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Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on UK solar photovoltaic deployment

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ABSTRACT

A growing literature highlights the presence of spatial differences in solar photovoltaic (PV) adoption patterns. Central to forward planning is an understanding of what affects PV growth, yet insights into the determinants of PV adoption in the literature are limited. What factors do drive the adoption at local level? Are the effects of these factors geographically uniform or are there nuances? What is the nature of these nuances? Existing studies so far use aggregate macro datasets with limited ability to capture the role of peer effects. This paper considers some established variables but also broadens the base of variables to try to identify new indicators relating to PV adoption. Specifically, it analyses domestic PV adoption in the UK at local level using data on the number of charities as a proxy to capture the opportunities to initiate social interactions and peer effects. A geographically weighted regression model that considers the spatially varying relationship between PV adoption and socio-economic explanatory variables reveals significantly more variability than the global regression. Our results show that charities and self-employment positively influence PV uptake while other socio-economic variables such as population density has bidirectional impacts.

1. Introduction

Using solar energy to produce electricity creates mitigation opportunities within energy security, climate change, and affordability (the so-called 'energy trilemma' (WEC, 2013)). In forward planning of system design and investment, an understanding of the effects of solar photovoltaics (PVs) growth is required. Yet insights into the determinants of PV adoption are limited. What factors drive adoption at local level? Are these factors geographically uniform or nuanced, given the presence of spatial regularities in PV adoption patterns (Balta-Ozkan et al., 2015b; Hofierka et al., 2014; Schaffer and Brun, 2015; Snape, 2016).

Following the first law of geography that '*everything is related to everything else, but near things are more related than distant things*' (Tobler, 1970, p. 236), it is unlikely the effects of different factors on PV adoption will be spatially (or temporally) uniform. While greater insight can be invaluable in designing policies to utilize such differences, literature in this area is scarce (excepting peer effect studies). Recent studies highlight spatial variation in the impacts of peers (Rode and Müller, 2016) and their diminishing nature over time (Graziano and Gillingham, 2015; Rode and Müller, 2016). It has been argued that installation of a PV panel creates a persistent signal that peers can observe which may generate externalities, reducing uncertainties associated with the adoption of an innovation (Rogers, 2003). In the literature, the magnitude of peer effects are commonly measured via the number of pre-existing installations in a preceding period (Bollinger and Gillingham, 2012; Müller and Rode, 2013). However, the use of such an aggregate variable does not distinguish the different levels through which peer effects might be realized: pairwise communication (micro), more intensive interactions within a subgroup (meso) and global influences such as social norms (macro) (Xiong et al., 2016). One example of meso-level interactions is solar community organizations which catalyze peer effects and foster PV adoption (Noll et al., 2014). Yet, the role of community organizations is not accounted for by quantitative studies of peer effects (Noll et al., 2014). Environment and energy related charities can help increase environmental awareness, provide dissemination channels, and reduce uncertainties for new technology adoption. This study aims to identify the effects of different factors on spatial patterns of PV adoption in the UK at local level whereby peer effects are captured by the intensity of subgroup membership. This

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paper seeks to answer two questions: What is the nature and effect of different factors on PV adoption spatially? Does the intensity of group membership in related charities contribute to PV adoption?

Answering these questions is important. Firstly, while spatial regularities in PV adoption patterns are established, understanding the spatial heterogeneity of socio-economic factors driving these patterns are overlooked. This means the influence of these factors may be under or overestimated, limiting their ability to beneficially influence the development of future policies at local level. Secondly, insights on the importance of peer effects in diffusion of innovative technologies (Eppstein et al., 2011; among others, Robinson and Rai, 2015; Schwarz and Ernst, 2009) are not empirically validated in econometric models to explain the determinants of PV uptake. This is important because generalizable approaches such as these can reveal the importance of factors previously unknown to scholars. By using a proxy for group membership in related charities, this study quantifies for the first time their impact on PV uptake. Thirdly, while this study focuses on PV uptake in the UK, the peer effects method developed here can be applied to the uptake of other low carbon technologies in other geographical contexts (among others, Wang and Zhu, 2020).

The two research questions identified are analyzed via global ordinary least squares (OLS) and local geographically weighted regression (GWR) models. The results indicate that peer effects positively impact domestic PV adoption, while demand for electricity, housing types and irradiation level affect PV uptake at the local level. Furthermore, a GWR model significantly improves parameter estimates and handles the spatial non-stationarity that could not be addressed by global OLS model.

The paper is organized as follows: section 2 offers a review of the relevant literature. Methodology is presented in section 3. Model specification and data are summarized in section 4. Results are presented in section 5 and then discussed in section 6. Section 7 is devoted to conclusions and policy implications.

2. Literature review

The background to the paper draws on two areas of research: analyzing determinants of PV adoption and the modelling of peer effects.

2.1. Determinants of PV adoption

Variation in temporal resolution, geographical scale and resolution in different studies means that a relatively large number of explanatory variables are used to explain the determinants of PV adoption. These variables can be grouped into five categories: household and built environment characteristics, environmental attitudes, economic and physical factors, and peer effects. These variables and their impacts on PV uptake are summarized in Table 1.

Regarding household characteristics, several studies report a positive influence of education level, percentage of male and white population on PV adoption. Only one study, Balta-Ozkan et al. (2015b) suggests a negative relationship between PV adoption and household size. Built environment characteristics in terms of population or housing density are the most commonly used variable, with the likelihood of installing PV being greater in less densely populated areas, characterized by a higher share of single and double family homes (Müller and Rode, 2013; Rode and Weber, 2016). Some characteristics of less densely populated areas including longer than 30-min commutes (Bollinger and Gillingham, 2012), more availability of roof space (Briguglio and Formosa, 2017), higher number of rooms (Davidson et al., 2014) and percentage of detached homes (Balta-Ozkan et al., 2015b) positively influence PV adoption. However the percentage of wood heating systems has a negative effect (Davidson et al., 2014), possibly suggesting trade-offs between sparseness of settlements and PV adoption.

The authors use several variables here to analyze the relationship

Table 1
Determinants of PV adoption and their effects.

Factors	Variables used	Effects
Household characteristics	Education level	More highly educated (Bollinger and Gillingham, 2012; Davidson et al., 2014; Jager, 2006; Keirstead, 2007) or those with vocational and technical qualifications (Balta-Ozkan et al., 2015b) are more likely to adopt PV
	Household size	Smaller families might have higher disposable income to spend on PV (Balta-Ozkan et al., 2015b)
	Ethnicity and gender	Higher PV adoption is associated with the percentage of male and white population (Bollinger and Gillingham, 2012)
Built environment characteristics	Population density	Less dense areas are more likely to install PV due to the larger roof space and lack of split incentive (Balta-Ozkan et al., 2015b; Müller and Rode, 2013; Rode and Müller, 2016)[a]
	House density	Higher number of homes would enable better exploitation of sunlight (Schaffer and Brun, 2015)[b]
	Longer commuting distance	Longer than 30-min commute might increase the visibility of other installations (Bollinger and Gillingham, 2012)
	Availability of roof space	The higher ratio of dwellings that have their own roof space to the total households would facilitate PV adoption (Briguglio and Formosa, 2017)
	Wood heating	High reliance on wood heating is negatively correlated with PV adoption (Davidson et al., 2014)
	Number of rooms	Larger houses may consume more electricity, increasing the cost savings from PV systems (Davidson et al., 2014; Sommerfeld et al., 2017)
	Detached homes	Compared to terraced homes, construction work could be easier (Balta-Ozkan et al., 2015b)
Environmental factors	Share of green votes	PV penetration are likely increase with the ecological attitude of a region's population (Schaffer and Brun, 2015)
	Share of hybrid cars	PV adoption increases with a higher share of hybrid vehicle adoption (Bollinger and Gillingham, 2012; Davidson et al., 2014)
	Pollution levels	Households in more polluted areas could be more eager to contribute to decarbonising energy system (Balta-Ozkan et al., 2015b)
	Environmental awareness	The higher the number of children enrolled in Junior Eco-Clubs may indicate higher environmental awareness and positive influence on PV adoption (Zhang et al., 2011)
	Electricity demand	Households with higher demands might be more interested in becoming self-sufficient (Balta-Ozkan et al., 2015b)
Economic factors	Income	Higher income groups may be more able to afford costs of solar

(continued on next page)

Table 1 (*continued*)

Factors	Variables used	Effects
		PV installation (Briguglio and Formosa, 2017; Müller and Rode, 2013; Rode and Müller, 2016; Rode and Weber, 2016; Sardianou and Genoudi, 2013; Schaffer and Brun, 2015). Some statistically insignificant results are also reported (Richter, 2013; Zhang et al., 2011)
	Accumulated capital	Rather than level of income, accumulated capital is more important (Balta-Ozkan et al., 2015b)
	Home ownership/share of renter-occupied dwellings	Home owners may be more likely to install than tenants as PV systems are fixed capital investments (Briguglio and Formosa, 2017; Graziano and Gillingham, 2015; Keirstead, 2007; Schaffer and Brun, 2015; Sommerfeld et al., 2017)
	Second home ownership	Having a second mortgage or home equity loan is found to positively correlate with PV adoption (Davidson et al., 2014)
	Investment in new housing	Higher investments in new housing is likely to promote the diffusion of PV systems as these new homes are likely to be equipped with the PV system (Zhang et al., 2011)
	Installation costs	Installation costs negatively influence PV adoption (Zhang et al., 2011)
	Subsidies	Regional (Zhang et al., 2011) or local (Best et al., 2019a) subsidies help to promote PV system adoption
	Governance of subsidies	Issuing, management and promotion of financial scheme by the government can influence household sentiment (Briguglio and Formosa, 2017)
	Electricity cost	Areas with higher electricity costs (Graziano and Gillingham, 2015; Müller and Trutnevyte, 2020) or higher average electricity prices (Best et al., 2019b) are more likely to see higher rates of adoption
Physical factors	Solar irradiation levels	Higher solar irradiation means greater electricity generation from the same panel system, with direct implications for the economics of panel installation (Balta-Ozkan et al., 2015b; Rode and Müller, 2016; Schaffer and Brun, 2015; Šúri et al., 2007)
Peer effects	Number of preexisting installations	The propensity to install PV panels increases with the number of previously installed systems in spatial proximity due to social interactions among the individuals (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Richter, 2013; Rode and Weber, 2016)

[a] Graziano and Gillingham (2015) refer to housing density which is calculated by dividing population by land area. However, they concede this variable might have included land uses that should not be included such as wetlands and forest. As a result of this ambiguity, it is not included in this list.

[b] This variable is defined by number of residential buildings per sq. km.

between environmental factors and PV adoption. Pro-environmental attitudes such as share of green votes (Schaffer and Brun, 2015), ownership of hybrid electric vehicles (Bollinger and Gillingham, 2012; Davidson et al., 2014) and membership in eco-clubs (Zhang et al., 2011) are positively correlated with PV adoption. Higher pollution levels and demands for electricity (Balta-Ozkan et al., 2015b) induce PV uptake by encouraging householders to decarbonize and become self-sufficient. The influence of cost on PV adoption is inconclusive as some studies highlight the importance of accumulated wealth rather than income (Balta-Ozkan et al., 2015b). While owning a home, a second home and investment in new housing each positively influence PV adoption, installation costs have the opposite effect. Unsurprisingly, subsidies promote the adoption of PVs. One study takes into account the governance of subsidies and reveals positive influence of pro-government sentiment in the uptake of PV scheme (Briguglio and Formosa, 2017). As higher solar irradiation means greater electricity generation (for the same size and cost of solar panels) which means more favorable economics via both access to subsidy and greater displacement of network supplied power, it has a positive influence on PV adoption. Lastly, peer effects assume that the propensity to install PV increases with the number of previously installed systems in spatial proximity, which is discussed in detail in the next section.

Snape (2016) takes the research further by considering how PV adoption varies over time, suggesting effects including the emergence and growth of clustering around areas of early adoption. He suggests that early adoption persists for some time, which supports peer observation as a driver for adoption.

2.2. Modelling peer effects

Peer effects are '*the various influences on taking a specific action that an individual receives from other individuals in the same group*' (Xiong et al., 2016, p.1). However, identifying causal peer effect presents difficulties (Bollinger and Gillingham, 2012) due to Manski (1993)'s '*identification*' problem. Manski (1993) classifies the effect of group membership on an individual's behavior as endogenous, contextual, and correlated effects. Individual behavior influences the average group behavior while simultaneously being influenced by group behavior, leading to endogenous effects. Conversely, an individual's behavior can be directly influenced by the exogenous characteristics of his or her group. Furthermore, individuals within a group behave similarly, as they tend to have consonant characteristics or face similar political, institutional or environmental conditions.

Rai and Robinson (2015) categorize peer effects into passive and active. Passive effects accrue through witnessing PV systems in the neighborhood, increasing confidence and motivation, while active effects see peer-to-peer communications play a role. They highlight trustworthiness as an important factor of peer effects, amongst others such as motivation, confidence, convenience, and relevance. Yet, according to Xiong et al. (2016), there are three underlying mechanisms of peer effects: information transmission, experience sharing and externalities. The individual receives awareness and cost-benefit information from his/her peers initially. But depending on the individual's risk preferences, volume of information and proficiency in evaluating costs and benefits, information transmission may or may not lead to adoption. Knowledge gained from prior implementers is the *experience effect*. When an individual's decision to adopt is influenced by the decision of other peers, the *externality effect* is in force. Externalities might emerge via one-on-one communication at the micro level, subgroup membership at the meso level or collectively through networks at the macro level. As information transmission and experience sharing indicate direct knowledge exchange between the individuals which can be construed as active peer effects (Rai and Robinson, 2013), externality effects point to passive channels.

Several approaches have been used to analyze the nature and scope of peer effects (Table 2). A common approach to analyzing peer effects

Table 2
Different approaches used in the modelling of peer effects.

Study	Data Granularity	Method	Number of observations	Scale	Peer effects	Results
Bollinger and Gillingham (2012)	Cumulative number of installations in a zip code	Linear Probability Model	85,046 installations in 1652 zip code areas	A single state in the USA, California	Cumulative number of completed installations at a given time in a zip code	Peer effect may increase over time; stronger on the street level than on the zip code level
Müller and Rode (2013)	Individual installations	Binary panel logit model	324 installations	A single city in Germany, Wiesbaden	Actual physcial distance between installations of up to 1 km in distance	Diminishing effect of existing installations on the propensity of a new installation as distance between them increases.
Richter (2013)	Aggregate installations by postcode	Linear dynamic econometric model	332,216 PV installations in 2239 postcode districts	Devolved administrations of England and Wales in the UK	Cumulative number of completed installations in a postcode by the end of a particular month	Social effects are positive and significant but diminish over time, stronger effects in higher educated postcodes
Graziano and Gillingham (2015)	Block group level	Geospatial analysis and econometric model	3833 PV installations distributed across 2574 census blocks	A single state in the USA, Connecticut	Number of pre-existing installations at certain distances (0.5, 1, 4 mile radius) over certain timescales (6, 12 and 24 months prior to installation)	Smaller towns acting as centers of diffusion where peer effects diminish over space and time.
Balta-Ozkan et al. (2015b)	Aggregate number of installations by regions	Spatial econometric model	374,445 PV installations distributed across 134 regions	Great Britain	Total number of installations at a region and its neighbouring regions	Coordination or similarities in voluntary activities led by Local Enterprise Partnerships or other voluntary environmental charities at regional level may reinforce knowledge spillovers that entail consideration of spatial effects.
Rode and Müller (2016)	Individual and potential adopters	Discrete choice model with spatial panel data	877,114 PV systems installed across 77,847 spatial areas	Germany	Spatio-temporal lag: number of preexisting PV installations within a certain radius where the importance of each location declines in distance (baseline: 200 m)	Higher peer effect in the early stages of diffusion. The peer effects are highly localized where distance further than 200 m does not add any explanatory power.
Rode and Weber (2016)	Aggregate installations by 500 m grid of rings	Epidemic diffusion model	576,056 installations across 1.4 million spatial areas	Germany	Cumulative number of completed installations within a distance band	Decreasing influence of distance on localized imitation up to 1 km radius.

has been the use of cumulative number of completed installations in a geographical area. However, this assumes that peer effect is only realized when the installation is complete and ignores prior potential word-of-mouth interactions across individuals (Zhang et al., 2011). Bollinger and Gillingham (2012) find that peer effects increase in magnitude over time and are greater for larger installations and at the localized street level. This is contrasted by other studies reporting diminishing nature of peer effects over time (Graziano and Gillingham, 2015; Rode and Müller, 2016). Despite Rode and Müller (2016)'s caution in using high level of geographical aggregation to capture peer effects, a number of different spatial units have been used in different studies, confirming the spatially varying nature of peer effects. Even though the effect of social contacts might be argued to have a limited spatial reach within a region, definition of regions might be too small to capture Manski (1993)'s contextual factors and the relevance of the group membership in environment and energy related charities in facilitating low carbon transitions has been overlooked.

3. Estimation method

OLS and geographically weighted regression (GWR) are employed for exploring the spatial relation between PV uptake and the selected explanatory variables. Linear regression is employed as a diagnostic tool and for selecting the appropriate predictors for the GWR model. The spatial independency of the residuals is assessed with Moran's I statistic.

OLS methods assume that the relationship under study is constant over space and produces global parameter estimates. As an extension of traditional regression, the GWR method incorporates, detects, and accounts for spatial non-stationarity in variable relationships (Fotheringham et al., 2001; Fotheringham and Brunsdon, 1999; Thapa and Estoque, 2012; Tu and Xia, 2008; Xu and Lin, 2017). The GWR model generates a set of local line regression models rather than a global model, with estimates for every sample in space under the assumption that relationships between regression variables may vary over space (Fotheringham et al., 2003). The GWR method explores spatial heterogeneities in regression models of geo-referenced data and produces local parameter values for each region in the data set. The spatial variability of the estimated local regression coefficients is investigated to determine whether the underlying data generating process exhibits spatial heterogeneities or local deviations.

An ordinary linear regression model can be expressed as

$$Y_i = \beta_0 + \sum_{i=1}^{p} \beta_i X_i + \omega_i \tag{1}$$

where the dependent variable Y is represented as a linear combination of explanatory variables X_i; p is the number of independent variables and ω_i are independent normally distributed error terms with zero mean and constant variance.

The GWR model, which allows local rather than global parameters to be estimated, can be expressed as

$$Y_i = \beta_0\left(u_j, v_j\right) + \sum_{i=1}^{p} \beta_i\left(u_j, v_j\right) X_{ij} + \varepsilon_{ij} \tag{2}$$

Where u_j and v_j are the coordinates for each location j, $\beta_0\left(u_j, v_j\right)$ is the intercept for location j, $\beta_i\left(u_j, v_j\right)$ is the local parameter estimate for independent variable x_i at location j. $\beta_0(u_j, v_j)$ and $\beta_i(u_j, v_j)$ are $p+1$ continuous functions of the location (u, v) in the geographical study area, and ε_{ij} is are random error terms, which are independently normally distributed with zero mean and common variance σ^2 (Fotheringham et al., 2003).

In estimating the parameters in the GWR equation, it is important to choose a criterion to decide on the weighting matrix, which will represent the importance of each observation among locations. A common way to choose a weighting matrix at location i is to exclude observations that are further than a specified distance, assuming that the observations closer to the location of the sample point have higher impact on the local parameter estimates for the location (Tu and Xia, 2008). In this paper the weighting function used by Brunsdon et al. (1999) has been employed, this takes the form

$$W_{ij} = exp\left(\frac{-d_{ij}}{b^2}\right) \tag{3}$$

where W_{ij} is the weight of observation j for observation i, d_{ij} is the between observation i and j, and b is the kernel bandwidth. Generally, the cross-validation score or AIC test is employed to determine the optimal bandwidth distance as described in (Fotheringham et al., 2003).

Within the GWR modelling framework separate regressions at each location are estimated taking into account only other observations within a specific distance to that location (Lo, 2008; Zhou et al., 2019). GWR extends the ordinary least squares regression model by allowing the parameters to be estimated by a weighted least squares procedure. As the weighting system depends on the location, GWR method enables researches to estimate local parameters for an observation at a given location (u, v) and weighted values of nearby observations (Huang and Leung, 2002; Kontokosta and Jain, 2015). The global OLS models cannot account for local variation in influences. Local models, such as the GWR model, decompose the global model and produce results which are location dependent. These models address the spatial non-stationarity directly as they allow relationships to vary over space. The employment of spatial data techniques enables researchers to identify spatial regimes and convergence clubs. In order to compare GWR with OLS models an approximate likelihood ratio test, based on the F-test is performed (Fotheringham et al., 2003).

4. Data and model specification

The spatial unit of analysis is local authority districts (LADs) as defined by the Office for National Statistics (ONS), numbering 348 in England and Wales. The corresponding areal unit in Scotland is council areas, of which there are 32. Of these 380 areas, Isles of Scilly is excluded because of unavailability of data for some explanatory variables as is the City of London as it is not a residential area, following (Diacon et al., 2008). Overall, the study is based on 378 observations.

4.1. Dependent variable

The data on PV deployment comes from the Central FIT Register, published by the Ofgem E-serve Database and includes installations qualifying for the GB Feed In Tariff as of December 31, 2014 (Ofgem, 2014). The database lists installed and declared capacities (kW) for different technology and installation types, along with other locational variables. Following (Balta-Ozkan et al., 2015b), all UK domestic PV installations under 10 kW are included in the study. Of the locational variables included in the FIT registry, lower layer super output areas[1], (LSOA, based on 2001 classification) and postcode district were used in aggregating PV data at LAD level for England and Wales[2]. In Scotland, equivalent areas to LSOAs are called data zones (DZ). These are aggregated to the corresponding local areas, i.e. council areas (CA). With the exclusion of observations with no locational data, 532,577 PV installations with over 1661 MW installed capacity are included in the analysis (Table 3).

The spatial distribution of these installations is presented in Fig. 1. There appears to be a concentration of PV uptake in the South West, East and some parts of the West Midlands regions, Wales and Scotland. There is some degree of match to higher levels of solar irradiation with Wales and these English regions. The spatial patterns of accumulated capacity and number of installations are very similar, suggesting there is little variance in average number of panels per installation at the district level[3].

4.2. Explanatory variables

Existing literature identifies several variables of interest; the aim here is to revisit some of these but also to expand the range of variables considered. Following (Müller and Rode, 2013; Rode and Weber, 2016)'s analysis, population density and the presence of detached homes (Balta-Ozkan et al., 2015b) emerge as proxies to measure the effect of sparseness of PV adoption. As the presence of wood heating systems are shown to have a negative influence on PV uptake (Davidson et al., 2014), it remains to be tested whether greater frequency of other heating systems such as gas heating or less common heating systems can be a predictor of PV adoption. Even though (Rogers, 2003) states that higher income households tend to adopt early and observational learning might therefore play a less important role, evidence from other studies is inconclusive. Following (Graziano and Gillingham, 2015; Müller and Rode, 2013), we use median income to capture the effect of income on PV adoption. Given the positive relationship between prevalence of homes with second mortgages or which have drawn down home equity loans and PV adoption (Davidson et al., 2014), it is unclear whether outright home ownership has any influence in the British context.

Concerning household characteristics, there is some evidence that education level may influence the likelihood of PV adoption (Balta-Ozkan et al., 2015b; Bollinger and Gillingham, 2012; Davidson et al., 2014) though some studies don't identify a statistically significant relationship (Sommerfeld et al., 2017). One variable receiving little attention in the literature, and which may influence adoption, is self-employment. The management literature depicts a positive relationship between self-employment and risk-taking behavior (Nieβ, 2014; Obschonka and Stuetzer, 2017) which may indicate a predilection to early adoption. They might also have more developed skills in payback analysis or be keen to manage household electricity costs (Best et al., 2019b). Moreover, as some self-employed people may be working from home, they may want to reduce electricity costs, increase their sustainability credentials or might be able to benefit from tax incentives to carry the cost of PV as a business cost rather than a household one. Higher demand for electricity has been shown to motivate householders to greater interest in self-sufficiency (Balta-Ozkan et al., 2015b); whether it can predict the adoption at local level is unaddressed.

The literature notes the effectiveness of local initiatives (Dewald and Truffer, 2012) and solar community organizations (Noll et al., 2014) in facilitating PV adoption. It might be argued that energy and

[1] LSOAs are small area statistical units based on measures of proximity and social homogeneity, with a minimum size of 1000 residents and 400 households. For further details, see https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography (11/10/2016).

[2] ONS provides lookup tables to aggregate data from lower geographical areas to higher units http://geoportal.statistics.gov.uk/datasets?q=Census%20Lookups&sort_by=name (11/10/2016).

[3] This could be due to similarities in the housing/roof types at a district level; and/or characteristics of PV panels offered by local installers (selling a particular size system as 'standard'). We haven't identified any data on the number of solar installation companies at local district which could be explored further in future research.

Table 3
Photovoltaic adoption statistics by devolved administrations and missing observations.

	Number of installations			Installed capacity (kW)		
	England	Wales	Scotland	England	Wales	Scotland
Domestic PV (<10 kW)	459,277	36,411	36,916	1,431,340.6	108,929.1	121,146.8
Matched LSOA/DZ to LAD/CA	458,364	36,364	1603	1,429,636.4	108,854.4	5607.4
Matched by postcode	888	45	35,313	1664.0	71.7	115,539.4
Unmatched	25	2		40.2	3.1	
Observations included in the analysis	459,252	36,409	36,916	1,431,300	108,926	121,147
No locational data to match to LAD/CA	283			1262.09		
Post codes not matched to LSOA/DZ or LAD/CA	90			166.01		
Excluded observations	400			1471.34		
Total number of observations included in the analysis	532,577			1,661,373		

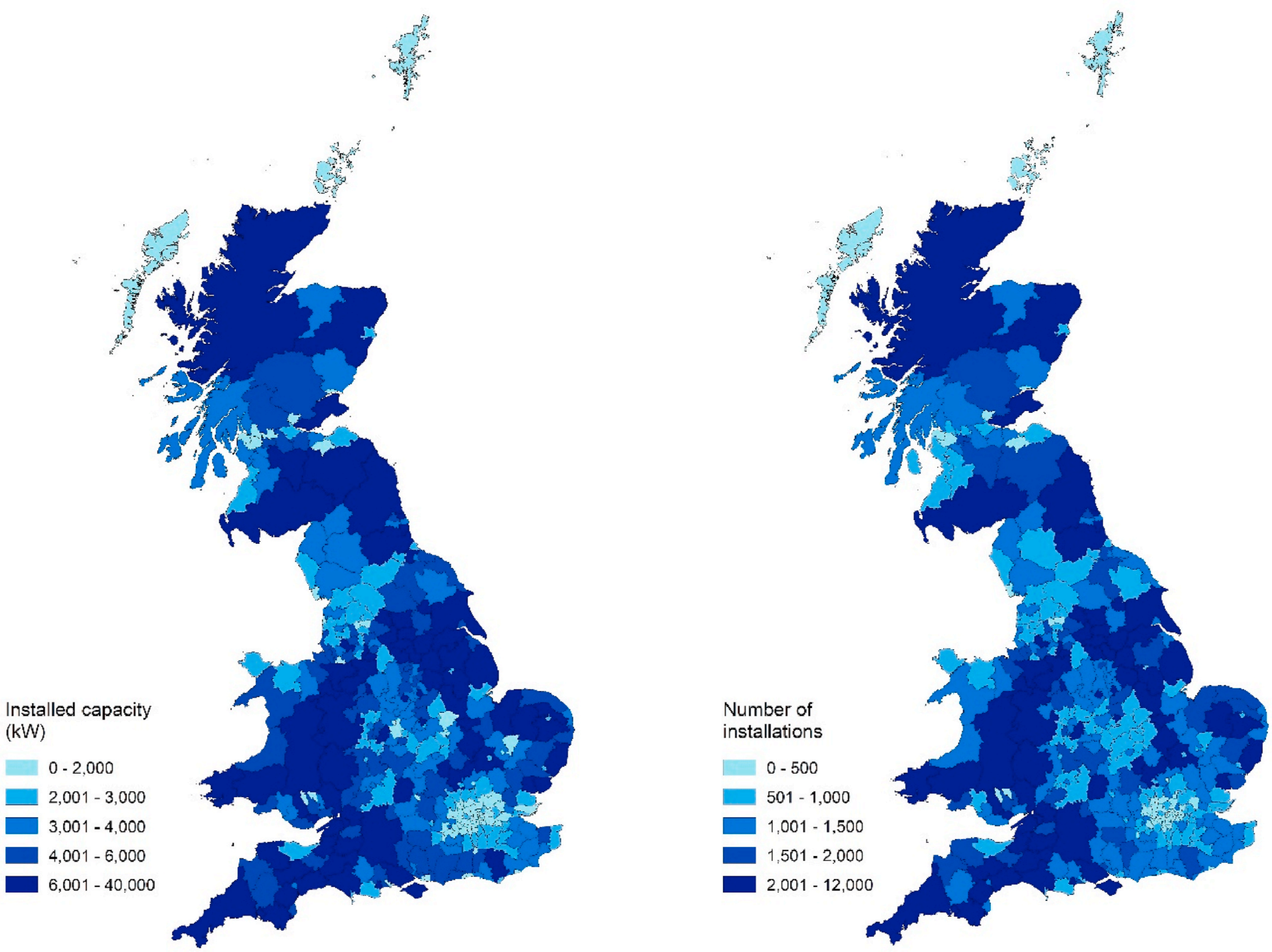

Fig. 1. Local Distribution of Residential Solar PV Installations (installed capacity, GW (left) and number of installations (right)).

environmental charities may facilitate social interactions among interested individuals in local areas[4]. Existing peer effect studies do not recognize the role of such community organizations (Noll et al., 2014) nor subgroup membership in charities. The role of group membership in charities in creating peer effects has been documented for creating public engagement in nature conservation (Cook and Inman, 2012) or facilitating coping strategies for visual impairment (Stevelink et al., 2015). Due to lack of data on membership to environment and energy related charities as well as a measure of their actions (or inaction), we use the number of such charities at local level as a proxy to capture meso-level externalities (Xiong et al., 2016).

Another factor influencing solar PV uptake is policy incentives., Feed in tariff (FIT) were introduced in the UK in 2010 via payments on actual generation where domestic users had to get a second meter which measured total output from the PV panels. Payments were made per kWh of output plus another payment (the export tariff) for 50% of the

[4] While we are specifically interested in the impact of presence of charities in an area, this does not mean that their impacts are limited to physical proximity. Social media and internet would definitely extend the reach of such local, national or international organizations. We also note that depending on the national context, some of these organizations may not have formal recognition and maybe informal clubs and organizations.

output (Balta-Ozkan et al., 2015b). The 50% was a fixed fraction regardless of how much the consumer used on their premises or sent to the grid. The third key element of the FIT was that any self-consumption by the user defrayed imports from the grid, reducing energy bills. Since the export payment was fixed as a percentage, this defrayal of costs was variable depending on the energy profile of the premises and its users; someone at home all day benefitted more than someone who was absent for most of the daylight hours. FITs had a significant impact on PV uptake (Muhammad-Sukki et al., 2013) the effectiveness of which is shown to depend on the degression patterns and administration structure (Dijkgraaf et al., 2018). This scheme has degressed over the years and ceased for new entrants as of March 2019. All these changes over the years were implemented UK wide, offering the same level of incentive per unit energy everywhere in the country. Practically though, since FIT payment depends on actual power output, someone in the south (i.e. with more irradiation) would get more subsidy for the same capital spend. This is not included in this analysis as our study is a snapshot in time rather than a longitudinal one. It does however provide an explanation as to why uptake increases with irradiance. The full list of explanatory variables included in the analysis is summarized in Table 4. The data on these socio-economic variables come from latest UK census data, 2011[5].

4.3. Spatial autocorrelation

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 neighbors. A positive Moran's I index value indicates a tendency toward clustering, a negative value indicates a tendency toward dispersion. Table 5 presents Moran's I statistics for all variables that are considered in this paper. To calculate the Moran's I, an inverse distance weight matrix is used, where the element w_{ij} is equal to $1/d_{ij}$ with d_{ij} being the distance between two local areas, i and j ($i \neq j$). This specification assumes that as the distance between localities i and j increases (decreases), W_{ij} decreases (increases), implying less (more) spatial weight to the pair (i, j). All 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 all variables of interest.

4.4. Model specification

Following the existing literature (among others (Balta-Ozkan et al., 2015b; Bollinger and Gillingham, 2012; Jayaweera et al., 2018; Poruschi and Ambrey, 2019)), a semilogarithmic model has been employed to investigate the drivers of PV uptake across 378 local areas:

$$lnPV_i = \beta_0 + \beta_1\, lnELEC_i + \beta_2\, lnCHARITY_i + \beta_3\, DENS_i + \beta_4\, EMPLOY_i + \beta_5\, DETAC_i + \beta_6 lnSOLAR_i + \beta_7\, HEATING_i + \beta_8\, EDUC_i + \gamma\, INCOME_i + u_i \tag{4}$$

where i denotes regions and u is an independently and identically distributed error term with zero mean and variance σ^2. Among these variables, for income, electricity sales, number of charities and solar irradiation levels their natural logarithmic values are used for scaling purposes. Given the semilogarithmic specification of the model, while parameters of the variables in logarithmic form can be interpreted as elasticities, the other parameters are semielasticites indicating that one unit change in an explanatory variable can result in a ($100 \times \beta_i$) percentage change in the dependent variable.

In this study the number of installations is the preferred PV uptake variable. The dependent variable is the natural logarithm of the number of domestic PV installations under 10 kW[6]The explanatory variables natural logarithm of median income (INCOME), natural logarithm of electricity consumption (ELEC), logarithm of charity numbers (CHARITY), population density (DENS), share of self-employed people (EMPLOY), share of detached houses (DETAC), natural logarithm of average solar irradiation (KJ/m^2/day) (SOLAR), share of gas central heating (HEATING), an educational level equivalent to 3 or more A-levels, HNC, HND, SVQ level 4 or equivalent qualifications (QL3 – equal to or better than FHEQ level 3 in UK terms) is applied as a proxy for education (EDUC). Explanatory spatial data analysis are conducted in Stata 14; GWR analyses were conducted in GWR4.09 software (Nakaya, 2016); and all maps are generated using Stata 14.

5. Results

Global Regression Model estimates for Eq. (4) are presented in Table 6, where R^2 denotes the coefficient of determination and AIC denotes Akaike Information Criterion. The Variance Inflation Factor (VIF) index has been computed to detect problems of collinearity among the independent variables. The results in Table 7 indicate that the level of collinearity among independent variables is low. The global Moran's I is calculated for the residuals from the global OLS model to investigate the presence of spatial correlation. These indicate the existence of significant positive spatial autocorrelations, suggesting that the OLS model is unsuitable for identifying the relationships between solar PV uptake and the explanatory variables.

If analysis were to rely on OLS results, they reveal that median income and population density have a negative impact on the local installation of PV systems. Whereas increases in electricity expenditure, share of detached houses, irradiation levels, education level, share of self-employed people and number of charities show positive effects.

A GWR model was employed to estimate the determinants of PV uptake at local level and to explore the spatial relationships between of PV uptake and its covariates. Table 8 presents the estimation results for GWR model, where ranges and the mean values of parameter estimates are provided. The model selection criterion (AIC) indicates the selection of the GWR model. The global OLS provides global estimates of the relationships between PV uptake and explanatory variables, whereas the GWR model generates local regression coefficients, local standard error, and local R^2 values at each geographic location. Potential presence of heterogeneity is visually apparent in Fig. 2 where the local estimate of R^2 for each LAD is presented. The local R^2 values range from 0.64 to 0.89, well above the global model R^2 of 0.63, indicating a large improvement in explained variance. Moreover, comparison of the OLS model with the analogous GWR model based on the ANOVA F-test ($F = 5.152$; $P < 0.001$) revealed the GWR model was a statistically significant improvement over the OLS model.

Rather than a visual analysis of R-squared values (Fotheringham et al., 2003), suggest comparing the range of the GWR local parameter estimates with a confidence interval (CI) around the OLS global estimate of the equivalent parameter. It is expected that 50% of the GWR local parameter estimates should fall between the 25% and 75% quartiles. The relationship under study could be non-stationary if the interquartile range of the local estimates is greater than the range of one standard deviation above and below the equivalent global parameter. Following (Fotheringham et al., 2003) and (Ocal and Yildirim, 2010) global

[5] The Office for National Statistics (ONS) publishes socio-economic data for England and Wales, while in Scotland this is done by Scottish Neighborhood Statistics (SNS).

[6] Unless stated otherwise, regions refer to Wales, Scotland and 9 regions of England, including North East, North West, Yorkshire and Humber, East Midlands, West Midlands, East of England, London, South East and South West.

Table 4
List of explanatory variables used in the analysis and data sources.

Name of variable	Description	Data Availability	Year	Data Source[1]	Scale of Data
Density (DENS)	Population density	United Kingdom	2011	ONS Census data	Local authorities
Detached (DETAC)	Percentage of households living in detached and semi-detached homes	United Kingdom	2011	ONS Census data	Local authorities
Self-employment (EMPLOY)	Percentage of self-employed economically active people	United Kingdom	2011	ONS Census data	Local authorities
Education (EDUC)	Percentage of residents aged 16 and over with highest level of qualification 2 or more A-levels, HNC, HND, SVQ level 4 or equivalent qualifications	United Kingdom	2011	ONS Census data	Local authorities
Electricity consumption (ELEC)	Domestic electricity consumers -Sales 2011 (GWh)	Great Britain	2011	DECC Sub-national electricity sales	Local authorities
Income (INCOME)	Total median income	United Kingdom	2011–12	HM Revenue & Customs Income and tax by borough and district or unitary authority,	Local authorities
Solar irradiation (SOLAR)	Average annual solar irradiation data[c]	Great Britain	2014	European Agri4Cast data portal[a]	25 km[a] 25 km
Number of charities[d] (CHARITY)	Predefined charity code 112: Environment/Conservation/ Heritage	England and Wales	As of Sept. 2015	Charity Commission	Areas of operation
	Keyword ‘environment’ is included in the purpose of registered charities	Scotland	As of January 5, 2016	Scottish Charity Regulator (OSCR)	Main Operating Location
Heating system (HEATING)	Percentage of households with gas central heating	England and Wales	2011	ONS Census data	Local authorities
		Scotland	2011	Scotland statistics[b]	Council areas

[a] http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx?o=d (accessed January 28, 2016).
[b] http://www.scotlandscensus.gov.uk/bulletin-figures-and-tables (accessed October 12, 2016).
[c] Average daily solar irradiation data is collected from the European Agri4Cast data portal on a 25 km*25 km grid between 1/12,014–31/12/2014. For each 25 km grid cell, average annual figures were calculated. These were then converted to a raster layer with a resolution of 50 m. We then ran zonal stats using the 50 m raster and the LAD boundary data. This provided the mean annual solar irradiation for each LAD. The data wasn’t available for the Isles of Scilly at the far south-west of England.
[d] Balta-Ozkan et al. (2015) employed both installation numbers and capacity of utilization as dependent variables and investigated the drives of PV uptake by estimating two separate models for these two PV uptake variables. They report that the estimation results for each specification is similar.

Table 5
Moran’s I statistics for variables.

Variable	Moran’s I	p-value
Accumulated capacity	0.313	0.000***
Number of installations	0.215	0.000***
DENS	0.657	0.000***
CHARITY	0.070	0.000***
SOLAR	0.358	0.000***
INCOME	0.587	0.000***
ELEC	0.056	0.000***
EDUC	0.462	0.000***
DETAC	0.449	0.000***
EMPLOY	0.212	0.000***
HEATING	0.072	0.000***

Note: ***$p < 0.01$.

Table 7
Multicollinearity tests.

Variable	VIF	1/VIF
DENS	2.950	0.339
DETAC	2.910	0.344
EMPLOY	2.480	0.404
EDUC	1.160	0.863
ELEC	2.630	0.380
CHARITY	2.370	0.422
SOLAR	1.390	0.718
INCOME	1.680	0.597
HEATING	1.800	0.556
Mean VIF	2.15	

Table 6
OLS estimation results.

Variables	parameters	Std. deviation	95% CI Lower Bound	95% CI Upper Bound	−1 std. deviation	+1 std. deviation	Std. deviation range
DENS	−0.009***	0.002	−0.013	−0.005	−0.011	−0.007	0.004
DETAC	0.016***	0.003	0.011	0.022	0.013	0.019	0.005
EMPLOY	0.031**	0.015	0.001	0.060	0.016	0.045	0.030
EDUC	0.052***	0.016	0.020	0.084	0.036	0.068	0.032
ELEC	0.741***	0.082	0.576	0.905	0.658	0.823	0.164
CHARITY	0.312***	0.074	0.164	0.461	0.238	0.386	0.149
SOLAR	1.333***	0.370	0.593	2.072	0.963	1.702	0.739
INCOME	−1.685***	0.267	−2.219	−1.152	−1.952	−1.419	0.534
HEATING	0.007**	0.003	0.001	0.012	0.004	0.009	0.005
Intercept	3.795	4.468	−5.140	12.730	−0.673	8.262	8.935
R-squared						0.63	
AIC						561.577	
Moran’s I test for the residuals						0.039 [0.000]***	

p-values in brackets.***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 8
GWR estimation results.

Variable	Min	Lwr Quartile	Median	Upr Quartile	Max	Interquantile Range
DENS	−0.020	−0.014	−0.012	−0.010	0.016	0.004
DETAC	0.010	0.013	0.014	0.017	0.046	0.004
EMPLOY	−0.058	−0.017	0.003	0.052	0.107	0.069
EDUC	−0.020	0.034	0.046	0.059	0.126	0.025
ELEC	−0.436	0.629	0.748	0.892	1.279	0.264
CHARITY	−0.248	0.174	0.275	0.374	1.199	0.200
SOLAR	0.272	0.624	1.153	2.147	5.974	1.522
INCOME	−4.147	−1.769	−1.415	−1.212	−0.405	0.557
HEATING	−0.008	−0.003	0.002	0.010	0.015	0.013
Intercept	−46.700	−6.088	4.377	9.260	17.24548	15.348
R-squared					0.786	
AIC					517.313	
Moran's I test for the residuals					0.003 [0.366]	
F statistic					5.152***	

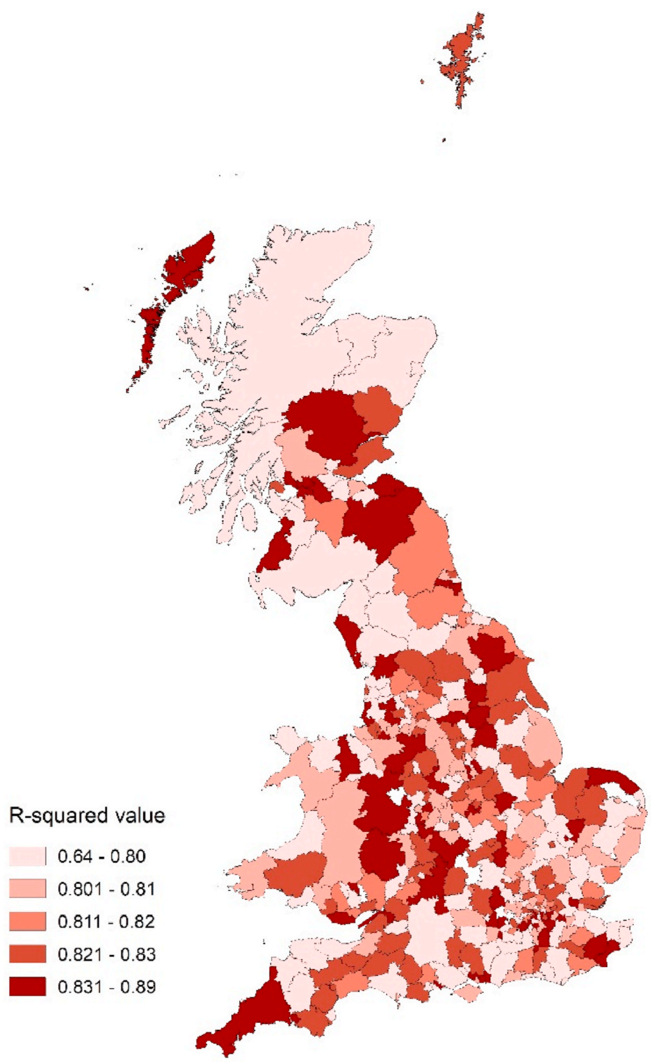

Fig. 2. The spatial distribution of R-squared values from the GWR model.

parameter estimates are compared with the interquartile range of the local estimates in order to assess the impact on the estimated associations of allowing coefficients to vary over space. Additionally, GWR local coefficients are mapped to highlight the spatial variability in the relationships between PV uptake and its covariates.

Table 8 clearly indicates that, excepting detached housing and education, the interquartile ranges of parameter estimates from GWR are outside the range of ±1 standard deviation of the OLS equivalent parameters estimates, implying that these variables are spatially non-stationary. Specifically, for the CHARITY variable, the interquartile range (0.174, 0.374) of the GWR local parameter estimates is outside the range (0.238, 0.386) of one standard error of the OLS parameter estimate.

The spatial distribution of the peer effect coefficient (**CHARITY**) for each LAD (Fig. 3a) indicates that estimates of the local coefficients range from −0.248 to 1.199 instead of a constant 0.312 of global OLS estimates, suggesting that the OLS parameter estimate is relatively higher than the local beta coefficient values. Charities have more significant impact than OLS estimates in an arc from the south of Scotland through North West England to Yorkshire and the Humber ('Northern arc', displayed in Fig. 3a). Another arc expands from East of England along its border with East Midlands to join South East England ('Eastern arc'). Across both arcs, the share of homes heated by oil is higher than the national average (16% vs 4%, reaching up to 30% in some LADs). As heating oil is bought on demand through a spot market that is unpredictable, coupled with the inefficiency of housing stock, these types of households are more likely to be fuel poor than with those with mains gas heating (Ofgem, 2015). High heating bills may lead households to look for routes to cutting energy costs or might create concerns for environmental matters, promoting PV uptake. Of the three highly urbanized areas located in these arcs, Norwich and Cambridge are university towns characterized by high population density (over 30 persons/hectare) and low share of detached homes (around 35%), possibly accentuating the visibility of rooftop solar PV panels and facilitating knowledge sharing among the early adopters. Peterborough is more sparsely populated than these towns, with 60% of housing stock made up of detached homes, shown to facilitate PV uptake (Balta-Ozkan et al., 2015b). The above average PV deployment in Peterborough might facilitate more knowledge sharing about PVs via community groups/charities. As the sunniest part of the country, the South West of England is another area where charities appear to significantly reinforce the adoption of PVs.

Both DENS and HEATING variables emerge as having bidirectional impacts on PV uptake with significant positive impacts across both arcs. The spatial distribution of the density (DENS) parameter estimates, see Fig. 2b, indicates parameters ranging from (−0.02) to (0.016). Residents located in less densely populated areas are more likely to install a PV system (Balta-Ozkan et al., 2015b; Müller and Rode, 2013). In South West England the negative impacts are much more pronounced. Lower densities and high solar irradiation levels facilitated the deployment of more than 40% of solar farms within the region between 2011 and 2013 (BEIS, 2020), the visibility of which might have stimulated further PV uptake. Yet along the arcs, DENS has positive impact as higher population densities accentuate the visibility of rooftop PVs.

The global estimate from the OLS model reveals that the higher the percentage of gas heated homes (HEATING), the higher the likelihood of

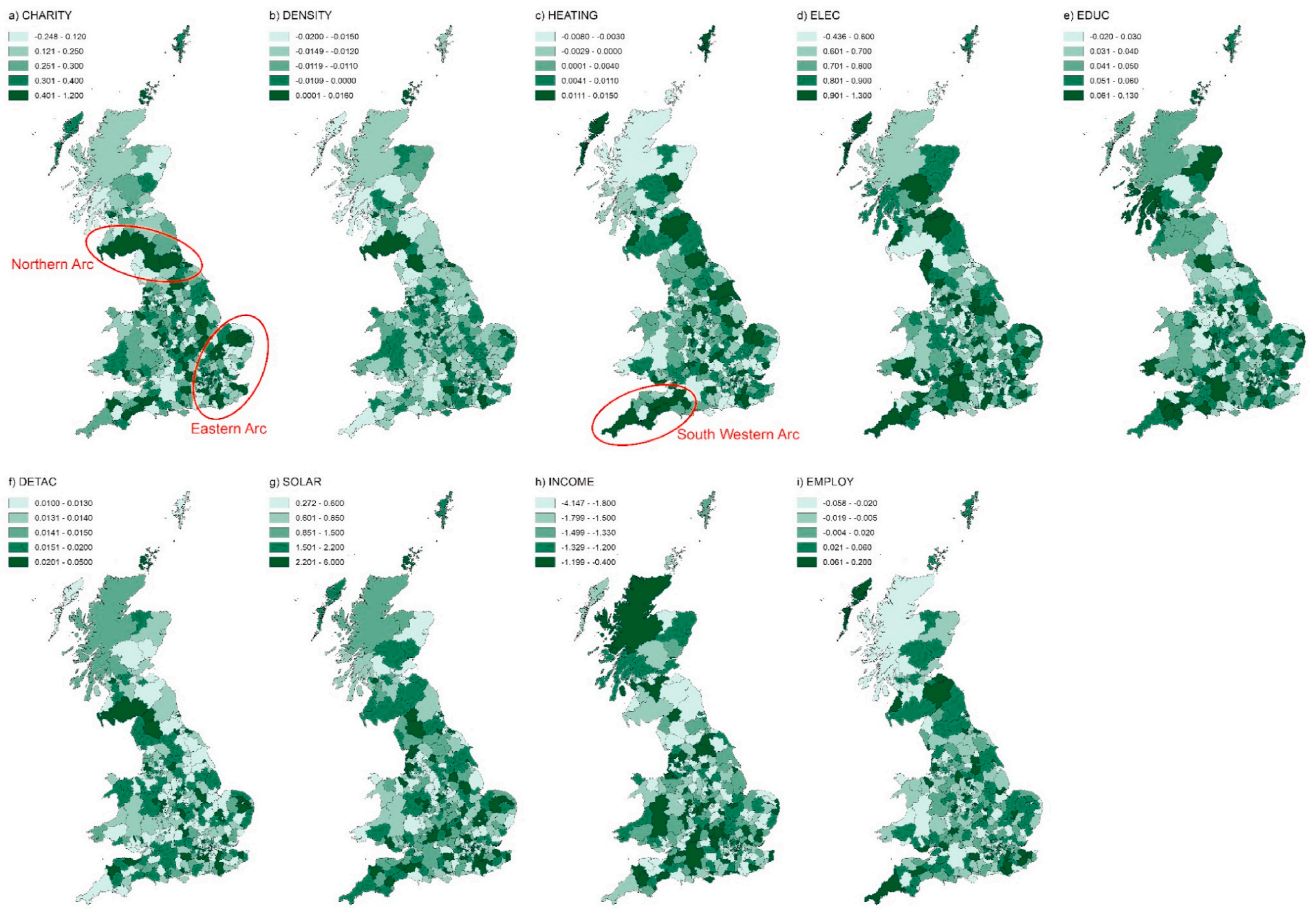

Fig. 3. The spatial distribution of the GWR local coefficients on PV uptake.

PV adoption, with a coefficient of (0.007). However, the GWR model presents a more nuanced indication for this variable where local parameter estimates range from (−0.008) to (0.015). The 95% CI of local parameter estimates ranges approximately from the median to the upper interquartile of local coefficients, indicating that there is a significant degree of spatial variability, see Fig. 3c. In the South West of England, gas central heating influences PV uptake for three main reasons. In densely populated cities (over 25 people/ha in Exeter and Plymouth, compared to the South West UK regional[7] population density of 2 people/ha), nearly 80% of housing stock is heated by gas, creating a motive to reduce emissions or become self-sufficient and manage increasing energy costs. Lower population density LADs means less access to gas networks, and more use of oil and electric heating systems which might create incentives to reduce emissions or energy costs. Thirdly, higher levels of sparseness (share of detached homes, 69% c. w. regional average of 58%), wealth (higher outright home ownership, 44% c. w. 35%, and higher share of properties subject to council tax bands D or above[8], 41% vs 35%) and elderly population (61% over the age of 40 vs 54%) pointing the residence of many retirees, reveal a negative impact of HEATING on PV uptake. This is in line with Mills and Schleich (2012)'s finding that households with high share of elderly population seek financial savings in preference to concerns for environmental matters. On the East England coast there are a few clusters where gas heating and PV uptake are positively correlated. In some areas of East Anglia sparseness (over ¾ of houses are detached) and high oil dependency for heating (over 1/3 of houses) facilitate PV uptake. From East Midlands to Yorkshire and Humber to North East England and south of Scotland, high dependency on gas networks (around 70% of households) influence PV uptake positively. In very sparsely populated Scottish Borders and Dumfries and Galloway, oil and electricity heating serve around 30% of households, creating an incentive for PV uptake.

[7] Property taxes depend on factors such as the size, location and layout of a house and number of tax bands and their corresponding values differ between the local administrations. In England, there are 8 bands where Band A is less than £40 K and Band H is over £320 K. In Wales, Band A starts with less than £44 K and differentiates between £324 and £424 and over £424. These last bands are merged to align with tax band definition used in England. In Scotland, it starts under £27 K and goes over £212 K.

[8] 12,619 of 27,833 charity registrations in the Charity Commission database list particular counties as their area of operations. The Register is supplied as BCP unix compressed files which are then populated into a database using Microsoft SQL server. The registered charities where aootype is defined by local authority and metropolitan county (B and C) are included in the analysis. We used population shares of LADs within each county to disaggregate them by local authority. For Scotland, 128 of 2714 registered charities list 'Outwith Scotland' as their main operating location. As these couldn't be allocated to any council areas, they are excluded from the database.

Electricity consumption (ELEC) is another factor with a bidirectional effect on PV uptake. As with heating, it might be expected that greater volumes of electricity use (Fig. 3d) would correlate with greater impetus to consider (and perhaps implement) alternative ways to source power or as a route to reducing utility bills. This is complicated by the specific application of the FIT. If we assume rational consumers, then those with load patterns closer to likely solar generation should be more incentivized towards PV uptake, since they will benefit from the most gain in terms of displaced network consumption while still receiving export payments. This would also require they are informed, as well as rational. However, no data exists allowing us to test this correlation. A better metric might be actual electricity costs, but this data is not available. Higher electricity sales might be suggestive of different underlying reasons such as a greater preponderance towards consumption, which suggests either a greater ability to select for greater expenditure or low-income households who live in less energy profligate homes. It might be expected that those in fuel poverty would be less likely to be able to afford PV installation but there are ways around this, for example, via contractual agreements with third parties to cover investment costs. Electricity use has the most positive impacts in South West England, Southern and Eastern Scotland, Yorkshire and Humber, and East Anglia where it is more likely to be used for heating. In the latter region, Broadland and South Norfolk are the areas where ELEC has negative impact on the PV uptake, with increased reliance on gas and oil for heating, creating a desire to become self-sufficient or to lower energy costs (Balta-Ozkan et al., 2015b). High shares of outright home ownership, over 65 population, and Council Tax Band E, F and G properties (31% vs regional average of 19%) reveal that higher electricity consumption does not facilitate PV uptake in East Devon or in Cornwall as elderly households exhibit different priorities (Mills and Schleich, 2012).

Global estimates presented in Table 8 indicate that as the share of **self-employed people (EMPLOY)** increases, so does PV uptake. However, local parameter estimates exhibit a high degree of spatial variability. The 95% CI of local parameter estimates ranges approximately from median to upper interquartile of local coefficients indicating that a larger share of these coefficients are lower than the OLS global estimate. According to 2011 census data, 10% of Great Britain's economically active population is self-employed. In regions with higher self-employment rates than national average, the EMPLOY variable positively influences PV uptake which is consistent with the OLS estimates. These regions include the Northern arc, East England and South West with the exception of West Devon. While share of self-employment in West Devon (17%) is higher than both national and regional (11%) averages, high share of oil heating (22%) and lower median incomes (£19 K c. w. national £21 K) point to an indication of high energy costs. The negative relationship between EMPLOY variable and PV uptake is prevalent along the coast of Wales, where oil is the main fuel for 20%–35% of households.

Although **INCOME** has often been adopted as the variable indicative of the financial constraints and risk-bearing possibilities a consumer may face (Rode and Weber, 2016), previous empirical research does not agree about the effect of income on solar panel uptake (Müller and Rode, 2013; Rogers, 2003). report a positive effect, whereas (Balta-Ozkan et al., 2015b; Richter, 2013; Zhang et al., 2011) report a statistically insignificant impact. Graziano and Gillingham (2015) argue that income has relatively less importance for PV diffusion as the decision to invest is a question of accumulated capital rather than of marginally higher income. Empirical results presented here suggest a negative income impact on PV uptake. The local estimates range from −4.147 to −1.212, while the global estimate is −1.685. As shown in Fig. 2h, in the North of England, along the coast of Yorkshire and the Humber and the East of England increases in INCOME will proportionally lead to less PV uptake than that in South West of England, Wales and Scotland. In the latter, 20%–40% homes use oil for heating, possibly creating an incentive to lower overall energy costs and become self-sufficient. In South West England, the INCOME variable has the most negative effect in North Devon, a district which has lower median income (£18,200) than the regional average (£19,700). Moray in Scotland, with higher use of oil for heating (15% of households compared to regional average of 5%) and lower median income (£19,000 compared to regional average of £20, 000), is another area where increases in income do not necessarily translate to higher PV uptake.

As reported previously, the **share of detached homes (DETAC)** positively contributes to PV uptake (Balta-Ozkan et al., 2015b). The local estimates range from 0.010 to 0.046 instead of a constant 0.016 of global OLS estimate. The Northern arc apparent in CHARITY and DENS variables is present for DETAC variable too; the higher the percentage of detached homes the higher the PV uptake. Another spatial cluster occurs in Wales and in the Eastern English coast up to the North East England region, where lower impacts of detached homes on PV uptake as shown. For the rest of the country, the spatial results are variable; high positive impact localities are surrounded by low positive impacts, such as South West and East England, highlighting the importance of other socio-spatial structures (e.g. off gas grid, houses subject to high property taxes). In Plymouth in the South West, a densely populated LAD compared to regional average, around 40% of housing stock are subject to the lowest property tax band and only 40% of houses are detached, yielding a limited contribution to facilitate PV uptake further. Even though South Hams and Cornwall have higher shares of detached housing and outright home ownership rates, the marginal contribution of DETAC to PV uptake is very limited, due to lower median income level in Cornwall and seeming a lack of interest in South Hams (similar to low marginal contribution of ELEC variable as shown in Fig. 3d).

Solar irradiation (SOLAR) in the UK decreases with increasing latitude. Existing literature agrees that solar irradiation has a positive impact on solar PV adoption, which is as expected since each unit should be more economically productive for the owner. The local parameter estimates a range from 0.272 to 5.974 instead of a constant 1.333 of global OLS estimates. Almost 38% of estimates are higher than the global parameter estimate. SOLAR has highest impacts on PV uptake in South West, East Midlands and Yorkshire and Humber (Fig. 2g). While Wales has higher irradiation than East Midlands, SOLAR has lower impact on PV adoption. Whilst Scotland has the lowest solar irradiation levels, a marginal change in irradiation levels has more impacts on PV uptake.

Global model estimation results indicate that the **education (EDUC)** variable, has a positive impact on PV uptake. This is in agreement with the earlier findings of Davidson et al. (2014) and Jager (2006) who report positive influence of university and postgraduate education on PV uptake. Conversely, the local estimates exhibit a significant degree of spatial variation as the coefficient of education variable ranges from −0.02 to 0.126, instead of a constant global estimate 0.052 (Fig. 3e). In the South West of England, EDUC improves PV adoption rates significantly, with the exception of North and East Devon. North Devon has fewer university graduates or higher qualifications (27% vs 32%), lower employment in professional and associated technical occupations (23% vs 29%) and higher share of no formal qualifications (24% vs 21%) compared to the wider region, possibly indicating a lack of understanding of benefits of solar PVs or concern regarding environmental issues. High shares of 65+ population, households with no dependents, outright home ownership and properties subject to band D and higher taxes mean that EDUC isn't a variable that significantly improves PV adoption in East Devon. The EDUC variable has mostly positive impacts in South East of England which has the largest share of population with first and higher degrees after London. Yet in England's manufacturing centers, the North West of England and Yorkshire and the Humber, it has negligible impacts. While the share of EDUC variable in these regions are slightly above the national average (13% compared to the national average of 12%), the share of population with no qualifications is higher (26% compared to the national average of 23%), highlighting that higher (than L3) qualifications accentuates the impact on PV uptake.

6. Discussion

While a large body of literature have adopted aspatial lenses to explain the factors influencing PV adoption, the geographically diverging nature of low carbon transitions (Balta-Ozkan et al., 2015a; Bridge et al., 2013) highlight the importance of geographical context. This study presents the application of GWR to analyze spatial patterns of PV adoption in the UK at local level, revealing significant local variations in statistical relationships.

Conventional OLS estimates reveal that population density (DENS) and income (INCOME) influences PV uptake negatively, while share of detached homes (DETAC) and those with gas central heating (HEATING), share of self-employed people (EMPLOY), share of population with level three qualifications (EDUC), number of charities (CHARITY), irradiation (SOLAR) and electricity use (ELEC) positively influence PV adoption. GWR model suggests that the impact of these variables varies locally, with geographically nearer LADs having greater influence on these parameters than those that are further away (Wang et al., 2019). Of the two variables that indicate a negative relationship, the GWR model reveals that the impact of the INCOME variable varies significantly across the LADs while the DENS variable has bidirectional impact on PV adoption. Of the remaining variables, the GWR model suggests that rather than uniform positive values, the impact of EMPLOY, EDUC, ELEC, CHARITY and HEATING vary from negative to positive values. DETAC is the only variable that has the same sign between OLS and GWR models though its value varies significantly with geography in GWR.

In areas identified in this work as the Northern Arc and the Eastern arc, CHARITY, DETAC and DENSITY parameters contribute to PV uptake positively.

Membership in environmental and energy related charities can create meso-level interactions (Xiong et al., 2016) across the member individuals, increasing awareness and providing dissemination channels amongst adopters and possible adopters, reducing uncertainties for the adoption of low carbon technologies. For the first time, we quantitatively measure the impacts of the influence of the existence of environmental and energy related charities on PV adoption patterns. We use the number of charities in each LAD as an approximation of charitable engagement in that location. While the number of individuals who are members of a charity could potentially give a better indication of its network of influence, such data is not available. Using the number of charities also avoids double counting relating to multiple memberships and we think this makes for a better approximation of the higher chances of individuals being more aware of, or concerned, with energy and environmental matters. Most positive impacts of the CHARITY variable prevail in areas where oil is more commonly used for heating, highlighting either concerns for environmental matters or the desire to manage higher energy bills. However, as the impact of CHARITY becomes negative for areas characterized by higher share of detached homes, built environment characteristics might play a key role in facilitating or inhibiting peer effects among those individuals. It could be that higher share of detached houses indicates greater sparseness and longer distances between the households. Further research might analyze how distance between detached houses varies as the sparseness of the LAD increases, by analyzing adoption patterns at a finer geographical resolution. While Graziano and Gillingham (2015) argue that neighbor effect is conveyed through social interaction and visibility of PVs, Bollinger and Gillingham (2012) report a positive influence of longer commuting journeys, by extended PV observation time and occurrence rate. Consequently further work could qualitatively analyze the mechanisms, the range of activities and at what frequency peer effect influences are increased.

Balta-Ozkan et al. (2015b) and Müller and Rode (2013) note that lower population densities create a more favorable environment for PV adoption as they tend to indicate more single-family homes with available roof space. Our analysis shows that DENS has bidirectional impacts. For the sunniest part of the country, with high number of PVs per households, lower densities result in marginally higher PV adoption. While the estimates for DETAC variable aren't statistically significant, lower income and being off the gas grid seem to counteract the impact of this variable on PV uptake.

While Davidson et al. (2014) report negative impact of wood heating on PV adoption, our analysis shows bidirectional impacts of gas heating for the first time. Heating oil is typically more expensive than conventional grid supplied gas (Ofgem, 2015)[9]. Around 84.2% of British households (England: 85%, Wales: 79%, Scotland: 78%) are on the gas grid, with off-grid homes skewing to rural areas. The positive impacts of HEATING sourced from a centralized gas network are prevalent in South West of England, along the Northern arc and in the East of England. These areas see nearly 20%–40% of homes lacking access to gas networks, and a desire to become self-sufficient, to manage increasing energy costs or concerns around emissions from use of fossil fuels might facilitate PV adoption. On the other hand, HEATING has a negative impact in areas with a large share of detached homes that are either heated by oil, subject to higher property taxes and/or owned outright by a population over 40. These factors point to wealthy households living in potentially larger houses in sparsely populated settlements where energy costs or environmental issues get less consideration. This is consistent with (Urban and Scasny, 2012)'s finding that high-income households tend to be less concerned about environmental problems and tend to curtail less. The timing of adoption, whether early or late adopters, might reveal different motivations (Müller and Rode, 2013). argue that late adopters might be more interested in the earnings from PVs while early adopters might be driven by a more altruistic or social motivation.

Earlier research shows that households with higher electricity demands (ELEC) might be more interested in becoming self-sufficient (Balta-Ozkan et al., 2015b). A key factor that will derive high electricity use (ELEC) is electric heating. Where households don't have electric storage heaters, the costs of electric heating may be double that of average mains gas costs (Ofgem, 2015). Our model suggests that ELEC has bidirectional impacts on PV adoption. We find that high outright home ownership, high share of houses subject to high taxes and high share of over 65 population do not result in increased PV uptake in response to increases in the ELEC variable, as elderly households undertake less energy efficiency activities (Mills and Schleich, 2012).

INCOME is a variable with no conclusive evidence in the literature as to how it influences PV adoption. Our analysis yields a statistically significant negative relationship between INCOME and PV adoption. In Scotland and South West England, there are local areas with low median income on which any improvements in wealth will not necessarily translate into PV uptake. Yet, in areas where 20%–40% homes rely on oil heating, including the South West of England, Wales and Scotland, small changes in welfare may facilitate PV uptake.

For the first time, our study notes the impact of self-employment (EMPLOY) on PV uptake, exhibiting bidirectional influence. EMPLOY may be an indication of a willingness to take risks in uncertain market conditions, and within the Northern arc, East England and South West of England it has a positive impact. When local areas face potentially high energy bills due to oil heating (e.g. areas in Wales) this influence becomes negative.

While other authors note the positive impact of graduate education on PV adoption (Davidson et al., 2014; Jager, 2006), our model reveals statistically insignificant and bidirectional impact below graduate level (EDUC). While the figures are contested, there is evidence that UK graduates can expect to earn more than non-graduates (DfE, 2019). This may thus represent a further source of conflict with the income metric, adding to the disagreement concerning its impacts on PV uptake. We

[9] It has been reported that prices may increase by over 60% with falling temperatures as evidenced in the winter of 2010 (Ofgem, 2015).

find further interaction between wealth and high share of elderly population which negate the impact of this variable.

The results further confirm the significance of irradiation (SOLAR) on PV uptake. This is in line with expectations about the relative economics of PV location. The UK's use of a feed in tariff (FIT) in the period since 2010 has driven substantial growth in PV, helped by declines in global costs. The FIT can be expected to reinforce irradiation differences since it will reward sites with greater generation. In April 2019, the UK government closed the FIT scheme to new applicants. However, anyone already in the scheme will continue to receive payments for the total twenty year period (BEIS, 2019a). The FIT was replaced with a Smart Export Guarantee (SEG) from January 2020 (BEIS, 2019b). The SEG will see supply companies pay an amount per unit of PV output going into the local grid. The impacts of the SEG vs. FIT may be worth investigating once it has been operating for enough time to generate meaningful data. Moreover, as noted by some authors (Müller and Trutnevyte, 2020) electricity prices might play an important role on PV uptake. As UK households can change their suppliers, there is no data on actual electricity prices. However, future research can look at if the network costs has any bearing on PV adoption rates.

7. Conclusions and policy implications

The approaches taken in this paper provide further evidence that peer effects can influence uptake of PV. Since the goal of PV and wider UK renewable energy policy is to maximize additional capacity then it makes sense for policy to building in positive peer effects where possible while avoiding any negative effects. The UK energy system is seeing a significant volume of increased distribution of generation in the domestic and non-domestic sectors, effectively allowing greater engagement of the public with renewable energy sources, most notably solar PV. Many variables are used in the literature to explain what drives PV uptake. These variables can be broadly grouped into five groups: household and built environment characteristics, environmental attitudes, economic and physical factors, and peer effects.

Existing studies use aggregate macro datasets with limited ability to capture the role of peer effects. This paper considers some established variables but also broadens the base of variables to try to identify new indicators. Specifically, it analyses domestic PV adoption in the UK at local level, using data on the number of charities as a proxy to capture the opportunities to initiate social interactions and peer effects.

Our results reveal the presence of a Northern, Eastern and South Western arc with a statistically significant variation in the socio-spatial structure at local level. Our results show that location within the UK has a significant bearing on PV adoption behavior, and thus on the impact of the investigated variables. As a result, GWR model reports bidirectional impacts of many socio-economic variables on PV uptake.

The differences in the magnitude of income variable suggest that any changes that can influence disposable income will be more likely to facilitate PV adoption if they are implemented in Scotland, Wales and South West England.

While low population density is shown to support PV uptake in the literature, we find that the impact of this variable is non-stationary. In South West England, home to a significant number of solar farms as a result of its high comparative irradiation, the lower the population density the higher the PV uptake. Further research could analyze whether there is any spatio-temporal dependency between the deployment of solar farms and rooftop PVs. Yet along the Northern and Eastern arcs, more dense settlements positively influence PV adoption due to the visibility of rooftop PVs. As more dense settlements have an impact on solar PV output (kWh) due to shading issues, urban heat island effect etc., PV systems with the same size and efficiency characteristics might yield different outputs between urban and rural areas.

We see mixed indicators concerning the impact of access to heating in our results. However, positive correlation of uptake with irradiance in the SW maps well with the impacts of being off the gas grid for heating purposes. This suggests a potentially more receptive population who might be targeted to encourage adoption to minimize their energy costs, potentially improve comfort and with likely implications for displacing more carbon where households move away from oil for heating. The data arising from considerations of housing density may also offer clues as to which areas may provide a more fruitful focus for applied policy. The overlap of the positive impacts of both low density housing and an above average fraction of households on oil heating may signal that stimulus policies could more fruitfully focus on a specific geographic region where uptake is already high and where consumers may be more open to uptake.

The converse of this is that areas with less uptake may benefit from other tools, for example, educational instruments designed to raise awareness.

Maybe more importantly for policy, our analysis yields the impact of energy and environment related charities in PV adoption. This variable has positive impacts in areas where oil is more commonly used for heating. It may be the case that the appearance of a charity in an area is a catalyst for a self-selecting group who may already be knowledgeable and motivated towards that charity's aims, but which has not previously been sufficiently mobilized to action. As charities receive most donor response when messaging and practices are tailored to specific groupings (Schlegelmilch et al., 1997), meso-level exernalities they create may be amplified by recognizing interactions between heating systems, built environment characteristics and demographics. This messaging is lent weight when linked to roll-out of PV energy systems in areas where the population is more concerned with climate and environmental issues (younger, graduate and less asset wealthy). This may be a useful finding for action groups and charities.

Another variable impacting PV adoption, that we identify for the first time, is the rate of self-employment in an area. Tailored messaging and active engagement with sector level organizations can help with changing the low carbon agenda from a distant utopia into the practical realms of the daily lives of households. One may envision the adoption of PVs as an initial building block of low carbon transitions, with more transformative changes to emerge such as enabling of peer to peer trading, addition of batteries or electric vehicles. The pace of this transformation will depend on how knowledge of spatial heterogeneity in socio-economic structures are utilized.

Data statement

The study uses publically available data sources as outlined in Table 4. The raw data used in the analysis can be accessed via DOI: 10.17862/cranfield.rd.13160030.

CRediT authorship contribution statement

Nazmiye Balta-Ozkan: Conceptualization, Data curation, Writing - original draft, Writing - review & editing. **Julide Yildirim:** Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Peter M. Connor:** Writing - original draft, Writing - review & editing. **Ian Truckell:** Data curation, Visualization. **Phil Hart:** Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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