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Published in:
Journal of Financial Management of Property and Construction

Publication Status:
Accepted/In press: 14/09/2022

DOI:
10.1108/JFMPC-12-2021-0071

Document Version
Peer reviewed version

Emerald Journal of Financial Management of Property and Construction

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Journal:	*Journal of Financial Management of Property and Construction*
Manuscript ID	JFMPC-12-2021-0071.R2
Manuscript Type:	Research Paper
Keywords:	Solar PV installations, Housing Markets, tenure, socio-economic standing, energy policy

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Abstract

Purpose: An abundance of extant literature has examined the role of solar photovoltaic (PV) adoption and user costs, with an emerging corpus of literature investigating the role of the determinants of PV uptake, particularly in relation to the built environment and the spatial variation of PV dependency and dissimilarity. Despite this burgeoning literature, there remains limited insights from the U.K. perspective on housing market characteristics driving PV adoption and in relation spatial differences and heterogeneity that may exist.

Study design: Applying micro-based data at the Super Output Area level geography, this study develops a series of OLS, spatial econometric models and a logistic regression analysis to examine built environment, housing tenure and deprivation attributes on PV adoption at the regional level in Northern Ireland, UK.

Findings: The findings emerging from the research reveal the presence of some spatial clustering and PV diffusion, in line with several existing studies. The findings demonstrate that an urban-rural dichotomy exists seemingly driven by social interaction and peer effects which has a profound impact on the likelihood of PV adoption. Further, the results exhibit tenure composition and 'economic status' to be significant and important determinants of PV diffusion and uptake.

Originality/value: Housing market characteristics such as tenure composition across local market structures remain under-researched in relation to renewable energy uptake and adoption. This study examines the role of housing market attributes relative to socio-economic standing for adopting renewable energy.

Key words: Solar PV installations, renewable energy, housing markets, tenure, socio-economic standing, energy policy.

1. Introduction

In response to mounting concerns pertaining to global warming and environmental degradation related to raising the standard of living for the world's population, the UN General Assembly convened the World Commission on Environment and Development (WCED) in 1983 to propose long-term solutions for fostering sustainable development. The subsequent Brundtland Report (1987) introduced the concept of sustainable development which attempted to identify the interconnections between social equity, economic growth and environmental challenges. Implicit within the Bruntland reports definition of sustainable development was the concept of needs and the belief that technology and social organisation imposes limits on the ability of the environment to provide for the present and future needs. In response, the UN Programme of Action on Sustainable Development was established to carry out the directives and laid the foundations for the Rio Summit (1992), leading to the creation of the UN Commission on Sustainable Development (Hajian and Kashani., 2021).

On the back of this, the introduction of the Kyoto Protocol in 1997, and more recently the Paris agreement (2016), has placed an emphasis on the reduction of energy consumption attributable to buildings, with the abatement of energy consumption within the built environment becoming a core government policy to improve the environmental performance and carbon neutrality within housing stock (Fuerst *et al.,* 2013).

In 2019 the United Kingdom government introduced The Climate Change Act 2008 (2050 Target Amendment) Order 2019 which set a target, known as “net-zero carbon”. This order outlined that the net UK carbon account for the year 2050 to be 100 per cent lower than the 1990 baseline, changing the Climate Change Acts initial 80% reduction goal. This ‘net zero carbon’ aim is also nestled within an international framework and aligns with the UN Sustainable Development Goals, two of which namely “Affordable and Clean Energy” and “Climate Action” are particularly germane to “net zero” initiatives. In addition to these National and International objectives, local administrations have devised interim action plans for this decade, outlining how progress towards net zero carbon will be achieved. In Northern Ireland for example, objectives have been set to “meet at least 70 percent of electricity consumption from a diverse mix of renewable sources” and to “develop proposals for a support scheme for renewable electricity to ensure that a diverse range of renewables can be brought forward, including those where we have already proven resources such as onshore wind and solar” (Northern Ireland Executive, 2022:7).

Accordingly, the UK has just under 28 years remaining to achieve its net-zero objective, which amounts to a very challenging 87 percent reduction in CO_2 emissions compared to 2017 levels. In order to achieve this target, its attainment necessitates societal, behavioural and technological changes, in the ways and extent to which we generate and consume energy. The Committee for Climate Change (2019) report, that in part prompted the adoption of the Net Zero target, foresees the ‘extensive electrification’, particularly of transport and heating, supported by a major expansion of renewable and other low-carbon power generation.

Therefore, tackling climate change via the decarbonization process will invariably necessitate the increasing use of renewable energy sources as a means of achieving these strategic objectives. A component of this is likely to be an extension of renewable energy production away from largely centralised fossil fuel based electricity generation and towards home energy production and consumption. Indeed, this is a core remit of the UK’s strategic energy objectives are ‘to ensure that the UK’s energy system is reliable and secure; deliver affordable energy for households and businesses; and support clean growth and promote global action to tackle climate change’ (House of Commons, 2020).

This clear policy context in relation to carbon abatement initially seemed promising and notably for the uptake of Solar Photovoltaic (PV) systems within the residential sector. As discussed by Chapman et al. (2016), in order to achieve desired installation targets, governments used a variety of stimulatory policies and tools including Feed-in Tariffs (FiT), point of sale rebates, including Renewable Energy Certificates (REC) or ROCs (Renewable Obligation Certificates), and tax benefits, all of which addressed the ‘energy trilemma’ (WEC, 2013) creating mitigation opportunities within energy security, climate change, and consumer affordability (Balta-Ozkan et al., 2021).

Consequently, the deployment of solar PV in the UK context experienced rapid growth between 2012 and 2017 due to these incentives such as ROC payments. However the financial incentives to promote the uptake of PV ceased in 2017 in Northern Ireland (2019 in the UK) and new installations within the residential sector have subsequently stalled. Currently, based on OFGEM data, 19,644 PV systems of 6.5 Kw or less capacity giving an output of 79.6 MWh exist in Northern Ireland, equating to a modest 2.5% of the housing stock having a PV system installed[1]. As contended by Fawcett and Boardman (2009), despite the sustained focus on enhancing construction and renewable technologies within the residential sector to reduce the carbon emissions for new housing stock, this does not impact upon the existing housing stock which represents approximately 90 percent of total market stock, and where renewable energy policy tackling efficiency is truly needed. Energy performance within the residential housing sector therefore remains a challenge within the UK, and particularly Northern Ireland.

Indeed, existing research for Northern Ireland has shown that despite the decline in residential Greenhouse gas emissions since 1990, as a proportion of total greenhouse gas emissions, the residential sector has seen an increase in the percentage of the total greenhouse gases emitted (*Greenhouse Gas Inventories, 2019)*[2]. Further, existing research into measuring the level of the carbon emissions within the residential stock has also provided empirical evidence of the energy performance challenges. The study by Davis et al. (2017) into the assessment of the level of CO_2 emissions of housing in NI, revealed that most benefits can be gained by improving performance of dwellings located in rural, as opposed to urban areas. More specifically, they identified that core urban areas appear to be the best or ‘greenest’ in terms of the level of carbon dioxide per kilogram per annum (CO_2Kgm^2p.a.), suggesting that the composition of the housing stock and more rurally based properties, on average, are the poorest in terms of their energy performance. Similarly, McCord et al. (2020) scrutinised the heterogeneity of building stock and typology models for measuring the impact of energy efficiency measures, finding terrace properties and apartments to obtain higher energy efficiency, with larger detached properties showing poorer energy performance. These differences and heterogenous effects continue to make the understanding of energy performance within residential dwellings complex and challenging.

Whilst research has examined the nature of energy performance within the residential housing sector in relation to environmental and economic based sustainability and carbon abatement, there has been limited studies undertaken which examine whether the uptake and location of renewable energy sources and the diffusion, if any, are related to the socio-cultural environment, and if social interactions drive

[1] As per the Land Registry Pointer Database, based on 785,684 built dwellings in 2020
[2] for England, Scotland, Wales and Northern Ireland.

energy diffusion within a housing market context. As Balta-Ozkan et al. (2021) contend, insights into the determinants of PV adoption remain somewhat limited, and particularly in relation to the spatial regularities in PV adoption pattens. Notably, whilst the role and nature of 'peer effects' has been continuously investigated (Bollinger and Gillingham, 2012; Müller and Rode, 2013; Rode and Müller, 2016; Graziano and Gillingham, 2015), to date there has been more limited insights as to the impact of housing based attributes – particularly tenure composition and whether there are rural and urban differences in terms of micro, meso and macro influences on the PV adoption.

In view of this current hiatus in residential PV installations, this research seeks to quantify the extent of uptake of PV in Northern Ireland and in particular to assess the socio-economic and spatial characteristics of the households that have chosen to adopt PV. Existing research has tended to evaluate urban and rural development primarily through an economic lens (such as per capita income). However, issues surrounding the social dimensions of sustainability that are relevant to human development and human rights are significant for closely knit communities and their sustainable development. Therefore, we examine whether there are local drivers and patterns of PV adoption and if they are geographically related (Schaffer and Brun, 2015). Moreover, for policy and practice, the understanding of the spatial patterns and structure of housing stock composition is important in terms of PV uptake as this provides local level empirical evidence for targeting and incentivisation of future PV adoption, and for achieving UN sustainability goals.

The paper is organized as follows; Section two offers a review of the relevant literature with the data and methodological considerations presented in Section three. The results and discussion of the key findings are offered in Section four with Section five discussing the conclusions and policy implications.

2. Literature

Sustainability in the Built Environment

An extensive corpus of research has investigated the concept of sustainability, which, in the main, comprises a three-dimensional model of economic, environmental and social aspects. This model therefore describes sustainable development as a dynamic state of equilibrium attained by balancing these aspects to improve citizen life by enabling individuals to live in a healthy and safe environment (Oritz et al., 2009; Dempsey, Bramley, Power, & Brown, 2011). These aspects are clearly relevant to the built environment with environmental and economic issues largely dominating the debate on sustainability (Gibson, 2006; Park, Yoon, and Kim, 2017). Although the social dimension has received less attention, the emerging body of research indicates that the social aspect of sustainability is complex, particularly in the context of the urban form and residential development, with aspects such as social equity, health and well-being, quality of life, cultural identity, social cohesion, decent housing, and local environmental quality and amenities perceived as key aspects to identify and prioritise the social aspects to be considered in the design of more sustainable residential buildings (Bramley, Power and Brown, 2011; Ročak, Hospers and Reverda, 2016; Ardda et al., 2018). In this context, a number of research studies have investigated social sustainability in the built environment, highlighting that the urban fabric, urban renewal and human need and behaviour are essential components for ensuring social sustainability, reducing environmental risk and improving well-being (Yıldız et al., 2020).

Eizenberg and Jabareen (2017) suggest that classifications such as mixed land use, solar design, greening and renewal are critical to the sustainable urban form and can enhance the social dimensions of a healthy community. Likewise, Woodcraft et al. (2011) suggest that adaptability and resilience of planning regime, housing, infrastructure, public space and service provision are integral to social sustainability. Arguably then, for social sustainability and citizen satisfaction and participation, urban sustainability through the urban fabric and environmental conservation needs to be both maintained and improved.

With regards to residential dwellings, research has considered social sustainability in the context of the urban built environment. Tapsuwan, et al. (2018) suggest that housing affordability, energy saving designs and neighbourhood safety are the most desirable features of the residential properties. Research has also noted that the urban landscape, green spaces and energy conservation are important for social sustainability since they create sustainable places that promote wellbeing to increase urban comfort (Dixon et al., 2019; Jennings, Larson and Yun, 2016). Others such as Li, Liu, Gibson, and Zhu, (2015) also contend that built environment related factors such as poverty, shortage of environmental resources, pollution and poor-quality housing are comorbid with poor health and well-being.

Related to this is the climate change debate which has assumed greater significance. In this context, research highlights that the excessive consumption of natural resources can affect urban security, safety and the well-being of urban residents (Eizenberg and Jabareen, 2017). This notion is supported by Yıldız et al (2020) who found that the conservation of resources is important for environmental and economic sustainability but also critical for social sustainability. Similarly, Folke, Biggs, Norström, Reyers, and Rockström (2016) contend that communities depend on resources and services of the ecosphere, which in turn supports future generations through the provision of primary resources. This also indicates that access to resources is fundamental to social sustainability, underpinning the need to conserve such resources (Weingaertner and Åsa, 2014; Peterson, 2016). From this perspective, social sustainability can be viewed as a process for creating sustainable, successful places that promote wellbeing combining design of the physical realm with the design of the social world to support social and cultural life and space for people and places to evolve (Bacon and Caistor, 2014).

Photovoltaic uptake and diffusion

The literature pertaining to PV deployment, uptake and adoption is pervasive and has a long established history, particularly from a (user)cost perspective, understanding consumer behaviour, and the barriers and motivations for PV adoption. Given the vast and expansive array of studies, we restrict the literature to concentrate on the 'spatial distribution' of PV adoption and associated neighbourhood and socioeconomic factors and determinants of PV uptake.

International studies such as Walters, Kaminsky and Huepe (2018) for Santiago, Chile, have explored the factors influencing household solar adoption and illustrated that the diffusion of PV technology is influenced by complex technical, economic, and social factors. In the case of Colombo, Sri Lanka, Jayaweera et al. (2018) studying PV implementation employed a zero-inflated negative binomial regression model and compared the influencing factors of PV adoption. They uncovered that highly educated middle-aged persons and retirees were more likely to adopt PV, with early adopters of PV residing in larger, often detached housing of average, or above average, housing quality. Similarly, Opiyo (2015) scrutinised the impacts of socio-economic factors on temporal diffusions of PV systems using an agent-based model (ABM). Their findings, aside from the cost aspect, highlighted that social acceptance is important for PV diffusion, and that neighbourhood influences play a significant role in PV diffusion.

In the US context, studies have also identified the role of socio-economic and built environment attributes in conjunction with peer effects. The study conducted by Bollinger and Gillingham (2012) highlighted the role of social interaction (peer effects) as an important factor in the diffusion of PV uptake in California. Empirically testing the diffusion of PV panels, they establish that a unitary installation of a PV system (at the zip-code level), increases the probability of PV adoption by 0.78 percentage points. In a concomitant study for California, Davidson et al. (2014), augmenting address-level PV adoption trends with geospatial information, established that the number of rooms, heating type and dwelling age were significant determinants of PV adoption – which the authors stipulate are consistent with the expected archetype of a PV adopter. Graziano and Gillingham (2015), also using PV installation data for Connecticut, empirically assessed the spatial patterns of PV diffusion. The authors found strong evidence of clustering of PV adoption which they herald does not 'simply' follow the spatial distribution of population or income. Indeed, their findings indicated that smaller or rural communities to adopt PV more so than larger urban areas which they described as a wave-like centrifugal fashion which diminished.

From a European perspective, a wealth of research has examined PV diffusion. In the case of Malta, Briguglio and Formosa (2015) assessed the determinants of household investment in PV panels. The authors established that the prevalence of younger households, higher incomes, dwelling ownership and unshared roof space resulted in increased uptake, but notably that educational attainment was not a significant predictor. A number of studies have been conducted in the German context. Focusing on the spatial diffusion of PV systems and associated determinants, Baginski and Weber (2019) considering cross-regional spill-over effects using spatial lag (SLM) and error (SEM) models, indicated that spatial dependence is a relevant determinant for explaining regional clusters of PV adoption, which the authors infer may be explained by peer-effects due to 'recurrent visual perception'. Nonetheless, they acknowledged that unobserved regional characteristics are at play and the share of detached houses, electricity demand and inverse population density of a region favour PV uptake. Müller and Rode (2013) applying geocoded data within a binary panel logit model, whilst controlling for spatial variation in population density and purchasing power, observed a significantly positive influence of previously installed systems located nearby on the decision to install a PV system. In an updated study, Rode and Müller (2016) also utilised granular geo-coordinated data and studied the Spatio-temporal variation of peer effects in PV adoption within a discrete choice approach. Their analysis revealed localised peer effects which they found to dissipate non-linearly with distance which decreased over time. In a similar vein, Rode and Weber (2016) tested whether localised imitation drives the Spatio-temporal diffusion of PV adoption using a unique dataset of 576,000 PV systems. Applying an epidemic diffusion model to control for temporal and spatial heterogeneity, they discovered that imitative adoption behaviour or peer effects is highly localised and an important factor for the diffusion of household PV systems.

Two further studies also analysed geographical factors. Schaffer and Brun (2015) using 820,000 small-scale PV installations registered between 1991 and 2012, revealed house density, homeownership, per-capita income and neighbourhood effects to be significant determinants of PV adoption. Notably, they also observed a households' ecological attitude has limited impact on their investment decisions. More recently, Müller and Trutnevyte (2020) using a dataset of 68,341 PV installations tested techno-economic and socio-demographic variables within spatial frameworks, and also found household size, population density, and electricity prices to comprise positive effects. The authors also emphasised the importance of spatial spill-overs across adjacent districts.

In Sweden, Mundaca and Samahita (2020) investigating subsidy effects and non-economic variables affecting the likelihood to adopt PV, applied a web-based survey with homeowners. Employing logistic regression models, they recognised that subsidies and peer effects are significant factors driving the likelihood to adopt PV which they contend is due to environmental awareness, but noted that the visibility of technology and related pro-social behaviour were not significant. From a UK perspective, Allan and McIntyre (2017) conducted analysis into the spatial uptake of small-scale renewable technologies. Acknowledging that throughout the UK the spatial pattern of PV uptake has been uneven, driven by policy incentives and pointing towards the effects of local and neighbourhood socio-economic factors, they found that wealth, housing type and population density are significant in explaining uptake and that there are existing spatial (between neighbourhood) processes which explain the adoption of PV technology. Interestingly, they found that local green attitudes were not important.

The role of the spatial variation and distribution of photovoltaic deployment in the UK and its determinants was undertaken by initial research undertaken Balta-Ozkan, Yildirim and Connor (2015b). Applying a spatial Durbin model using the cross-sectional data relating to the UK NUTS level 3 data, the authors established that regional spill-over effects are evident with PV uptake, driven by demand for electricity, population density, pollution levels, education level of households and housing types. Similarly, earlier research by Rae et al. (2009) noted that one-storey detached dwellings within the residential building stock offered the most potential for uptake of renewable electricity generation technologies in an urban setting. More recently, Balta-Ozkan et al. (2021) enhanced insights into PV adoption at the local level for the U.K. by incorporating the number of charities as a proxy to capture social interactions and peer effects. Applying a Geographically Weighted Regression (GWR) model to account for the spatially varying relationship between PV adoption and socio-economic explanatory variables, they revealed that charities and self-employment positively influence PV uptake whilst other socio-economic variables such as population density demonstrated bidirectional effects.

The existing literature has established many social, economic, residential and environmental factors affecting PV adoption, and equally indicated that there exists geographic and temporal peer effects. The role of socio-economic and built environment attributes in conjunction with peer effects display some disparate findings – at the global level. Arguably, the nature of PV adoption varies by culture, solar irradiation and neighbourhood characteristics. Indeed studies have consistently shown there to be clustering effects evident for PV diffusion is not always tied to economic attributes and can be non-linear across geography which may be explained by localised spatial neighbour peer-effects due to recurrent visual perception, social interaction and acceptance. This corresponds with the social dimension of sustainability within the built environment relating to harmony between the accessible technologies, procedures of development and health and comfort, accessibility, inclusiveness, participation and education (Volenbroek, 2002; Wan and Ng, 2018), and the development of sustainable communities (Woodcraft et al., 2011). In light of these findings, this study proceeds to examine these determinants of PV adoption at the regional level in the UK, focusing on Northern Ireland.

3. Data and Methodology

3.1 Data

The data was obtained from the Office of Gas and Electricity Markets (OFGEM), which contained anonymised details of 22,084 PV installations and system size only available at the Super Output Area geography.[3] Out of the 890 SOAs in Northern Ireland, all except four contained PV installations, with the average number of PV installations per SOA equating to 22 with the maximum number of PV installations in a single SOA totalling 173 (Table 1). The PV installations listed kW capacity per SOA ranged in size from 0 kW to 910kW, with an average capacity of 89.50kW (Figure 1).

Table 1 Descriptive statistics of PV installations and kW capacity within SOAs

As observed in Figure 1, and concomitant with the wider UK study of Balta-Ozkan et al. (2021), there appears to be evidence of spatial concentration and correlation between the accumulated capacity and the number of installations indicating limited variance in the average number of panels per installation at SOA level. Initial relationship testing between the number and kW of PVs displays a correlation coefficient of .987 (p<.001) indicating this collinearity.

Figure 1 Local distribution of PV installations and KW output at SOA level across NI

3.2 Model Development and Selection

The literature illustrated that many aspects of social, economic, and environmental factors can impinge on PV adoption. Set against the theoretical backdrop of social sustainability and with regards to integrating renewable energy into residential dwellings, there have been however fewer studies which have examined whether key housing market determinants impact upon the adoption of renewable energy. In order to accurately measure the association between renewable energy PV uptake and its diffusion within the residential housing market, a number of housing market composition and characteristics are investigated.

Previous research questioned the role of income on PV adoption and tended to present inconclusive results (Balta-Ozkan et al., 2015). Equally, the nature and role of employment and educational attainment has dominated the literature (Somerfield et al., 2017). Mountain and Kars (2018) found that PV uptake is proportionately more common in households in the middle and lower socio-economic deciles than in the higher socio-economic deciles with PV uptake proportionately the highest in the lowest socio-economic decile and lowest in the highest socioeconomic decile. In light of this, local variation of these factors is tested using the Multiple Deprivation Measure (MDM) produced by the Northern Ireland Statistics and Research Agency (NISRA) at the SOA statistical geographic level. This measure of deprivation provides a mechanism for ranking areas in the order of the most deprived to the least deprived and is characterised by Seven distinct domains[4] of deprivation which are made up from

[3] Northern Ireland is split into 890 spatial areas known as Super Output Areas (SOAs), with an average population of around 2,100 people (NISRA, 2017).

[4] The Seven domains of deprivation are: Income Deprivation Domain; Employment Deprivation Domain; Health Deprivation & Disability Domain; Education, Skills & Training Deprivation Domain; Access to Services Domain; Living Environment

one or more indicators. Thus, MDMs are incorporated to assess the location of PV installations against the constituent domains of MDM (Figure 2).

The average house price per SOA is also included within the analysis in order to establish if there is any linkages between PV adoption and a house price premium. As Mountain and Kars (2018) indicate, PV is proportionately more popular with people who live in less valuable houses than it is with people who live in more valuable houses. Similarly, Lan, Gou and Yang (2020) and Hoen et al. (2013) established that houses with PV exhibit a premium in terms of property value, inferring that higher solar rebates and subsidy leads to a higher premium and encourages PV adoption. To investigate whether there is a spatial effect, data was obtained from the Ulster University Quarterly House Price Index[5], with the data joined at SOA level to produce average price statistics[6].

The role of urban structure is important for understanding the social dimension of sustainability and particularly whether housing market homogeneity (clustering), and indeed, heterogeneity (randomness) are factors impacting upon the spatial distribution and diffusion of PV adoption. Further, the differences in rurality we conjecture may be borne out of the level of social interactions, community cohesion and decision making. Therefore, urban-rural classification was also incorporated in order to establish whether PV installations have been driven, or are differentiated by, an urban-rural dichotomy (Figure 2). We therefore test whether SOA classification comprises an effect on PV installation and uptake. This was achieved by layering the PV data against the Settlement Development Limits data available from the NISRA. As the settlement development limits and SOA boundaries are not co-terminus, the PV data was converted to centroids (as opposed to polygons) to facilitate the best fit between the datasets. Given that a number of SOA boundaries stray over the settlement development limits, NISRA has introduced an intermediate category of "Mixed' alongside 'urban' and 'rural" to categorise the SOAs (Figure 2). Descriptive analysis indicates that 8.2% of SOA classification is 'mixed', with 61.8% urban and 30.0% classified as rural.

Figure 2 The Classification and spatial distribution of SOAs and MDM

Finally, tenure and homeownership rates remains an under-researched area within PV adoption. As intimated in the research of Davidson et al. (2014), it remains unclear whether home-ownership has an influential effect – particularly within the U.K. context. Though it is notable in other studies such as

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Domain; Crime & Disorder Domain. The ranks of the 7 domains are weighted and combined, to provide a ranking of multiple deprivation (MDM) for the 890 SOAs (NISRA, 2017:2).

[5] The UU HPI was established in 1984 and records circa 40% of residential property transactions across the region of NI. The HPI measures the current price and quantities in relation to the base period. The index is based on quarterly returns obtained from 103 contributory estate agency practices from across Northern Ireland and supplemented with recorded and verified sale transactions from Propertynews.com. The sales information is also cross-correlated with the domestic capital valuation register for inspection and verification of attribute information..

[6] The data was extracted over a three year time series (2017-2020) and a time-adjustment sales price (TASP) approach undertaken to provide a 'one point' in time price statistic for comparability with the PV installation data.

Briguglio and Formosa (2017) found that home-owners may be more likely to install PVs as they are fixed capital investments. Therefore, to further investigate this dynamic we include data on the type of tenure, namely the percentage of Owner-Occupied, Social- and Private-Rented housing rates by SOA obtained from NISRA and layer this with the PV SOA dataset. The data shows that across the SOAs, the average SOA comprises 68.15% of owner-occupiers, 14.65% social renters and 17.2% private renters. The full list of explanatory variables included within the analysis is summarized in Table 2 below.

Table 2 Explanatory variables descriptions and data sources

The PV Super Output Area dataset was subsequently imported into the GIS software (QGIS, ArcMap 10.4 and ArcView 3.3)[7] and a series of spatial joins were undertaken to encompass wider built environment and socio-economic datasets with the PV data. Akin to other studies controlling for density, this study applies the ratio of housing density per hectare in order to control for differences in SOA size and the total number of residential households contained within each SOA as a proxy to measure the effect of sparseness of PV adoption.

3.2.1 Spearman's rho and Principal Component Analysis

Spatial and neighbourhood characteristics provide information which can enable the examination and representation of composite inter-relationships. Whilst important, the spatial interactions and relationships between variables often display multicollinearity and autocorrelation making multivariate analysis challenging. Consequently, we test the association between the variables and undertake an optimisation process. Initial examination of the relationships between the various domains of deprivation displayed elevated levels of correlation and thus multicollinearity (Table 3).

Table 3 Spearman's (rho) correlation coefficients between deprivation domains

In light of this, Principal Component Analysis (PCA) is undertaken for reducing the dimensionality of the MDM domain attributes, address multi-collinearity whilst mitigating against potential omitted variables bias and retaining the underlying nature of the dataset to account for the linear combination of the original variables. This spectral decomposition approach calculates eigenvalues which is the factorisation of a matrix into a canonical state thereby decomposing the original dataset into a set of linear variates (Field, 2013). The resulting components explain all the variance held within the correlation matrix (Kline, 1994), and maximises the variance (sum of the squared loadings) explained for any number of factors and detects a structure in the relationships between the variables[i].

[7] Three different programs were used as they comprise a different range of functions required for further modelling purposes.

To identify the number of components to be retained, the analysis applies a prior criteria to select the number of components that explain the maximum amount of variance. The eigenvalue criteria of >.9 along with the Scree test and the interpretability of each component is applied. Criteria are that each principal component explains at least 5 per cent of the variance and, cumulatively, 75 per cent of variance. Variables with absolute scoring coefficients >0.5 were considered important contributors to a pattern and appropriate for interpretative purposes (Field, 2013).

3.2.2 Principal Component Analysis extraction

The Principal component extraction initially examined the Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's test of Sphericity for ensuring that the data was appropriate for further analysis. The KMO value of .786 and Bartlett's test of Sphericity significant (χ^2; 5778.26, df.21, p<.001) indicate that PCA is appropriate for the data[8]. The extraction of the principal components reveals three components to display latent roots (eigenvalues) of >.9, with the proportion of variance explaining 89.9% (Table 4). Scrutiny of the Scree plot further indicates that three components should be retained. The first component displays an eigenvalue of 3.54 and explains 50.5% of the variance, with the second component explaining 24.4% of variance and the third component explaining 15.0% of the variance.

Table 4 Extraction variance

The rotation of the component structures applying the orthogonal (varimax) solution can be observed in both Table 5 and Figure 3 which also presents the correlation biplots between each of the factors (components).

Figure 3: Correlation Biplots for extracted factors

The findings (Table 5) show Employment, Education, Income and Crime load onto the first component representing 50.54% of the underpinning variance. The first component can therefore be regarded as 'Economic'. Component two explains 24.39% of the variance and encompasses both the Access to Services (-.945) and the Crime and Disorder domain (.645) and is termed 'Social'. The third component represents 14.99% of the explained variance and shows both Health (.887) and Living Environment (.979) as rotated loadings, which is referred to as 'Environment'.

Table 5 Rotated loadings of the principal components

[8] The anti-image matrix further revealed that the diagonal elements are all above the minimum threshold of 0.5, with the off-diagonal values also revealing that the partial correlations are relatively small, therefore confirming the KMO statistic. The results indicate that the *R*-matrix is not an identity matrix – rejecting the null hypothesis (Kaiser, 1974).

The spatial representation of the three rotated components can be observed in Figure 4 which accounts for the underpinning dimensionality of the various domains of MDM. Overall, the components display some evidence of spatial concentration and clusters within the 'Economic' and 'Social' domains, however show more spatial dissimilarity or randomness within the 'Environment' domain.

Figure 4 Spatial representation of the extracted and retained Principal Components

3.2.3 Multi-Model interface testing and optimisation

To avoid overtly complicated models and the loss of information pertaining to determination of key relationships, alternative approaches to data analysis have emerged to approximate the likelihood of data and select the optimal model structure. This approach is envisaged to safeguard model parsimony without reducing predictability and overcomplexity based on minimising the Akaike Information Criteria(c)[ii], which ensures retention of the highest level of explanation as depicted by the Adjusted R^2, and remove unwanted influential variables and multicollinearity[9]. Within this research, this model interface process is based on 9 variables and a total of 511 OLS models assessed filtered by the AICc. The optimal (and parsimonious) model structure excluded the average House Price parameter (Table 6)[10].

Table 6 OLS Model Selection procedure sorted by AICc

In light of the model optimisation procedure, the final "base" model specification takes the form[11]:

$$nPV_i = \beta_0 + \beta_1 Mixed_i + \beta_2 Urban_i + \beta_3 SocialRent_i + \beta_4 PrivateRent_i + \beta_5 House/Ha_i + \lambda_1 Economic_i + \lambda_2 Social_i + \lambda_3 Environ_i + \beta_6 xcor_i + \beta_7 ycor_i + \mu_i$$

where i denotes regions (SOAs) and μ_i is an independently and identically distributed error term with zero mean and variance σ^2. Both the *xcor* and *ycor* reflect various tested polynomial expansions or spatial dummy variables incorporated to control for space across the modelling frameworks.

3.3 Spatial Structural Analysis and Moran's I

The first step in all spatial analysis, as in any other statistical procedure, is to undertake exploratory data analysis (EDA) to uncover (usually) hidden patterns in datasets in order to quantify relationships

[9] This procedure estimates the relative quality of the models for the given set of data, relative to each of the other models premised on the relative information lost by a given model: the less information a model loses, the higher the quality of that model. This therefore estimates the trade-off between the 'goodness of fit' of the model and the simplicity of the model.
[10] The relative importance of each parameter also available upon request.
[11] Note: the 'hold-out' model is a rurally located SOA of owner-occupation status.

between variables (values) and further examining these across spatial units [31][12]. In order to test the spatial structure of the data, geographic distances are determined using a symmetric distance matrix (Upper right distance matrix)[13]. The Moran's *I* coefficient is the most commonly used statistic for autocorrelation (AC) analyses in spatial studies (Stevens, 2002) as it evaluates whether the pattern expressed is clustered, dispersed, or random[14]. For this analysis, the Moran's *I* for the PVs reveals the initial (first) distance class (immediate short distance) to exhibit a positive and statistically significant *p*-value (0.398, $p<.001$) - demonstrating the maximum value of Moran's *I* with this connectivity structure (Table 7)[15]. This decreases to 0.226 ($p<.001$) and .066 ($p<.001$) and .014 ($p<.05$) by the fourth distance class within the connectivity structure – and remains relatively negligible over the remainder of the spatial geography. This indicates some evidence of spatial clustering of high (low) values but also spatial dispersion which is often reflective of competitive process - a feature with a high value repels other features with high values; similarly, a feature with a low value repels other features with low values. The analysis also indicates that the spatial distribution of PVs may be the result of random spatial processes or complete spatial randomness (CSR).

Table 7 Moran's I values across the distance classes

In addition, we examine the Local Indicator of Spatial Autocorrelation (L.I.S.A)[16] to measure the contribution of each sampling unit to the overall (global) level of spatial autocorrelation, which is tested for statistical significance (of Moran's *I*) using randomization undertaken via Monte Carlo simulation to analyse the regression residuals[17] (Rossi et al., 1992). The L.I.S.A results for PVs (Figure 5) reveal that the spatial distribution of the local autocorrelation structure to appear heterogenous across the market geography with clustering evident across the region, particularly in urban areas.

Figure 5 L.I.S.A spatial structure (PV installations)

This can also be observed in the Moran's Scatterplot and normalised *Z*-score scatterplots as presented in Figure 6. The scatterplots, generated for each distance class[18], exhibit correlations ranging between 49.5% which reduce to 12.2% between the variables values and those of the neighbouring cells (average neighbour values) showing limited violation of homogeneity which reduces across space.

Figure 6 L.I.S.A Scatterplots for PV across avg. nearest neighbour classifications

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[12] see Rossi *et al*. (1992) for a discussion of EDA within the framework of spatial analysis.
[13] based on a default number and equal distance classes with significance tested using 199 permutations There are 18 Distance classes. These are not presented due to space limitations. All Distance classes are available upon request.
[14] This calculates the Moran's I Index value and both a z-score and *p*-value to evaluate the significance of that Index. *p*-values are numerical approximations of the area under the curve for a known distribution, limited by the test statistic.
[15] Visual representation of Moran's I for each variable over the distance units are available in the Appendices
[16] The local Moran's I can be interpreted as a leverage statistic showing the importance of each cell to the analysis of the overall pattern. See Anselin (1995).
[17] Monte Carlo method is selected and we employ 199 permutations (randomisations).
[18] Only six distance class units are presented due to space limitations. There are 162 L.IS.A. maps and Scatterplots in total (available upon request for all variables).

3.4 Spatial Modelling approaches

Studies examining energy transitions, peer effects and PV installations have tended to try and account for spatial dependence and heterogeneity (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015). This approach, by undertaking various approaches and incorporating geographic information systems (GIS) to facilitate spatially-adjusted model structures, incorporates weights or distance based matrices to examine (auto)correlation between geographical proximity and similarity (Tiefelsdorf, 2006). In a similar vein, this paper employs an OLS based model (incorporating spatially delineated coordinates) along with a Poisson specification, an Eigenvector Spatial Filter (ESF) model and a variety of geo-statistically based models including two Spatial Lagged Models (SLMs) and Geographically Weighted Regression (GWR) to examine the role of the selected parameters on PV installations (uptake). The OLS models are used to serve as a base model to analyse the role of socio-economic and housing tenure attributes on PV installation uptake.

3.4.1 OLS and Poisson Models

The standard OLS fixed effects linear model takes the form:

$$nPV_i = \beta_0 + \beta_1 Mixed_i + \beta_2 Urban_i + \beta_3 SocialRent_i + \beta_4 PrivateRent_i + \beta_5 House/Ha_i + \lambda_1 Economic_i + \lambda_2 Social_i + \lambda_3 Environ_i + \beta_6 xcor_i + \beta_7 ycor_i + \mu_i$$

where; β_0- is the Constant; $\beta_1 ... \beta_n$ are the coefficients; $\lambda_1 .. \lambda_n$ are the orthogonal components and u is the Error term.

We also test the model specification based on a Poisson regression approach. We apply this form of multiple regression (generalised linear model) due to the PV installations acting as the dependent variable may be regarded as having a Poisson distribution where the mean is logarithmically linked to a linear combination of explanatory variables and due to PV installations being based on count data (i.e. they can only be an integer and cannot be negative). As discerned by Flowerdew and Amrhein (1989), when counts are large, it is acknowledged that the normal distribution (OLS model) can provide a reasonable approximation to the 'true' discrete distribution, however when they have small values this can impact on the reliability of OLS results. Thus, the Poisson regression approach is akin to fitting an unconstrained spatial interaction model and applies a deviance statistic based on the log likelihood as the measure of goodness of fit – the measure of the overall difference between observed and estimated values. In line with the error sum of squares in OLS regression, the Poisson regression takes the form:

$$d = 2 \sum_{i=1}^{N} y_i \, In \, ({}^{y_i}/\hat{y}_i)$$

where d is the deviance, y_i is one of the n observed values, and $\hat{y}_i$ is the equivalent estimated value. The deviance statistic displays a distribution approximating chi-square with degrees of freedom equal to n minus the number of parameters fitted[19].

3.4.2 Eigenvector Spatial Filter (ESF) model

The Eigenvector Spatial Filter (ESF) method applies geographical coordinates which are subject to an eigen analyses of geographical distances to establish a set of spatial filters (eigenvectors) expressing the spatial structure of the region (Griffith, 2003). Thus, this approach uses a decomposition approach for alleviating heterogeneity through the extraction of orthogonal components using the spatial dependence diagnostic Moran's coefficient formulated as follows:

$$MC = \frac{N \quad y'MCMy}{1'C1 \quad y'My}$$

where **1** is an $N \times 1$ vector of ones, **y** is an $N \times 1$ vector of variable values, **C** is an $N \times N$ connectivity matrix whose diagonal elements are zero, and M = IN –11′/N is an $N \times N$ matrix for double centring, where **I**N is an $N \times N$ identity matrix. Notably, M is replaced with MX = IN–X(X′ X)-1X′ if **y** is a residual vector of a linear regression model. MC is positive if the sample values in **y** display positive spatial dependence, and negative if they display negative spatial dependence. The l-th eigenvector of MCM, el, describes the l-th map pattern explained by MC, while the set of eigenvectors of MCM, E*full* ={e1, ..., eN}, provides all the possible distinct map pattern descriptions of latent spatial dependence, with each magnitude being indexed by its corresponding eigenvalue (Griffith, 2010).

Griffith (2010) further extended the basic linear model as rather than using the final EVs to correct for SAC on a global level, interaction terms were introduced between the selected eigenvectors and the predictors to model spatially varying coefficients in the following manner:

$$\hat{Y} \approx (\beta_0 1 + \sum_{K=1}^{K_0} E_{k0}\beta_{k0}) + \sum_{P=1}^{P} (\beta_p \mathbf{1} + \sum_{K_p=1}^{K_p} EK_p\beta_{kp}) \cdot X_p + \varepsilon$$

where $\hat{Y}$ is the n×1 vector of prices, X_p is a n×1 vector of independent variable p (p=1,2,3, ...,P), EK_p is the K_pEV (k=1,2,3, …,K) that describes the variable p, β_0, β_{k0}, β_{kp} are estimated regression coefficients, and **ε** is an independent and identically distributed error term.

Note that the element-wise matrix multiplication and the interaction terms are given by $\beta_{kp} \cdot X_p$. The parameters are estimated by means of OLS. The first part of the equation represents the spatially varying intercept, and the second part represents the spatially varying coefficients. After rearranging, the regression coefficients constitute the global impact, while the individual EVs mimic local modifiers of these global effects across space:

$$Y = \beta_0 1 + \sum_{p=1}^{P} X_P \cdot 1\beta_P + \sum_{K=1}^{K} E_k\beta_{E_k} + \sum_{p=1}^{P}\sum_{k=1}^{K} X_P \cdot E_k\beta_{pE_k} + \varepsilon$$

[19]See Wang & Famoye (1997) and Flowerdew & Amrhein (1989) for a full methodological discussion on generalised Poisson model specification.

The Eigenvectors are created using geographical coordinates which were initially truncated applying a maximum distance connectivity estimation where all the sampling units under a minimum spanning tree criterion[20]. The filter selection were based on PV installations as the response variable and by minimising residual Moran's *I*, with the threshold set at $p<.05$. Overall, the filter selection resulted in the determination of 246 eigenvector 'filters'. A filter extraction method was subsequently applied using the AICc with each filter included where it reduced the AICc statistic. This culminated in retention of 21 spatial filters to be used within the OLS regression analysis (Figure 7).

Figure 7 Extracted Spatial Filters[21]

3.4.3 Spatial Lag models

When it is suspected that Tobler's (1970) law of geography applies[22], and as demonstrated through short-scale distance classes in the L.I.S.A analysis, spatial dependence models may be necessary to correct for this effect - and other spatial attributes not captured within the model structure. Such indirect impacts are in addition to the direct effects associated with the standard explanatory variables that capture the structural features of the social and natural environment (Kim et al., 2003). The spatially lagged response model is expressed as:

$$y = \rho W y + X\beta + u$$

where y is a $n \times 1$ vector of observations on the dependent variable, X is a $n \times k$ matrix of observations on explanatory variables, W is a $n \times n$ spatial weights matrix, u an $n\times1$ vector of i.i.d. error terms, ρ the spatial autoregressive coefficient, and β a $k\times1$ vector of regression coefficients.

An alternative interpretation is to examine a lagged predictor model which extends the response model to include a weight matrix of the predictors which can be expressed as:

$$y = \rho W y + X\beta + WXy + u$$

Initial modelling examined a set of spatial weights matrices ($\mathrm{W}_{\mathrm{i,j}} = 1/d_{i,j}$ and $\mathrm{W}_{\mathrm{i,j}} = 1/d_{i,j}^2$) in order to obtain the best 'goodness of fit'. The spatial weights approach $\mathrm{W}_{\mathrm{i,j}} = 1/e^{d_{i,j}}$ produced the best 'goodness of fit' which applies the average of spatial lagged PV information of other SOAs, thereby accounting for spatial dependencies in the residuals[23].

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[20] For this study, the truncation distance connecting all sampling observations displayed a distance class upper bound of 11739.539. In total, 19 distance classes were determined.

[21] A selected number of Spatial Filters are displayed due to space limitations. The full list of the extracted 21 Filters are available upon request.

[22] The first law of geography is that '*everything is related to everything else, but near things are more related than distant things*' (Tobler, 1970:236).

[23] SL residuals should not be distinguishable from random noise.

3.4.4 Geographically Weighted Regression Model

Geographically Weighted Regression is a non-parametric approach applied to mitigate the issue of spatial heterogeneity and autocorrelation as it permits coefficients to vary continuously. GWR as outlined by Fotheringham et al. (2003) is as follows:

$$y_i = \beta_0(x_i, y_i) + \sum \beta_k (x_i, y_i) x_{ik} + \varepsilon_i$$

where: yi = ith PV SOA; β0 = model intercept; βk = kth coefficient; xik = kth variable for the ith PV SOA; εi = error term of the ith PV SOA; (xi, yi) = x,y coordinates of the ith regression point

GWR measures the relationships around each regression point *i*, where each set of regression coefficients is estimated by weighted least squares using kernel densities. In this study, an *n*X*n* spatial weights matrix is constructed to indicate the weight applied to each observation (SOA), assigned relative to the subject based on geographic distance:

$$w_{ij} = exp[-d_{ij}/b^2]$$

where: w_{ij} = weight applied to the j^{th} SOA at regression point *i; d_{ij}* = geographical distance in kilometres between regression point *i* and SOA *j ; b* = geographical bandwidth.

The bandwidth in GWR specifies the radius of the weighting function which is either fixed, based on absolute distance, or adaptive - fluctuating, based on a predetermined number of nearest neighbours. An optimum bandwidth can be found by minimising the model goodness-of-fit. This study applies the Golden Section Search, and Akaike Information Criterion (AICc), searching from 26084.26 to 39126.39 distance units. The analysis examined various spatial weighting functions (Bi-Square; Moving Window; Adaptive Spatial Kernel for minimising nearest neighbours using AIC optimisation) and applies a Bi-square function.

3.4.5 Logistic Regression

To further examine whether an urban-rural difference is evident, we create a dichotomous dependent variable to assess predictions based on likelihood of urban and rural. When categorical, the assumption on linearity is violated and logistic regression can be used to transform the linear model in logarithmic terms (*logit*) permitting the prediction of categorical outcomes based on the probability of occurrence. Instead of predicting the value of *Y* from a predictor variable(s) $X_{(n)}$ we examine the dichotomous prediction of probability of *Y* occurring (P)*Y* from known values (e = natural logarithms) resulting in probability of *Y* occurring equating to the case belonging to a particular category culminating in a binary estimation (0; 1).

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i})}} \text{ or } P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} \dots b_n X_{ni})}}$$

A value close to 0 suggests that Y is very unlikely to have occurred, with a value close to 1 implying that Y is very likely to have occurred employing a maximum-likelihood estimation procedure which selects the coefficients (β) that make the observed values most likely to have occurred. Assessing the model, *the log-likelihood*, is based on summation of the probabilities associated with the predicted, P(Y_i) and actual Y_i, outcomes – similar to residual sum of squares (RSS):

$$\sum_{i=1}^{N}[Y_i In(P(Y_i)) + (1 - Y_i) In\,(1 - P(Y_i))]$$

The model is assessed using the likelihood ratio, illustrating that a negative coefficient value implies that as a predictor value increases, the likelihood of the outcome decreases, with a positive value indicating that as the predictor variable increases, so does the likelihood of the event occurring[iii].

4. Results and discussion

4.1 Ordinary Least Squares and Poisson regression models

The Global OLS and Poisson model findings are presented in Table 8, with the Adjusted and pseudo R^2 denoting the coefficient of determination, the AIC and the Variance Inflation Factor (VIF) index. The results show the variance inflation to be low and that no undue influence is being exerted within the regression parameters. The OLS model displays a 47.7% level of explanation with the Poisson model showing a slightly better level of explanation of 50.8%. The global Moran's I alongside the L.I.S.A. scatter plots demonstrated the presence of some spatial correlation at initial short-distances, thereby indicating that caution should be treated when applying the OLS model for identifying the relationships between solar PV uptake and the explanatory variables. The results of both model coefficients do however show Urban SOAs to comprise a negative effect (-7.716, p<.001; -0.213, p<.001), indicating that more urban based SOAs demonstrate lower PV adoption and uptake. In terms of tenure, both models show the percentage of social rented housing to be statistically insignificant, albeit, the OLS reveals a negative effect whereas the Poisson model displays a negligible but positive effect. The findings do however show the percentage of the private rental housing to constitute a negative impact on PV adoption (0.194, p<.001; -0.015, p<.001). In terms of density, as depicted by the number of houses per hectare, this reveals a negative influence on the number of PV installations, similar to Balta-Ozkan et al. (2021), suggesting that residents located in less densely populated areas are more likely to install a PV system.

Turning to the role of deprivation, the coefficient 'Economic status' (1.464, p<.05; 0.05, p<.001) displays a positive effect suggesting that the underpinning dimensions of income, employment and education comprise a positive impact on PV adoption. Conversely, the level of social cohesion, as depicted by the latent dimensions of access to services and crime and disorder, exhibits a negative effect (-6.247, $p<.001$; -0.246, $p<.001$) on PV uptake, in conjunction with Wellbeing (health and living environment deprivation) which is also negative (-3.122, $p<.001$; -0.079, $p<.001$) for both models.

Table 8 OLS and Poisson model results

4.2 Eigenvector Spatial Filter findings

Examination of the ESF model (Table 9) shows a 52.4% level of explanation in the variation of PV adoption, with an AIC statistic of 7214.52, outperforming the standard OLS and SLMs. Interestingly, the partial regression analysis reveals the predictors to explain 46.3%, with the filters explaining 33.5% and the shared explained variance to account for 27.3%. The model coefficients, controlling for spatial variation, indicate that Urban-based SOAs comprise a statistically significant negative effect (-7.376, $p<.001$), with 'Mixed' urban-rural SOAs also negative (-1.099, $p>.05$) although this is not statistically significant. Again, this finding illustrates that urban SOAs tend to have less PV adoption than rural-based SOAs. Both the percentage of social and private rental housing within each SOA demonstrate negative coefficients (-0.055, $p>.05$; -0.179, $p<.001$), however the social housing coefficient is not statistically significant. Conversely, the private rental coefficient is statistically significant as is much more pronounced in terms of magnitude inferring that the percentage of rental stock within an SOA, particularly private rentals decreases the likelihood of PV installation/adoption. Turning to the Economic status coefficient, this reveals a positive effect on PV uptake symbolising that increased PV adoption is related to the overall income, education and employment levels within a particular SOA. In contrast, both the Social capital (-6.523, $p<.001$) and wellbeing (-4.104) coefficients demonstrate negative effects indicating that the wider living environment, health and crime impact upon the level of PV uptake.

Table 9 Eigenvector Spatial Filter model coefficients

4.3 Spatial Lag and Geographically Weighted Regression models

The SLM and GWR models were employed to explore and estimate the spatial determinants of PV uptake at local level using lagged predictors, responses and generate local regression coefficients to account for heterogeneity and incorporate spatial dependence to capture both the direct and indirect effects of the attributes. Table10 presents the estimation results for the SLMs. For the lagged response model, this displays an R^2 of 43.4% with the lagged predictor model displaying an R^2 of 50.7%, with an interactive autoregressive term (rho) of 61.4%. The results show the Urban coefficient within both model structures to comprise statistically significant ($p<.001$) negative effects.

Table 10 Lagged response and predictor models

The GWR model shows a *pseudo*-R^2 of 57.9% and is the best performing spatial model with the most stable Moran's I residual error. Further, apparent spatial differences in the explained variance are discernible and demonstrate ranges in the local R^2 values between 25% and 88% (Figure 8) demonstrating that the built environment, tenure and deprivation characteristics explain more variation within some SOAs. Whilst this is an obvious limitation of the GWR technique which can be masked by the global "pseudo" R^2 estimate produced by the analysis, it also highlights that OLS is also, to an extent, misleading - only presenting the mean conditional estimate. The findings nonetheless show the efficacy of the GWR approach for understanding the nature and extent of PV adoption. The variation in the local R^2 reveals a number of clustered SOAs, particularly in urban areas, to display the lowest levels of explanation, notably in the Belfast basin, a corridor to the South-East and pocket in the North-West. Upon further inspection, the geographic variation in the level of explanation is more pronounced for rural areas as opposed to urban areas indicating that the determinants show higher explanation in the variation of PV uptake for rural SOAs. The model parameter estimates (Table 11) indicate substantial spatial variation and non-stationarity providing strong evidence that the marginal PV installations estimates of tenure, urban-rural classification and components of deprivation fluctuate across geographic space.

Table 11 Local Regression Parameter Descriptive Statistics

In terms of the coefficients, as evidenced in Table 11, there is sizable variation. For the Urban coefficient, the local estimates range from -24.78 to 15.02, however the upper quartile is negative (-1.65) demonstrating that urban areas, in the main, tend to comprise a negative effect on PV uptake in comparison to rural areas and inferring that PV adoption is an urban problem. That said, the largest positive effect of the urban coefficient appears to be in the North- and South-West urban SOAs (Figure 8). The Mixed coefficient sees value ranges between -6.44 to 3.99, symbolic of heterogeneity and demonstrating that these more peri-urban/peri-rural areas comprise spatially differential effects in PV uptake.

The percentage of social and private rental housing show local estimates ranging between -2.56-1.77 and -2.10-1.31, with both median negative and the private rental coefficient remaining negative at the upper quartile range (Table 11). Spatially, the social rent coefficient demonstrates a relatively consistent spatial effect, however does show the band to the South-East and an enclave in the South-West to comprise more pronounced negative effects. There is however evidence of positive local effects in the South-West and also an arc-type corridor in the Mid-West area. A similar spatial relationship is observed for the private rental sector coefficient, however subtle spatial differences are notable particularly in the South-West region which displays a small cluster of positive effects.

Figure 8 GWR coefficient maps

Economic status appears to be a more influential driver in the West to South-West region, with the South-East noting the opposite effect. For the Social cohesion coefficient, this comprises a negative effect spatially with corridor spanning to the West of the region and South comprising the largest negative effect. The findings do however show a localised positive effect towards the South-East region. The Wellbeing coefficient shows more regional disparity with the Northern SOAs exhibiting much more localised negative effects compared to remainder of the region with the exception of the South-East area which exhibits a positive effect.

4.4 Logistic regression findings

For the logistic regression findings, the binary models are run based upon the expectation that, if Urban, it is equal to 1, (meaning it is present if the SOA is Urban), thus if Rural it is equal to zero. The model tests exhibit the significant Chi-Square (intercept only) prediction model to fit the data than a null model (non-predictors), revealing a statistically significant improvement in the overall model 'fit'. The model findings (Table 12) reveal that for the Urban logistic model, the number of PV installations is negative (-0.022, p<.001) in terms of unstandardised beta coefficient, signifying that a unitary increase in PVs comprises a decrease in the likelihood of it being urban. When examining the exponential of beta (Exp(β)) or odds ratio (calculated as the ratio of probability), the results show that the odds of Urban is lower for a higher number of PVs, implying that the probability of Urban is lower for the increase in PVs.

This indicates that for an additional unit increase in PV uptake, the odds of Urban is lower and decreasing by a factor of 0.978 for an additional one unit increase in PV installations. In the results, this illustrates the odds of 'urban' is lower by 2.2% (0.978*100-100). In terms of tenure composition, the percentage increase in Owner, Social and Private rented display positive coefficients, with the odd ratios suggesting that as the tenure rates increase the likelihood of it being an Urban SOA increases between 94-99.1%. For the deprivation constructs, Economic status displays a negative coefficient (-0.766, p<.001) with an odds ratio of 0.465. This suggests that decreases in economic status increase the likelihood of an urban SOA. More specifically, the Log odds likelihood of falling into the urban classification decrease by a factor of 0.465 - simply put, the odds ratio shows that a one unit change in economic status results in a 0.465 times (or 545%) decrease in the logit probability of likelihood of being an urban SOA.

Table 12 Logistic Regression and Odds Ratios

The rural model presents contrasting findings. The results show that PV uptake coefficient is positive (0.002, $p<.05$) with the odds ratio indicating that for every additional increase in PV uptake, there is increased likelihood of it being 'rural', with the odds of being rural higher by 0.2%. Interestingly, the Economic status measure shows a positive coefficient (0.528, $p<.001$) and odds ratio of 1.695, indicating that as economic status increases the likelihood of it being a rural SOA increase by 69.5%. Alternatively, both the Social capital and Wellbeing coefficients are negative (Table 13), illustrating that as these measures increase the likelihood of the SOA classification being rural decreases by 88.7% and 50% respectively.

5. Discussion

This study has applied various spatial modelling methodologies to examine the localised insights to accurately represent the complex intra-urban spatial variability of PV system uptake to help inform policy targeting and direction. Specifically, it analyses domestic PV adoption at the regional level in the U.K., to establish whether housing market characteristics and composition – fed by localised demand and supply factors, demonstrate potential 'peer effects' and the understanding of the profile of typical PV uptake across the region. The empirical findings support the presence of geographical segmentation and clustering in relation to PV adoption and diffusion. This localised disequilibrium clearly illustrates that peer effects and the structure of the wider built environment and composition of housing stock, density and tenure coupled with deprivation levels do seemingly have an impact upon PV uptake. Pertinently, we find that a rural-urban dichotomy exists for PV adoption, a finding in accordance with Graziano and Gillingham (2015) who demonstrated smaller or rural communities adopt PV more so than larger urban areas.

Nonetheless, a caveat to point out is that whilst the nature and role of these effects are significant, there remains approximately 45-50% of unexplained variance – notably larger in urban locals - suggesting that wider 'unknown' behavioural, cultural idiosyncrasies are also undoubtedly driving the uptake of PV installations. This is in accordance with Baginski and Weber (2019) who indicated that spatial spill-over is not always driven by social imitation but also by unobserved regional characteristics.

The study of Balta-Ozkan et al. (2021) questioned whether PV systems yielded different outputs between urban and rural areas, with Balta-Ozkan, Yildirim and Connor (2015a) establishing that less dense areas were early adopters. The findings here have identified that there are spatial trends evident, and particularly that an urban-rural divide (difference) in PV adoption is notable. Whilst we do note some of the urban SOAs exhibit pockets of clustering of PVs, as identified in the locally weighted coefficients, this was primarily concentrated in the key conurbation the North-West region, suggesting that at the regional level this is very much an urban problem. Accordingly, behavioural factors seem to certainly play a key role, and this appears to be more prominent in rural areas in relation to PV uptake, and arguably driven by small scale one-off development such as 'green jewellery' self-builds – through integrated renewable energy design and desirability for 'going green' and/or the identification of 'cost savings' achievable through the adoption of PV systems. Indeed, this finding, in accordance with Davies et al. (2017) which also revealed an urban-rural divide in energy efficiency in the housing stock, pointing towards a potentially more receptive population regarding environmental consciousness and awareness driven by peer effects networking within the agriculture community. This is further substantiated when considering the nature of the existing housing stock in rural versus urban locales. Rural housing tends to be detached, larger in floor area and thus increased availability of roof space - with larger PV systems[24], which conforms with the findings of existing research (Davidson et al., 2014; Briguglio and Formosa, 2017; Rode and Weber, 2016; Balta-Ozkan et al., 2015a).

In line with this finding, the role of tenure appears to be an important dynamic impacting upon the adoption or transition to solar PV. While the Social rented coefficient was negative, enclaves of positive PV effects are evident which avers that the role of social housing provision is important for increasing PV installations *en masse*. Indeed, the positive localised coefficients appear to be driven by *new* large scale social housing development which comprise solar PV systems. In a similar vein, the findings clearly demonstrate that the proportion of private sector rental housing within an SOA comprises a negative effect on PV installations. Rather worryingly, and whilst the tenure data used in the study is borne from the 2011 census, there has been a manifest increase in the level of private sector rental housing stock since this period – certainly within the NI and wider UK context, which only serves to reinforce the importance of this study's findings. In addition, density was shown to display a negative impact upon PV uptake with residents located in less densely populated areas seemingly more likely to install a PV system, consistent with extant research (Müller and Rode, 2013).

The role of deprivation appears significant, particularly for potential peer effects. Economic status or accumulated capital, as identified by Balta-Ozkan et al. (2015a) clearly displays a positive impact on PV uptake. When considered alongside urban-rural typology, the interaction between deprivation disadvantage and urban setting impedes PV adoption. This suggests that differences in income and educational attainment (higher versus lower status) result in the ability to afford the costs of PV installations in line with studies other studies (Bollinger and Gillingham, 2012; Briguglio and Formosa, 2017). Or alternatively, those potentially residing in urban environments which are harmful to health and wellbeing, comprising more dense and lower quality housing stock lack any incentive or capacity for PV uptake.

6. Conclusions

Given that residential housing is such a significant contributor to greenhouse gas emissions, it is important to understand from a housing market perspective what determinants can impact upon the

[24] Analysis of the rural and urban average system size shows the average size of a PV system in an urban area is 9.2kW, with rural PV systems 17.4kW, on average.

uptake of much needed renewable energy sources and ascertain a spatial understanding of the significant determinants and adoption. Therefore, this research set out to add a contribution to knowledge and scientific rigour by identifying (i) the effects of different housing market factors on local spatial patterns of PV adoption in Northern Ireland and (ii) to determine whether geographical differences exist, not just in the environmental nature of sustainability across the urban form, but also whether social (cohesion) and behavioural dynamics are playing their part.

The study, by empirically assessing the spatial diffusion of PV installations has provided localised insights, applying several nuanced spatial regression approaches, to accurately represent the complex intra-urban spatial variability of PV system uptake to help inform policy targeting and direction in relation to the 'greening' of the built environment. The results reveal some subtle differences in PV uptake and diffusion, which seemingly appear to be linked to housing market structure and composition. The application of these spatially based (local) models also confirmed the presence of spatial dependency and clustering which would seem to suggest that some aspect of 'peer effects' are evident, and where there appears very localised adoption conforming with aspects of social sustainability. This tendency for spatial randomness, and more characteristic of the pepper-potting of PV installations consistently within and across more rural areas which infers that single-dwelling 'self-builds' are more likely to adopt PV uptake, than urban based development (housing) schemes.

This confirms that there are clear prosocial behavioural dynamics, environmental consciousness and rational economic decisions at play when considering PV installation, and more so, limited social, environmental and economic appetite from the more wholesale development community to incorporate PV into scheme design. These behavioural, and perhaps cultural tastes are also undoubtedly driving the uptake of PV installations which suggest that from a social sustainability lens, rural communities seemingly have more formal and informal hues (relationships; processes; structures) to create and influence more healthy and liveable communities through integrated renewable design and identification of 'cost savings' achievable through the adoption of PV systems, pointing towards a potentially more receptive population regarding environmental consciousness and awareness driven by peer effects networking within more rural communities.

Further, the findings detect that economic standing does comprise a positive effect on renewable energy adoption, indicating that owner-occupied and those from least deprived areas, particularly rural residents, are more likely to install renewable energy sources such as PV systems. It is therefore axiomatic that the converse is also case in that those households in rented (especially private rented) accommodation, exhibiting lower levels of income, employment and education, located in urban areas are least likely to have installed solar PV systems, which presents quite the quandary for policy makers and targeting initiatives within the housing system.

From a ‘greening’ of housing through the lens of adopting renewable technology, the results show that previous policy levers have, by-and-large, been unsuccessful in the adoption and uptake of renewable solar energy – certainly when considering the spatial nature of the uptake, and in terms of the UN Sustainable Development Goals of affordable and Clean Energy, sustainable cities and communities and combating fuel poverty. The previous policy lever to encourage PV adoption with financial incentivisation via the ROCs scheme was clearly an attractive proposition to a particular section of the community, but this research has established that as a policy driver its success was far from spatially uniform, with urban areas in particular not availing of financial incentives or initiatives, something which government need to take account of for future policy development.

Indeed, recent events within the global political economy, allied with heightening inflationary pressures, has thrown the green agenda and aspects of affordability in terms of the cost of living crisis and fuel poverty into sharp focus. The findings emanating from this research indicate that the installation of this type of renewable energy source, has the ability to alleviate the mounting cost of living pressures primarily from energy pricing, however, and most notability, not primarily for those who are in most ‘need’, with limited uptake exhibited by communities residing in areas of low(er) deprivation. Moreover, the findings show that tenure has an important role to play both in policy and practice. The advancement of the Private Rental Sector has obvious implications for the transition towards net-zero carbon neutrality in the housing sector. Our results show that the higher percentage of rental housing within an SOA, particularly urban based SOAs, lack PV adoption. This finding ties in with some important policy questions in relation to rental market regulation and some practical implementations for the split incentive debate.

Key questions for any targeted policy intervention are *where* and *how* to implement successfully. Our findings suggest that from an planning and urban policy perspective, the dichotomy that exists between uptake of PV adoption provides important insights as to where to target incentives such as differential grant funding and policy levers to areas where uptake would be supported, or conversely encourage the adoption in areas of lower socio-economic standing. This is not only critical information to help account for energy modelling and energy costing, but for providing access to those more disadvantaged groups of urban renters, or the hidden rural poor to key low cost at the point of use renewable energy resources.

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Endnotes

[i] PCA requires that the correlation matrix R = (R[Rmm]) is obtained through the transformation of the data matrix X = (X[mn]) into a matrix of standardised scores [Z] which are computed using the mean and standard deviation for each row *m* of the data matrix where *m* is the number of elements (variables) and *n* is the number of observations (column vectors) in the dataset. This is represented by the following formula:

$$Y^T = X^T W = V \sum T\ (X)$$

where the matrix is a diagonal [m x n] diagonal matrix with non-negative real numbers on the diagonal and W ∑ VT is the singular value decomposition of X. The variance is equal to the trace of the matrix, the sum of the diagonals or the number of observed variables in the analysis, minimising the sum of the squared perpendicular distance to the component axis. The factor scores [Snp] for the original *n* observation, on each p component are calculated by the following formula:

$$S_{np} = (Z_{mn} * L_{pm}^T)(X)$$

ii As de Smith et al. (2007) suggest the most common of which is the small sample corrected (asymptotic) Akaike information criterion (AICc)[ii]. This statistic applies the maximum likelihood estimates of the model parameters which is expressed as:

$$AIC = \; -2\ln\left(L(\hat{\beta}\,\middle|\,data)\right) + 2K$$

where $L(\hat{\beta}\,|\,data)$ is the log-likelihood function. In the regression setting, the estimates of β_i are based on least squares and the maximum likelihood estimates which are identical. The estimates are based on maximum likelihood estimates of the model parameters which provide an approximate AIC value:

$$AIC = n + nln(2\pi) + n\log\left(\frac{RSS}{n}\right) + 2K$$

iii The predictors are assessed within the model by examining the individual 'fit' employing the Wald statistic (z) and odds ratio (Exp of β). The z statistic[iii] indicates whether the β-value for the predictor is significantly different from 0; illustrating its significant contribution to the prediction of the outcome (Y). The odds ratio reflects the exponential of β and is an indicator of the change in odds resulting from a unit change in the predictor, with the odds of an event occurring defined as the probability of an event occurring divided by the probability of the event not occurring:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1X_{1i} + b_2X_{2i} \cdots b_nX_{ni})}}$$

Where the Odds = $\frac{P\ (event)}{P\ (no\ event)}$; $P(event\ Y) = \frac{1}{1 + e^{-(b_0 + b_1X_{1i}}}$; $P(event\ Y) = 1 - P(event\ Y)$

This provides the odds before and after a unit change in the predictor variable, thereby demonstrating the proportionate change in odds (Odds ratio) which can be interpreted as a value exceeding 1 (>1) to show that as a predictor increases, the odds of the outcome occurring increase, with <1 indicating that as a predictor increases, the odds of the outcome occurring decrease.

Parameter estimates averaged across OLS models using AICc Weights (wi)

Variable	Importance	Coeff.	Std Coeff.	Std Error	t	95% Lower	95% Upper
Constant	-	30.857	0	2.092	14.753**	26.757	34.956
Mixed	0.428	-2.386	-0.033	0.85	-2.808**	-4.051	-0.72
Urban	1	-7.915	-0.197	1.811	-4.37**	-11.465	-4.365
Social Rented %	0.419	-0.083	-0.061	0.032	-2.62**	-0.145	-0.021
Private rented %	0.926	-0.159	-0.076	0.057	-2.782**	-0.271	-0.047
House/Ha	0.884	-0.161	-0.088	0.058	-2.787**	-0.274	-0.048
Avg. HP	0.303	0.001	0.017	0.001	1.856	0.0003	0.0018
Economic [1st PC]	0.92	1.362	0.143	0.406	3.36**	0.568	2.157
Social [2nd PC]	1	-6.964	-0.386	0.772	-9.024**	-8.477	-5.452
Environment [3rd PC]	1	-3.296	-0.162	0.578	-5.707**	-4.428	-2.164
n	890						
R	0.686						
R^2	0.470						
Adj. R^2	0.466						
AICc.	7,275.08						

Note: Spatial parameters are excluded from initial model testing. PC = Principal Component.

Tables and Figures

Tables

Table 1 Descriptive statistics of PV installations and kW capacity within SOAs

	PV installations per SOA	kW capacity per SOA
Mean	22.072	89.501
S.E. of Mean	0.656	2.82
Std. Deviation	19.566	84.131
Minimum	0	0.4
Maximum	173	909.62
Range	173	909.62
1st Quartile	8	33.32
Median	16	63.855
3rd Quartile	30	123.04
n	890	890

Table 2 Explanatory variables descriptions and data sources

Variable	**Description**	**Year**	**Data Source**
PV installations	The number of PV installations within each SOA	2020	OFGEM
Houses per Hectare (House/Ha)	Number of houses per Hectare within each SOA	2017	NISRA
Multiple Deprivation Measure (domains)	Ranking of MDM domains from least deprived to most deprived across each SOA	2017	NISRA
Average House Price	The average house price within each SOA	2020	UU HPI
Rural-urban classification	The composition of SOAs by their urban, rural or mixed determination	2020	NISRA
Household tenure	The percentage of Owner-occupied, rental and social housing within each SOA	2011	ONS Census

Note: All data is presented at SOA scale level.

Table 3 Spearman's (rho) correlation coefficients between deprivation domains

	Income	Employment	Health	Education	Access	Environment	Crime
Income	1						
Employment	.693**	1					
Health	.595**	.955**	1				
Education	.713**	.859**	.888**	1			
Access	0.047	-.334**	-.424**	-.397**	1		
Environment	.230**	.208**	.187**	.182**	-.227**	1	
Crime	.424**	.701**	.733**	.707**	-.630**	.277**	1
PVs per SOA	-.149**	.566**	.250**	.240**	-.659**	.069*	.407**

**denotes significance at the 1% level; *denotes 5% level.

Table 4 Extraction variance

Components	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.195	59.930	59.930	3.537	50.535	50.535
2	1.175	16.792	76.722	1.708	24.394	74.929
3	30.924	13.205	89.927	1.050	14.998	89.927

Note: Extraction method; principal component analysis.

Table 5 Rotated loadings of the principal components

	Component loading 1	Component loading 2	Component loading 3
Explained variance	50.54%	24.39%	14.99
Employment	0.929		
Health			0.887
Education	0.870		
Income	0.855		
Access		-0.945	
Crime	0.615	0.645	
Environment			0.979

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 5 iterations.

Table 6 OLS Model Selection procedure sorted by AICc

Model	Variables	nVars	R^2	Cond.Num.	AICc	Delta AICc	L(gi|x)	AICc wi
Mod #334	1, 2, 3, 4, 5, 7, 8, 9	9	0.471	3.755	7267.74	0	1	0.189
Mod #79	1, 2, 3, 4, 5, 7, 8, 9	8	0.472	4.166	7268.20	0.459	0.795	0.15
Mod #271	2, 3, 4, 5, 7, 8, 9	7	0.471	4.777	7268.82	1.08	0.583	0.11
Mod #16	1, 2, 3, 4, 5, 7, 8, 9	8	0.472	4.9	7269.47	1.726	0.422	0.08
Mod #327	2, 4, 5, 6, 7, 8, 9	7	0.471	3.773	7269.62	1.878	0.391	0.074
Mod #72	1, 2, 4, 5, 6, 7, 8, 9	8	0.472	4.19	7270.04	2.3	0.317	0.06
Mod #264	2, 3, 4, 5, 6, 7, 8, 9	8	0.472	5.003	7270.58	2.831	0.243	0.046
Mod #9	1, 2, 3, 4, 5, 6, 7, 8, 9	9	0.472	5.115	7271.19	3.442	0.179	0.034
Mod #349	2, 4, 7, 8, 9	5	0.467	3.168	7271.97	4.223	0.121	0.023
Mod #274	2, 3, 4, 5, 8, 9	6	0.468	3.428	7271.99	4.254	0.119	0.023
Mod #286	2, 3, 4, 7, 8, 9	6	0.468	4.274	7272.06	4.316	0.116	0.022
Mod #365	2, 5, 7, 8, 9	5	0.467	3.622	7272.21	4.461	0.107	0.02
Mod #267	2, 3, 4, 5, 6, 8, 9	7	0.469	3.481	7272.39	4.645	0.098	0.019

Note: In total 511 OLS models run with the first 13 presented. Response variable is No. Res PV by SOA. Variable #1: Mixed; #2: Urban; #3: % Social rented; #4: % Private rented; #5: House/Ha; #6: Avg. House Price; #7: Economic status (PC1); #8: Social capital (PC2); #9: Wellbeing (PC3). Spatial parameters are excluded from initial model testing

Table 7 Moran's I values across the distance classes

D. Class	Dist. Cntr	PVs	Social Rent	Private Rent	Houses/Ha	Economic status	Social Capital	Wellbeing
1	3670.8	0.398**	0.311**	0.081**	0.969**	0.269**	0.744**	0.058**

2	9874.3	0.226**	-0.031**	-0.074**	0.174**	-0.127**	0.467**	0.016**
3	15213.1	0.066**	-0.034**	-0.038**	0.054**	-0.061**	0.211**	0.028**
4	20234.1	0.014**	-0.073	0.011	-0.016*	-0.078**	0.116**	-0.032**
5	25369.0	-0.064**	-0.053**	0.014**	-0.12**	-0.032**	-0.02**	-0.012**
6	30773.3	-0.061**	-0.011	0.038**	-0.071**	0.052**	-0.047**	0.009
7	36082.3	-0.044**	-0.024**	0.029**	-0.128**	0.004	-0.114**	0.009
8	41396.1	-0.048**	-0.035**	-0.013**	-0.115**	0.003	-0.095**	0.028**
9	46792.1	-0.055**	-0.038**	-0.04**	-0.138**	-0.008	-0.136**	0.011
10	52154.3	-0.013*	-0.028**	0.037**	-0.158**	0.026**	-0.121**	0.023**
11	57778.2	0.002	-0.047	.001	-0.158**	-0.016**	-0.164**	-0.006
12	64158.2	-0.044**	-0.025**	-0.028**	-0.101**	0.005	-0.214**	-0.059**
13	71240.1	-0.06	.001	-0.013**	-0.054**	-0.009	-0.162**	-0.051**
14	78706.7	-0.092**	0.015**	-0.006	-0.052**	-0.005	-0.136**	-0.021**
15	86919.7	-0.031**	-0.013**	0.019**	-0.067**	-0.01**	-0.086**	<.001
16	95564.4	-0.021**	0.08**	-0.025**	0.009	0.068**	-0.038**	0.002
17	105146.6	-0.093**	0.066**	-0.013**	0.004	-0.041**	-0.143**	-0.006
18	137843.7	-0.1**	-0.082	0.003	-0.051**	-0.06**	-0.083**	-0.016**

Note: Urban and mixed variables are binary and cannot be produced. **denotes significance at the 1% level; * 5% level.

Table 8 OLS and Poisson model results

Variable	OLS model			Poisson model		
	Coeff.	VIF	*t*	Coeff.	VIF	*z*
Constant	52.506		5.2**	3.99		29.571**
Urban	-7.716	2.879	-4.655**	-0.213	2.879	-8.241**
Mixed	-1.235	1.207	-3.157**	-0.151	1.207	-6.135**
Social Rented %	-0.036	3.891	-0.557	0.001	3.891	0.95
Private rented %	-0.194	1.412	-3.189**	-0.015	1.412	-10.91**
House/Ha	-0.098	2.205	-1.483	-0.028	2.205	-17.328**
Economic status [PC1]	1.464	4.604	2.942**	0.05	4.604	5.576**
Social capital [PC2]	-6.247	2.77	-8.568**	-0.246	2.77	-21.237**
Wellbeing [PC3]	-3.122	1.302	-5.541**	-0.079	1.302	-9.469**
X coord.	<.001	1.508	-3.962**	<.001	1.508	-9.41**
Y coord.	<.001	1.158	-0.178*	<.001	1.158	1.367*
R^2	0.482			0.508		
Adj. R^2	0.477					
F	90.817					
AICc	7255.72			9703.58		
n	890			890		

Note: Various polynomial expansions were applied to the geographic coordinates to increase explanation and model stability. The R^2 for the Poisson model is a pseudo-R^2.

Table 9 Eigenvector Spatial Filter model coefficients

	Coefficients	V.I.F.

Intercept	31.02**	
Urban	-7.376**	3.784
Mixed	-1.099	1.333
Social Rented %	-0.055	4.357
Private rented %	-0.179**	1.479
Houses/Ha	-0.097	2.568
Economic status [PC1]	1.932*	4.701
Social capital [PC2]	-6.523**	2.914
Wellbeing [PC3]	-4.104**	1.384
Filter 1	-80.354**	1.97
Filter 2	11.885	1.059
Filter 3	29.971*	1.094
Filter 6	-5.625	1.146
Filter 7	58.38**	1.061
Filter 8	-24.393*	1.051
Filter 10	-31.873*	1.069
Filter 12	3.286	1.043
Filter 13	-55.404**	1.022
Filter 25	-45.01**	1.012
Filter 31	23.883	1.01
Filter 38	-9.131	1.05
Filter 50	-20.96	1.03
Filter 51	-28.022*	1.043
Filter 54	-22.143	1.024
Filter 64	-33.237**	1.027
Filter 71	28.688*	1.007
Filter 93	-46.492**	1.012
Filter 122	38.191**	1.015
Filter 228	40.503**	1.005
Filter 229	-27.686*	1.007
[a] Predictors only R^2	.463**	
[b] Filters only R^2	.335**	
Shared explained variance	.273**	
Full model (Predictors + filters)	.524**	
AICc	7214.52	

Note: **denotes significance at the 1% level, *5% level.

Table 10 Lagged response and predictor models

	Lagged response		Lagged predictor		
Variable	Coefficient	*t*	Coeff.	Gamma	*t*
Constant	-0.571	-1.063			
Urban	-0.375	-4.248**	-0.189	0.647	-4.314**
Mixed	0.008	0.08	-0.014	0.146	-0.496
Social Rented %	0.007	2.125*	-0.06	0.541	-1.132
Private rented %	-0.012	-3.686**	-0.094	0.59	-2.615**
House/Ha	0.008	2.277*	-0.125	0.703	-3.137**
Economic Status [PC1]	0.108	4.096**	0.091	0.582	1.543
Social Status [PC2]	-0.143	-3.686**	-0.323	0.691	-7.338**
Wellbeing [PC3]	-0.183	-6.115**	-0.161	0.387	-5.643**
X coord	<.001	3.481**	-0.273	0.942	-3.696**

Y coord	<.001	-0.372*	-0.07	0.926	-1.078
R	0.484		0.554		
R^2	0.434		0.507		
Autoregressive (ρ)[1]	0.614		0.614		
SE of rho	0.637		0.637		
AICc	7327.18		7257.438		
n	890		890		

Note: [1]Response Variable Spatial Autoregressive Coefficient (rho).

Table 11 Local Regression Parameter Descriptive Statistics

Variable	Min.	Lower Q.	Median	Upper Q.	Max.
Constant	11.4623	27.7003	30.0051	35.2714	105.639
Urban	-24.7811	-10.1705	-9.1423	-1.6533	15.0238
Mixed	-6.5463	-2.8750	-1.0260	0.0321	3.9867
Social Rented %	-2.566	-0.2305	-0.0424	0.0036	1.7739
Private rented %	-2.0967	-0.4402	-0.1136	-0.0735	1.3108
House/Ha	-2.6108	-0.5268	-0.1404	-0.1184	1.4711
1st Principal Component	-16.5704	0.53643	1.0767	1.1383	18.874
2nd Principal Component	-14.3369	-7.0982	-4.6302	-4.0915	7.4530
3rd Principal Component	-10.6866	-3.1638	-1.8728	-1.5004	13.1481
R^2	.625				
Adj. R^2	.579				
F	12.968				
AIC	7185.35				
n	890				

Optimization using The Golden Section Search, and Akaike Information Criterion (AICc), searching from 26084.26 to 39126.39 distance units. The analysis examined various spatial weighting functions (Bi-Square; Moving Window; Adaptive Spatial Kernel for minimising nearest neighbours using AIC optimisation).

Table 12 Logistic Regression and Odds Ratios

	Urban			Rural		
Variable	Coefficient	t	Exp(β)	Coefficient	t	Exp(β)
Constant	-64.737	-3.682**	.001	66.572	4.611**	.001
No. of PVs	-0.022	-2.069*	0.978	0.002	2.211*	1.002
Owner	0.663	3.662**	1.94	-0.701	-4.698**	0.496
Social	0.689	3.668**	1.991	-0.743	-4.717**	0.476
Private	0.682	3.721**	1.978	-0.699	-4.642**	0.497
House/Ha	0.331	5.448**	1.392	-0.117	-2.544*	0.889
Economic status	-0.766	-3.93**	0.465	0.528	3.275**	1.695
Social capital	2.353	7.348**	10.514	-2.178	-8.508**	0.113
Wellbeing	1.089	4.939**	2.97	-0.694	-4.279**	0.500
McFadden's ρ^2	0.7656			0.6436		
Chi-Squared	906.272**			699.844**		
AIC	295.5088			405.494		
LL(0)	-591.891			-543.669		
LL(N)	-138.754			-193.747		
2*[LL(N)-LL(0)]	906.2723			699.844		

Note: Results for Urban & Rural as response variables. Classification Table and Measures of Accuracy available upon request. **denotes significance at the 1% level; *5% level.

Figures

Figure 1 Local distribution of the number of PV installations and KW output at SOA level across NI

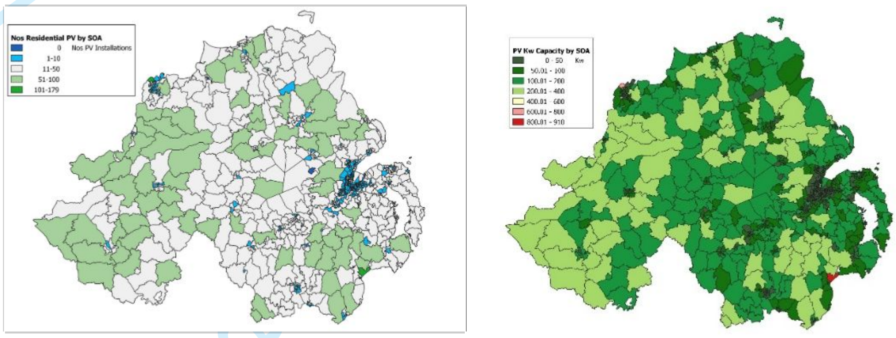


Figure 2 The Classification and spatial distribution of SOAs and MDM

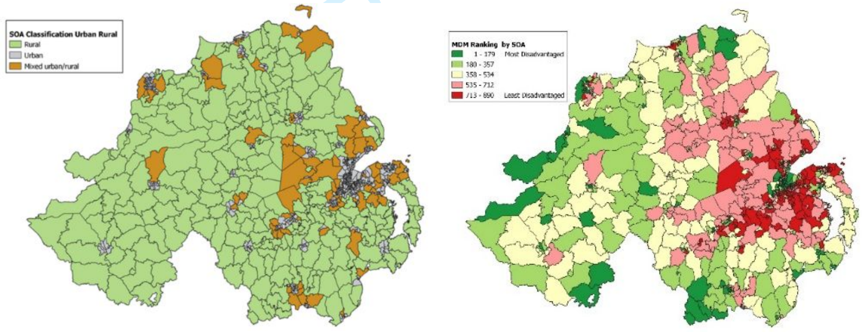


Figure 3: Correlation Biplots for extracted factors

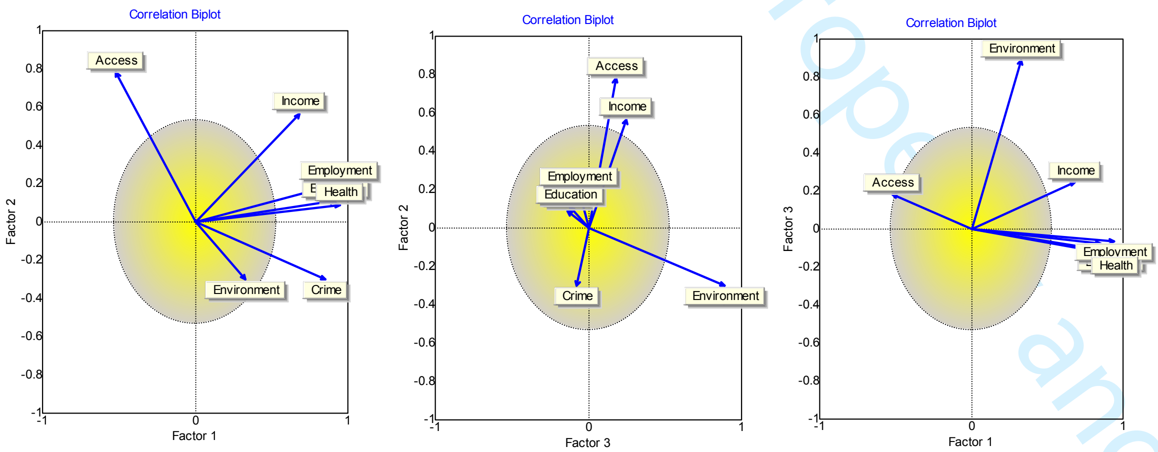


Figure 4 Spatial representation of the extracted and retained Principal Components

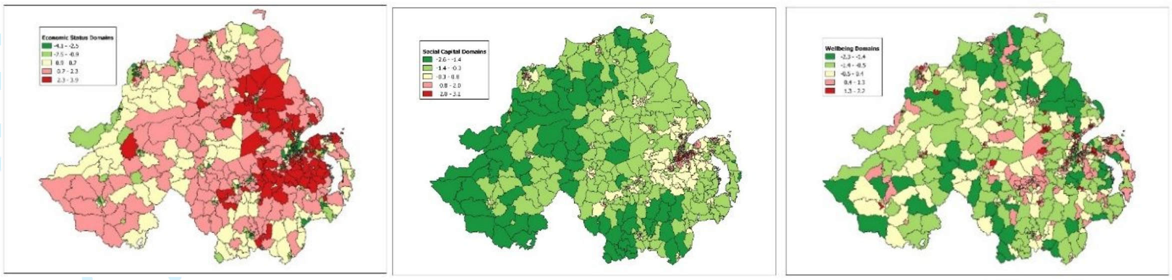


Figure 5 L.I.S.A spatial structure (PV installations)

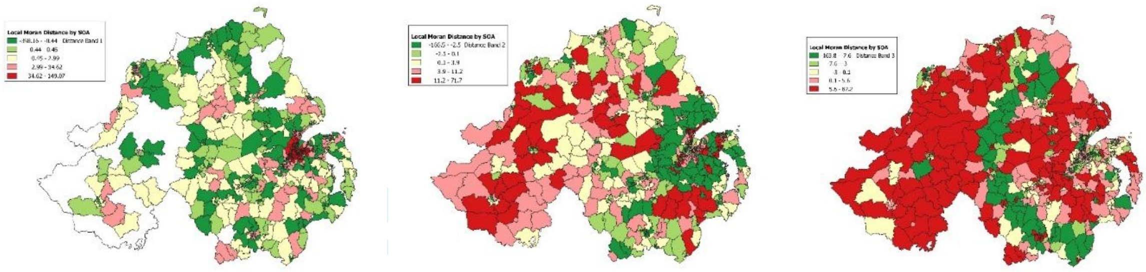


Figure 6 L.I.S.A Scatterplots for PV across avg. nearest neighbour classifications

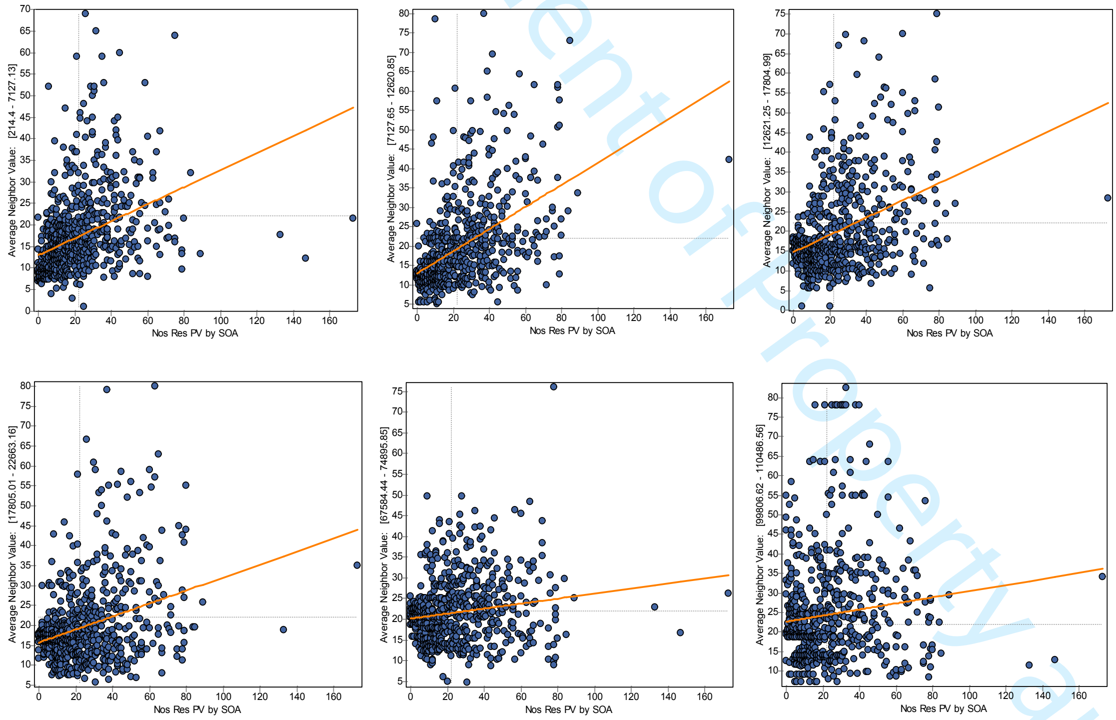


Figure 7 Extracted Spatial Filters[1]

[1] A selected number of Spatial Filters are displayed due to space limitations. The full list of the extracted 21 Filters are available upon request.

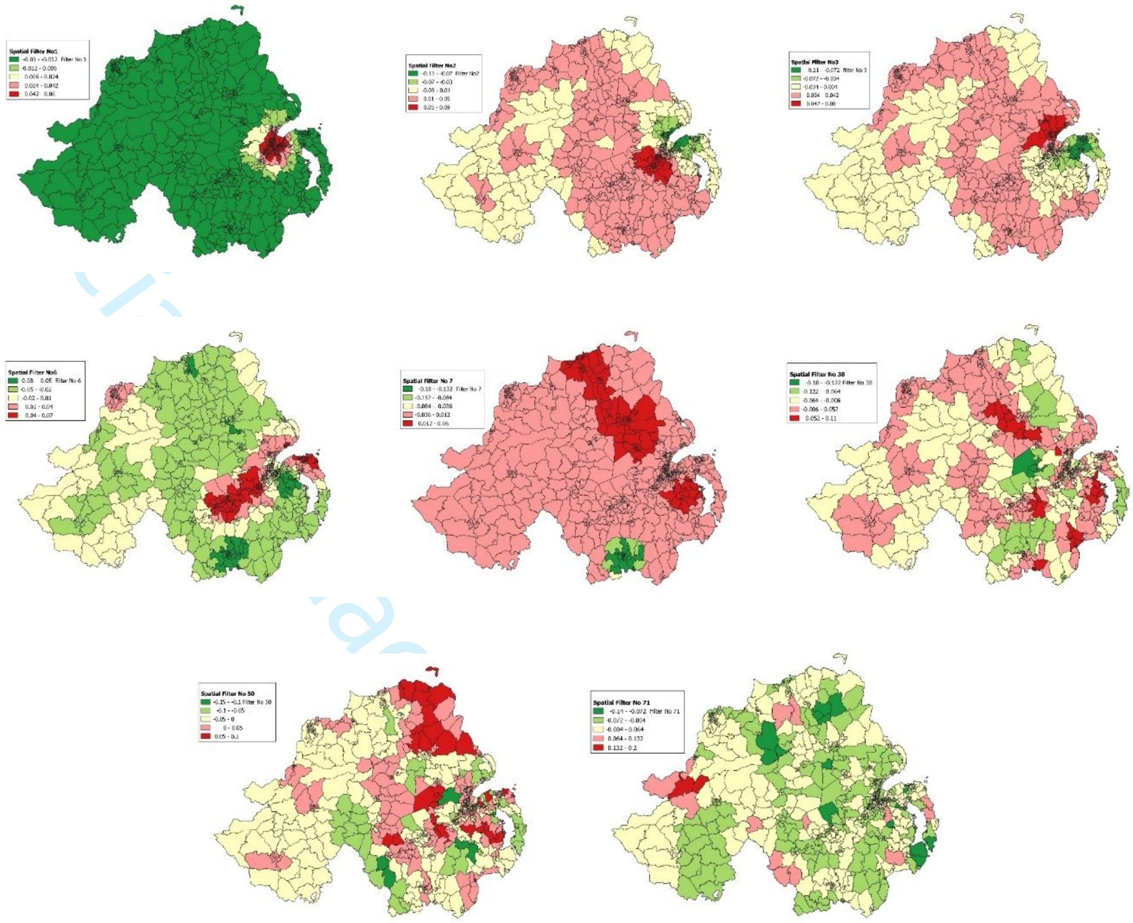
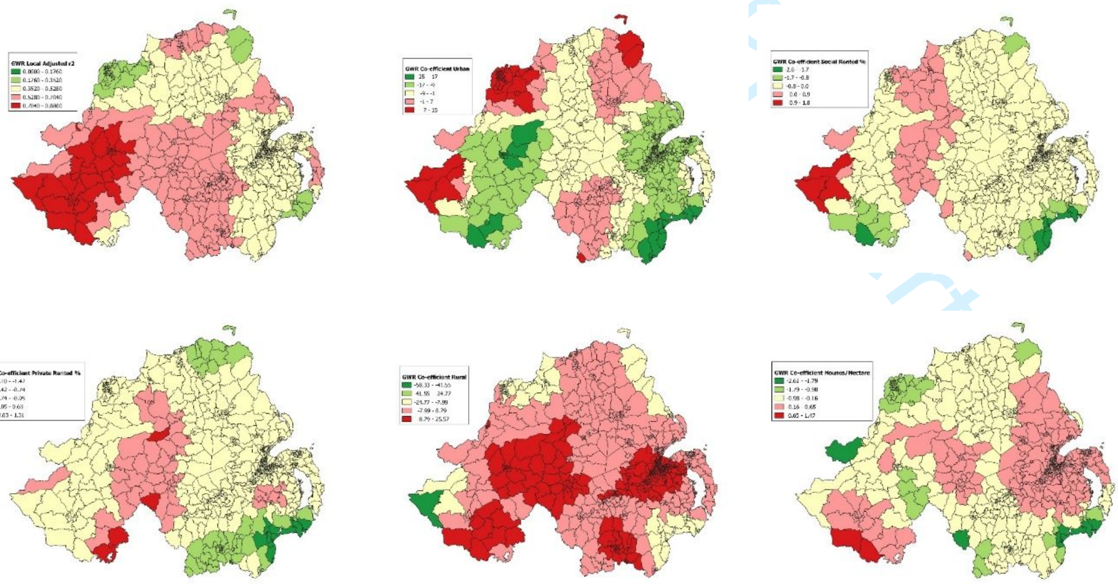
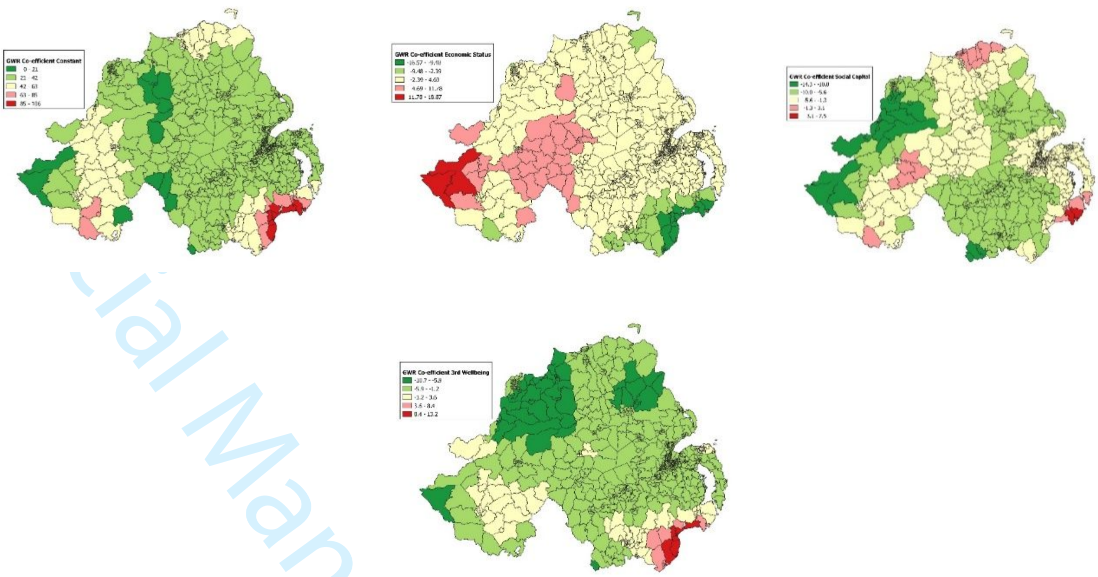


Figure 8 GWR coefficient maps




GWR Co-efficient Constant
0 - 21
21 - 42
42 - 63
63 - 85
85 - 106
GWR Co-efficient Economic Status
-16.57 - -9.48
-9.48 - -2.39
-2.39 - 4.69
4.69 - 11.78
11.78 - 18.87
GWR Co-efficient Social Capital
-10.0 - -5.6
-5.6 - -1.2
-1.2 - 3.1
3.1 - 7.5
GWR Co-efficient 3rd Wellbeing
-10.7 - -5.9
-5.9 - -1.2
-1.2 - 3.6
3.6 - 8.4
8.4 - 13.2