_4_share*, two dummy variables for education level[8]; 6) *rent*, the zonal number of rented houses; 7) *detached*, the zonal number of detached dwellings; 8) *electricity_consumption*, the zonal domestic electricity consumption; 9) *green_electorate*, the zonal electoral data[9]; 10) *solar_radiation*, the zonal average of solar irradiation.

The second model specification follows the Cronbach model, in other words, the independent variables values, are centred on their group mean, while the second level variables are the group mean values, as following[10]:

$$
\begin{aligned}
log(nPV_{ij}) = & \beta_0 + \beta_{ij}(dens_{ij} - \overline{dens}_J) + \beta_{ij}(hhsize_{ij} - \overline{hhsize}_J) + \\
& + \beta_{ij} low\_inc_{ij} + \beta_{ij} high\_inc_{ij} + \beta_{ij}(med\_age_{ij} - \overline{med\_age}_J) + \\
& + \beta_{ij}(edu1_{ij} - \overline{edu1}_J) + \beta_{ij}(edu4_{ij} - \overline{edu4}_J) + \beta_{ij}(rent_{ij} - \overline{rent}_J) + \\
& + \beta_{ij}(detach_{ij} - \overline{detach}_J) + \beta_{ij}(elect_{ij} - \overline{elect}_J) + \\
& + \beta_{ij}(green_{ij} - \overline{green}_J) + \beta_{ij}(sol_{ij} - \overline{sol}_J) + \beta_j \overline{dens}_J + \\
& + \beta_j \overline{hhsize}_J + \beta_j low\_inc_j + \beta_j high\_inc_j + \beta_j \overline{med\_age}_J + \\
& + \beta_j \overline{edu1}_J + \beta_j \overline{edu4}_J + \beta_j \overline{rent}_J + \beta_j \overline{detach}_J + \beta_j \overline{elect}_J + \\
& + \beta_j \overline{green}_J + \beta_j \overline{sol}_J + e_{ij} + u_j
\end{aligned}
\tag{3.12}
$$

The index i indicates the level 1 index, the index j is the index of the level 2.

[8] *edu_1_share* is the share of population with education level equal to one; *edu_4_share* is the share of population with education level equal to three;

[9] Electoral data report the regional votes in favour of the six principles party in UK. The variable green electorate indicates the number of regional votes in favour of the labourist party, liberal democrats party, the Scottish National Party and the green party. The other two categories in electoral data are represented of CON category indicating the regional votes in favour of the conservative party and UKIP party, while OTHER indicates all other votes.

[10] In this model the independent variables are indicated by means of abbreviations.

3.5 Results and Discussion

3.5.1 OLS Results

As a first step an OLS regression for all geographical granularity was run. Table 3.1 reports results, the coefficient of determination (R^2), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

Table 3.1: OLS estimation results. NUTS3. LA and Wards level

	NUTS3	Local Authority	Wards
Constant	7.378**	0.721	-4.096***
	(0.001)	(0.614)	(0.000)
Density	-0.021***	-0.015***	-0.010***
	(0.000)	(0.000)	(0.000)
Hh Size	-0.759 **	-0.177	0.595
	(0.007)	(0.419)	(0.000)
Low Income	0.007	0.050	0.037.
	(0.933)	(0.438)	(0.051)
High Income	-0.286 **	-0.362***	-0.246***
	(0.001)	(0.000)	(0.000)
Median Age	-0.059 ***	-0.024*	0.018***
	(0.000)	(0.021)	(0.000)
Edu 1 Share	-0.510	0.415	0.103***
	(0.724)	(0.707)	(0.000)
Edu 4 Share	-1.281.	-1.210*	-0.147***
	(0.085)	(0.031)	(0.000)
Rented Houses	0.048*	0.031	0.008***
	(0.011)	(0.119)	(0.000)
Detached Dwellings	0.108***	0.212***	0.005***
	(0.000)	(0.000)	(0.000)
Electricity Consumption	2.908*	4.880***	0.423***
	(0.012)	(0.000)	(0.000)
Green Electorate	0.119	0.549**	0.408***
	(0.674)	(0.002)	(0.000)
Solar Radiation	0.114	0.127*	0.012***
	(0.150)	(0.026)	(0.000)
R2	0.88	0.75	0.54
AIC	107.718	3.610.583	14891.71
BIC	151.030	415.99	14990.53
Number of observations	163	374	8591

OLS results (Table 3.1) show that some covariates present the same results in all geographical granularities in terms of sign and significance. On one hand, it seems that the number of PV installations negatively correlates with population density and the dummy variable for the last quartile of income distribution (high income). This implies that wealthy region and highly populated presents a lower up taking of PV systems. On the other hand, the number of PV installations positively correlates with the share of detached dwellings and domestic electricity consumption. The number of PV is also positively influenced by share of rent houses as reported for NUTS 3 and Ward zone.

Other variables present a significant effect only at greater geographical granularity as percentage of people with high education, green electorate and solar radiation. Contrary, household size is significant only at NUTS3 level. Population median age, instead, present opposite signs at NUTS and ward level.

We run a Moran's I statistic and Lagrange Multiplier tests in order to check for spatial autocorrelation. The Moran test is run for testing OLS regression residuals, while LM error and lag tests, verify the null hypothesis of no spatial dependence against alternatives of spatial error and lag dependence.

Table 3.2: Test for spatial dependence in OLS regression

Test	NUTS 3	LA	WARD
Moran's I	0.162***	0.178**	0.371***
	(0.000)	(0.000)	(0.000)
LM (error)	7.870**	27.164***	3,457***
	(0.005)	(0.000)	(0.000)
LM (error robust)	3.748.	3.409.	941.9***
	(0.052)	(0.064)	(0.000)
LM (lag)	9.883**	33.744***	2631***
	(0.001)	(0.000)	(0.000)
LM (lag robust)	5.762*	9.989**	115.194***
	(0.016)	(0.001)	(0.000)

The Moran's I statistics (Table 3.2) present a considerable evidence of spatial autocorrelation in the OLS regression residuals. LM tests (Table 3.2) confirm the inadequacy of the OLS model. Both versions, testing for spatial correlation of the error terms and the spatial correlation of the lagged dependent variable term, are strongly significant.

3.5.2 The Spatial Econometrics Approach: a local spillover specification

In this section we develop a spatial econometric analysis, presenting two local spillover models: Spatial Lag in X Model (SLX) and Spatial Durbin Error Model (SDEM). Both models, as already mentioned, allow to control for the spatial local patterns of studied phenomena. The SDEM differs from the SLX as it controls also for the spatial lag in the error term, modelling the global diffusion shocks in the error component.

The choice to apply a local spillover model is largely discussed in the second chapter (*Innovation and Technology Diffusion for green energy pathways: GB domestic photovoltaic (PV) systems*). For the purposes of our analysis a local spillover framework seems to be the most appropriate, as observing the neighbour installing a rooftop PV system can have a snow ball effect in the closer neighbourhoods.

The choice of applying a SDEM is driven by the inspection on residuals from the SLX estimation which still present spatial autocorrelation (Moran Index test on the residuals).

The used weight matrix is a parameterized inverse distance matrix. The estimation technique is based on the concept of distance decay already discussed in the second chapter. The weights within the matrix are as following:

$$w_{ij} = 1/d_{ij}^{\gamma} \tag{3.13}$$

where d_{ij} is the distance between region i and j, and γ is the distance decay parameter to be estimated. This methodology allows more flexibility and information on regionals dependencies (to a more complete discussion on the parameterization method see the methodological part of the second chapter).

Table 3.3 summaries estimation results.

Table 3.3: Spatial local spillover models estimation results

	NUTS3		Local Authority		Wards	
	SLX	SDEM	SLX	SDEM	SLX	SDEM
Constant	17.231***	16.516***	12.023***	10.653**	-2.153***	-3.504***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Hh Size	0.141	0.151	0.551*	0.508*	0.885***	0.902***
	(0.606)	(0.540)	(0.012)	(0.014)	(0.000)	(0.000)
Low Income	0.007	0.010	0.008	0.028	0.002	0.016
	(0.911)	(0.869)	(0.897)	(0.623)	(0.905)	(0.341)
High Income	-0.155.	-0.157*	-0.089	-0.111.	-0.101***	-0.099***
	(0.063)	(0.038)	(0.209)	(0.094)	(0.000)	(0.000)
Median Age	-0.043*	-0.043**	-0.023*	-0.021*	0.031***	0.032***
	(0.012)	(0.005)	(0.041)	(0.043)	(0.000)	(0.000)
Edu 1 Share	0.662	0.765	0.448	0.270	0.375***	0.364***
	(0.807)	(0.751)	(0.844)	(0.898)	(0.000)	(0.000)
Edu 4 Share	-0.585	-0.504	-0.584	-0.537	-0.086***	-0.092***
	(0.527)	(0.544)	(0.458)	(0.464)	(0.000)	(0.000)
Green Electorate	-0.481.	-0.504*	0.239	-0.236	0.227**	0.272***
	(0.068)	(0.034)	(0.215)	(0.190)	(0.009)	(0.000)
Rented Houses	0.063***	0.063***	0.019	0.015	0.013***	0.013***
	(0.000)	(0.000)	(0.318)	(0.380)	(0.000)	(0.000)
Detached Dwellings	0.069***	0.070***	0.133***	0.138***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Electricity Consumption	4.611**	4.857***	6.147***	6.136***	0.465***	0.469***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Density	-0.018***	-0.018***	-0.010***	-0.009***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Solar Radiation	0.242	0.236	-0.315	-0.525	-0.011	-0.006
	(0.586)	(0.573)	(0.512)	(0.257)	(0.621)	(0.963)
W*Density	-0.004	-0.004	-0.013***	-0.011**	-0.008***	-0.007**
	(0.237)	(0.217)	(0.000)	(0.002)	(0.000)	(0.000)
W*Hh Size	-2.373***	-2.307***	-2.680***	-2.357***	-0.668***	-0.459***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
W*Low Income	-0.276	-0.283	-0.577**	-0.483*	-0.178***	0.019***
	(0.117)	(0.104)	(0.001)	(0.010)	(0.000)	(0.000)
W*High Income	-0.546**	-0.553**	0.123	0.058	-0.386***	-0.283***
	(0.003)	(0.001)	(0.439)	(0.737)	(0.000)	(0.000)
W*Median Age	-0.033	-0.032	-0.062*	-0.069*	-0.037***	-0.027***
	(0.339)	(0.333)	(0.013)	(0.013)	(0.000)	(0.000)
W*Edu 1 Share	-0.155	0.022	-5.538.	-4.422	-0.487***	-0.318***
	(0.967)	(0.995)	(0.069)	(0.154)	(0.000)	(0.000)
W*Edu 4 Share	0.939	0.899	-4.779***	-4.359**	-0.077	-0.006
	(0.571)	(0.564)	(0.000)	(0.003)	(0.299)	(0.851)
W*Rented Houses	0.135**	0.135***	0.049	0.015	-0.005***	-0.007***
	(0.001)	(0.000)	(0.361)	(0.787)	(0.000)	(0.005)
W*Detached Dwellings	0.071*	0.067*	0.156.	0.174.	0.002***	0.001***
	(0.042)	(0.047)	(0.067)	(0.063)	(0.000)	(0.000)
W*Electricity Consumption	-5.244*	-4.996*	-3.704**	-3.389*	-0.021	-0.035
	(0.021)	(0.024)	(0.009)	(0.032)	(0.477)	(0.398)
W*Green Electorate	-1.515*	-1.433*	0.819.	0.787.	0.303**	0.259*
	(0.010)	(0.013)	(0.051)	(0.091)	(0.004)	(0.042)
W*Solar Radiation	-0.186	-0.169	0.559	0.791.	0.026	0.021
	(0.702)	(0.712)	(0.257)	(0.097)	(0.273)	(0.262)
λ W*error		0.184		0.304**		0.667***
		(0.176)		(0.002)		(0.000)
AIC	53.34	53.52	283.56	276.29	14324.69	11708
BIC	133.78	137.05	385.59	382.25	14508.21	11898.43
Number of observations	163	163	374	374	8591	8591

If we look at direct impact. at finer granularities (Wards). a set of variables become significant and with expected sign. Household size. Education 1 variable. income variables and share of "green parties" are all significant. Contrary, other variables show the same effect. in terms of sign and significance in all three analyses. as population density. share of rent houses. share of detached dwellings. consumption of domestic electricity.

Observing the spillover effects, results are more heterogeneous. The spatial lag of the household size variable shows a negative effect at all granularity levels. Some variables are significant only for wards or wards and LAs. i.e. population density. the spatial lag of the dummy variable low income. spatial lag of median age and spatial lag of the Edu 1 variable.

There are other effects which appear only for NUTS and Wards level as the dummy variable high income (always negative). the spatial lags for rent houses, which present an opposite sign (positive for NUTS. negative for wards) and W*Green electorate. The spatial lag of detached dwellings is positive and significant both in NUTS and Ward analysis. In term of domestic electricity consumption the spatial lag has an impact in NUTS3 and Local Authority analysis.

Results analysis lead to several considerations. One, we already mention, is that the same variables could show different impacts on photovoltaic systems diffusion. depending on which is the geography considered. so estimation results are sensible to the Modifiable Aeral Unit Problem. Another consideration is that considering bigger areas means make homogeneous smaller areas. which could be more heterogeneous. explaining why the same variables show opposite results at different levels of geography.

3.5.3 The Multilevel analysis

The multilevel modelling technique, as already mentioned, allows to control for nested data. The model structure is such that variables are organized in different levels. one for each geographical dimension.

In our analysis we consider two geographical levels: the level one is the more geographically fragmented (i.e. the ward level). the level 2, instead, consider wider geographies (i.e. the LA level).

As a first step of our analysis we run the simplest model which allows to control for local authority effects, without explanatory variables. The model specification is the following:

$$log(PV_{ij}) = \beta_0 + u_{0j} + e_{ij}$$

Where $log(PV_{ij})$ is the logarithm of the number of PV installations in Ward i in Local Authority j. β_0 is the overall mean across local authorities. u_{0j} is the effect of local authority j on the number of PV installations, and e_{ij} is Ward level residual.

Table 3.4: Empty Model results

	Empty Model
Constant	4.155*** (0.000)
Between-variance	0.39
Within-variance	0.35
LR test vs. linear model	4907.27*** (0.000)
Number of observations	8591
Number of groups	374

Table 3.4 reports main results. The overall mean of the logarithm of the number of PV systems installations across all LAs is estimated as 4.155. The mean of PV at Local Authority j is estimated as $4.155 + \hat{u}_{0j}$, where $\hat{u}_{0j}$ is the residual of LA j. A local authority with $\hat{u}_{0j} > 0$ has a mean that is higher than the average, while a local authority with $\hat{u}_{0j} < 0$ is a below-average LA.

The variance between local-LA is estimated as 0.39, the variance within-LA is 0.35. The total variance is the sum of the two: 0.74. The Variance Partition Coefficient (VPC) is equal to $3138/6460 = 0.52$. it means that the 52% of the variance in the number of PV installations systems could be attributed to the difference between LAs. It is clear from this result that a multilevel analysis could result useful for our research question.

Moreover, the likelihood ratio test, comparing the model in Tab. 3.4 (the empty model) with a linear, show that there is a strong evidence of LA effects on the number of PV systems.

We run two different random intercept models. in the first we include just the level 1 variable. the second one is a full model including both the levels. The model specification follows the Cronbach Model specification (i.e. Cluster Mean Centring) as seen above. Indeed. level 1 variables are defined as the difference between the value observed for Wards and the average value of the cluster (the mean value observed for the LA); level 2 variables are measured as group means.

If we look at the effects of level 1 variables, results are absolutely comparable in terms of sign and significance to direct effects of spatial econometrics models run at Ward level. Also the magnitude of coefficients is comparable for the majority of variables such as population density. household size. dummy variables low income and high income. median age. rent houses. detached dwellings and domestic electricity consumption.

Level 2 estimates describe the LA aggregated effect of variables in PV installations and overall results are comparable to spillover effects at different granularities as seen in the spatial econometrics specifications. In particular, the comparability is valid for population density. household size. high income dummy. median age. Education at level 1. detached dwellings. Two exceptions exist for rent house the level of domestic electricity consumption.

Table 3.5: Wards spatial models point estimates results

	Ward Level Model	Ward-LA Level Model
$Density_{ij}$ - $Density_J$	-0.005***	-0.005***
	(0.000)	(0.000)
$HhSize_{ij}$ - $HhSize_J$	0.913***	0.906***
	(0.000)	(0.000)
$LowIncome_{ij}$	0.039***	0.025***
	(0.023)	(0.143)
$HighIncome_{ij}$	-0.106***	-0.087***
	(0.000)	(0.000)
$MedianAge_{ij}$ - $Median\ Age_J$	0.034***	0.034***
	(0.000)	(0.000)
$Edu\ 1\ Share_{ij}$ - $Edu\ 1\ Share_J$	0.497***	0.491***
	(0.000)	(0.000)
$Edu\ 4\ Share_{ij}$ - $Edu\ 4\ Share_J$	-0.021	-0.028***
	(0.124)	(0.037)
$Rent\ House_{ij}$ - $Rent\ House_J$	0.012***	0.012***
	(0.009)	(0.000)
$Detached\ Dwellings_{ij}$ - $Detached\ Dwellings_J$	0.004***	0.004***
	(0.000)	(0.000)
$Electricity\ Consumption_{ij}$ - $Electricity\ Consumption_J$	0.451***	0.451***
	(0.000)	(0.000)
$Green\ Electorate_{ij}$ - $Green\ Electorate_J$	0.319***	0.319***
	(0.000)	(0.000)
$Solar\ Irradiation_{ij}$ - $Solar\ Irradiation_J$	-0.014	-0.014
	(0.235)	(0.252)
$Density_J$		-0.015***
		(0.000)
$Hh/Size_J$		-0.011
		(0.951)
$LowIncome_J$		-0.073***
		(0.202)
$HighIncome_J$		-0.252***
		(0.000)
$MedianAge_J$		-0.019**
		(0.027)
$Edu1Share_J$		-0.022**
		(0.041)
$Edu4Share_J$		-0.207***
		(0.000)
$RentHouses_J$		0.012**
		(0.002)
$DetachedDwellings_J$		0.007***
		(0.000)
$LnElectricityConsumption_J$		0.344***
		(0.000)
$GreenElectorate_J$		0.408***
		(0.000)
$SolarIrradiation_J$		0.017***
		(0.000)
N of observation	8591	8591
N of groups	374	374

3.5.4 Residuals analysis

The standard approach to evaluate a multilevel model is the residual diagnostics. The objective of this analysis is to verify if model's residuals are normally distributed. Residuals should lie on a straight line: this would imply that the assumption of normality is well supported by the data. Indeed, a non-linearity trend in residuals would suggest departures from normality. Figure 3.4, 3.5 and 3.6 report the graphical analysis of residuals and we can see a slightly departure from normality mainly due to some outliers. However, the overall distribution of residual lies on a straight line. This suggests that the data well support the assumption of normality implied by multi-level modelling.

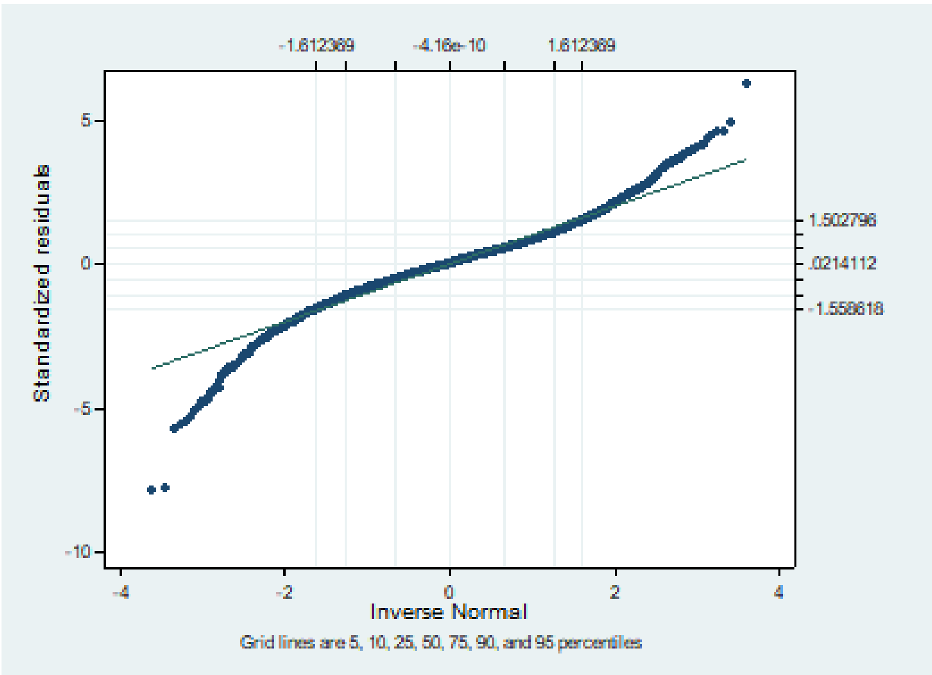

Figure 3.4: Normality check for standardized residuals

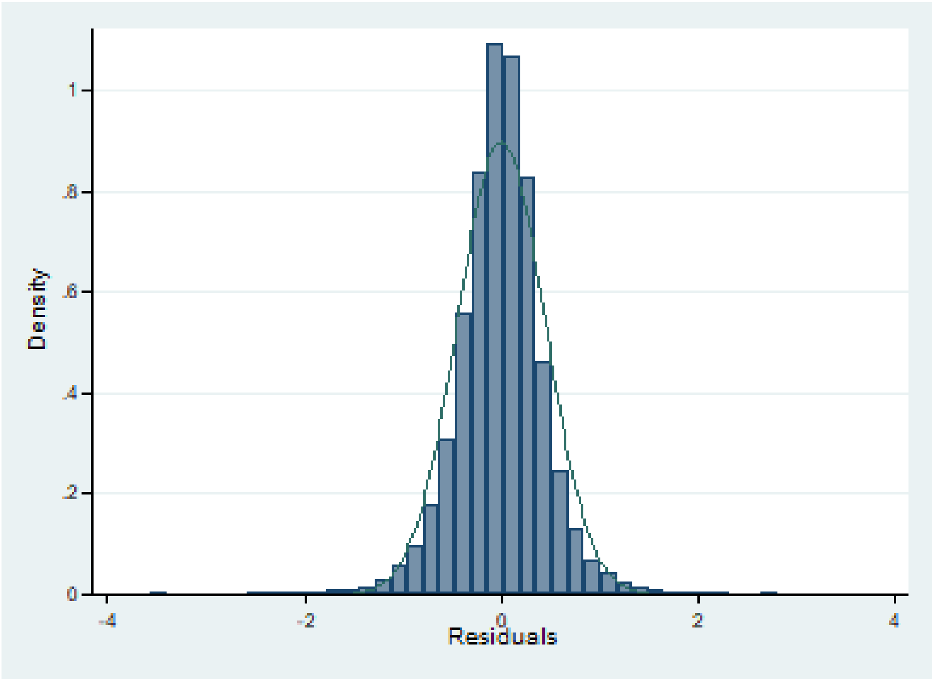

Figure 3.5: Normality approximation of standardized residuals

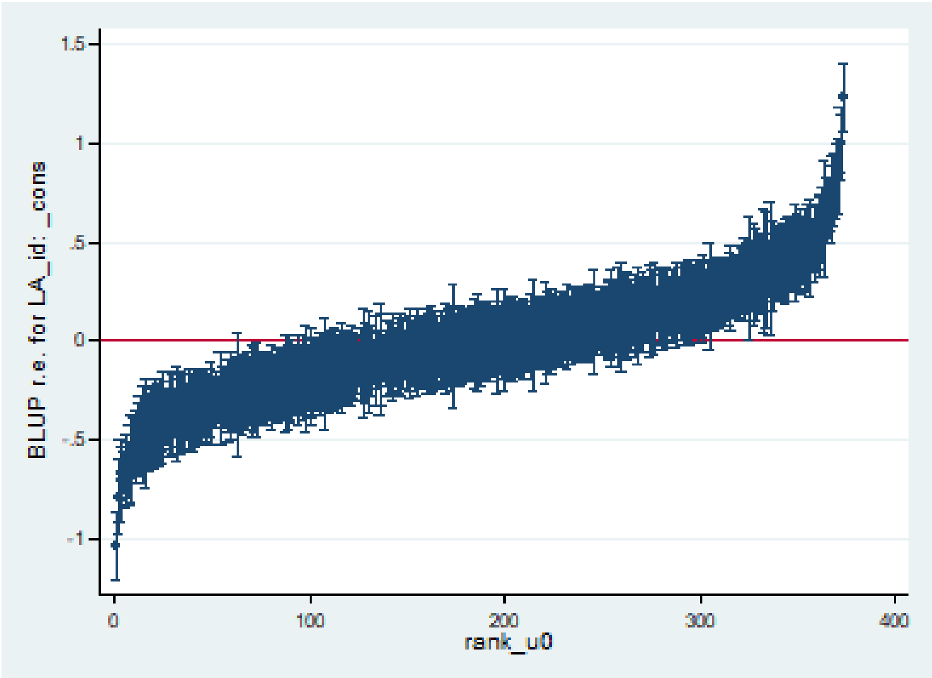

Figure 3.6: Caterpillar Plot. Plot of residuals vs. rank of residuals using comparative standard errors

3.6 Discussion and Conclusions

The spatial econometrics analysis of PV systems in GB is initially carried out by two local spillovers models (SLX and SDEM) considering three different geographical granularities (Nuts3. Local Authority and Ward level). Results indicate some sensitivity to the so called Modifiable Aeral Unit Problem; indeed, at ward level some variables have a different effect with respect to wider geographical zones. Comparing results could be a good exercise, but it is not useful for the choice of which kind of geographical granularity is the most appropriate for designing policy interventions. Models suggest that some drivers of PV adoption consistently apply at all granularities. However other factors have more local specific effects.

Multilevel models represent a methodology which allows to simultaneously control for different geographical level, in one unique estimation routine. Despite this technique cannot take into account the spatial correlation. the hierarchical structure of data supports the estimation of which source of variability is due to the heterogeneity of smaller areas. and which part is due, instead, to the variability between groups.

Multilevel results are perfectly comparable to spatial econometrics analysis applied at Ward data. both in terms of direct effects and spillover effects. This findings are encouraging as drivers of PV system are clearly identified despite the advantages and disadvantages of the two employed techniques.

This analysis is useful for the policy maker who would like to incentivize the diffusion of photovoltaic systems by means of ad hoc policy interventions. Indeed, some characteristics have a constant impact at all geographical levels others present more locally specific effects. Methodologically, the results show that when space play a role spatial econometric and multilevel models can be applied to data and lead to comparable results. As we claim the importance to research new hybrid models (e.g. a coherent multilevel spatial model) the current set of tools for spatial analysis is adequate to support policy decision making.

A.3 Appendix A.3

Table A.3.1: List of collected variables

	Variable	Geographical Availability	Data Source	Granularity of Data
Characteristics of adopters	Population Density	England and Wales (LSOA[11])	ONS[12]	Aggregated to NUTS3
		Scotland (Datazone)[13]	NRS[14]	
	Household Size	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS[15]	
	Low Income (Dummy variable = 1 for income in first quartile)	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS	
	High Income (Dummy variable = 1 for income in last quartile)	England and Wales (LSOA)	ONS	Aggregated to NUTS3
		Scotland (Datazone)	SNS	
	Median Age	England and Wales (LSOA)	NOMIS[16] (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Edu 1 Share (Share of people with education level = 1)[17]	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Edu 4 Share (Share of people with education level = 4)[18]	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Costituency)	NRS	
	Green Electoral Data	England and Wales (Costituency)	The electoral Commission	Aggregated to NUTS3
		Scotland (Costituency)		
	Domestic Electricity Consumption	England and Wales (LSOA)	DECC[19]	Aggregated to NUTS3
		Scotland (DataZone)		
Settlement Structure	Accomodation/Dwelling Type (Number of detached dwellings)	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland (Datazone)	NRS	
	Rented Houses (Number of owned houses)	England and Wales (LSOA)	NOMIS (ONS)	Aggregated to NUTS3
		Scotland	NRS	
Metereological Data	Solar Radiation	England and Wales (LSOA)	JRC	Aggregated to NUTS3
		Scotland (Datazone)		

[11] A (LSOA) is a geographic area, designed to improve the reporting small area statistics in England and Wales. Lower Layer Super Output Areas are built from groups of contiguous Output Areas and have been automatically generated to be as consistent in population size as possible, typically the mean population is 1500.

[12] Office of National Statistics

[13]The data-zone geography covers the whole of Scotland and nests within local authority boundaries. A datazone has a population of between 500 and 1,000 household residents

[14]National Records for Scotland

[15]Scottish Neighbourhood Statistics

[16]Official Labour Market Statistics

[17]Level 1: 1-4 O Levels/CSE/GCSEs (any grades), Entry Level, Foundation Diploma, NVQ Level 1, Foundation GNVQ, Basic/Essential Skills. Source: Nomis: Official Labour Market Statistics

[18]Degree (for example BA, BSc), Higher Degree (for example MA, PhD, PGCE), NVQ Level 4-5, HNC, HND, RSA Higher Diploma, BTEC Higher level, Foundation degree (NI), Professional qualifications (for example teaching, nursing, accountancy)

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