Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach

Nazmiye Balta-Ozkan, Julide Yildirim, Peter M. Connor

PII: S0140-9883(15)00224-8
DOI: doi: 10.1016/j.eneco.2015.08.003
Reference: ENEECO 3130

To appear in: *Energy Economics*

Received date: 4 August 2014
Revised date: 2 June 2015
Accepted date: 9 August 2015

Regional distribution of photovoltaic deployment in the UK and its determinants: a spatial econometric approach

Nazmiye Balta-Ozkan[a,1], Julide Yildirim[b] and Peter M. Connor[c]

[a] School of Energy, Environment and Agrifood, Cranfield University, Cranfield, Bedfordshire MK43 0AL, UK

[b] TED University Department of Economics, Ziya Gökalp Cad. No. 48, 06420, Ankara, Turkey

[c] University of Exeter, Penryn Campus, Treliever Road, Penryn, Cornwall, TR10 9EZ, UK

Abstract:

Photovoltaic (PV) panels offer significant potential for contributing to the UK's energy policy goals relating to decarbonisation of the energy system, security of supply and affordability. The substantive drop in the cost of panels since 2007, coupled with the introduction of the Feed-in Tariff (FiT) Scheme in 2010, has resulted in a rapid increase in installation of PV panels in the UK, from 26.5MWp in 2009 to over 5GW by the end of 2014. Yet there has been no comprehensive analysis of the determinants of PV deployment in the UK. This paper addresses this gap by employing spatial econometrics methods to a recently available data set at a fine geographical detail. Following a traditional regression analysis, a general to specific approach has been adopted where spatial variations in the relationships have been examined utilizing the spatial Durbin model using the cross-sectional data relating to the UK NUTS level 3 data. Empirical results indicate that demand for electricity, population density, pollution levels, education level of households and housing types are among the factors that affect PV uptake in a region. Moreover Lagrange Multiplier test results indicate that the spatial Durbin model may be properly applied to describe the PV uptake relationship in the UK as there are significant regional spillover effects.

Key words: photovoltaic, PV, spatial spillover, FIT, spatial econometrics, spatial energy

JEL Classification: C21, Q28, Q42, Q55

[1] Corresponding author: E-mail: n.ozkan@cranfield.ac.uk; Tel: +44 1234 750111, Fax: +44 1234 752971.

1. Introduction

UK climate change and energy policy goals legislate an 80% emissions reduction target from 1990 levels by 2050 via the Climate Change Act (CCA, 2008) while ensuring security of supply and affordability. Additionally, the European directive 2009/28/EC imposes a target for the UK to meet 15% of all energy consumption from renewable energy sources by 2020 (EC, 2009), a commitment reaffirmed in various UK policy documents (e.g., DECC, 2012a). Photovoltaic (PV) panels offer a significant opportunity to achieve both these goals. By transforming domestic consumers into 'prosumers'[2] PV allows them to self-generate and export remaining electricity, consequently reducing their purchases from the grid whilst contributing to decarbonising and diversifying UK electricity supply.

Installed global PV capacity has increased from 1.4GW in 2000 to 70GW in 2011 (IEA/IRENA, 2013), and on to 177GW by the end of 2014 (IEA, 2015), a rise both linked to and driving improved performance and efficiency due to technological progress and economies of scale. There is a growing literature focusing on large-scale, commercial PV applications, including comparison of their performance (Sueyoshi and Goto, 2014); analysis of their market value (Hirth, 2013); optimal size and timing of investments (Massetti and Ricci, 2013) and effect of policy framework on investor preferences (Lüthi and Wüstenhagen, 2012). Policy incentives such as the Feed-in Tariff (FiT) schemes have played a significant role in promoting domestic applications (Zhang et al., 2011). Indeed following the 2010 introduction of the UK Feed-in Tariff (FiT) Scheme, annual installation rates for PV panels has increased by a factor of nearly two hundred in the UK in under five years (from 26.5MW in 2009 to over 5GW by the end of 2014, DECC (2015a)). The Government estimates that the FIT will engender 7.5GW of PV capacity by 2020, with other mechanisms stimulating a further 1.8-3.2 GW at larger scale capacity (DECC, 2013b). A typical domestic PV (at 2.6kWp capacity) costs around £5300 according to data collected relating to FiT eligible PV installations (DECC, 2014b), a figure which has reduced significantly in a relatively short period of time as cell costs and thus overall installation costs have reduced sharply. FiT rates have been reduced significantly since 2010 to try to match the real world cost reductions.

[2] Prosumers also includes consumers who produce their own power from a range of different onsite generators (e.g. diesel generators, combined heat-and-power systems, wind turbines, and PV systems) (IEA-RETD, 2014).

However only a small fraction, (2.4%), of the UK's nearly 26 million households have installed a rooftop PV panel as of December 2014. A variety of factors, from social (e.g. reserving roofspace for PVs, Wolsink, 2012) to economic (e.g. cost reductions Muhammad-Sukki et al., 2013) to policy incentives (Faiers and Neame, 2006; Grau, 2014) have been highlighted in the literature to explain the drivers and barriers to the uptake of PVs. Thus far studies of domestic adoption of PV are characterized by either detailed, qualitative analysis based on interviews/surveys (Cherrington et al., 2013; Faiers and Neame, 2006) or quantitative analysis via econometric methods (Jenner et al., 2013; Zhang et al., 2011). Following the first law of geography, '*everything is related to everything else, but near things are more related than distant things*' (Tobler, 1970, p.236), there is an understanding that low carbon technologies like PV or electric vehicles are likely to form local clusters (Balta-Ozkan et al., 2014a). Yet, by ignoring the spatial proximity and clustering of PVs, we argue that these methods do not offer a framework to understand the spatially dependent nature of low carbon transitions (Bridge et al., 2013).

A key characteristic of this study is to analyse the determinants of PV uptake in association with neighbouring regions, building on a similar study carried out for Germany (Schaffer and Brun, under review). Such a spatial analysis is important for a number of reasons. Firstly, the availability of solar energy varies by location as well as time (weather conditions and time of day/season). Secondly, distributed PV can create reverse flows on the networks that were designed for uni-directional electricity flows from centralised, dispatchable sources to demand points. These two factors jointly diminish predictability of load, voltage and demand flows, especially on low voltage networks. As a result, domestic PV, which is highly distributed, presents a key challenge for network operators in managing the grid such that there is enough capacity and voltage headroom available to accommodate these flows. Thirdly, an analysis based on large datasets, rather than a limited number of observations, is likely to produce more robust findings to understand PV deployment patterns and their determinants across the UK.

Moreover, in a related literature, the theory of social action highlights the importance of social associations on an individual's consumption decisions (among others, Bagozzi, 2000; Weber, 1978). Kaplan (1999) applies an adoption theory framework to understand the factors that influence electric utility managers' interest in solar power. He emphasizes the importance of prior knowledge or familiarity with the new technology in diffusion of solar panels[3]. Similarly social influence, attitudes towards the environment and consumer lifestyles are key factors for energy consumption decisions (Lutzenhiser, 1992, 1993; Weber and Perrels, 2000; Wilson and Dowlatabadi, 2007). Jager (2006) discusses consumer motives for adopting photovoltaic systems from a behavioural-theoretical perspective. He identifies different types of needs, such as belongingness, the ownership of a PV system by friends/neighbours and participating/collaborating with other people in installing a PV system which may lead to peer effects. Installation of a PV panel creates a persistent signal that peers (neighbours) can observe which may generate externalities affecting the overall diffusion process (Bollinger and Gillingham, 2012; Snape and Rynikiewicz, 2012). Given that such peer effects will be stronger in spatially adjacent areas than more distant ones, to capture such social spatial spillovers a spatial analysis framework is needed in establishing the drivers of PV uptake. Spatial econometrics offers a framework to test the influence of these externalities using large data sets where the smaller the spatial unit of analysis the better capabilities to capture these effects.

This paper addresses this gap by applying spatial data analysis and spatial econometrics methods for the first time, to the best of our knowledge, to analyse the determinants of domestic PV uptake at a regional level in Great Britain[4]. The research highlights that rather than income, accumulated capital and financial savings are the key drivers for PV uptake in the UK. The consumers with high electricity demands are the early adopters, indicating consumers' understanding of the economics of PV tariffs.

The paper is organised as follows: section 2 outlines UK PV policy while section 3 offers a concise literature review. The methodology is presented in section 4. Model specification and the data are summarized in section 5. The results are presented in section 6 whilst the last section is devoted to conclusions.

[3] On a related point, Hargadon & Douglas (2001) discuss how Edison framed incandescent light around contemporaneously familiar gas lighting system and how this impacted its acceptance and diffusion.
[4] While the study refers to the United Kingdom, the empirical analysis is limited to Great Britain, that is, the UK excluding Northern Ireland.

2. UK policy on photovoltaics

After years of slow progress, the UK has had a sudden rapid increase in deployment of solar PVs. According to the latest statistics, in 2013, over 2TWh of electricity was generated by solar PVs, compared to 20GWh in 2009 (DECC, 2014a). This can be seen as a direct response to the 2010 introduction of the ongoing Feed-in Tariff (FiT) scheme and its co-incidence with a substantive drop in the cost of PV panels since 2007 (DECC, 2013b).

The 2009 figure is indicative of the limited UK effort on PV until that point. Support prior to 2009 was largely limited to grants for small-scale applications, with the technology absent from early non-grant financial instruments like the Non-Fossil Fuel Obligation (NFFO) (Mitchell, 2000). The Solar Photovoltaics Major Demonstration Programme (2002 – 2006, £26m, extended to £31m) provided capital grants of 40-50% of costs, supporting 1,200 domestic and 180 commercial installations. The Low Carbon Buildings Programme (2006-2010, £30m, extended by £50m) superseded this and included support for PV. The Energy Efficiency Commitment (EC) (2005-2008), Carbon Efficiency Reduction Target (CERT) (2008-2011) and the Energy Company Obligation (ECO) (2012 onwards) each obligated large UK utilities to improve energy efficiency or reduce carbon emissions among domestic consumers. Micro-generation technologies, including PV, counted towards the CERT and ECO targets but cheaper options meant this did not happen in significant volume.

The Renewables Obligation (RO) is at time of writing the main source of financial support in the UK for renewable energy sources of electricity (RES-E) above 5MW, though it is currently being phased out. It is a form of quota mechanism which places an obligation on supply companies to source RES-E (Woodman and Mitchell, 2011). The RO included PV from its 2002 inception though its initial technology blind approach primarily directed financial support to more mature – and less costly – technologies. The RO was split into bands in 2009 and PV awarded two Renewables Obligation Certificates (ROCs) instead of one for every MWh generated. PV was then separated into two bands from April 1st 2013, 'building mounted solar PV' and 'ground mounted solar PV', with the latter receiving slightly more ROCs per unit energy, as in Table 1. Once a project is online it receives the specified number of ROCs per MWh generated for its start date over its eligible lifespan (Woodman and Mitchell, 2011). These two bands are expected to be available to new entrants until March 31st 2017 when the RO will close to new applicants.

Table 1. ROCs given per technology under the RO and RO Scotland Banding for Solar PV installed in the year to March 2017 (Ofgem, 2013b, 2013c)

	Pre 2013	2013/14 capacity	2014/15 capacity	2015/16 capacity	2016/17 capacity
PV	2				
Building mounted	New band	1.7	1.6	1.5	1.4
Ground Mounted	New band	1.6	1.4	1.3	1.2

The low UK PV capacity to 2009 is indicative of the RO's failure to provide any significant stimulus to PV. The few PV plants active by 2010 were under 50kW and at this point became eligible for transfer to a new Feed-in Tariff (FiT) scheme introduced for RES-E (only about 20kW remained within the RO) (Ofgem, 2013c).

The UK's FiT is a fairly straightforward example of a tariff mechanism, though it has increased in complexity since its introduction. The FiT pays qualifying RES-E technologies a fixed sum per unit of electricity generated, varying with the technology and the scale of the development. The PV tariffs have 'degressed' (that is, reduced according to a formula) on a quarterly basis since August 2012 to try to mimic the falling market price of PV technology (Ofgem, 2013b). Eligible generators receive the extant price when they begin to generate and continue to receive this price for a fixed term (currently 20 years for PV), rising with inflation (Retail Price Index).

PV is, by a large margin, the technology most frequently installed under the FiT. A total of 634,421 PV installations were registered in the Microgeneration Certificate Scheme (MCS) under the FiT by the end of December 31st 2014, 96% of which are under 4kW (DECC, 2015b).

The Government is phasing out the RO in favour of the Feed-In Tariff with Contracts for Difference (CfD) from 2014, fully replacing it by 2017. Generators in the RO will continue to be paid a subsidy through the RO until 2037 at the latest. The CfD will pay contracted RES-E generators a price per unit of energy generated (the strike price) minus an assumed reference (or market) price which represents the income the generator is assumed to have earned for selling their power. Only large PV installations are eligible under the CfD and will be able to access the strike prices shown in Table 2 based on the year they initially contract. Smaller installations will remain FiT eligible.

Table 2. PV Draft Strike Prices, 2014-19 (Ofgem, 2013a)

	2014/15	2015/16	2016/17	2017/18	2018/19
£/MWh	125	125	120	115	110

The level of the strike prices and the way that the reference price is calculated and whether it will be representative of prices that generators can actually access have been criticised by various trade associations and other commentators (Allen & Overy, 2012; Newbery, 2011; REA, 2012), however, the CfD is not designed to apply to domestic PV installations.

To be eligible for the domestic PV FiT, the panels have to be an accredited model and installed by an accredited installer under the MCS. The installation requires a meter which records all generation from the PV panels (Typically this means at least one additional meter, though the UK is at the beginning of a smart meter rollout and it is expected a single smart meter will be able to handle a household's demand and generation without interference). This meter records total generation from the panels, independently of the household's demand. The Government then pays 50% of the metered output at the tariff rate and the other 50% of the metered output at the tariff rate plus the export rate. This creates the possibility that householders who are more likely to use a greater fraction of their own generation might be more attracted to tariff-supported PV than those who tend to export more of it; the expectation is that domestic generators who are at home or whose energy demand which can be made to fit with daytime usage will be advantaged.

3. Literature Review

There has been a growing interest in examining the driving factors of PV installations. The process of adoption of new technologies is influenced by many factors, including geographic characteristics and peer effects (Bollinger and Gillingham, 2012; Snape and Rynikiewicz, 2012). A recent paper by Balcombe et al. (2013) provides a comprehensive review of drivers and barriers of microgeneration technology uptake. We summarize their findings here (Table 3) and instead focus on quantitative studies explaining domestic PV adoption.

Table 3. Summary of motivations and barriers for the uptake of microgeneration technologies

	Motivation	**Barrier**
Financial	- Save or earn money from lower	- Costs too much to buy/install

	fuel bills and government incentives - Increase value of my home	- Cannot earn enough/save enough money - Lose money if I move home - High maintenance costs
Environmental	- Help improve environment	- Environmental benefits too small
Security of supply	- Protects against future high energy costs - Makes households more self-sufficient/less dependent on utility companies - Protects against household power cuts	- Would make more self-sufficient/independent
Uncertainty and trust	- Use an innovative/high-tech system	- Home/location not suitable - System performance or reliability not good enough - Energy not available when I need it - Hard to find trustworthy information or advice - Hard to find trustworthy builders to install
Inconvenience	- None identified	- Hassle of installation - Disruption or hassle of operation - Potential requirement for planning permission - Reserving space on rooftops
Impact on residence	- Improve the feeling and atmosphere within my home - Show my environmental commitment to others	- Take up too much space - The installation might damage my home - Would not look good - Neighbour disapproval/annoyance

Source: Largely based on Balcombe et al. (2013, p.658), incorporating Wolsink (2012)

Using probit regression models Sardianou and Genoudi (2013) analyse the effect of gender, age, marital status, financial background and current income on solar PV installation in Greece. They conclude that middle-aged and highly educated individuals are much more likely to adopt renewable energy sources in their home. Furthermore, income positively affects consumers' acceptance of clean energy projects, while marital status and gender are not statistically significant factors.

Zhang et al. (2011) carry out a sub-national analysis of PV installations in Japan using panel data. The explanatory variables included are sunshine duration, installation costs, regional promotion policies, regional household income, and environmental awareness. They report that government subsidies, housing investment and environmental awareness promote PV adoptions whilst installation costs have a significant negative effect. Large initial payments have been reported as a barrier affecting consumer's willingness to pay for PV in other studies as well (Claudy et al., 2011).

Zhai and Williams (2012) analyse the effect of consumer perceptions on PV adoption using a fuzzy logic inference model. They focus on consumer perception of installation time and cost and its overall maintenance requirement. The study depicts the immense differences between adopters and non-adopters and point to perceived cost and maintenance as the most important barriers to solar cell installation.

More specifically to the UK, despite a large number of studies focusing on social aspects (Allen et al., 2008; Faiers and Neame, 2006; Keirstead, 2007) or impacts of FiT changes, wider socio-economic analysis has been limited. Cherrington et al. (2013) analysed the impact of changes on FiTs on return on investment using two case studies. Their real-life economic analysis shows that, given reductions in PV installation costs, a cut in the FiT can still result in a healthy return on investment (between 6-8%). However based on a typical domestic PV installation of 2.6kWp, Muhammad-Sukki et al. (2013) suggests that the return from a solar PV installation for the new tariff rate is significantly lower in the UK, about 2% to 3.6%, compared to a number of European countries like Spain or France (between 6-11% return).

Another strand of the literature focuses on the relationship between adoption of solar PV and nearby previously installed systems, i.e. social interaction or peer effects of solar panel diffusion. Theoretically, Manski (1993) distinguishes three ways to explain the effect of group membership on an individual's behavior (‘*identification*’ problem): endogenous effects, contextual effects, and correlated effects. Individual behavior influences the average group behavior while at the same time being influenced by group behaviour, leading to endogenous effects. Whereas an individual's behavior can be directly influenced by the exogenous characteristics of his or her group. Furthermore individuals within a group behave in a similar fashion as they tend to have similar characteristics or face similar political, institutional, or environmental conditions, resulting in correlated effects. Accordingly the knowledge about new technologies spills over within members of spatially defined networks, as consumers in local networks tend to face similar environmental and credit constraints, information constraints, have more direct interactions with one another and can directly observe the costs and benefits of new technologies.

Empirically, Rode and Weber (2012) investigate the spatio-temporal diffusion of solar panels in Germany using an epidemic diffusion model framework. Based on a dataset of 550,000 systems installed during 2009, they find that taking the spatial dimension into account has a considerable impact on parameter estimates and model performance, even though the control variables contribute less information than the spatial component. They also suggest that the lowest level of geographical aggregation produces better parameter estimates. While proximity and neighbourhood effects are drivers of PV deployment, imitative behaviour is highly localized.

Bollinger and Gillingham (2012) provide further evidence on the importance of peer effects on the diffusion of solar panels from California, USA. They report strong evidence for causal peer effects, which appear to increase in magnitude over time and are greater for larger installations and at the more localized street level. Müller and Rode (2013) analyse spatial spillover at the micro scale, focusing on Wiesbaden, Germany, by employing a geocoded data set of the grid-connected PV systems set up through 2009. They specifically examine if peer effects are influential in the individual decision-making process. Using a binary panel logit model, their findings support the findings of Bollinger and Gillingham (2012) and of Rode and Weber (2012) in that the propensity to install PV increases with the number of previously installed systems in spatial proximity. They further find that the likelihood of installing PV is greater in less densely populated areas. Snape and Rynikiewicz (2012) find stronger adoption in regions where agents first adopted photovoltaic systems and a concentric pattern, with lower adoption in the further areas, in line with the previous literature.

Similarly, Graziano and Gillingham (2014) analyse the spatial patterns of solar panel diffusion in Connecticut, USA. Their findings indicate that there is a considerable clustering of adoptions and smaller centres contribute to adoption more than larger urban areas, in a wave-like centrifugal pattern. They confirm the importance of spatial neighbouring effects as well as built environment and policy variables, supporting the findings of Bollinger and Gillingham (2012), of Müller and Rode (2013) and of Rode and Weber (2012). Another study by Davidson et al. (2014) highlights the importance of home age, heating source, number of rooms, mortgage status and household education as key variables affecting PV diffusion in California, USA.

More specifically for the UK, Richter (2013) explores whether the installation rate of solar PV is affected by social spillovers from spatially close households. By using the cumulative number of solar PV installations within a neighbourhood at the end of a particular month (the installed base) as a measure for social effects, she finds small, but positive and significant spillover effects: one more solar PV panel in a postcode district increases the number of new adoptions per owner-occupied households in a given month by 7.48e^{-06}. Besides, peer effects vary across months and overall diminish over time.

More recent studies recognise geographical aspects of low carbon transitions (Bridge et al., 2013) and focus on the spatial characteristics of PV installations. Hofierka et al. (2014) analyse the correlation between the solar resource potential and PV installations and how this relationship varies by different land uses in Slovakia and Czech Republic. They report that Slovakian installations follow solar resource potentials at higher rates than Czech ones. Schaffer and Brun (under review) investigate the determinants of geographical PV patterns in Germany using spatial econometrics. Their analysis focuses on PV installations of less than 16kWp. They take financial (disposable per capita income, home ownership), locational (annual solar irradiation, installation in the neighbouring regions) and ecological (share of green votes) factors into account. They find home ownership and neighbourhood effects as key determinants for domestic PV installations, to a less extent for per capita income and solar irradiation.

4. Methodology

Elhorst (2010) proposes a general-to-specific approach to arrive at the most suitable econometric model. Equation (1) offers a family of related spatial econometric models:

$$Y = \rho WY + X\beta + WX\theta + u \qquad (1)$$

where Y is a (N x 1) vector of observations on a dependent variable and X is an (N x K) matrix of observations on exogenous (explanatory) variables with an associated (K x 1) vector of regression coefficients β. As for the parameters in the estimated models, ρ is a spatial autoregressive parameter that measures the magnitude of interdependence across regions showing the effect of spatial lag in the dependent variable; θ stands for the spatial lag in the independent variables. WY is the spatially lagged dependent variable and WX denotes spatially lagged independent variables. u is independently and identically distributed error term with zero mean and constant variance σ^2. K denotes number of explanatory variables and N denotes number of observations.

W is the non-stochastic NxN spatial weights matrix which is employed to reflect the structure of potential spatial interaction. W may be constructed using information on physical distance between pairwise combinations of regions in the sample, or may be defined such that element w_{ij} = 1 if i and j are physically neighbours and 0 otherwise. The definition of neighbours used in the weights matrix is based on a notion of distance decay or contiguity. By convention, the diagonal elements of the weights matrix are set to zero and row elements are standardized such that they sum to one. In this study an inverse distance weight matrix is used[5], where the element w_{ij} is equal to $1/_{d_{ij}}$ with d_{ij} being the distance between two regions i and j (i≠j). This specification assumes that as the distance between regions i and j increases (decreases), W_{ij} decreases (increases), implying less (more) spatial weight to the pair (i, j). The additional terms, spatially lagged dependent variable or a spatial autoregressive process in the error term, in the above equation introduce the spatial aspects into the model. Moreover there may be spatially weighted explanatory variables in the model. The transformation of the spatial weight matrix provides for an intuitive explanation for the WY and Wu terms. Equation (1) can be estimated with the maximum likelihood estimation (MLE) techniques (Elhorst and Freret, 2009).

The general Spatial Durbin Model (SDM) model can be used to test for spatial interaction effects for two main reasons (LeSage and Pace, 2009). If unobserved but relevant variables following a first-order spatial autoregressive process are omitted in the model, and these variables happen to be correlated with independent variables not omitted from the model, the SDM will produce unbiased coefficient estimates, unlike the spatial lag model. Moreover the SDM model will still produce unbiased coefficient estimates in cases where the true data-generating process is the spatial error model.

Given this background, special cases can be obtained by restricting parameters in Equation (1). The likelihood ratio (LR) tests can be utilized to examine whether the SDM model can be simplified into a spatial lag model, spatial error model, or an OLS model. The spatial error model (SEM) arises when the restriction $\theta = -\rho\beta$ is in effect, resulting in spatial

[5] Baltagi & Rokicki (2014) highlight that the choice of the weight matrix may affect the magnitude but not the significance or sign, of the estimated parameters. We have re-estimated the model using the square of the inverse distance matrix and found our results are robust for both types of weight matrixes.

dependence in the error term alone. The spatial autoregressive (SAR) model is obtained by setting θ=0, which exhibits spatial dependence only in the dependent variable.

The spatial lag model assumes that the value of the dependent variable in one state/region affects the dependent variable in a proximate state/region. This paper examines the extent to which solar panel uptake in one region depends on the PV uptake in adjacent regions, providing an appropriate tool when capturing neighbourhood spillover effects:

$$Y = \alpha + X\beta + \rho WY + u_i \tag{2}$$

In the spatial lag model, the hypothesis of spatial correlation relates to the parameter ρ. If the null hypothesis of $H_0 : \rho = 0$ is rejected two possibilities arise. A positive and statistically significant parameter estimate of ρ indicates a positive correlation between solar panel uptake in neighbouring regions, implying that levels of solar panel uptake tend to spill over and have a positive effect on solar panel uptake in neighbouring regions.

Alternatively, the spatial error model in equation (3), assumes that the spatial dependence operates through the error process, where any random shock follows a spatial pattern, so that shocks are correlated across adjacent regional economies, such that the error term in equation (1) may reveal a significant degree of spatial covariance, which can be represented as follows:

$$Y = \alpha + X\beta + u \tag{3}$$

$$u = \lambda Wu + \varepsilon$$

where Wu denotes spatially autocorrelated error term, λ is the spatial error coefficient, ε is an independent white noise error component.

The OLS parameter estimates are unbiased in the spatial error model, but they are no longer efficient. Estimation must be based on either maximum likelihood or on a generalized moments approach (Kelejian and Prucha, 1999). The inclusion of the spatially lagged components in the model leads to an intrinsic endogeneity problem, which induces a two-way causality in the neighbour relation in space. In addition to the endogeneity in the spatial lag term, there is a possibility that explanatory variables other than the spatially lagged dependent variable may be endogenous. In that case the ordinary least-squares (OLS) estimators are biased and inconsistent for the spatial-lag model. Thus maximum-likelihood estimation (Anselin, 1988) or instrumental variables estimation (GS-2SLS) needs to be employed to obtain consistent estimators (Kelejian and Prucha, 1998; Kelejian and Robinson, 1993). In the GS-2SLS approach, the endogeneity of the spatially lagged dependent variable WY is accounted for by using the spatially lagged exogenous variables WX as instruments. The spatial two-stage least-squares estimates (GS-2SLS) are robust to non-normality and consistent, but not necessarily efficient.[6.]

The major advantage of employing SDM lies in the fact that SDM nests both the spatial lag model given in equation (2) and the spatial error model given in equation (3). Therefore SDM produces unbiased coefficient estimates under the data generating processes (1) to (3). If unobserved but relevant variables following a first-order spatial autoregressive process are omitted in the model, and these variables happen to be correlated with independent variables not omitted from the model, the SDM will produce unbiased coefficient estimates, unlike the spatial lag model (SAR). Moreover the SDM model will still produce unbiased coefficient estimates in cases where the true data-generating process is the spatial error model (SEM) (LeSage and Pace, 2009). If the true data generating process is the SDM, both the spatial lag model and the spatial error model will suffer from omitted variable bias, since these models do not include spatially lagged explanatory variables. As the SDM specification contains a spatially lagged dependent variable, it implies that shocks to both the error term and the explanatory variables at one location are transmitted to all other locations within the spatial system. Equation (1) can be estimated with the maximum likelihood estimation (MLE) techniques (Elhorst and Fréret, 2009). Then the likelihood ratio (LR) tests can be utilized to examine whether the SDM model can be simplified into spatial lag model (SAR), spatial error model (SEM), or an OLS model.

There have been some concerns expressed regarding the limitations of the various spatial econometric models. Gibbons and Overman (2012), reflecting on Manski (1993)'s problem of identification, state that for the various spatial econometric models only the overall spatial spillover is identified but not whether they work through exogenous or endogenous neighbourhood effects. Moreover they raise concerns as to the use of lagged values of the regressors as instrument variables (IV) for the spatial lag of the endogenous variable in the

[6] For technical derivations and the selection of optimal instruments, please see Kelejian and Prucha (1998) Kelejian and Prucha (1999) and Kelejian and Robinson (1993).

SAR-type models. Corrado and Fingleton (2012) further argue that the coefficient estimate for the WY variable may be significant because it may be picking up the effects of omitted WX variables or nonlinearities in the WX variables if they are erroneously specified as being linear. Thus it has been suggested that the applications of spatial models should be guided by economic theory and actual empirical questions (Brueckner, 2006; Pinkse and Slade, 2010; Corrado and Fingleton, 2012). Gibbons and Overman (2012) propose employment of experimentalist paradigm approaches such as instrumental variables (IV) and spatial differencing.

5. Data and Model Specification

5.1. Dependent variable: PV data

The data on PV deployment comes from the Central FIT Register, published by the Ofgem E-serve Database and includes FIT installations as of 30 June 2013. The database lists installed and declared capacities (kW) for different technology and installation types, along with other spatial variables (Table 4).

Table 4. List of variables in Central FIT Register

Variable	Description
Technology	Anaerobic digestion, hydro, wind, micro CHP, Photovoltaic, wind
Installation type	Picked by the FIT Licensee as the most appropriate 'type' for the installation – domestic, community, commercial or industrial
Locational variables	- Post code: the first half of GB post code, i.e. post code district - Local authority - Government Office Region - Supply MPAN No (first 2 digits): Metering Point Administration Number, a unique identity reference number for electricity meter where the first 2 digits denotes the distributor ID. - LSOA code: Lower layer super output areas, based on 2001 classification.

Some key observations from this dataset are as follows:

Designation of domestic category: A variety of installation capacities are listed in this database. As the mentioned database is used as a reporting tool, there are no definitions as to what constitutes 'domestic' vs non-domestic, though most domestic installations are associated with lower capacity tariff bands[7]. This is problematic as sizes of domestic installations vary from less than 4kW to 1.3MW, as discussed in the next section.

<u>The majority of FIT installations are PV:</u> Out of 390,198 FIT entries registered by 30 June 2013, 99% of them are PV, accounting for 88% of total installed capacity as registered in the FIT database (Table 5).

Table 5. Distribution of FIT installations by technology and type

	Number of installations					Installed Capacity (kW) (%)				
	Distribution by types (%)				Total numbers	Distribution by types (%)				Total capacity
	1	2	3	4		1	2	3	4	
Anaerobic digestion	1.9	60.4	37.7	0.0	53	0.0	63.6	36.3	0.0	45,879.0
Hydro	62.8	28.7	3.8	4.6	390	8.4	81.9	8.5	1.2	37,425.6
Micro CHP	98.9	0.9	0.0	0.2	454	98.8	1.0	0.0	0.2	462.8
Photovoltaic	96.9	2.5	0.2	0.4	392,470	74.1	22.1	2.7	1.1	1,683,515.5
Wind	72.8	23.0	1.0	3.1	4,831	23.2	64.4	7.2	5.2	150,804.9
Total	96.5	2.8	0.2	0.5	398,198	67.0	27.6	4.0	1.4	1,918,087.8

- 1: Domestic; 2: Commercial; 3: Industrial; 4: Community

Source: Authors own elaboration of Ofgem FiT database, as of 30/06/2013, available at https://www.ofgem.gov.uk/environmental-programmes/feed-tariff-fit-scheme/feed-tariff-reports/installation-reports

Given that there are a number of locational and different PV deployment sizes included in the dataset, it was important to identify a spatial unit of analysis[8]. As discussed extensively in Appendix 1, the European regional classification system, NUTS3 (Nomenclature of territorial units for statistics) is used as the spatial unit of analysis. There are a total of 134 NUTS3 regions in the UK based on the 2012 classification.

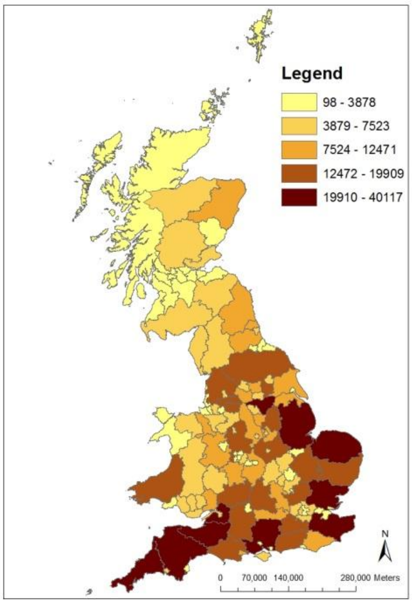
All UK domestic PV installations under 10kW are included in this analysis[9]. As presented in Figure 1, there appears to be a concentration of PV uptake in the Southern and Eastern England regions which are characterized by higher solar radiation rates. As the analysis is restricted to PV installations under 10kW, the spatial patterns of accumulated capacity and number of installations are very similar.

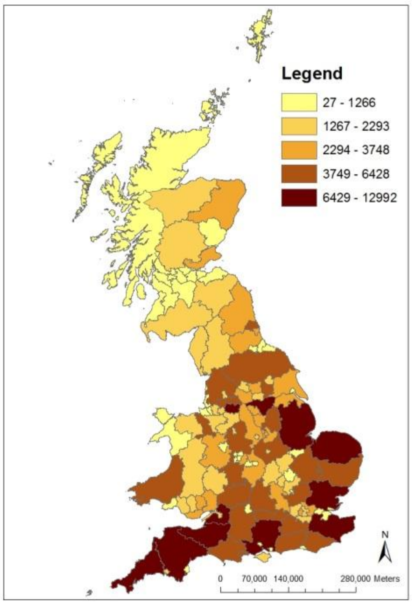
Figure 1. Regional distribution of typical domestic PV installations in Great Britain (accumulated capacity, GW (left) and number of installations (right))

[7] DECC confirmed that they do not check which types are selected against which tariffs. (Personal Communication, 2014)

[8] For data handling and processing please see Appendix 1.

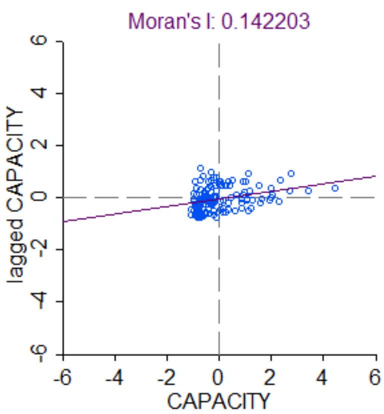
[9] While Cherrington et al. (2013) analyse a typical domestic system under 4kW, Schaffer and Brun (under review) focus on installations of less than 16kW. We analysed domestic PV installations of both under 4kW and 10kW and did not find any significant difference in results between these two types.

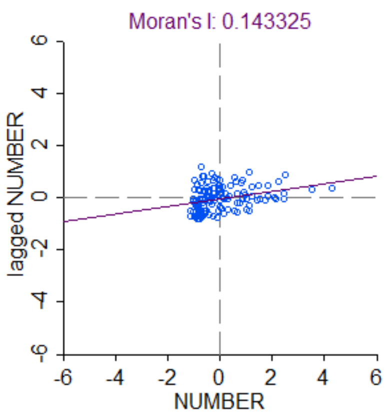




In order to explore the existence of spatial autocorrelation Global Moran's I Index was used. Moran's I statistic is a global indicator of spatial association as it summarizes the nature of the spatial dependence and illustrates different types of spatial association between a region and its neighbours. A positive Moran's I value indicates a tendency toward clustering while a negative Moran's I value indicates a tendency toward dispersion. Moran's I statistics for accumulated capacity and number of installations are 0.142 (p- value 0.001) and 0.143 (p- value 0.001), respectively. Both Moran's I statistics are significantly greater than the expected values for this statistic under the null hypothesis of no spatial autocorrelation (or spatial causality, or spatial randomness), indicating that there is statistically significant positive spatial association for accumulated capacity and number of installations.

Figure 2. Moran's I Scatterplot (accumulated capacity, (left) and number of installations (right))





5.2. Explanatory variables

Among the factors affecting PV installation, income reflects the financial constraints and risk-bearing possibilities a consumer may face (Rode and Weber, 2012). Even though Rogers (2003) states that in general terms higher income households tend to adopt early and observational learning might therefore play a less important role, evidence from other studies is inconclusive. Müller and Rode (2013) claim that low-income districts are more likely to be later adopters, supporting Rode and Weber (2012) and Sardianou and Genoudi (2013) who report a significantly positive impact of income. However, both Zhang et al. (2011) and Richter (2013) report a statistically insignificant impact. In analysing early British PV adopters, Keirstead (2007) reports that they have higher incomes and are more likely to be home owners than the general public. Though, this work predates the adoption of the FiT for PV; prior to this date most installations would not be economically viable and are likely to have been influenced by other motivations, most likely environmental and perhaps some niche applications. From 2010 onwards, the FiT was in place, designed at a level to allow an annual return at good sites and providing a considerable change in the incentives for installation. In a more recent study, income is argued to be a relatively less important factor for the diffusion of PV systems as the decision to invest in a solar PV panel is rather a question of accumulated capital than of marginally higher income (Graziano and Gillingham, 2014).

Yet, there are other socio-economic variables affecting the PV installation. Müller and Rode (2013) take into account the effect of density and income together and argue that consumers located in less densely populated areas, characterised by a higher share of single and double family homes, are more likely to be early adopters. While Davidson et al. (2014) report statistically significant influence of higher education, Jager (2006) and Keirstead (2007) interview some early adopters and find that they are better educated and are from middle-age groups. Solar irradiation is another factor directly affecting PV electricity generation (Šúri et al., 2007) and thus the economics of PV installation. Snape (2013) notes the importance of built environment on PV uptake where the ratio of sun facing roof space to occupants is lower in urban environments than suburban and rural ones, creating 'black holes' of PV adoption in cities.

In related literature concerning the installation of energy efficiency retrofits, Urban and Scasny (2012) report that householders more concerned about the environment are more likely to reduce their demand and retrofit their homes, which is positively influenced by age. On the other hand more well-off households tend to be less concerned about environmental problems, tend to curtail less, but are more likely to invest in energy efficiency. The level of formal education is not found to be an estimator of the likelihood to save energy. Mills and Schleich (2012) find that while families with young children are more likely to undertake energy efficiency and conservation activities, mostly for environmental reasons, the families with high share of elderly pay more attention to financial savings with lower levels of technology adoption.

The list of explanatory variables included in the analysis is summarized in Table 6. The data on these socio-economic variables come from latest census data, 2011. While the Office for National Statistics (ONS) publishes socio-economic data for England and Wales, in Scotland this is done by Scottish Neighbourhood Statistics (SNS). Unavoidably the description of variables (e.g. household sizes[10]) and their spatial units vary as a result. In this study, data was mostly collected at lower layer super output area (in Scotland Data Zone), LSOA/DZ, and then aggregated to NUTS3 level using reference lookup tables produced by ONS and SNS. Some other data is available at the local authority level, which are the same as level 1 Local Administrative Units (LAU) in England and Wales. As the definition of these geographies does not correspond to NUTS3 codes for Scotland[11], population shares are used here as a proxy.

Table 6. List of explanatory variables used in the analysis and data sources

Name of variable	Data Availability	Year	Data Source[1]	Scale of Data	Data processing
Age of Population	Scotland	2011	GROS	NUTS3	-
	England and Wales	2011	ONS -Census	LSOA	Aggregated to NUTS3
Number of Households	Scotland	2011	SNS	Data Zone	Aggregated to NUTS3
	England and Wales	2011	ONS -Census	LSOA	
Area (hectares) to calculate density	Scotland	2011	SNS	Data Zone	Aggregated to NUTS3
	England and Wales	2011	ONS -Census	LSOA	
Household size, local authorities	Scotland	2011	SNS	Data Zone	Aggregated to NUTS3
	England and Wales	2011	ONS	Local Authority[3]	

[10] ONS uses 'All household spaces with at least one usual resident' while SNS uses 'All occupied household spaces'.

[11] This mismatch is being discussed in an ongoing consultation (Planning Portal, 2014).

in the UK[2]					
Sub-national electricity sales and numbers of customers	Great Britain	2011	DECC	Local Authority[3,4]	Aggregated to NUTS3
Dwelling Type[5]	Scotland	2001	SNS	Data Zone	Aggregated to NUTS3
	England and Wales	2011	ONS	Local Authority[3]	
Gross Domestic Household Income	Great Britain	2011	ONS	NUTS3	-
Yearly global irradiation at 90 deg. (kWh/m^2)[6]	Great Britain	2011	Joint Research Centre[6]	NUTS3	-
Share of domestic and industrial emissions in total emissions	Great Britain	2011	DECC	Local authority district	Aggregated to NUTS3

[1] ONS: Office for National Statistics; SNS: Scottish Neighbourhood Statistics, DECC: Department of Energy and Climate Change; GROS: General Register Office for Scotland
[2] UK data is provided, but due to lack of look up tables from LA to NUTS3 level in Scotland, SNS data at DZ is used. Overall the sums match up across these two datasets.
[3] In England and Wales, ONS provides look up tables from LAs to NUTS3 regions.
[4] In Scotland, the boundaries of local authorities (LAs) do not correspond to NUTS3 codes. Out of 32 LAs, 11 LAs fall into more than one NUTS3 region. Hence, based on look up table at DZ level, population share of NUTS3 falling in each LA is calculated. These shares are then used to disaggregate LA values to NUTS3 regions.
[5] ONS data is by household spaces whereas SNS data is for dwellings.
[6] The solar radiation data are long-term average of yearly totals, calculated without taking into account shadowing from terrain (hills/mountains). A straight average is performed over each region at 90 deg. angle.

5.3. Model specification

In order to investigate the drivers of PV uptake across 134 regions, following on previous studies and within constraints on the available data, the following model has been employed[12]:

$$PV_i = \beta_0 + \beta_1\, lnypc_i + \beta_2\, density_i + \beta_3\, ownedshare + \beta_4\, detached_i + \beta_5 lnelectricity_i + \beta_6\, QL2_i + \beta_7\, avehousehold_i + \beta_8 irradiation_i\; + \beta_9 CO2 +\; u_i \qquad (4)$$

In equation (4) *i* denotes regions and *u* is an independently and identically distributed error term with zero mean and variance σ^2. Even though time index isn't shown in this equation, we have used cross-section data pertaining to 2011, due to data availability constraints.

The dependent variable is the logarithm of number of domestic PV installations of under 10kW at regional level. The explanatory variables include the natural logarithm of gross domestic household income "per capita (lnypc), population density (density), share of

[12] Age is not included in the model specification due to a multicollinearity problem. The results are available from the authors upon request.

owned houses (ownedshare), share of detached houses (detached), natural logarithm of electricity demand (lnelectricity), 2 or more A-levels, HNC, HND, SVQ level 4 or equivalent qualifications (QL2) as a proxy for education, average household size (avehousehold), solar irradiation (irradiation) and a CO_2 variable.

6. Estimation Results

6.1. Results

An OLS estimation was performed and the estimation results are reported in Table 7 where R^2 denotes the coefficient of determination and AIC is the Akaike Information Criterion. In order to check for the diagnostics of the model, Breusch-Pagan heteroscedasticity test and RESET misspecification test are carried out. The results indicate the presence of heteroscedasticity problem and misspecification in the model. Estimation results reveal that the per capita income, education level, electricity sales, irradiation, and share of detached houses have a positive impact on the regional installation of PV systems. Whereas increases in share of owned houses, population density and average number of households negatively affect the uptake of domestic PV installations.

Table 7. OLS Estimation Results

Variables	
Lnypc	**0.0080** **(0.903)**
Density	**-0.019** **(0.000)***
Detached	**0.858** **(0.100)*****
Ownedshare	**-0.221** **(0.264)**
Lnelectricity	**1.055** **(0.000)***
QL2	**0.0522** **(0.252)**
Avehousehold	**-0.491** **(0.208)**
Irradiation	**0.0032** **(0.000)****
CO2	**0.025** **(0.290)**

Constant	**0.592 (0.724)**
R^2	**0.75**
AIC	**203.127**
Breusch-Pagan Heteroscedasticity Test	**35.32 (0.000)***
RESET test	**4.88 (0.000)**
Number of observations	**134**

Note: The values in parentheses are p-values. (*), (**), (***) denote significance levels at 1 per cent, 5 per cent and 10 per cent, respectively. AIC=Akaike Information Criterion.

Ignoring the possible spatial dependence in disturbances may lead to biased and inconsistent estimates, hence loss of efficiency. In order to test for spatial correlation, Moran's I[13] (Moran, 1950) and Lagrange multiplier (LM) tests are carried out.

Table 8 provides three different test statistics to investigate the presence of spatial dependence in the error term: the Moran's I and two different versions of the Lagrange Multiplier tests (Anselin, 1988; Florax et al., 2003). Moran's I statistic is a global indicator of spatial association. Although it does not allow for discrimination between the two alternative forms of misspecifications, it is very powerful against spatial dependence both in the form of error autocorrelation and spatial lag. LM error and LM lag tests, in addition to their robust versions, test the null hypothesis of no spatial dependence against alternatives of spatial error and spatial lag dependence, respectively. If the results from the two LM tests are significant, the larger value is used to indicate which dependence to control for. Residual autocorrelation is tested for the models which do not contain a spatial error component and it is shown that there exists autocorrelation in the spatial lag model. Hence it is plausible to incorporate the spatial component into the disturbance terms, which is also in line with the previous test results.

[13] Moran's I statistic: $I = \frac{n}{S}\frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}$ and $S = \sum_i \sum_j w_{ij}$ where n corresponds to the total number of spatial units and z_i and z_j stand for the variables expressed in mean-deviation form. For a row-standardized weights matrix, $n = S$. Under the null hypothesis, there is no spatial autocorrelation, hence Moran's I equals to zero.

Table 8. Tests for Spatial Dependence in the OLS Regression

Test	
Moran's I	**3.036 (0.002)****
LM(error)	**25.407 (0.000)***
LM(error robust)	**23.205 (0.000)***
LM(lag)	**15.333 (0.000)***
LM(lag robust)	**13.243 (0.000)***

Note: The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

Table 9. Spatial Model Estimation Results

	SDM	SAR	SEM	GS-2SLS
Lnypc	0.009 (0.866)	0.005 (0.932)	0.027 (0.625)	0.002 (0.974)
Density	-0.011 (0.021)**	-0.025 (0.000)*	-0.020 (0.000)*	-0.019 (0.000)*
Detached	1.493 (0.041)**	1.110 (0.019)**	1.179 (0.015)**	1.717 (0.005)*
Ownedshare	-1.152 (0.023)**	-3.230 (0.004)*	-2.004 (0.018)**	-2.972 (0.007)*
Lnelectricity	1.152 (0.000)*	1.000 (0.000)*	1.0665 (0.000)*	1.012 (0.000)*
QL2	0.048 (0.082)***	0.033 (0.422)	0.042 (0.312)	0.47 (0.264)
Avehousehold	-0.875 (0.058) ***	-1.276 (0.002)**	-0.420 (0.037)**	-0.859 (0.046)
Irradiation	0.002 (0.048)**	*0.003* (0.000)*	0.003 (0.000)*	0.003 (0.002)**
CO2	0.045 (0.025)***	0.026 (0.217)	0.032 (0.122)	0.030 (0.153)
constant	0.723 (0.773)	4.269 (0.016)**	0.103 (0.473)	1.961 (0.339)
W* lnypc	0.0908 (0.601)			
W*density	-0.013 (0.186)			
W* detached	2.928 (0.070)***			
W*Owned share	-1.532 (0.646)			
W*lnelectricity	0.181 (0.390)			
W*QL2	0.034 (0.735)			
W*avehousehold	-0.815 (0.084)***			
W*Irradiation	0.0001 (0.612)			
W* CO2	0.201 (0.248)			
Lambda			0.175 (0.000)*	
Rho	0.122 (0.084)***	0.022 (0.000)*		0.076 (0.021)**
LR Test (WX=0)	43.214 (0.023)**			
LR Test (ρ=0)	2.988			

	(0.084)* **	
Sargan overidentification test		**31.115 (0.000)****
Hausman Specification Test		**3.259 (0.071)*****

Note: The values in parentheses are p-values. (*), (**), (***) denote significance levels at 10 per cent, 5 per cent and 1 per cent, respectively.

Table 9 presents the estimation results for spatial models where for the GS-2SLS model the Hausman statistic is adapted to test the difference between OLS and spatial errors. Compared to OLS estimates, spatial models capture the influence of share owned homes, education level, average household size and share of domestic and industrial emissions in affecting PV uptake. The fact that per capita income doesn't have any statistically significant effect, in line with Zhang et al. (2011) and Richter (2013), and the share of homeowners has negative effect on PV uptake suggest that it is not wealth that determines the decision to install PV. This could be due to the fact that wealthy homeowners may have less financial constraints that induce them to reduce their net energy use, in line with Urban and Scasny's (2012) findings on more well-off households tending to be less concerned about environmental problems and not undertaking energy efficiency measures.

Empirical results recognise the importance of the education variable, proxied by QL2, which has positive impact in all models and is statistically significant in the SDM model. While both Davidson et al. (2014) and Jager (2006) report positive influence of university and post-graduate education on PV uptake, our analysis reveals the effect of vocational and technical qualifications which are below university degree (captured by QL2). The findings presented here indicate that there is a statistically significant negative impact of population density on PV deployment which is in line with the existing literature, implying that residents located in less densely populated areas, characterised by a higher share of single and double family homes, are more likely to install a PV system (Müller and Rode, 2013). Yet, we find the influence of several other variables that have no precedent in the literature. PV uptake is positively influenced by detached homes. This could be due to easier access to the rooftops and management of construction works, compared to terraced homes. As a little more than half of the UK building stock is made up of detached homes (the remaining 19% by flats and 28% by terraced homes, DECC, 2012b), there could be further potentials to be exploited.

Households with higher demands for electricity, linked with higher levels of domestic emissions, are more likely to install PVs. However, another key factor that our study reveals is the negative relationship between PV installation and average household size that wasn't captured in the OLS estimation with no precedent in the literature: the smaller the average household size the higher the PV uptake. Taken together with higher levels of electricity consumption and Graziano and Gillingham's (2014) finding on the importance of accumulated capital, the early adopters seem to be post-family householders who are capable of raising funds to cover the high initial capital costs. Indeed, informal conversations with some PV installers revealed that many of their customers are elderly householders who spend most of their time at home with higher electricity demands and some savings to pay for the high capital costs. This could be due to a desire to reduce their net electricity use and costs (i.e. a substitution effect) or environmental awareness driving them to reduce the impacts of their higher demands, or a combination of these. The greater likelihood of their being at home during the day can be expected to improve the comparative economics of PV installation under the UK's FiT scheme. However, Mills and Schleich (2012) claim that families with a high share of elderly members are more motivated by financial savings in investing in energy efficiency activities than environmental reasons. There is insufficient evidence as to whether environmental or financial factors are the driving factors for PV uptake, or how these influence different potential domestic PV consumers.

Finally, our analysis suggests a statistically significant positive impact of solar irradiation on PV deployment. Since FiT payments for PV systems under 10kW are dependent on the actual amount of electricity produced this might be expected, but our data suggests a measurable spatial effect which does go to public understanding of this benefit of the overall economics implied by the scheme as it is currently applied. The UK tariff system for small users dictates that generators are assumed to export half their generation to the grid and use the other half. They receive a small additional subsidy for the half which they are assumed to have exported, regardless of the actual amount exported. The economics of small scale PV are thus predicated on generating X units of energy and getting payment of (i) a fixed subsidy per unit, (ii) a small additional export sum per X/2 units and (iii) displacement of billed tariffs for every unit of own solar energy use. The third of these means that for householders staying at home all day and using own solar power, the economics of PV panel are much better than the householders hardly ever using their own power (especially during sunny hours) and who likely export more than 50%.

We summarise and compare our findings on the factors determining British PV adoption with respect to the literature in Table 10. For the variables that have no precedent in the literature, their effect is explained in the last column.

Table 10. Summary of factors determining PV adoption

Variable	Findings in existing literature	Our findings
Income	Müller and Rode (2013); Rode and Weber (2012); Sardianou and Genoudi (2013) – higher income groups may be more able to afford costs of solar PV installation	Statistically insignificant impact – in line with Zhang et al. (2011); Richter (2013)
Home ownership	Keirstead (2007): home owners may be more likely to install than tenants as PV systems are fixed capital investments	Negative effect – together with income this highlights the importance of accumulated capital (Graziano and Gillingham, 2014)
Detached homes		Positive effect – compared to terraced homes, construction work could be easier
Density	Müller and Rode (2013) – less dense areas are more likely to install PV	Negative effect – higher uptake in less dense areas, characterized by a higher share of single and double family homes
Education level	Davidson et al. (2014); Jager (2006), Keirstead (2007) – More highly educated are more likely to adopt PV	Positive effect – Householders with vocational and technical qualifications are more likely to install PV
Pollution		Negative effect – Households in more polluted areas could be more eager to contribute to decarbonising energy system
Electricity use		Positive effect - households with higher demands might be more interested in becoming self-sufficient
Household size		Negative effect – smaller families might have higher disposable income to spend on PV
Solar irradiation	Šúri et al. (2007) – higher solar irradiation means greater electricity generation	Positive effect – More generation for the same investment cost which would be expected to enhance the economics of adoption of the technology. This remains the expectation under the UK PV FIT mechanism, which rewards increased

		generation.

Even though estimation results are quite similar for each specification, model comparison is essential to choose the correct specification. In order to investigate whether the SDM can be reduced to a spatial lag or error model, a likelihood ratio (LR) test was performed. The LR test results for null hypothesis $\theta = 0$ (51.36 with a p-value of 0.000) and LR test results for null hypothesis $\theta = -\rho\beta$ (47.80 with a p-value of 0.000) indicate that the Spatial Durbin model may be properly applied to describe domestic small scale PV installations.

In our analysis the coefficient of the spatially lagged dependent variable in the spatial Durbin model is statistically significant. Moreover the LR test testing the joint significance of all spatially lagged explanatory variables, indicates that they are jointly significant and should be included in the model ($\chi 2$= 43.214 with a p- value of 0.023). Hence our results reveal that PV uptake in one region has been enhanced by network effects.

In order to check whether the study's estimates suffer from potential endogeneity bias, a generalized spatial two-stage least squares (GS-2SLS) procedure has been employed. Kelejian and Prucha (1998, 2010), and Arraiz et al. (2010) suggest a three-step procedure to estimate models with spatially lagged dependent variables and spatially autoregressive disturbances based on a set of instruments. This strategy generates consistent and asymptotically efficient estimates under the assumption that the explanatory variables are indeed exogenously related to the dependent variable (Arraiz et al., 2010; Kelejian and Prucha, 1998; Kelejian and Robinson 1993). The GS-2SLS Model in Table 9 presents the instrumental variable estimates. The spatial two-stage least-squares estimates based on the use of the spatially lagged explanatory variables as instruments are robust to non-normality and consistent, but not necessarily efficient[14]. The estimates provided by the spatial Durbin and GS-2SLS are similar, suggesting the uptake of PV in one region tends to spillover to neighbouring regions. The Hausman specification test indicates that the instruments chosen for the GS-2SLS model satisfy the instrument relevance condition based on the first stage F test statistics, and the spatially lagged dependent variable is endogenous with a p-value of 7

[14] Please see Kelejian and Prucha (1998, 1999) for technical derivations and the selection of optimal instruments.

percent. Moreover the Sargan over-identification test suggests that the instruments satisfy the exogeneity condition.

6.2. Reflections on the method

McCullen et al. (2013) state that the adoption of innovations related to energy behaviours and technologies by individual households is generally based on multiple factors, taking into account not only individual preferences, but also whether or not an individual's social circle has adopted the innovation. The visibility of the panels can be a further contributing factor in addition to peer effects within the group. Indeed, the UK public's distinction between taking visible actions like installation of a solar panel versus non-visible actions such as building certificates and ratings has been noted in the literature (Balta-Ozkan et al., 2014b). While our method does not lend itself to differentiate the influence of social contacts vs visibility of the panels, it is clear that spatial proximity will increase the likelihood of visibility. Though the effect of social contacts, i.e. knowledge spillovers, might be argued to have a limited spatial reach which might be exhausted within a region; Manski's (1993) contextual factors might be at force. In particular, following the abolition of nine Regional Development Agencies (RDA) operating in England in 2010, there are 39 Local Enterprise Partnerships (LEPs) tasked on a voluntary basis to support economic growth by bringing together local authorities and businesses (BIS, 2015). Moreover, the devolved administrations in Scotland and Wales have their own energy policy priorities and targets. The Scottish Government for example aims to meet 50% of electricity demand from renewable sources by 2015 (Scottish Government, 2011). As the regional classification we have used is smaller than the definition of RDAs (nine of which correspond to ninety nine NUTS3 regions), it can be argued that even though peer effects might have been lessened, coordination or similarities in voluntary activities led by LEPs or other voluntary environmental charities[15] may reinforce knowledge spillovers that entail consideration of spatial effects[16]. By capturing these contextual factors, spatial econometrics offer richer insights into the spatial dynamics of the diffusion of innovations (new technologies) regarding PV uptake. This then can inform the development of future policies to enable transition to a low carbon economy that is just, efficient and effective.

[15] For example, UKH11 region in our analysis corresponds to Peterborough, home of the Peterborough Environment City Trust

[16] We thank our anonymous reviewer for this suggestion.

One variable we have not been able to account for is planning outcomes from the process of seeking permission to install PV. The planning regime relating to PV was amended in 2008 to make it easier for domestic scale installations to go through on a permitted basis rather than needing planning permission, provided they meet certain physical conditions regarding the location and so long as the installation is not in a protected area such as a national park. Interpretation of the more relaxed guidelines at local level may still have some impacts on installations but no data is available at the level required to be considered here.

Finally, we note that a cross-sectional analysis like this has limitations in the understanding of a technology diffusion process. The major disadvantage is that it is not possible to control for non-observational time invariant effects. Technology diffusion has a spatio-temporal dimension in that network spillovers may be enhanced in time, as new technology adopters could be the neighbors of older adopters (Nyblom et al., 2003). Although adoption of innovation is gradual and slow at the start, generally a dramatic and rapid growth is observed which is followed by a gradual stabilization and finally a decline Rogers (2003). Thus, given the importance on intertemporal spillover effects, further reaseach examining the factors affecting PV uptake should employ spatio-temporal methods, given that relavant data is avaliable.

7. Conclusions

Photovoltaic panels offer significant potential for contributing to the UK's energy policy goals of decarbonisation and improved security of supply and affordability. Existing studies focus on socio-economic determinants of PV uptake while overlooking spatial aspects. Yet, these can have important effects on the distribution network by influencing load, voltage and demand flows and thus their consideration represents a potentially significant influence for understanding and planning low carbon transitions and the evolution of existing networks to meet the needs of more diversified and distributed electricity generation. Our study is part of addressing this gap.

By using a large, spatially explicit dataset concerning PV deployments along with other socio-economic data, the determinants of PV uptake using exploratory spatial data analysis and spatial econometric methods were analysed. Our study reveals that domestic solar panel installation in a region is negatively related to its density, and the share of home ownership and positively to the share of detached homes and education level. Additionally an increase in household electricity spending leads to a rise in PV deployment in a region, highlighting the substitution effect. Surprisingly though, the average number of households in a region is negatively related to PV deployment in a region. This could be due to the fact that households residing in large houses are too wealthy to care about energy savings or are concerned about the visual impacts on their homes.

A statistically significant impact of solar irradiation on the PV uptake was apparent. This would be expected since this means more generation for the same capital investment. The nature of the UK FiT provides a reward on a per unit of energy generated, directly rewarding the greater generation in areas with greater irradiation, regardless of whether this is used by the generator or exported to the grid. This could be regarded as a positive in terms of applied policy in that it implies that consumers are being incentivised to invest in panels to a greater degree in areas where the economics of installation make more sense. This might be regarded as an equity issue as regards the ability of different householders to access tariffs, essentially those in areas with lower irradiation, have less access to public funding but in terms of maximising renewable energy generation against cost to the consumer or taxpayer than it would appear to be more efficient. An argument could thus be made to focus promotion in areas with higher irradiation. Further study of this area may be useful in informing future tariff setting since it is in the interests of policy makers to set a level of support which minimises costs while driving investment and this may mean a focus on areas with higher irradiation.

Householder's economic benefit from a PV panel can be expected to be advantaged by particular circumstances. Assuming similar costs, households with higher irradiance can expect to generate more energy and thus have greater income from both the tariff and export rates. This suggests that PV panels would be economically advantaged by being sited in the south over the north of the country.

DECC's consideration of the economics of PV comparative to other energy sources relies not just on income from the tariffs but also on the displaced value of electricity that a household would otherwise source from the grid. While the Government assume a 50/50 split it is clear that households who use a large amount of their own generation will be significantly advantaged since they will they will reduce the bill from their supplier while attracting the same tariff income as an identical property where a greater amount of the PV generation is exported. While the use of battery storage would alter the economics it is not thought that this has been adopted at significant levels, this may primarily be due to the lack of an economically attractive storage option applicable at this level. A domestic PV user who exports most or all of their self-generated power will still only attract the additional export rate for 50% of their total output. This creates the possibility that representatives of user groups more likely to use a greater fraction of their own generation might be more attracted to tariff-supported PV than those who see more of it exported, with the expectation that domestic generators who are at home or who have energy demand which can be made to fit with daytime usage will be advantaged. This might mean groups such as the unemployed, retired or stay at home parents might enjoy a cost advantage. Additionally, since members of groups who spend a large amount of time at home may have higher bills than those who do not, this may incentivise them to consider alternatives to traditional supply. The positive relationship between consumption and PV installation shown in our data may reflect these characteristics in application of the UK FiT mechanism. This may have implications for those considering reform of the FiT or in devising similar instruments in other territories.

The economics of PV in the UK depends on the costs of the installation, the available feed-in tariff at the time of connection and the price of grid-sourced electricity for which PV sourced electricity substitutes. Installation costs have decreased steadily in the last five years. The level of the feed-in tariff have also been subject to steady decreases to try to match real world cost reductions, and there is potential for a lag in reductions and a mismatch between modelled and real world cost reductions that may not be reflected in the available tariff. Meanwhile the price of UK domestic electricity has shown some variation but has trended generally upwards over the last decade (DECC, 2014c), implying an increasing benefit to substitution by self-generated PV power, and further underlining the economics of advantage of those with greater potential for substituting PV for grid electricity.

This study focuses on spatial aspects while Richter (2013) analysed temporal aspects. Future research might usefully consider spatio-temporal diffusion of patterns and how PV uptake interacts with other socio-economic factors such as the effects on house prices. Wider ranging work might consider how different populations respond in light of local financial incentives perform in driving PV growth in other territories, as well as considering wider policy frameworks and their application.

Our study is the first attempt to explain the patterns of British PV adoption using spatial econometrics. The spatial effects we have detected can be related to contextual factors on similarities and coordination of environmental and energy policies at sub-regional levels by local enterprise partnerships or other third sector organisations like charities, non-governmental organisations. Further research could adopt a more local level analysis to explore the nature of these spatial effects, whether they are peer effects or such contextual factors. Yet, there is scope for more representative survey based studies to distinguish the effect of such contextual factors from more centralised information providers such as the internet which may be used by households to learn about the costs and benefits of PV panels.

Further research questions could include the analysis of spatially differentiated FiT rates on PV deployment patterns and the evaluation of total costs and benefits of such differentiated tariff schemes. Given the strong neighbourhood effects obtained in our study, an alternative approach could be assessing costs and benefits by steering investments (Müller and Rode, 2013) into areas where there is available headroom capacity. Our analysis can also be used to support the development of more stochastic models to investigate optimum network reinforcement strategies under different deployment patterns.

Finally, whilst data availability dictated our selected spatial unit of analysis, the authors would expect results to differ at a more refined geographical level, another avenue of future research.

Acknowledgements
Partial research time for Balta-Ozkan is funded as part of the research programme of the UK Energy Research Centre, supported by the UK Research Councils under Natural Environment Research Council award NE/G007748/1 and NE/J005975/1. We acknowledge the research assistance and support by our interns, Noor Al-Mesad (Summer 2013, Boston University) and Michael Troy (Autumn 2013, Wake Forest University). We also acknowledge Thomas Huld's (Joint Research Centre of the European Commission, Ispra) help in recalculating solar irradiation data for the NUTS3 classification used in the paper.

References

Allen & Overy, 2012. UK Electricity Market Reform: The Draft Energy Bill. London.
Allen SR, Hammond GP, McManus MC., 2008. Prospects for and barriers to domestic micro-generation: A United Kingdom perspective. Applied Energy, 85, 528-544.
Anselin L., 1988. Spatial econometrics: methods and models. Springer, Netherlands.
Arraiz I, Drukker DM, Kelejian HH, Prucha IR., 2010. A Spatial Cliff-Ord-Type Model with Heteroskedastic Innovations. Journal of Regional Science, 50, 592-614.
Bagozzi RP, 2000. On the concept of intentional social action in consumer behavior. Journal of Consumer Research, 27, 388-396.
Balcombe P, Rigby D, Azapagic A., 2013. Motivations and barriers associated with adopting microgeneration energy technologies in the UK. Renewable and Sustainable Energy Reviews, 22, 655-666.
Balta-Ozkan N, Watson T, Connor P, Axon C, Whitmarsh L, Davidson R, Spence A, Baker P, Xenias D, Cipcigan L, Taylor G., 2014a. Scenarios for the Development Smart Grids in the UK - Synthesis Report. UKERC/RR/ES/2014/002, pp.74, February, UK Energy Research Centre: London, UK, available online at http://www.ukerc.ac.uk/support/RF3LSmartGrids.
Balta-Ozkan, N., Amerighi, O., Boteler, B., 2014b. A comparison of consumer perceptions towards smart homes in the UK, Germany and Italy: reflections for policy and future research. Technol. Anal. Strateg. Manag. 26, 1176–1195.
Baltagi, B. H., Rokicki, B., 2014. The spatial Polish wage curve with gender effects: Evidence from the Polish Labor Survey. Regional Science and Urban Economics, 49, 36-47.
BIS, 2015. Local Enterprise Partnerships (LEPs) and enterprise zones, available https://www.gov.uk/government/publications/2010-to-2015-government-policy-local-enterprise-partnerships-leps-and-enterprise-zones; accessed on 16/05/2015
Bollinger B, Gillingham K. Peer Effects in the Diffusion of Solar Photovoltaic Panels. Marketing Science 2012;31; 900-912.
Brasington, D. M., & Hite, D., 2005. Demand for environmental quality: a spatial hedonic analysis. Regional science and urban economics, 35(1), 57-82.
Bridge, G., Bouzarovski, S., Bradshaw, M., Eyre, N., 2013. Geographies of energy transition: Space, place and the low-carbon economy. Energy Policy, 53, 331-340.
Brueckner, J.K., 2006. Strategic interaction among governments in R. Arnott, D. McMillen (Eds.), Companion to urban economics, Basil Blackwell, Oxford, 322- 347.
CCA, 2008. Climate Change Act, Carbon Targeting and Budgeting, Chapter 27, Part 1—The Target for 2050. Her Majesty's Stationery Office Limited, London, UK. (available http://www.legislation.gov.uk/ukpga/2008/27/part/1, accessed 07/01/2012).
Cherrington, R., Goodship, V., Longfield, A., Kirwan, K., 2013. The feed-in tariff in the UK: A case study focus on domestic photovoltaic systems. Renewable Energy, 50, 421-426.

Claudy, M.C, Michelsen, C., O'Driscoll, A., 2011. The diffusion of microgeneration technologies - assessing the influence of perceived product characteristics on home owners' willingness to pay. Energy Policy, 39, 1459-1469.
Corrado L., Fingleton B., 2012, Where is the Economics in Spatial Econometrics? Journal of Regional Science 52(2), 210-239.
Davidson, C., Drury, E., Lopez, A., Elmore, R., Margolis, R., 2014. Modeling photovoltaic diffusion: an analysis of geospatial datasets. Environ. Res. Lett. 9, 1-15.
DECC, 2012a. UK Renewable Energy Roadmap Update 2012a. Department of Energy & Climate Change: London.
DECC, 2012b. United Kingdom's housing energy fact file 2012b. Department of Energy & Climate Change: London.
DECC, 2013a. Feed-in Tariff Generation Statistics. 23/01/2013. Department of Energy and Climate Change: London.
DECC, 2013b. UK Solar PV Strategy Part 1: Roadmap to a Brighter Future. Department of Energy and Climate Change: London.
DECC, 2014a. Digest of United Kingdom energy statistics (DUKES) 2014, Department of Energy and Climate Change, London.
DECC, 2014b. Solar PV cost data. Department of Energy and Climate Change, London.
DECC, 2014c. Quarterly Energy Prices - December 2014. Department of Energy and Climate Change, London.
DECC, 2015a. Solar photovoltaics deployment, 26 February 2015, Department of Energy and Climate Change, London. Available at https://www.gov.uk/government/statistics/solar-photovoltaics-deployment (accessed on 7/3/2015)
DECC, 2015b. FEED-IN TARIFFS: Commissioned Installations by Month, 20 February 2015, Department of Energy and Climate Change, London. Available at https://www.gov.uk/government/statistics/monthly-small-scale-renewable-deployment (accessed on 7/3/2015)
EC, 2009. Directive on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. 2009/28/EC European Commission, Brussels.
Elhorst, J.P., 2010. Applied Spatial Econometrics: Raising the Bar. Spatial Economic Analysis, 5, 9-28.
Elhorst J.P., Freret, S., 2009. Evidence of Political Yardstick Competition in France using a Two Regime Spatial Durbin Model with Fixed Effects. Journal of Regional Science, 49, 931-951.
Faiers, A., Neame, C., 2006. Consumer attitudes towards domestic solar power systems. Energy Policy, 34, 1797-1806.
Fell, D., King, G., 2012. Domestic energy use study: to understand why comparable households use different amounts of energy. A report to the Department for Energy and Climate Change. Brook Lyndhurst. DECC, London.
Florax, R., Folmer, H., Rey, S.J., 2003. Specification searches in spatial econometrics: the relevance of Hendry's methodology. Regional Science and Urban Economics, 33, 557-579.
Gibbons, S., Overman, H. G., 2012. Mostly Pointless Spatial Econometrics?. Journal of Regional Science, 52(2), 172-191.
Grau T., 2014. Responsive feed-in tariff adjustment to dynamic technology development. Energy Economics, 44, 36-46.

Graziano M, Gillingham K., 2014. Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment J. Econ. Geogr., 1–25.
Hargadon, A.B., Douglas, Y., 2001. When Innovations Meet Institutions: Edison and the Design of the Electric Light. Adm. Sci. Q. 46, 476–501.
Hirth L., 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Economics, 38, 218-236.
Hofierka, J., Kaňuk, J., Gallay, M., 2014. The Spatial Distribution of Photovoltaic Power Plants in Relation to Solar Resource Potential: The Case of the Czech Republic and Slovakia. Morav. Geogr. Reports, 22, 26-33.
IEA, 2015. 2014 Snapshot of global PV markets. Photovoltaic Power Systems Programme, Retrieved 11/05/2015, from http://www.iea-pvps.org/index.php?id=trends0.
IEA-RETD, 2014. Residential Prosumers - Drivers and Policy Options (RE-PROSUMERS). International Energy Agency - Renewable Energy Technology Deployment: http://iea-retd.org/wp-content/uploads/2014/06/RE-PROSUMERS_IEA-RETD_2014.pdf, accessed 11/07/2014.
IEA/IRENA., 2013. Solar Photovoltaics – Technology Brief. IEA-ETSAP: Paris, http://www.irena.org/DocumentDownloads/Publications/IRENA-ETSAP Tech Brief E11 Solar PV.pdf., accessed 9/4/2014.
Jager W., 2006. Stimulating the diffusion of photovoltaic systems: A behavioural perspective. Energy Policy, 34, 1935-1943.
Jenner S, Groba F, Indvik J., 2013. Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. Energy Policy, 52, 385-401.
Kaplan AW., 1999. From passive to active about solar electricity: innovation decision process and photovoltaic interest generation. Technovation, 19, 467-481.
Keirstead J., 2007. Behavioural responses to photovoltaic systems in the UK domestic sector. Energy Policy, 35, 4128-4141.
Kelejian HH, Prucha IR, 1998. Generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. Journal of Real Estate Finance and Economics,17; 99-121.
Kelejian HH, Prucha IR, 1999. A generalized moments estimator for the autoregressive parameter in a spatial model. International Economic Review, 40, 509-533.
Kelejian HH, Robinson DP. A., 1993. Suggested Method of Estimation for Spatial Interdependent Models with Autocorrelated Errors, and an Application to a County Expenditure Model. Papers in Regional Science, 72, 297-312.
LeSage, J.P., Pace R. K., 2009. Introduction to Spatial Econometrics, Boca Raton, Taylor & Francis.
LeSage, J.P., Pace R.K., 2010. Spatial Econometric Models, In: Fischer MM, Getis A (Eds), Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications. Springer, Berlin Heidelberg, pp. 355-374.
Lüthi, S, Wüstenhagen R., 2012. The price of policy risk — Empirical insights from choice experiments with European photovoltaic project developers. Energy Economics, 34, 1001-1011.
Lutzenhiser L., 1992. A Cultural Model of Household Energy Consumption. Energy, 17, 47-60.
Lutzenhiser L., 1993. Social and behavioral spects of energy use. Annual Review of Energy and the Environment, 18, 247-289.
Manski, C.F., 1993. Identification of Endogenous Social Effects: The Reflection Problem, The Review of Economic Studies, 60(3), 531-542.

Massetti E, Ricci E.C., 2013. An assessment of the optimal timing and size of investments in concentrated solar power. Energy Economics, 38, 186-203.
McCullen, N. J., Rucklidge, A. M., Bale, C. S., Foxon, T. J., & Gale, W. F. (2013). Multiparameter models of innovation diffusion on complex networks. SIAM Journal on Applied Dynamical Systems, 12(1), 515-532.
Mitchell, C., 2000.The England and Wales Non Fossil Fuel Obligation: History and Lessons. Annual Review of Energy and the Environment, 25, 285-312.
Moran, P.A.P., 1950. Notes on continuous stochastic phenomena. Biometrika, 37, 17-23.
Muhammad-Sukki F, Ramirez-Iniguez R, Munir AB, Mohd Yasin SH, Abu-Bakar SH, McMeekin SG, Stewart BG., 2013. Revised feed-in tariff for solar photovoltaic in the United Kingdom: A cloudy future ahead? Energy Policy, 52, 832-838.
Müller S, Rode J., 2013. The adoption of photovoltaic systems in Wiesbaden, Germany. Economics of Innovation and New Technology, 22, 519-535.
Newbery, D., 2011. Contracting for wind generation. Cambridge, University of Cambridge.
Nyblom, J., Borgatti, S., Roslakka, J., & Salo, M. A. (2003). Statistical analysis of network data—an application to diffusion of innovation. Social Networks, 25(2), 175-195.
Ofgem, 2013a. Feed in Tariff Annual Report 2012-13. Office of Gas and Electricity Markets: London.
Ofgem, 2013b. Renewables Obligation 2011-12. Office of Gas and Electricity Markets: London.
Ofgem, 2013c. Renewables Obligation – Guidance for Generators. Office of Gas and Electricity Markets: London.
Pinkse, J., Slade, M. E., 2010. The future of spatial econometrics. Journal of Regional Science, 50(1), 103-117.
Planning Portal, 2014. UK Government planning portal 'Solar Panels'. See http://www.planningportal.gov.uk/permission/commonprojects/solarpanels/ Accessed 08/02/2014.
Rai, V., Scott A.R., 2013. Effective information channels for reducing costs of environmentally- friendly technologies: evidence from residential PV markets. Environmental Research Letters, 8, 014044.
REA, 2012. REA Written Evidence to the Energy and Climate Change Select Committee:
Inquiry to Examine the Draft Energy Bill. Renewable Energy Association. London.
Richter, L-L., 2013. Social Effects in the Diffusion of Solar Photovoltaic Technology in the UK, EPRG Working Paper 1332, Cambridge University.
Rode, J., Weber, A, 2012. Does Localized Imitation Drive Technology Adoption? A Case Study on Solar Cells in Germany. mimeo TU Darmstadt.
Rogers, E.M., 2003. Diffusion of Innovation. 5th ed. Free Press: New York.
Sardianou E, Genoudi P. Which factors affect the willingness of consumers to adopt renewable energies? Renewable Energy 2013;57; 1-4.
Schaffer A.J., Brun, S., under review. Beyond the sun – main drivers of photovoltaics' spatial distribution in Germany.
Scottish Government, 2011, 2020 Routemap for Renewable Energy in Scotland, The Scottish Government, Edinburgh.
Snape, J.R., 2013. Smart grids , local adoption of distributed generation and the feed in tariff policy incentive, ECEEE Summer Proceedings, 93-99.
Snape, R., Rynikiewicz, C., 2012. Peer effect and social learning in micro-generation adoption and urban smarter grids development? Netw. Ind. Q. 14, 24–27.

Sueyoshi T., Goto, M., 2014. Photovoltaic power stations in Germany and the United States: A comparative study by data envelopment analysis. Energy Economics, 42, 271-288.

Šúri M, Huld TA, Dunlop ED, Ossenbrink H.A., 2007. Potential of solar electricity generation in the European Union member states and candidate countries. Solar Energy, 81, 1295-1305.

Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography, 46, 234-240.

Urban, J., Scasny, M., 2012. Exploring domestic energy-saving: The role of environmental concern and background variables. Energy Policy 47, 69–80.

Weber, M., 1978. Economy and society: an outline of interpretive sociology. Univ of California Press, California.

Weber C, Perrels A. Modelling lifestyle effects on energy demand and related emissions. Energy Policy 2000,28, 549-566.

Wilson C, Dowlatabadi H. Models of decision making and residential energy use. Annual Review of Environment and Resources 2007,32, 169-203.

Wolsink, M., 2012. The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources. Renew Sust Energ Rev,16, 822-835.

Wood, G., Newborough, M., 2003. Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design. Energy and Buildings, 35(8), 821-841.

Woodman, B., Mitchell, C., 2011. Learning from experience? The development of the Renewables Obligation in England and Wales 2002-2010. Energy Policy,39, 3914-3921.

Zhai, P., Williams, E.D., 2012. Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model. Renewable Energy,41, 350-357.

Zhang, Y., Song, J., Hamori, S., 2011. Impact of subsidy policies on diffusion of photovoltaic power generation. Energy Policy,39, 1958-1964.

Appendix 1: Data handling and processing

<u>The selection of locational variables:</u> Among the locational variables identified, LSOAs are small area statistical units based on measures of proximity and social homogeneity, with a minimum size of 1,000 residents and 400 households, but average 1,500 residents[17]. They are intended to provide an improved basis for comparison across the country as they are similar in size. LSOAs are used for England and Wales by the Office for National Statistics (ONS). An equivalent area for Scotland is Data Zones (DZs)[18]. Following 2011 Census, there are 32,844 LSOAs in England, 1909 in Wales and 6505 DZs in Scotland.

On the other hand, post codes and distributor ID numbers in MPANs don't correspond to any other statistical units for which socio-economic data is available. Given a total of 11 Government Office Regions in Great Britain, they are not deemed to provide a detailed analysis. As a result, the European regional classification system, NUTS3 (Nomenclature of territorial units for statistics) has been selected as spatial unit of analysis. There are 134 NUTS3 regions in Great Britain, based on 2012 classification. Even though the FIT database uses 2001 LSOA categories, by using the look up tables provided by the ONS[19] these are aggregated at NUTS3 level. There are 99 NUTS3 regions in England, 12 in Wales and 23 in Scotland, resulting in 134 observations in total.

<u>Missing observations and cross-checking:</u> Out of 380,158 domestic PV installations, 8.9% of the sample either had their LSOA/DZ codes missing or blank entries. By using the post code look up tables[20], for 72% of data their corresponding LSOA/DZ codes were matched. As only the first half of post codes were given, in some instances there were more than one possible LSOA/DZ area which were located in different NUTS3 regions. These as well as the observations where post codes could not be matched were excluded from the analysis, resulting in 374,445 observations to work with. A breakdown of this data cross-checking process is summarized in Table 11.

Table 11. Missing observations and cross-checking of data

Raw data characteristics			Number of installations	Installed capacity (kW)
Total domestic PV installations			380,158	1,207,342.7
Domestic installations missing some locational reference			33,769	130,169.6
Processing of observations with missing locational reference				
		NUTS3 matched	NUTS3 not matched –excluded	Falling in 2 NUTS3 regions – excluded
3942	LSOA codes not available but post code districts enabling matching	3397	517	28
293	First half of post code falling in more than one DZ/ LSOA	229	64	
24430	LSOA codes found based on post code look up tables	24430		

---

[17] For further details, see http://neighbourhood.statistics.gov.uk/dissemination/Info.do?page=aboutneighbourhood/geography/superoutputareas/soa-intro.htm.

[18] Current boundaries of DZs are based on 2001 Census. The Scottish Government is running a consultation on redrawing of boundaries of DZs to address significant population changes in some geographies, to bring them alignment with higher or lower level (e.g. Census Output Area) geographies or to reflect local circumstances. As this consultation is expected to be concluded in Spring 2014, this analysis is based on 2001 Data Zone boundaries and relevant look up tables (Rai and Scott, 2013).

[19] https://geoportal.statistics.gov.uk/geoportal/catalog/content/filelist.page

[20] http://www.ons.gov.uk/ons/guide-method/geography/products/census/lookup/other/index.html

5104	Neither post code nor LSOA codes provided		5104	
Number of observations		28056	5685	28
Installed capacity (kW)		88,385.2	41,652.5	131.9
Final data set with observations matched at NUTS3 level				
Number of installations				374,445
Installed capacity (kW)				1,205,518.3

Regional distribution of photovoltaic deployment in the UK and its determinants: a spatial econometric approach

Research Highlights

Spatial econometrics models applied to UK PV installation for the first time.
Significant regional spillover effects are apparent.
Smaller households in highly polluted, less dense areas are the early adopters
Strong substitution effect as high electricity spending induces PV installations.
Solar irradiation data are found to be significant.