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"When Kermit the Frog sang 'It's Not Easy Bein' Green' I want you to know he was wrong - and he was also unnecessarily rude to Miss Piggy. "We have the technology: we have the choice before us."

- *Boris Johnson, UK Prime Minister, at COP26*

Abstract

The urgent decarbonisation of domestic power and transport sectors in England is crucial for enabling the green transition and mitigating against the potentially adverse effects of climate change. Solar panels (PV) and battery electric vehicles (BEV) are the low carbon technologies at the heart of the domestic green transition, with their market share soaring over the past decade in England. Effective decarbonisation requires a uniform and just transition to clean energy and transport, yet the spatial distribution of domestic solar panels and battery electric vehicles remains relatively unexplored in England. To understand these patterns of PV and BEV diffusion, literature has studied the determinants of adoption, constructing consume profiles to explain the key characteristics of adopters.

This study explores domestic solar panel and battery electric vehicle diffusion in England through time and space, from 2011 to 2021 across English local authorities, and finds solar panel markets to be more mature. Using local indicators of spatial autocorrelation, this study determines distribution of PV and BEV to be spatially organised, finding their regions of high adoption to contrast, appearing almost inverse. This has implications for the smart energy transition which intends to integrate the transport and mobility sectors using these low carbon technologies. Selecting a variety of social, economic, built environment and lifestyle characteristics, this study analyses the relative control of local factors in explaining solar panel and battery electric adoption using both simple and multiple regression models, and a Spearman's Rank correlation analysis. The local characteristics offered conflicting control over determining PV and BEV adoption, explaining the observed distinct spatial distribution of these technologies in England. These local characteristics were deemed more effective in explaining solar panel adoption, with battery electric vehicle adopters appearing a more diverse group. Whilst further research is necessary to better understand the forces behind these determinants of adoption and to identify the differing determinants of battery electric vehicle adoption, this study is a very useful starting point for significantly enhancing understanding of the geographies of the green transition in England. To overcome the spatial and temporal mismatch in solar panel and battery electric vehicle adoption, this dissertation advocates a more local approach to incentivising domestic investment in low carbon technologies. Arguably reducing the observed local barriers to adoption could stimulate the necessary urgent and uniform diffusion of residential solar panels and battery electric vehicles in England. A rigorous and just green transition is fundamental for enhancing unanimous accessibility to aspirational low carbon futures and to enable the construction of smart energy systems.

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1. Introduction

1.1. Context

The UK Government is committed to achieving net zero greenhouse gas emissions (GHGs) by 2050 as outlined in their 2021 'Net Zero Strategy' (Department for Energy Security and Net Zero and Department for Business, Energy & Industrial Strategy, 2021). As the second largest emitter of GHGs in EU14 (the 14 EU member states prior to 2004) (Office of National Statistics, 2022a), a thorough and extensive decarbonisation of the UK economy, shifting dependence away from non-renewable, carbon-intensive forms of energy is vital to enhancing energy security and avoiding the potentially adverse impacts of climate change (Castaneda et al., 2020; Balcombe et al., 2014). With transport and energy, the two most polluting sectors in the UK, cumulatively contributing to 45% of GHG emissions in 2020 (Department for Business, Energy & Industrial Strategy, 2022), it is also imperative for the UK to focus decarbonisation efforts within these sectors. More specifically, decarbonisation efforts must be focused within the home. As households are responsible for 26% of national energy emissions (Office of National Statistics, 2022b) and 83% of the emissions from the transport sector (Office of National Statistics, 2023a), UK consumers must play a critical role in the reduction of fossil fuel consumption (Bergman and Eyre, 2011) to achieve ambitious net zero targets.

Domestic decarbonisation is enabled by energy transition technologies (ETT) (Heymann et al., 2019). Photovoltaics/solar panels (PV), the most common domestic renewable energy installation (UK Alternative Energy, 2023), and electric vehicles (EV), the UK's primary mechanism deployed to reduce GHG emissions in the transport sector (Morton et al., 2018; Egbue and Long, 2012), are the low carbon technologies at the heart of the domestic energy transition. To achieve the UK Government's recent ambition for all new cars and vans to be fully zero emission at tailpipe by 2035 (Department for Transport, 2022), the decarbonisation of the mobility sector must specifically focus on deployment of battery electric vehicles (BEV) (Hardman et al., 2017) which, unlike their rival the plug-in-hybrid (PHEV), produce no tailpipe emissions (EPA, 2023). Whilst the BEV was introduced in 2008 with the Tesla Roadster, very few units were sold until 2012 when BEVs began to enter domestic markets (Hardman et al., 2017). The first residential PV was installed in the UK in 1994, with PV markets acknowledged as more mature than BEV markets (Wind and Sun, 2014), although it wasn't until 2011 that domestic PV adoption began to take off (Brighton Energy Cooperative, undated). Literature observes rapid growth in BEV and PV adoption over the last decade (e.g., Balta-Ozkan et al., 2021; Morton et al., 2018).

However, the total market share of PVs in conventional energy and vehicle markets remains low (Balcombe et al., 2014).

1.2. Study Rationale

Increasing pressure on enhancing ETT adoption has motivated research into the characteristics of EV and PV diffusion/spread through society, identifying possible barriers and motivators to EV and PV adoption (van der Kam et al., 2018). Understanding patterns of PV and EV adoption is vital for gauging the timeframes associated with visions of a smart clean energy system in the UK (van der Kam et al., 2018). To enable decarbonisation processes, the UK government are reliant on the construction of smart energy infrastructure which involves an integration of the power and mobility sectors (van de Kam et al., 2018). With ETTs operating either the production or consumption of electricity, smart energy systems intend to relieve resulting heightened pressure on the electricity grid, including the prospective drain from BEVs (Department of Transport, 2022). PVs and BEVs present a prime opportunity to integrate these sectors; the intermittent power generation of PVs is optimal to match the discontinuous electricity demand from EVs, connected through smart charging infrastructure (Gomes and Suomalainen et al., 2020). Adoption of EVs and PVs in synergy facilitates the necessary simultaneous decarbonisation of both the energy and mobility sector. Although still in the development process, the vehicle-to-grid (V2G) system is the forthcoming technology designed to enable the construction of smart energy infrastructure. Essentially, when electricity supply is low but demand is high, V2G infrastructure allow EVs plugged into the grid to release power back into circulation, thus alleviating the excess pressure on the grid (House of Commons Library, 2023). The UK Government has expressed serious interest in deploying the V2G technology, launching innovation campaigns and £30 million of investment in 2017 and 2018 for technology development (House of Commons Library, 2023).

The construction of smart energy systems is dependent on co-adoption of PVs and BEVs, yet literature has observed spatially and temporally distinct patterns of PVs and BEVs in the UK (Balta-Ozkan et al., 2021; Morton et al., 2018). BEV and PV diffusion is rarely studied simultaneously, so the feasibility and pace of the smart energy transition in the UK remains relatively unknown (Gomes and Suomalainen et al., 2020). Analysis of the spatial distribution of BEVs and PVs and defining their corresponding consumer groups, can help to determine the readiness of the UK in its transition to a sustainable smart energy system (van der Kam et al., 2018). Studying the geographies of BEV and PV diffusion is vital to understanding the local characteristics which motivate their adoption (Collier et al., 2023). Critical insight into the current status of BEV and PV diffusion patterns in the UK can help shape more effective policies to stimulate the crucial further growth of domestic ETTs necessary to meet ambitious decarbonisation targets in the UK (Nayum et al., 2016; Plotz et al., 2014).

1.3. Aims

This dissertation intends to analyse patterns of both BEV and PV adoption in English local authorities from 2011 to 2021. Employing well established techniques, this study presents pioneering research exploring the changing spatial distribution of BEVs and PVs in England throughout the last decade. Using a regression model, this dissertation will also explore the relative importance of selected barriers and motivators to ETT adoption taken from the most recent Census data (2021) which has not yet been analysed in literature. Drawing together the spatial and temporal diffusion patterns of BEV and PV adoption, this study will finally determine the feasibility of the smart energy transition by assessing the spatial convergence of ETT uptake within English local authorities in 2021.

1.4. Research Questions (RQs)

a. How has the distribution of domestic PVs and BEVs in England changed from 2011 to 2021?
b. How does the distribution of domestic PVs and BEVs differ in England?
c. To what extent do social, economic, built environment and lifestyle characteristics explain adoption patterns of domestic PVs and BEVs in England?

2. Literature Review

2.1. Innovation Adoption Theory.

The term ‘early adopter’ refers to the early user group of a new technology (Rogers, 2003; Santini and Vyas, 2005). This first large group of adopters play a crucial role in catalysing/defining roll-out of technology diffusion (Nath, 2016; van der Kam et al., 2018). Rogers’ technology adoption diffusion theory (2003) characterises pathways of technology adoption, shifting from initial ‘innovators’ (first 2.5% of adopters) to ‘early adopters’ (following 13.5%) and then to ‘majority markets’. The penetration of new technologies into larger markets is a slow process (Nygren et al., 2015; Snape, 2016) as consumers do not act as rational economic agents. Whilst investing in a technology might make financial sense, this often does not translate into an investment (Hardman et al., 2017). The differing socio-demographic characteristics of adopter groups may determine their decision to invest in a technology at certain periods in time (van der Kam et al., 2018). Studying the spatial configuration of diffusion and the timing of adoption can help identify various motivations and barriers to adoption, useful for developing appropriate and effective incentive policies (Müller and Rode, 2013).

Literature suggests that the UK is in the early adopter stage for both BEV and PV diffusion (Morton et al., 2018; Balta-Ozkan et al., 2021). These ETTs are still developing and are yet to become financially competitive with traditional mobility vessels (i.e., cars with combustion engines) and power sources (i.e., fossil fuel combustion) (Mukherjee and Ryan, 2020). Like Plotz et al. (2014) this dissertation also applies the innovation adoption theory in a more practical manner, using the term 'early adopter' to refer to the current private BEV and PV consumer groups.

2.2. Determinants of Adoption.

Understanding the socio-economic and behavioural attributes of innovation adopters and local characteristics which determine ETT adoption, is useful for defining the predictors of technology diffusion (Rogers, 2003).

The socio-psychological controls over early adoption of ETTs is a prominent consideration in literature. These are factors which influence consumer perception, behaviour and acceptance of a technology (Egbue and Long, 2012). The theory of planned behaviour and the rational choice theory come up most frequently in literature to explain the behaviour of early ETT adopters, suggesting people act based on an evaluation of consequences (Ajzen, 1991; Moons and De Pelsmacker, 2012; Wang et al., 2019; Nayum and Simsekoglua, 2016). Intentions and attitudes of potential adopters, including knowledge and experience of a technology, therefore act as useful predictors of behaviour (Egbue and Long, 2012; Rezvani et al., 2015; Lane and Potter, 2007; Moons and De Pelsmacker, 2012; Sovacool and Hirsh, 2009). Technologies can help individuals express and define themselves thus embodying symbolic meaning, with ETT adopters potentially looking to convey a particular message (Burgess et al., 2013; Noppers et al., 2014; Schuitema et al., 2013). Finally, the influence of 'peer/neighbourhood effects' is the subject of a huge body of literature on technology adoption, found to play a very important role in determining ETT adoption tendencies (e.g., McCoy and Lyons, 2014; Palm, 2018; Mcshane et al., 2012). This phenomenon can be used to explain the development of social norms and 'green neighbourhoods' which contain significant high clusters of ETTs (Kahn, 2007).

Previous studies have identified a wealth of potential determinants of both domestic EV and PV adoption. Figure 1 captures the key barriers and motivators to adoption divided into the eight recurring categories found in literature. The relative importance and effect on adoption varies for most characteristics outlined in figure 1, with most identified as both a barrier in some studies and a motivator in others. For EVs, literature emphasises the importance of distinguishing between BEVs and PHEVs due to their often-contrasting influence over adoption tendencies, with BEVs more frequently purchased as a second car (Anable et al., 2013). Generally, EVs are found to cluster in more densely populated areas, particularly small towns or suburban locations, whilst PVs are located in more rural regions (Kihm and Trommer, 2014). High purchase price has consistently been identified as a barrier to adoption (Nayum and Simsekoglua, 2016), therefore BEV and PV markets are generally located in economically prosperous regions (Morton et al., 2018). Whilst environmental attitudes have been shown to influence both EV and PV adoption (Ziegler, 2012), literature generally suggests environmental values do not necessarily translate to a willingness to pay, proposing economic motives as a more decisive factor for early adoption (Hidrue et al., 2011; Egbue and Long, 2012).

Range anxiety specifically applies to EVs. The concern that EVs will not be able to travel far without needing recharging (Plotz et al., 2014; Skippon and Garwood, 2011) is a crucial barrier to adoption. Literature has therefore observed a positive impact of charging infrastructure on EV adoption to manage range anxiety (Sierzchula, 2014). However, the complex chicken and egg causal relationship of charging infrastructure and EV adoption makes it difficult to determine the genuine effect of charging infrastructure (Merksy et al., 2016; Coffman et al., 2017). Solar irradiation is the only factor specifically relevant for PV installation, with literature emphasising its importance for early adopters (e.g., Balta-Ozkan et al., 2015; Snape, 2012).

Literature identifies conflicting socio-demographic factors characterising PV and BEV adopters. Early PV adopters are generally determined to be white, well-educated, middle-aged males, (e.g., Balcombe et al., 2013; Sardianou and Genoudi, 2013, Bartiaux et al., 2016), who reside in larger houses, particularly detached houses (Claudy et al., 2011; Balta-Ozkan et al., 2015), located in less densely populated areas (Graziano and

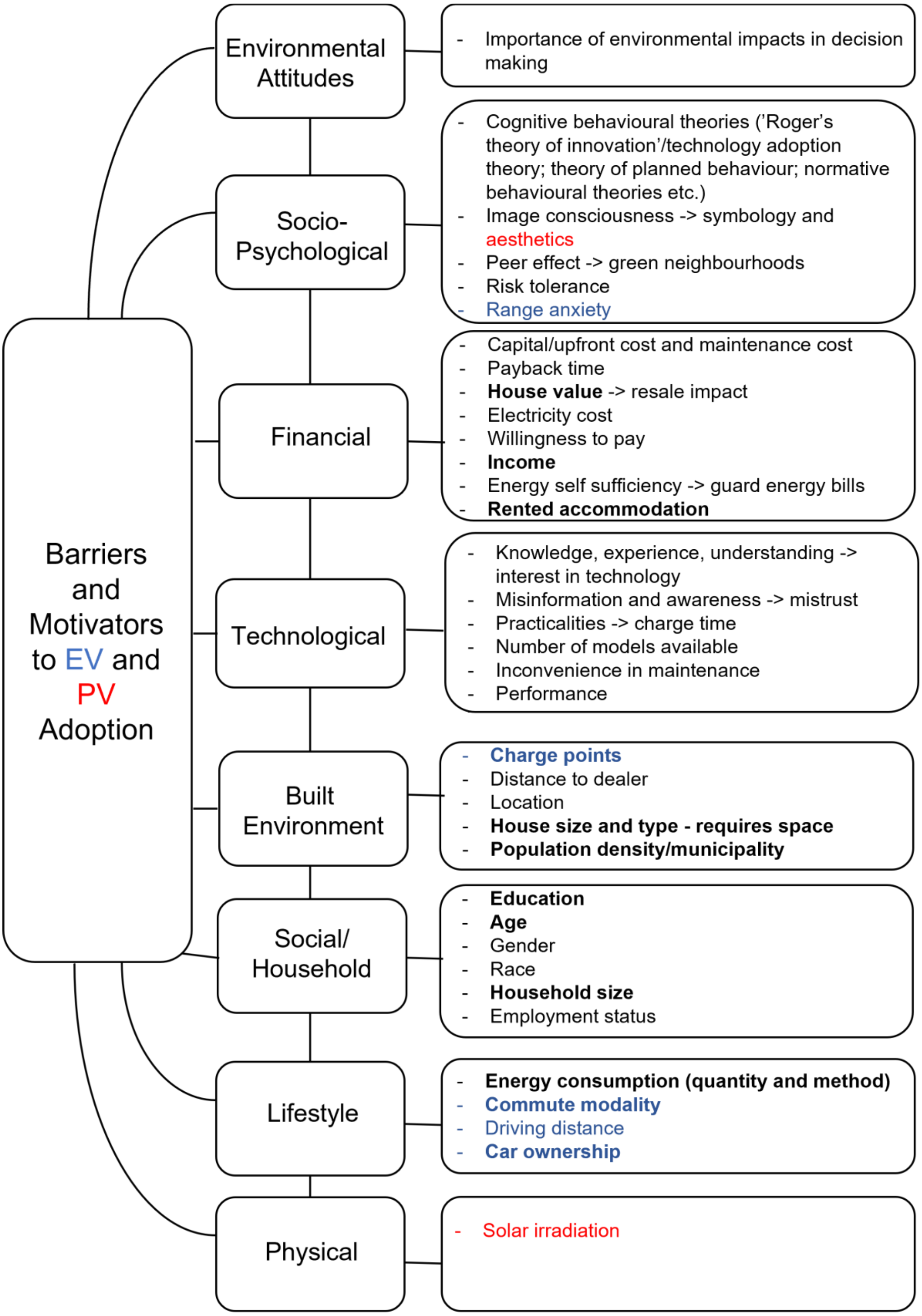


Figure 1. Summary diagram of the key determinants of electric vehicle and solar panel adoption identified in literature (references cited in text). Those explicitly relevant to EVs are marked in blue and for PVs are marked in red. The variables marked in bold text are studied in this dissertation.

Gillingham, 2015; Comello et al., 2018). Whilst literature has found potential PV adopters to be excited by opportunities for protection from energy prices, uncertainties about the nature of PV technology, particularly regarding payback, reliability and maintenance, could possibly negate installation (Balcombe et al., 2014). Ample studies have found income to positively correlate to PV adoption (Kwan, 2012; Müller and Rode, 2013), suggesting that high earners are more likely to install due to the high capital cost (van der Kam et al., 2018). Others suggest disposable income is more important than gross annual income (Balta-Ozkan et al., 2015). Conversely, EV adopters generally have a higher social status, work full-time and own their own homes (Muhkerjee and Ryan, 2020; Plotz et al., 2014). This group of early adopters are typically young or middle aged, live in larger households, own more cars, are well educated and are typically male, (e.g., Muhkerjee and Ryan, 2020; Morton et al., 2018) although the effect of gender is also contested in literature (Wang et al., 2016; Nayum and Simsekoglua, 2018). Literature emphasises the vast and complex network of local characteristics which determine the unique patterns of ETT diffusion.

To stimulate PV and BEV adoption, monetary and non-monetary policies produced by national governments have been designed to address these barriers to adoption (Hirdue et al., 2011; Heymann and Miranda et al., 2019). Literature determines financial policies as the most common method of incentivising uptake (Rezvani et al., 2015), as overcoming fiscal barriers, like high purchase price and long payback times, is fundamental to accelerating the initial growth in early adoption. The UK has traditionally developed national incentives, notably the Plug-in Car Grant for EVs and the Feed-in-Tariff for PVs (International Council on Clean Transportation, 2016).

To meet the mandatory emissions reduction targets for new cars implemented by EU legislation by 2009, the UK government has successfully introduced policies to incentivise adoption of EVs (House of Commons Library, 2023; Egbue and Long, 2012; Hardman et al., 2017). Literature emphasises difficulties measuring the actual effect of incentives, however generally, a positive relationship between EV incentives and EV sales is observed in the UK (Sierzchula et al., 2014).
These incentives are largely fiscal, moderating the high costs associated with investing in an EV. The UK government has spent £1.5 billion funding the Plug-in Car Grant (PIG) introduced in 2010, and although the categories and thresholds have become more stringent over the decade, it has supported the purchase of almost half a million vehicles (House of Commons Library, 2023). However, in 2020 a managed exit from the scheme was announced. Additionally, exemption from the Vehicle Exercise Duty (VED), the tax

applicable to all vehicles driving on UK roads (Office for Low Emission Vehicles, 2018; Santos and Rembalski, 2021), further reduces the costs associated with EV adoption. The UK government have more recently shifted their focus towards extending public EV charging infrastructure (International Council on Clean Transportation, 2016; Hardman et al., 2016). This includes the £950 million rapid charging fund introduced in 2020 to fund the rollout of 6000 high powered charge points across England, and the £500 million of funding allocated to local authorities to enhance charge point coverage (Department for Transport, 2022).

PV government incentives are also predominantly fiscal (Palm, 2018; Bunea et al., 2020). Since initial incentives have been implemented in the UK in 2010, small-scale PV uptake has flourished (Balcombe et al., 2014; Cherrington et al., 2013). The Feed-in Tariff (FiT) is the main government policy designed to promote the uptake of household renewable energy/low carbon technology, encompassing PVs alongside other ETTs like wind and hydropower (Ofgem, 2023; Cherrington et al., 2013). The tariff is paid to PV owners, receiving a payment for each kWh of PV energy produced and selling excess electricity back to suppliers at an export tariff rate (Castenda et al., 2020). Introduced in 2010, the initial FiT rates were generous but since 2011 the severe decline in PV costs and rise in PV installations has seen the value of the tariffs steadily reduce (Smith et al., 2014; Candelise et al., 2013). Despite the subsidy cuts, triggering an increase in payback periods for the technology, domestic installations continued to increase throughout the last decade. The announcement of scheme closing in April 2019, prompted a rush in PV installations before the deadline, despite being replaced with the Smart Export Guarantee in 2020 (Castenda et al., 2020).

2.3. Co-adoption of EVs and PVs

The co-adoption of EVs and PVs is relatively understudied in the literature (Araújo et al., 2019). Van der Kam et al. (2018) present a novel paper comparing the influence of socio-demographic factors on diffusion patterns of EVs and PVs in the Netherlands, identifying a geographical misfit in spatial adoption patterns. They note the implications of this mismatch for the smart energy transition which is dependent on the adoption of EVs and PVs in synergy (Heymann and Miranda, 2019) and advocate a policy shift to promote the co-adoption of EVs and PVs.

3. Methodology

This dissertation analyses the dynamic and diverging patterns of BEV and PV diffusion in England from 2011 to 2021. Local Moran's I statistics are deployed to identify areas of significant BEV and PV clustering for their 2021 datasets. Using a regression model and further Moran's I spatial analysis, local characteristics are also applied to the 2021 BEV and PV datasets to determine which variables offer the most explanatory power over the adoption of BEVs and PVs in England.

3.1. Dependent variables

The dependent variables, BEV and PV adoption, used in the regression model are outlined in table 1. Data on BEV registrations originates from the Department for Transport (DfT) and Driver and Vehicle Licensing Agency (DVLA). This dissertation is specifically focusing on fully electric vehicles as they will characterise the green mobility transition given the UK Government is committed to removing tailpipe emissions by 2035. The BEV dataset for this study therefore only includes privately owned battery electric or range extended cars (both have no tailpipe emissions). Data for residential PVs is taken from the Department for Business, Energy and Industrial Strategy (BEIS), specifically small-scale (not exceeding 5MW) domestic FiT accredited PVs. Whilst this does not cover all domestic PV investments, as some individuals may have installed PVs without utilising the government grant, this is the most thorough and extensive dataset on PV adoption in England. However, the slow FiT accreditation process might produce a lag in the PV data, running a few months behind real time instalments.

All BEV and PV data has been extrapolated, compiled and processed in MS Excel, with maps produced in ArcGIS. To enable comparison, PV and BEV adoption have been normalised to the number of instalments/registrations per 1000 people. Figure 2 depicts the distribution of both BEVs and PVs per 1000 people in English local authorities for 2021, with datasets composed of local authority scale data. These local authority district boundaries (LADs) are defined by the Office for National Statistics (ONS) in April 2021 (ONS, 2021) and compose the seven wider regions in England marked in figure 3. The analysis of PV and BEV diffusion, including the spatial autocorrelation analysis and regression analysis, is all performed for 2021 datasets. However, this dissertation also contrasts the distinct patterns of BEV and PV adoption from across the past decade, 2011 to 2021.

Code	Description	Detailed Description	Units	Year	Data Scale	Data Source
PV	PV Adoption	The number of domestic Feed-in-Tariff (FiT) accredited photovoltaic installation per 1000 people within each local authority. It often takes several months for the FiT accreditation to be registered by the BEIS so this is not a direct representation of December 2021.	Per 1000 people	December 2021	Local authority	Department for Business, Energy and Industrial Strategy (BEIS)
BEV	BEV Adoption	The number of Battery Electric Vehicles (BEV) and Range Extended Electric Vehicles (REEV) registered per 1000 people within each local authority. This does not include Plug-in-Hybrids. This only includes privately owned vehicles, not company vehicles. This only includes cars, not vans. The vehicle location is based on where the keeper's address is registered, this does not necessarily reflect the exact location of the vehicle.	Per 1000 people	December 2021	Local authority	Department for Transport (DfT) and Driver and Vehicle Licensing Agency (DVLA)
AGE	Age	The median age of usual residents* in each local authority population. Age is taken as the age as of someone's last birthday. Infants under one years old are classed as 0.	Median (of residents)	March 2021	Local authority	Census 2021
ED0	Education Level - Qual None	Percentage of usual residents (aged over 16) in each local authority with no formal qualifications.	% (of residents)	March 2021	Local authority	Census 2021
ED1	Education Level – Qual 1 & 2 [c]	Percentage of usual residents (aged over 16) in each local authority with Level 1 or 2 as their highest level of qualification. Level 1: 1 to 4 GCSEs grade A* to C, any GCSEs at other grades, O levels or CSEs (any grades), 1 AS level, NVQ level 1, Foundation GNVQ, Basic or Essential Skills. Level 2 qualifications: 5 or more GCSEs (A* to C or 9 to 4), O levels (passes), CSEs (grade 1), School Certification, 1 A level, 2 to 3 AS levels, VCEs, Intermediate or Higher Diploma, Welsh Baccalaureate Intermediate Diploma, NVQ level 2, Intermediate GNVQ, City and Guilds Craft, BTEC First or General Diploma, RSA Diploma.	% (of residents)	March 2021	Local authority	Census 2021
ED3	Education Level – Qual 3 & Apprenticeship	Percentage of usual residents (aged over 16) in each local authority with Level 3 or an apprenticeship as their highest level of qualification. Level 3 qualifications: 2 or more A levels or VCEs, 4 or more AS levels, Higher School Certificate, Progression or Advanced Diploma, Welsh	% (of residents)	March 2021	Local authority	Census 2021

		Baccalaureate Advance Diploma, NVQ level 3; Advanced GNVQ, City and Guilds Advanced Craft, ONC, OND, BTEC National, RSA Advanced Diploma.				
ED4	Education Level – Qual 4	Percentage of usual residents (aged over 16) in each local authority with Level 4 qualifications. Level 4 qualifications and above: degree (BA, BSc), higher degree (MA, PhD, PGCE), NVQ level 4 to 5, HNC, HND, RSA Higher Diploma, BTEC Higher level, professional qualifications (including teaching, nursing, accountancy).	% (of residents)	March 2021	Local authority	Census 2021
SIZ	Household Size	Modal number of usual residents in households** of each local authority.	Mode (of residents)	March 2021	Local authority	Census 2021
INC	Household Income	Median household income of usual residents. This does not cover the self-employed or those not paid in the reference period. The data includes furloughed employees under the Coronavirus Job Retention Scheme (CJRS).	Mean (£k) (per household)	April 2020 to April 2021	Local authority	Annual Survey of Hours and Earnings (ASHE)
VAL	House Value	Median house price for all dwelling types by local authority.	Mean (£100k) (per household)	Year ending December 2021	Local authority	House Price Statistics for Small Areas (HPSSAs) data release by the Office of National Statistics
REN	Renter Occupied	Percentage of the local authority households which rent a property. Includes socially rented and privately rented accommodation.	% (of residents)	March 2021	Local authority	Census 2021
DEN	Population Density	Estimated 1000 usual residents who live within an area per km^2. Calculated using population estimates to the nearest hundred.	1000 residents per km^2	March 2021	Local authority	Census 2021
HOU	Dwelling Type – House	The proportion of households within a local authority whose accommodation*** is a detached house (whole house or bungalow not divided into flats or other living accommodation and not attached to another property).	% (of residents)	March 2021	Local authority	Census 2021
DUP	Dwelling Type – Duplex	The proportion of households within a local authority whose accommodation is a either a semi-detached house (living accommodation is joined to another house or bungalow by a common wall that they share) or a terraced house (house is located between two other houses and shares two common walls).	% (of residents)	March 2021	Local authority	Census 2021

UNI	Dwelling Type – Unit	The proportion of households within a local authority whose accommodation is a either a flat/apartment/maisonette, a shared house, or in a commercial building.	% (of residents)	March 2021	Local authority	Census 2021
CHA	Charging Points	The number of public electric charging points per 1000 people in each local authority. This does not include charging devices not open to the public such as private or domestic chargers. A charging device may have more than one charging connector and be able to charge more than one vehicle at a time, therefore these figures do not reflect overall charging capability.	Per 1000 people	April 2021	Local authority	Department for Transport (DfT) and Office for Zero Emission Vehicles (OfZEV), 2021
GAS	Gas Heating	Proportion of households who only use mains gas as their fuel source for central heating****. This does not include households which use gas in addition to another fuel source.	% (of residents)	March 2021	Local authority	Census 2021
CAR	Cars per Household	Median number of cars owned or available for use by household members. This does not include vans motorbikes, trikes, quad bikes or mobility scooters.	Median (per household)	March 2021	Local authority	Census 2021
DRI	Car driver or car passenger to work	The proportion of the local authority usual residents (aged over 16) who drove or are a passenger in a car or a van to work. People who were furloughed (about 5.6 million) were advised to answer the transport to work question based on their previous travel patterns before or during the pandemic. This means that the data does not accurately represent what they were doing on Census Day.	% (of residents)	March 2021	Local authority	Census 2021

** A usual resident is anyone who on Census Day, 21 March 2021 was in the UK and had stayed or intended to stay in the UK for a period of 12 months or more, or had a permanent UK address and was outside the UK and intended to be outside the UK for less than 12 months (Census, 2021).*

*** A household is defined as one person living alone or a group of people living at the same address who share cooking facilities and share a living room or sitting room or dining area. A household must have at least one usual resident at the address (Census, 2021).*

**** Accommodation is defined as the type of building or structure used or available by an individual or household.*

***** Central heating is a heating system used to heat multiple rooms in a building by circulating air or heated water through pipes to radiators or vents.*

Table 1. Description and source of data sets for the independent and dependent variables in the regression analysis.

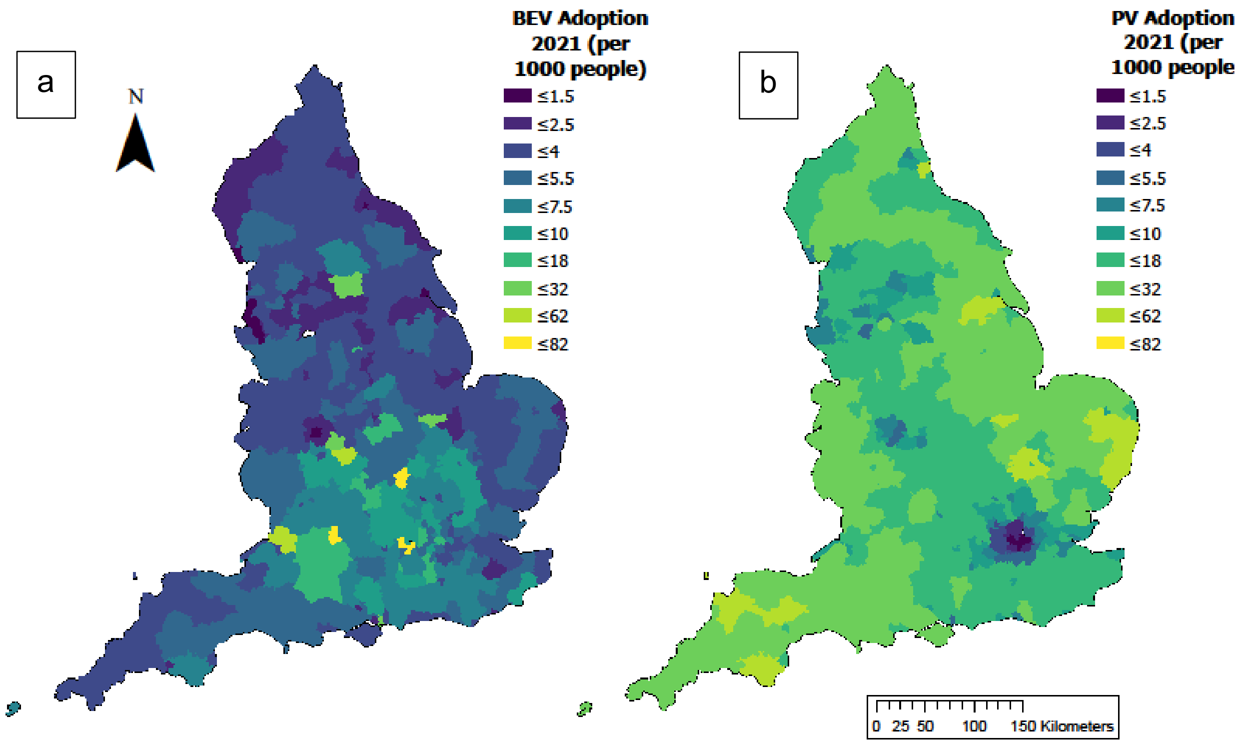


Figure 2. BEV (a) and PV (b) adoption by English local authority in 2021

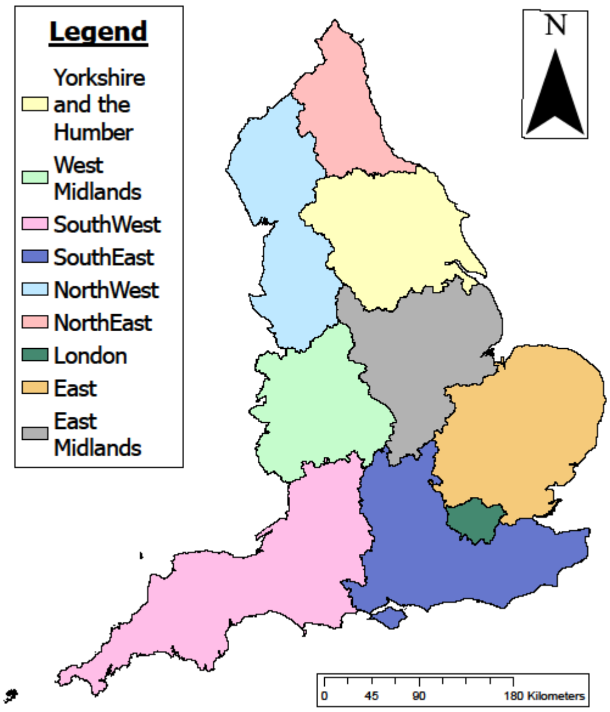


Figure 3. The regions of England

Both ETTs only began to hit consumer markets in 2011, although Section 1.1. notes BEVs lag slightly behind more the mature PV markets. Therefore, this ten-year period has been selected to analyse the evolution of BEV and PV adoption as they transition from innovator to early adopter markets (Rogers, 2003). Figure 4 captures the rapid growth in BEV and PV adoption from 2011 to 2021, as the ETTs begin to enter much larger markets.

3.2. Independent variables

This dissertation has identified twelve local characteristics, two of which are divided into hierarchical categories, as the independent variables for the regression model. These local characteristics were selected from literature and quantifiable with available data sources, so were identified as appropriate proxies for ETT adoption. The twelve independent variables have been divided into four categories: social, economic, built environment and lifestyle (marked in table 2), ensuring a

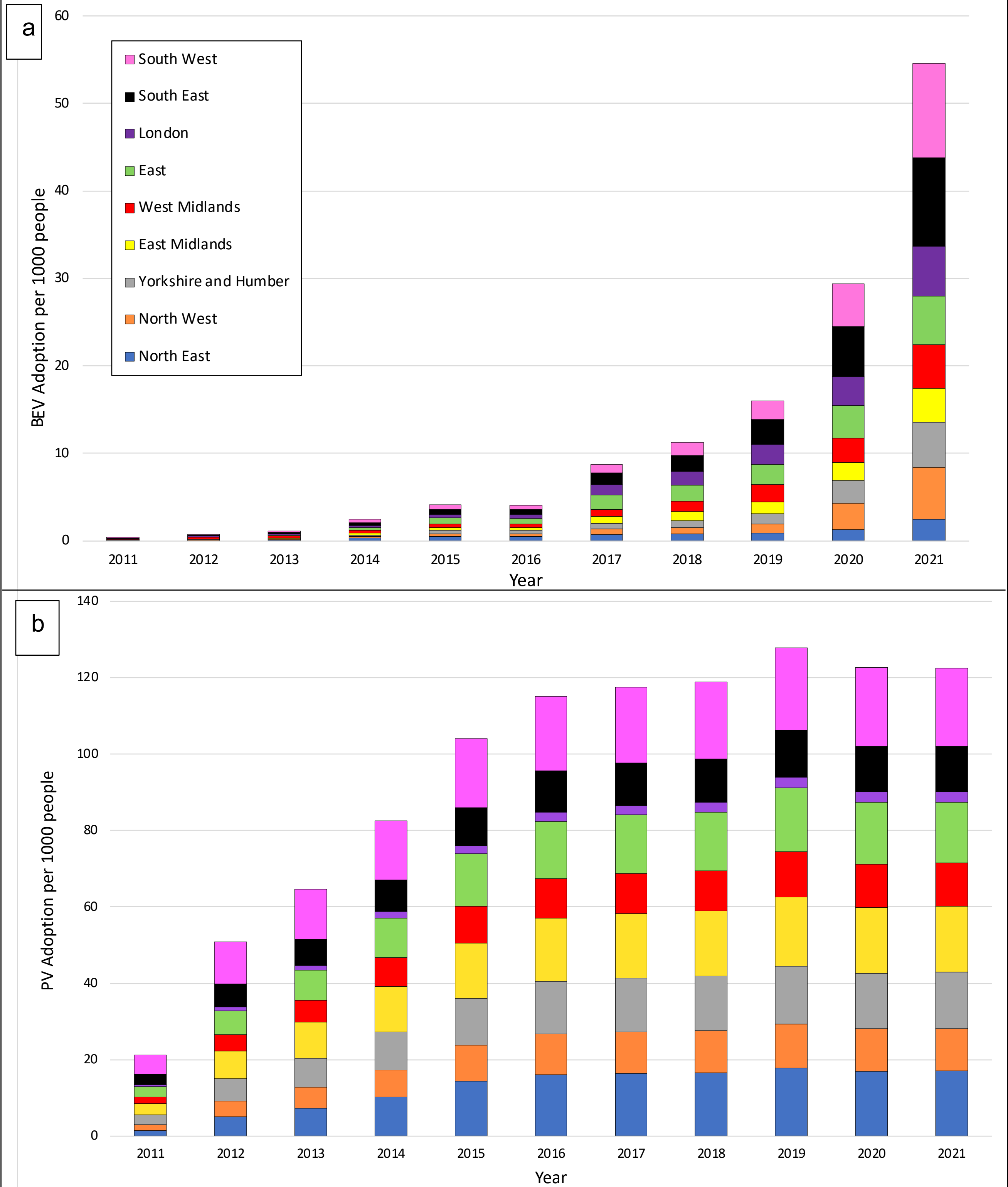


Figure 4. Change in the number of battery electric vehicles (a) and solar panels (b) per 1000 people by region in England from 2011 to 2021.

diverse range of characteristics were included. Table 1 contains the descriptions and parameters of each independent variable. The datasets have all been taken from 2021, with the majority included in the most recent Census, taken on the 21st of March 2021 and others from reliable data collection bodies. Census data is collected every 10 years in the UK, with the recent Census data only released in late 2022/early 2023. Resultingly, the contemporary Census data is relatively unexplored in literature, with this dissertation undertaking pioneering research into the latest determinants of PV and BEV adoption. Table 3 encloses the descriptive statistics for each of the local characteristics, an average value for each variable from across the whole of England in 2021, their units are enclosed in table 1. The influence of each independent variable on BEV/PV adoption discussed in literature is outlined in table 4, a useful benchmark for comparing the results of this dissertation. It is important to note that although this study exclusively assesses BEVs, previous studies typically explore all EVs so this could explain some potentially conflicting results. Whilst some variables have a decisive and universal impact in either stimulating or obstructing EV and PV adoption, the influence of other variables is often contested in literature. For example, previous studies consistently observe that PVs are clustered in lower density, suburban or rural environments (e.g., Davidson, 2014), whereas EVs are predominantly clustered in higher density urban areas (e.g., Sierzchula et al., 2014).

Local characteristic	Category	Mean	Standard deviation	Median
PV Adoption	Dependent variable	13.890	8.008	12.782
BEV Adoption	Dependent variable	6.186	10.283	3.949
Age	Social	41.935	4.934	42
Education – Qual None		17.7	3.932	17.4
Education – Qual 1 & 2		23.523	3.604	24.3
Education – Qual 3 & Apprenticeship		22.6	3	23.2
Education – Qual 4		33.429	8.652	32.1
Household Size		1.838	0.368	2
Household Income	Economic	25.679	5.821	25.567
House Value		306	141.587	277
Renter Occupied		15.8	5.902	14.2
Population Density	Built Environment	1.804	2.537	0.746
Dwelling Type – House		25.776	12.613	26.9
Dwelling Type – Duplex		53.626	11.656	53.8
Dwelling Type – Unit		19.306	15.521	14.5
Charging Points		0.337	0.479	0.237
Gas Heating	Lifestyle	74.358	9.786	77.1
Cars per Household		1.226	0.360	1.242
Car driver or car passenger to work		50.697	13.350	54.4

Table 2. Descriptive statistics for the independent and dependent variables and their respective thematic categories used in the regression model for England in 2021.

Variable	PV Adoption		EV Adoption	
	Description	Reference	Description	Reference
Age	Contested in literature but generally found that older or middle-aged people are more likely to adopt. *Younger age groups more willing to install but are less likely to invest due to financial barriers.* *Middle age groups more likely to install.* *Positive relationship between age and PV adoption.*	(Islam, 2014; Balcombe et al., 2013 ; Willis et al., 2011) (Araujo et al., 2019; Sardianou and Genoudi, 2013) (Dharshing, 2017; Graziano and Gillingham, 2015; Balcombe et al., 2013; Kwan, 2012)	Bell shaped curve with adopters – the adoption peak lay with middle aged people. *Positive relationship between age and EV adoption.* *Negative relationship between EV adoption and residents aged over 59 years.* *Bell curve of adoption – early adopters of EVs are typically younger or middle-aged.*	(Hidrue et al., 2011; Westin et al., 2018) (Araujo et al., 2019) (Plotz et al., 2014; Hidrue et al., 2011; Nayum et al., 2018; Bollinger and Gillingham, 2012; Kwan, 2012)
Education Level - Qual None Education Level – Qual 1 & 2 Education Level – Qual 3 & Apprenticeship Education Level – Qual 4	Generally, positive relationship between education status and PV adoption observed. Possible alternative is that those with technical/vocational qualifications could be more likely to adopt. *Positive relationship with education status and PV adoption.* *No statistically significant relationship of education status.* *Those with technical/vocational qualifications more likely to adopt.*	(Van der Kam et al., 2015; Bollinger and Gillingham, 2012; Kwan, 2012; Palmer et al., 2015, Claudy et al., 2011; Balta-Ozkan et al., 2021; Davidson et al., 2014; Jager, 2006; Keirstead, 2007) (Sommerfeld et al., 2017) (Balta-Ozkan et al., 2015)	Largely, a positive relationship between education status and EV adoption but some studies found no link. *Positive relationship with education and EV adoption.* *No relationship between EV adoption and education status – ambiguous predictor of adoption.* *EV owners have more university degree level qualifications compared to non-EV owners.*	(Westin, 2018; Dickerson and Gentry, 1983; Im et al., 2003; Vergis and Chen, 2015; Coffman, 2017; McCoy, 2014, Kwan, 2012; Balcombe, 2014, Claudy et al., 2010; Mukherjee and Ryan, 2020; Nayum et al., 2016, Plotz et al., 2014; Nayum et al., 2018; Araujo, 2018) (Sierzchula et al., 2014) (Westin et al., 2018; Keirstead, 2007)

Household Size	Smaller households more likely to adopt.	(Balta-Ozkan et al., 2015; Keirstead, 2007)	Larger households are more likely to adopt.	(Nayum et al., 2016; Morton et al., 2018)
Household Income	Contested in literature. Some studies show income to have no effect, others a positive effect, and some a negative influence on PV adoption. *Statistically insignificant relationship reported.* *Positive effect of income on PV adoption.* *Positive impact until a certain threshold and then this begins to have the opposite effect.* *Negative impact of income.*	(Graziano and Gillingham, 2015; Sierzchula et al., 2014) (Briguglio and Formosa, 2017; Müller and Rode, 2013; Rode and Weber, 2012; Sardianou and Genoudi, 2013; Vasseur and Kemp, 2015; Kwan, 2012, Dharshing, 2017; Lan et al., 2021; Balcombe et al., 2014; Nayum et al., 2016). (Lan et al., 2021) (Balta-Ozkan, 2021; Bollinger and Gillingham, 2012; Schaffer and Brun, 2015; Islam and Meade, 2013; Van der Kam et al., 2018)	Generally, a positive relationship between income and EV adoption. *Positive relationship with EV adoption and income.* *Ambiguous results.*	(Araujo et al., 2019; Westin et al., 2018; Nayum et al., 2016; Curtin et al, 2009; Nayum et al., 2018; van der Kam et al., 2018) (Hidrue et al., 2011)
House Value	Contested in literature. Some studies find house value to have positive effect on adoption while others suggest its effect is ambiguous.	(Kwan, 2012) (Palm, 2018)	Positive influence of house value on EV adoption.	(Araujo et al., 2019; Kwan, 2012)
Renter Occupied	Residents in rented accommodation less likely to install PVs than homeowners.	(Briguglio and Formosa, 2017; Graziano and Gillingham, 2015; Keirstead, 2007; Schaffer and Brun, 2015; Sommerfeld et al., 2017; Balcombe et al., 2013; Davidson et al., 2014)	Residents in rented accommodation less likely to purchase EVs.	(Mukherjee and Ryan, 2020)
Population Density	PVs typically clustered in rural, or lower density suburban environments.	(Van der Kam et al., 2018; Davidson, 2014; Muller and Rode, 2013; Kwan, 2012;	Generally, EV adoption rates are higher in more densely populated/urban areas.	(van der Kam et al., 2018; Sierzchula et al., 2014)

		Balta-Ozkan et al., 2015 and 2021)	*EV adoption clusters with urbanity.* *Negative correlation between EV adoption and population density.*	(Araujo et al., 2019)
Dwelling Type – House Dwelling Type – Duplex Dwelling Type – Unit	Dwellings with their own roof space are more likely to install PVs.	(Briguglio and Formosa, 2017; Van der Kam et al., 2018)	Not studied in literature.	Not studied in literature.
Charging Points	Not studied in literature.	Not studied in literature.	Largely, a positive influence of charging infrastructure on EV adoption identified. *Positive association between charging infrastructure and EV adoption.* *Ambiguous effect.*	(Morton et al., 2018; Van der Kam et al., 2018; Mukherjee and Ryan, 2020; Mersky, 2016; Coffman et al., 2017; Sierzchula et al., 2014) (Plotz et al., 2014)
Gas Heating	No clear relationship between gas heating and PV adoption.	(Balta-Ozkan et al., 2021)	Not studied in literature.	Not studied in literature.
Cars per Household	Not studied in literature.	Not studied in literature.	Generally found a positive effect of owning more cars on EV adoption but some studies suggest this is ambiguous. *Positive effect of car ownership.* *Ambiguous results.*	(Morton, 2018; van der Kam et al., 2018; Kurani, 1996) (Plotz et al., 2014)
Car driver or car passenger to work	Not studied in literature.	Not studied in literature.	Negative relationship with EV adoption and using public transport to work.	(Araujo et al., 2019)

Table 3. The various influences of independent variables on electric vehicle and solar panel adoption observed in literature. Any conflicting results are marked in italics with respective literature sources identified in the adjacent column.

A similar phenomenon is observed for household size, with smaller households less likely to adopt PVs (e.g., Balta-Ozkan et al., 2015) whilst more likely to adopt EVs (e.g., Morton et al., 2018). The impact of variables like education status and household income are more contested in literature, with previous studies observing positive, negative and insignificant relationships with EV and PV adoption (e.g., Van der Kam et al., 2018). However, some variables exert the same influence on both EVs and PVs, for example tenants are determined as less likely to purchase EVs and PVs (e.g., Balcombe et al., 2013; Mukherjee and Ryan, 2020) than homeowners, and middle-aged people are the most likely age group to adopt EVs and PVs (e.g., Araujo et al., 2019).

The simultaneous diffusion of BEVs and PVs is unexplored across England. This study therefore intends to compare patterns of BEV and PV adoption and explore the extent to which these local characteristics explain the spatial variation of adoption in England using novel Census data.

3.3. Data limitations

The configuration of English LAD boundaries has changed throughout the study period, most recently in 2019 and 2020 when local authorities in Somerset, Suffolk, Dorset, Buckinghamshire and Northamptonshire were merged (ONS, 2021). These boundary changes presented complications when comparing changes in BEV and PV adoption through time, potentially tampering with data from these local authorities. The local authority scale data has historically been deployed for this type of study, providing a comprehensive and detailed overview of BEV and PV adoption at regional and national scales (Balta-Ozkan et al., 2018; Morton et al., 2019). However, the local authority scale is limited in assessing highly local processes like the peer/neighbourhood effect. Therefore, although the peer effect comprises a large portion of literature, it is omitted from this dissertation.

3.4. Spatial autocorrelation analysis

Moran's I spatial autocorrelation analysis is deployed to explore the degree of spatial clustering or dispersion within the dependent and independent 2021 datasets. By comparing values of BEV and PV adoption to neighbouring local authorities this analysis determines whether spatial diffusion patterns are random or clustered (Lan et al., 2020; Cliff and Ord, 1973; Getis, 2009). Global spatial autocorrelation analyses assess trends across all of England, assimilating local authority data. Conversely, local spatial autocorrelation focuses individual local authorities and their neighbouring districts (Moran, 1948; Rogerson, 2010; Morton et al., 2018). The Moran's I index falls between -1 and 1, with a value of 0 suggesting no spatial correlation present, a positive value suggesting a tendency towards clustering, and a negative value indicating an inclination towards dispersion/random spatial distribution (Lan et al., 2020; Morton et al., 2018; Anselin, 1995). Global Moran's I was used to independently quantify the extent of spatial association of all variables with neighbouring LADs (table 4). Moran's I was calculated in ArcGIS, with a distance band set at 100,000m, an appropriate scale to account for neighbouring local authorities. The p-values (significance level) and z-scores (degree of variation from absolute spatial randomness) were used to evaluate the significance of the spatial autocorrelation results (Moran's Index). Local indicators of spatial association (LISA), including local Moran's I, were also used in this dissertation to decompose the global statistics detailed in table 4. Local Moran's I analysis has been deployed to identify local patterns of PV and BEV spatial autocorrelation (Anselin, 1995), with results presented in figure 5 alongside an overlay of the major towns and cities in England as of 2015 (ONS, 2022c). For the local characteristics which displayed the strongest relationship with BEV or PV adoption, a final Local Moran's I analysis was conducted to explore the spatial organisation of these characteristics relative to BEV and PV geographic diffusion patterns.

Local Characteristic	Moran's Index	z-score
PV Adoption	0.053**	4.706
BEV Adoption	0.426**	33.948
Age	0.193**	15.357
Education Level - Qual None	0.279**	22.374
Education Level – Qual 1 & 2	0.274**	22.036
Education Level – Qual 3 & Apprenticeship	0.524**	41.950
Education Level – Qual 4	0.408**	32.700
Household Size	0.066**	5.352
Household Income	0.198**	16.270
House Value	0.700**	56.373
Renter Occupied	0.169**	13.747
Population Density	0.063**	5.318
Dwelling Type – House	0.274**	21.981
Dwelling Type – Duplex	0.438**	35.149
Dwelling Type – Unit	0.509**	41.092
Charging Points	0.207**	18.131
Gas Heating	0.087**	7.224
Cars per Household	0.137**	11.347
Car driver or car passenger to work	0.564**	45.145

*** p value < 0.01.*
** p value < 0.05.*

Table 4. Global Moran's I statistics for all variables.

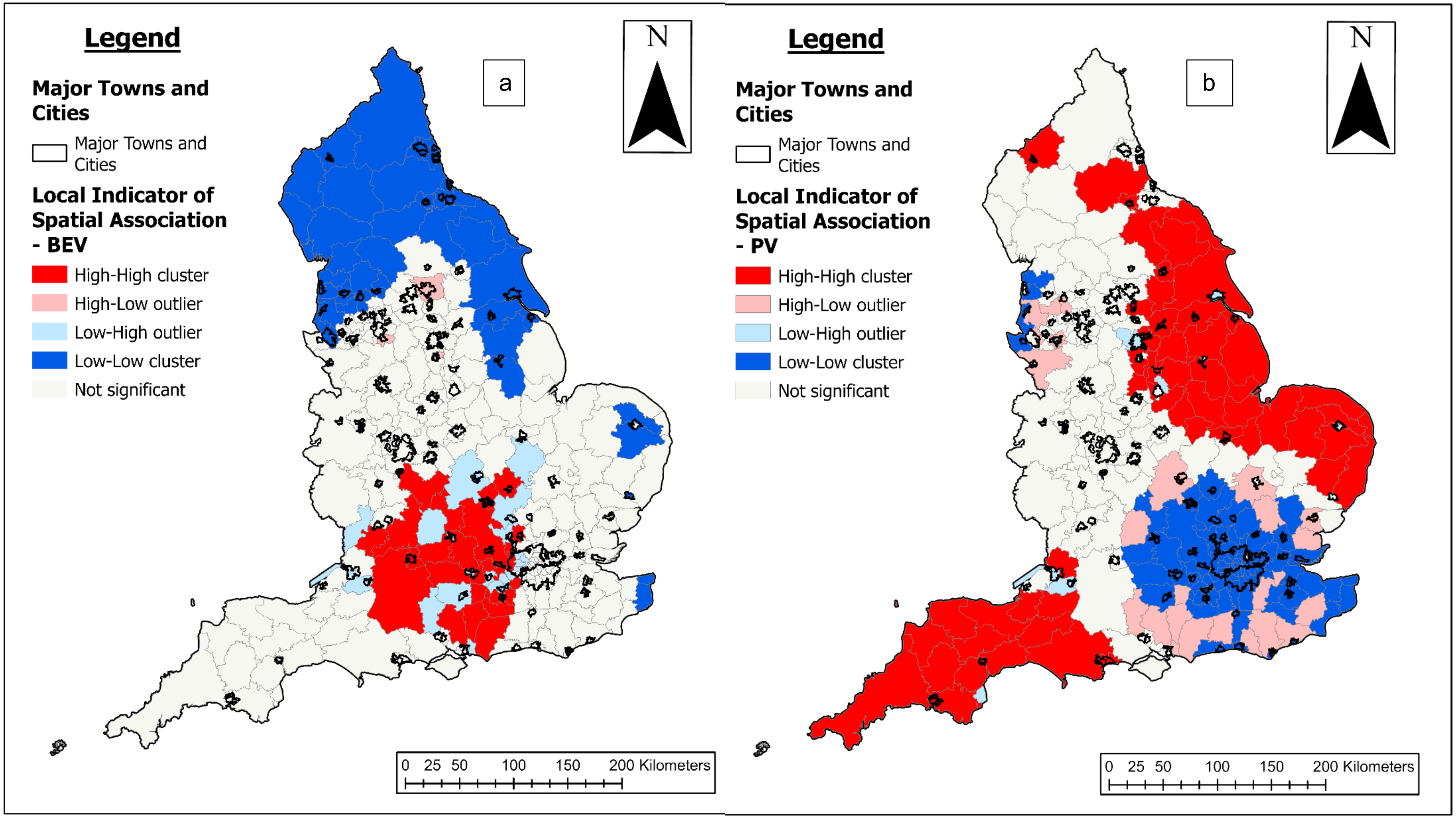


Figure 5. Local spatial autocorrelation analysis (Local Moran's I) of battery electric vehicle (a) and solar panel (b) adoption per 1000 people for the local authorities of England in 2021. An overlay of English major towns and cities are marked in black.

3.5. Linear regression analysis

To investigate whether the local characteristics (the independent variables) are useful in explaining residential BEV and PV adoption for the 2021 datasets (van der Kam et al., 2018), a series of global linear regression models have been conducted. Due to the high degree of interaction between the independent variables, a multicollinearity assessment was conducted (table 5). The variance of inflation factor (VIF) index was computed in RStudio, with VIF values less than 2.5 indicating no correlation, between 2.5 and 10 suggesting moderate correlation, and over 10 indicating severe correlation (Morton et al., 2018). The local characteristics which are split into hierarchical categories (education status and dwelling type), expectedly experience a high degree of collinearity so only one of these variables was selected for the final multicollinearity test (the others hatched in table 5). A threshold of VIF 10 is enforced, with higher VIF values omitted from regression analysis (Morton et al., 2018; Lan et al., 2020; Field, 2009). Aside from 'car or driver passenger to work' the level of collinearity is low among independent variables, so despite exceeding the VIF threshold, the regression analysis proceeded with all variables outlined in the left-hand column of table 5.

As the regression models are linear, a series of Spearman's Rank correlation analyses have also been conducted to investigate fluctuating dynamics between independent and dependent variables which are not detected in the linear regression analysis (Sierzchula et al., 2014). Table 6 presents the results of the Spearman's Rank correlation analysis computed in RStudio, quantifying the correlation coefficient and statistical significance of the relationships between all independent and dependent variables across English local authorities for the 2021 datasets.

Local Characteristic	VIF Index
Age	2.465
Education Level - Qual None	
Education Level – Qual 1 & 2	
Education Level – Qual 3 & Apprenticeship	
Education Level – Qual 4	6.858
Household Size	1.088
Household Income	1.458
House Value	5.454
Renter Occupied	2.427
Population Density	1.093
Dwelling Type – House	
Dwelling Type – Duplex	
Dwelling Type – Unit	7.811
Charging Points	2.032
Gas Heating	1.150
Cars per Household	1.587
Car driver or car passenger to work	15.997

Table 5. Variance of inflation factor (VIF) results for the independent variables.

To distinguish between BEVs and PVs, two linear regressions were performed, one with the number of BEVs per 1000 people for each English local authority, and the other with the number of PVs per 1000 people for each English local authority (respective dependent variables). Within these two models, a simple linear regression for each independent variable was conducted, with their units and data source outlined in figure 4. A simple linear regression was also performed between BEV and PV adoption, exploring whether investment in one ETT stimulates adoption of another, a phenomenon observed by Collier et al. (2023). The simple linear regression calculates a beta (β) coefficient for each independent variable to represent the degree to which BEV/PV adoption will change with a change in the independent variable, quantifying the predictive power of each local characteristic over ETT adoption. The respective standard error for each beta coefficient captures the accuracy of the regression result, with greater standard errors identifying a greater spread of data. The beta coefficients are all relative, enabling direct comparison of BEV and PVs for the same variable but not between variables due to differences in units. Subsequently, a multiple linear regression analysis for each local characteristic subgroup - social, economic, built environment and lifestyle – was conducted to gauge the relative importance of thematic control over BEV and PV adoption. The adjusted r^2, lying between 0 and 1, is calculated for each group to quantify the explanatory power of each independent variable, with the f-value recording the extent of variance. Adjusted r^2, opposed to regular r^2, accounts for differences in the number of independent variables enabling fair comparison between each group. Finally, a multiple linear regression encompassing all the variables was conducted for both BEV and PV adoption to determine which is most heavily influenced by the local characteristics specified in this analysis. It is important to note that although these variables may appear to exert control over the adoption of BEVs and PVs, they should not be interpreted as the actual determinants of adoption, instead results should be interpreted as a proxy for motivators of adoption (van der Kam et al., 2018). However, this regression analysis provides useful insight into the relative importance of these local characteristics, facilitating comparison between different types of ETT determinants and providing a unique comparison between BEV and PV diffusion.

Figure 6 lays out the methods, illustrating the role each analysis technique plays in determining the spatial patterns of BEV and PV adoption and in constructing the distinct BEV and PV adopter profiles. These feed into each other to explain the observed patterns of BEV and PV diffusion in England.

	PV	AGE	ED0	ED1	ED3	ED4	SIZ	INC	VAL	REN	DEN	HOU	DUP	UNI	CHA	GAS	CAR	DRI	EV
PV	1																		
AGE	0.680**	1																	
ED0	0.0612	-0.052	1																
ED1	0.362**	0.357**	0.571**	1															
ED3	0.485**	0.371**	0.254**	0.345**	1														
ED4	-0.308**	-0.196**	-0.860**	-0.819**	-0.535**	1													
SIZ	0.205**	0.155**	-0.119*	0.080	0.070	0.0235	1												
INC	-0.491**	-0.324**	-0.521**	-0.397**	-0.506**	0.600**	-0.037	1											
VAL	-0.355**	-0.134*	-0.676**	-0.375**	-0.612**	0.725**	0.110	0.641**	1										
REN	-0.329**	-0.645**	0.313**	-0.131*	-0.192**	-0.082	-0.147**	0.016	-0.145*	1									
DEN	0.053	0.138*	-0.038	0.047	0.058	-0.022	0.021	0.000	-0.033	-0.131*	1								
HOU	0.730**	0.781**	-0.175**	0.311**	0.284**	-0.094	0.297**	-0.167**	-0.026	-0.657**	0.138*	1							
DUP	-0.085	-0.270**	0.540**	0.223**	0.324**	-0.511**	-0.197**	-0.325**	-0.670**	0.372**	0.053	-0.417**	1						
UNI	-0.689**	-0.618**	-0.235**	-0.395**	-0.516**	0.439**	-0.146*	0.384**	0.524**	0.364**	-0.121*	-0.704**	-0.187**	1					
CHA	-0.075	-0.159**	-0.370**	-0.481**	-0.207**	0.475**	0.069	0.195**	0.326**	0.150**	0.001	-0.121*	-0.266**	0.217**	1				
GAS	0.158**	0.148**	0.075	0.210**	0.224**	-0.199	-0.057	-0.174**	-0.166**	-0.001	0.369**	0.055	0.180**	-0.087	-0.038	1			
CAR	0.381**	0.468**	-0.329**	0.222**	0.0157	0.101**	0.2486**	0.163**	0.225**	-0.514**	0.215**	0.719**	-0.268**	-0.423**	-0.042	0.081	1		

DRI	0.540**	0.446**	0.652**	0.670**	0.585**	-0.819**	0.083	-0.589**	-0.754**	-0.107	0.065	0.404**	0.389**	-0.754**	-0.387**	0.152**	0.123*	1	
EV	-0.033	0.095	-0.724**	-0.330**	-0.386**	0.674**	0.127*	0.509**	0.688**	-0.281**	0.088	0.274**	-0.531**	0.150**	0.304**	-0.077	0.608**	-0.508**	1

*** p value < 0.01.*
** p value < 0.05.*

Table 6. Spearman's Rank correlation analysis between all of the independent and dependent variables across English local authorities in 2021. The codes for each variable are outlined in figure 4.

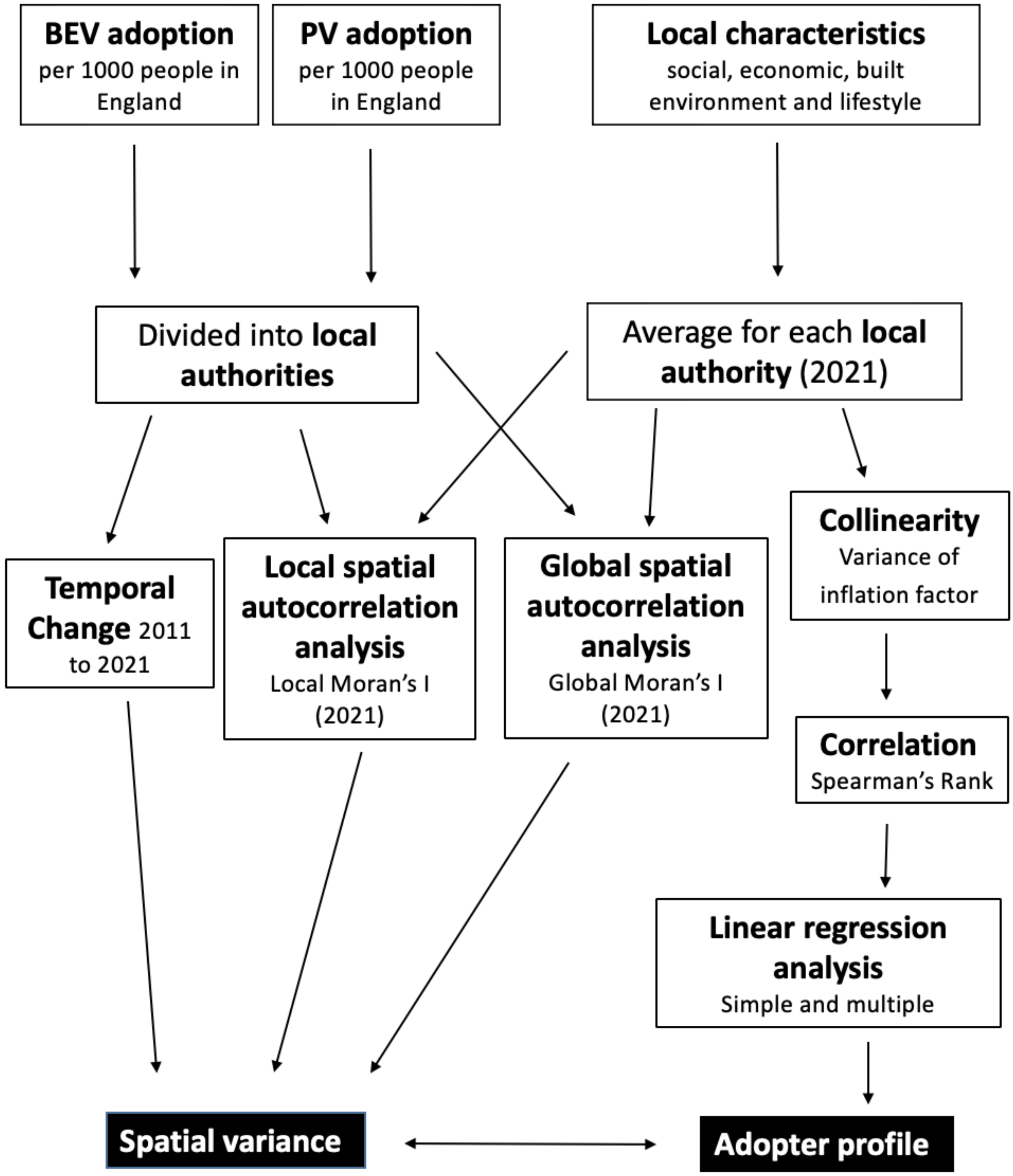


Figure 6. Diagram of methods.

4. Results

4.1. BEV and PV diffusion

The current distribution of domestic BEVs and PVs are spatially distinct in England. Figure 2 captures their differences, appearing geographically inverted. This is particularly evident around London and the South-East which generally enclose the largest proportion of BEVs but the smallest proportion of PVs in England, marked in figure 2 with light and dark shading respectively. Figure 4 confirms these observed distinct patterns of adoption. BEV diffusion was highest in the South-East and South-West (~10 BEVs per 1000 residents) whilst PVs were conversely most abundant in the South-West, North-East and East regions of England (~20 – 17 PVs per 1000 residents) in 2021. Although the South-West is a large adopter of both BEVs and PVs, these ETTs are not installed in synergy, with annual cumulative PV adoption rates evidently almost double BEV registrations. BEV adoption appears more sporadic than PVs. Figure 2 illustrates a more scattered spatial pattern of BEV registrations in local authorities, contrasting to the more smooth/uniform distribution of PVs.

This dissertation considers ETT growth trends, with the consistently higher accumulation of PV instalments in England across the period (marked by lighter shading in figure 2), a defining characteristic of relative PV adoption. By 2021 the domestic PV stock in England had cumulatively reached 712,512 units, compared to the less abundant BEV fleet of 368,524 units (figure 4). However, as aforementioned in Section 1.1 the PV market is more mature than BEVs; at the start of the period the PV stock (122,000 installations) was already larger than the BEV fleet of 2,425 registrations. Although less abundant, BEV adoption grew at a faster rate, experiencing in a 150,011% increase in England compared to PV which only grew by 484% throughout the decade. Figure 4 presents distinct patterns of PV and BEV adoption through time. The BEV registration rate consistently accelerated, with adoption doubling annually in 2018, 2019, 2020 and 2021. Conversely, PV installation growth appears slightly less regular, with some adoption troughs and peaks, beginning to plateau after 2016. Regionally, London consistently enclosed the lowest PV stock, containing only 2.51 PVs per 1000 people in 2021. Conversely, the South-West, North-East and East-Midlands, all contained over 17 PVs per 1000 people in 2021. The South-West not only experienced the greatest increase in PV adoption throughout the period, but it also unfailingly maintained the largest PV stock. Figure 9 illustrates the regional variation in PV growth diagrammatically throughout the period, with differences accelerating, particularly noticeable when comparing London with the South-West. The local authorities with the highest PV adoption levels in 2021 are presented in figure 7 dominated by the

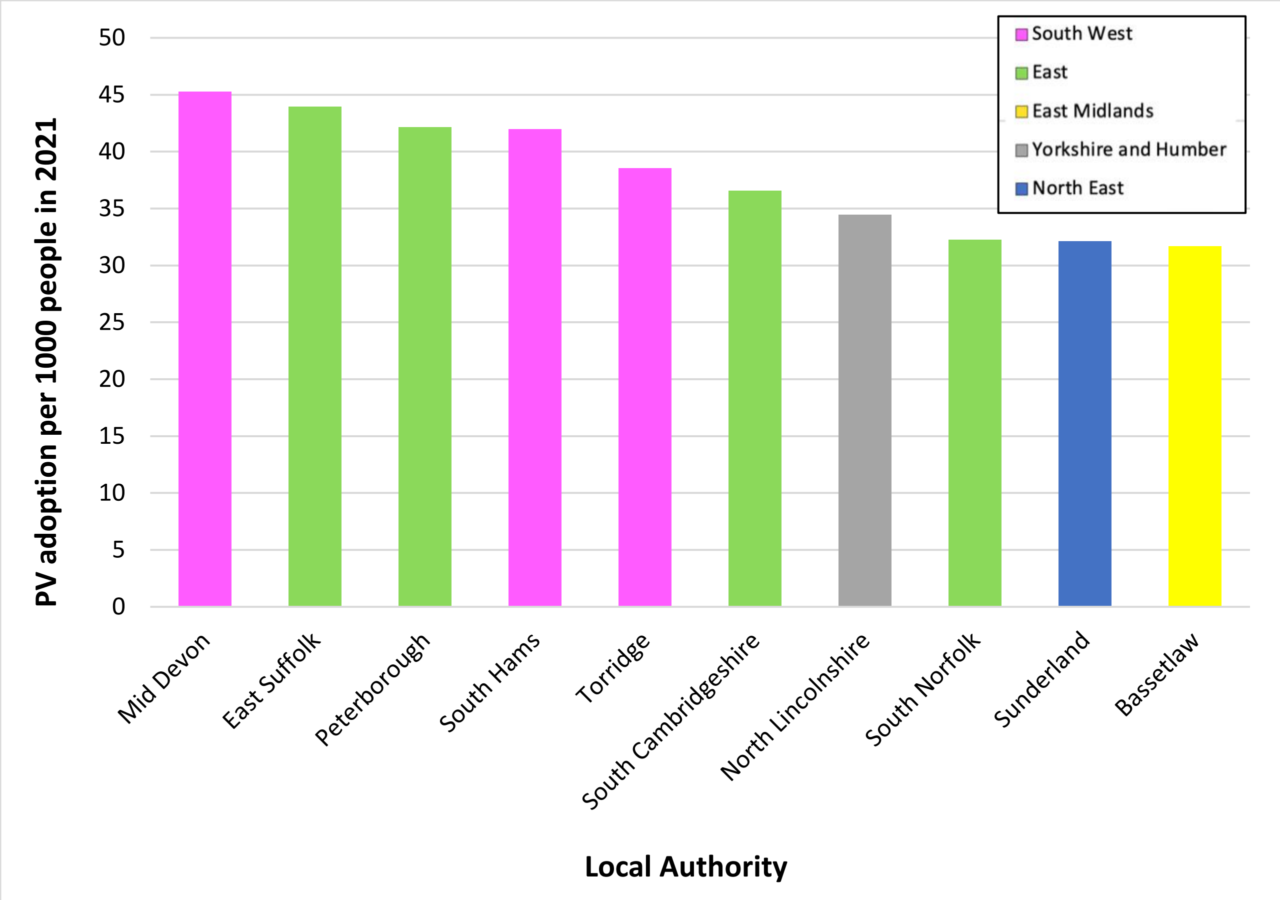


Figure 7. English local authorities with the greatest number of domestic solar panel installations per 1000 people in 2021, colour coded by region.

South-West and East as expected, with Mid Devon marginally containing the highest levels of adoption – 45 PVs per 1000 people.

In contrast, BEV adoption, lagging behind PV adoption, experienced more geographic turbulence in changing regional patterns of adoption, presented in figure 10. Although London started with the highest proportion of BEVs, 0.12 BEVs per 1000 people – 10 times larger than all other regions – the initial high adoption rate was not maintained. By 2014, London was overtaken by the South-East, South-West, West-Midlands and Yorkshire and the Humber. As a slight outlier, Stockport marginally enclosed the most (83) BEVs per 1000 people in 2021, highlighting the more sporadic and scattered distribution of BEVs. However, Stockport was closely followed by an expected flurry of local authorities from the South-West and South-East, illustrated in figure 8. The South-East and South-West experienced the greatest change in BEV adoption, a 10-fold growth in their BEV stock per 1000 people, with these regions ultimately enclosing the largest BEV stock. In contrast, the North-East experienced the least change, only doubling their BEV fleet in the same period, widening these uneven spatial diffusion patterns.

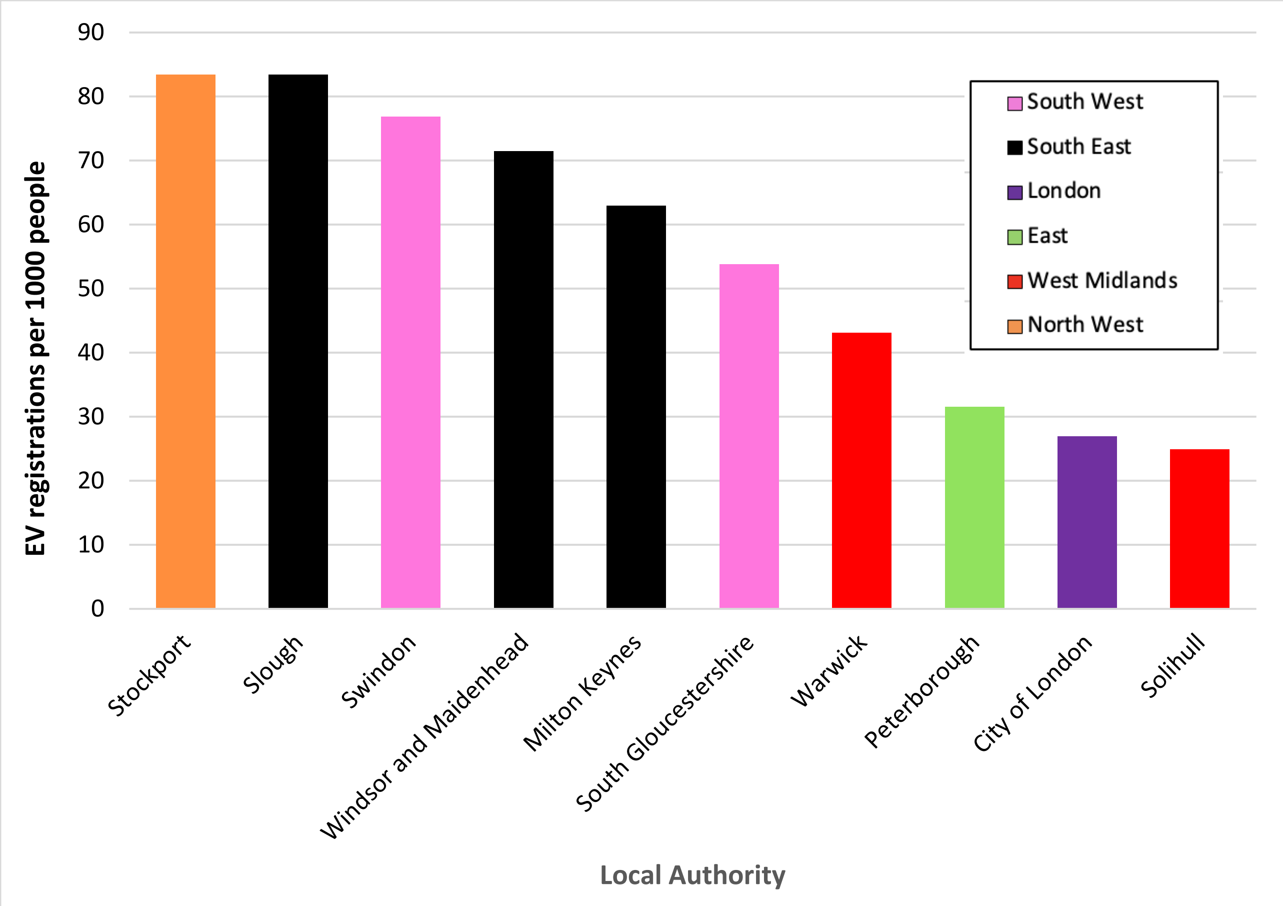


Figure 8. English local authorities with the greatest number of domestic battery electric car registrations per 1000 people in 2021, colour coded by region.

4.2. Spatial Autocorrelation

The local Moran's I test identified significant regions of BEV and PV clustering and dispersion, statistically confirming the empirical observations discussed above. The global Moran's I value of 0.426 for PVs compared to BEVs of 0.053 (table 4), suggests PVs are more prone to clustering whilst BEV adoption is more dispersed, statistically confirming that BEV distribution is more sporadic. Regions marked in dark blue in figure 5 represent significant clusters of low levels of BEV/PV adoption in 2021, displaying cold spots or dispersed adoption pockets. For BEV adoption, the cold spots are located in the North-East and North-West, and to a lesser extent in some local authorities west of London.

For PVs, the areas of dispersed adoption are concentrated in and around London and the North-West, correlating with some major towns and cities like London, Manchester, Liverpool and Bristol. Although not universal, PV diffusion appears to be inversely correlated with dense urban areas. This finding is most apparent places like Cambridge, Hull and Norwich. These cities are identified as significant cold spots of PV adoption but are paradoxically enclosed within regions of high PV clustering. In contrast, the diffusion of

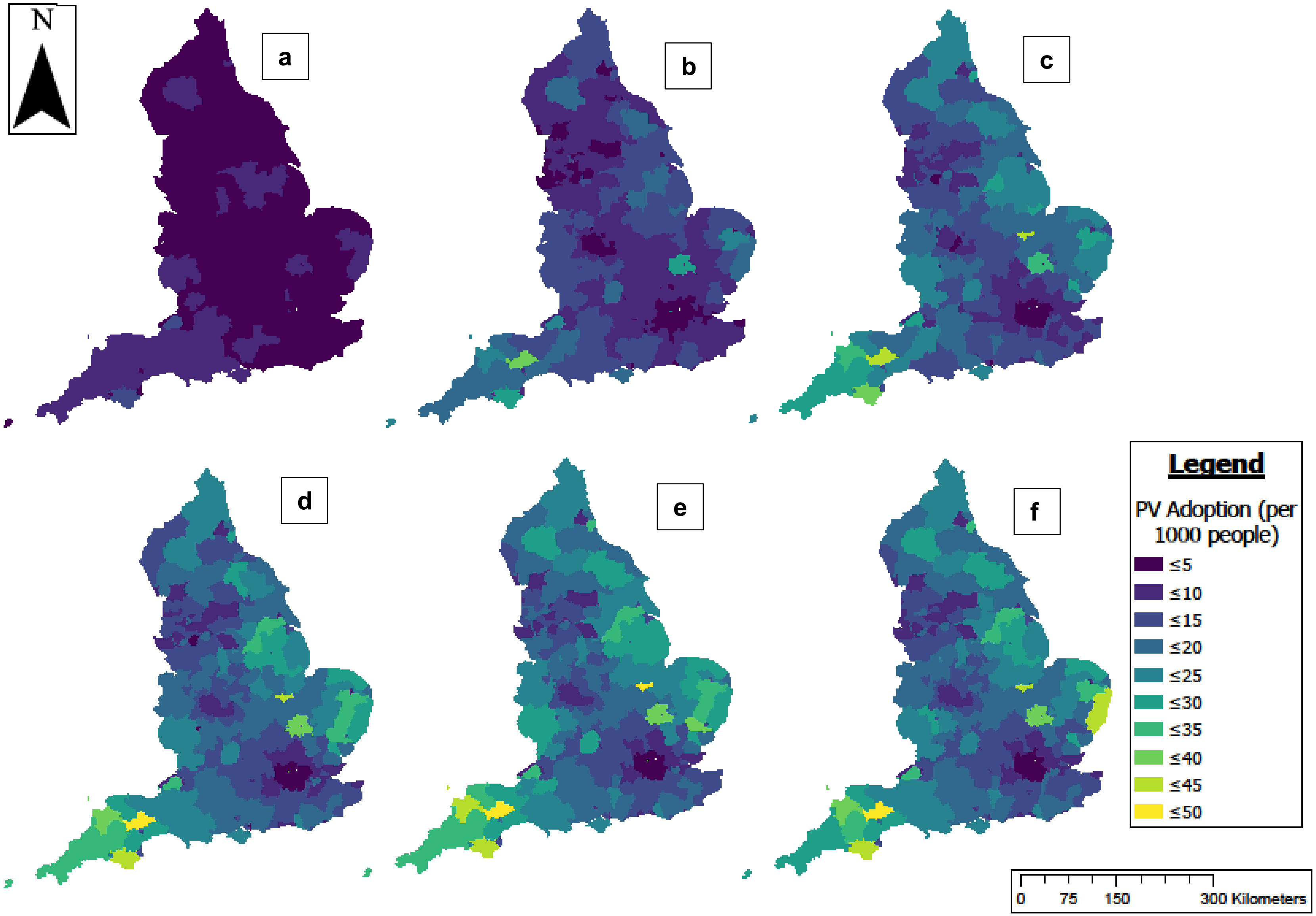


Figure 9. Choropleth maps of residential solar panel installations per 1000 people across English local authorities in (a) 2011, (b) 2013, (c) 2015, (d), 2017, (e) 2019, and (f) 2021.

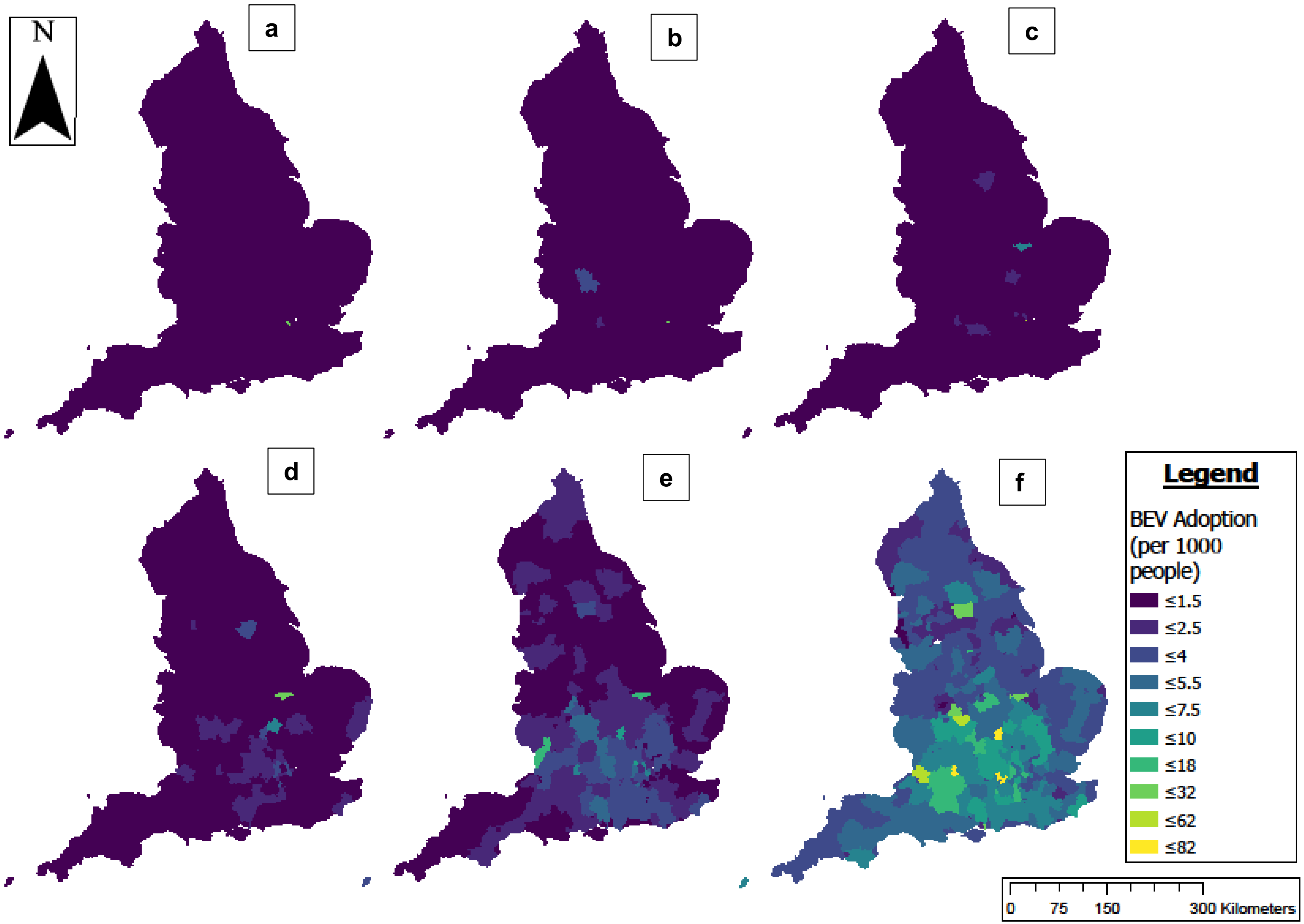


Figure 10. Choropleth maps of domestic battery electric vehicle registrations per 1000 people across English local authorities in (a) 2011, (b) 2013, (c) 2015, (d), 2017, (e) 2019, and (f) 2021.

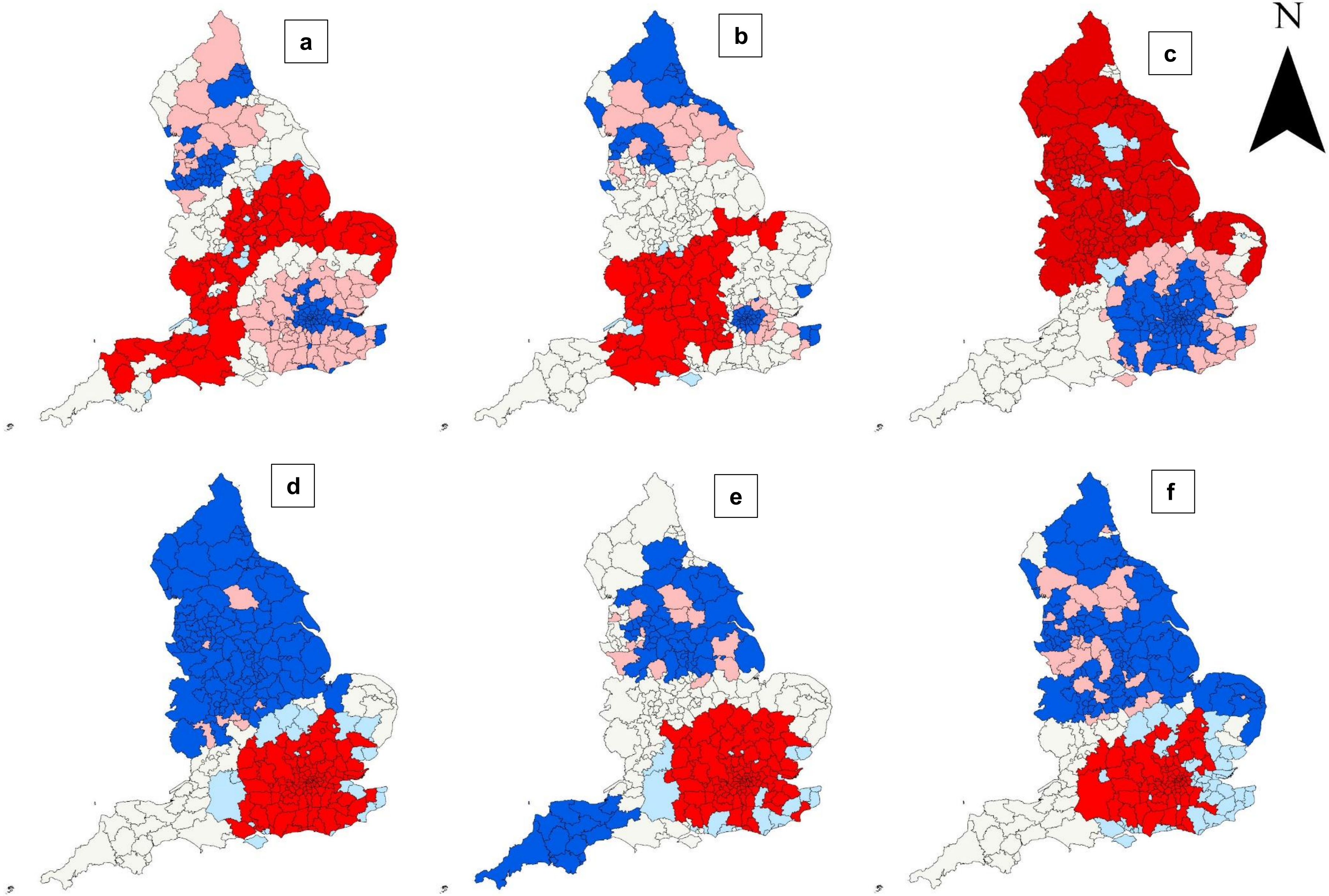
BEVs does not appear to relate to the distribution of major towns and cities, although like Morton et al. (2018), this dissertation also identifies cold spots in some of the large cities in northern England like Manchester and Liverpool.

Regions marked in dark red in figure 5 represent clusters of significant high levels of BEV and PV adoption. PV hotspots are abundant in the North-East, East and South-West, particularly near the coast. Comparatively, there are fewer regions of BEV hot spots. These are generally configured west of London in the South-East and West-Midlands. BEV and PV adoption appears almost inverse, with the hot spots of PV adoption often corresponding to the cold spots of BEV adoption vice versa, especially around London and in the North-East.

The results of the local Moran's I analysis conducted for chosen local characteristics, designed to enhance understanding on the determinants of PV and BEV adoption is presented in figure 11. Although all variables displayed evidence of clustering, exemplified by the unanimous positive Global Moran's I result presented in table 4, nine variables were selected due to their strong correlation and regression with either BEVs (cars per household, no education, high education, median house value and drive to work) or PVs adoption (age, dwelling type (house and unit), and income). By comparing the PV/BEV LISA results (figure 5) with these independent variables (figure 12), this dissertation can determine whether these local characteristics universally control BEV/PV diffusion or whether their influence is regional. Each of the maps in figure 11 is distinct, with the influence of different local characteristics highly regional.

4.3. Regression Analysis

A Spearman's Rank correlation analysis was conducted to investigate the strength of the relationship between the dependent and independent variables (table 6). Like Morton et al. (2018), this dissertation considers correlations less than 0.2 as insignificant, determines weak correlations as those between 0.2 and 0.4, moderate correlations between 0.4 and 0.6 and stronger correlations greater than 0.6. The majority of correlations exceeded 0.2 and almost a third surpassed 0.4, with an abundance of significant moderate and strong correlations detected from the Spearman's Rank analysis. This indicates a substantial degree of interaction between all the variables. The strongest correlation was identified between education and drive to work (coefficient = -0.819). Significant positive strong correlations were identified between BEV adoption and level 4 education qualifications (0.674), house value (0.688), and cars per household (0.608). The strongest relationship for BEV adoption was the significant negative correlation detected with median age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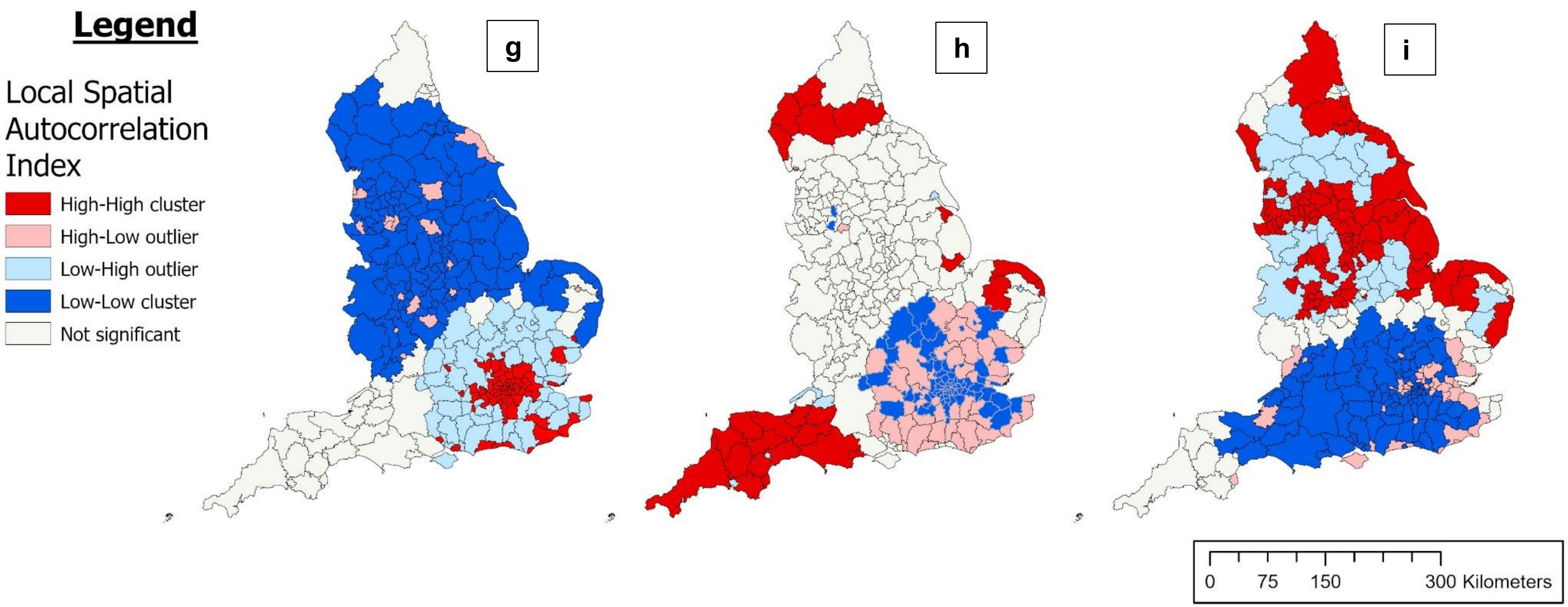

Figure 11. Local spatial autocorrelation analysis (Local Moran's I) of selected local characteristics: (a) dwelling type: house, (b) cars per household, (c) car drive to work, (d) house value, (e) household income, (f) education level 4, (g) dwelling type: unit, (h) age, and (i) no qualifications for the local authorities in England in 2021.

(-0.724). Conversely, significant strong positive correlations were identified between PV adoption and median age (0.680) and living in a house (0.730), complementing the significant strong negative correlation with living in a unit (-0.689).

The regression analysis, presented in table 7, considers the effect of social, economic, built environment and lifestyle variables over BEV and PV adoption. The four exemplar regression plots for one of the social, economic, built environment and lifestyle variables presented in figure 11, illustrate the extent to which the dependent variable changes with the independent variable. The high spread of results, particularly evident in figure 12a, highlights variance within datasets, stressing the importance of using local data analysis techniques, like local Moran's I, to decompose these global statistical tests.

The results of both the correlation and regression analysis enabled construction of an adopter profile for both BEV and PV adoption. The identification of a moderate/strong correlation and a significant complementary regression for local characteristics indicates a higher degree of predictive power over ETT adoption. Some convergence was identified between PV and BEV adoption, for example rented accommodation had a negative effect on adoption of both. However, this study predominantly observes divergence in the determinants of BEV and PV adoption, with most variables exerting a contradictory effect over BEV and PV adoption. For example, dwelling in a house stimulated PV adoption (β = 1.064), but discouraged BEV adoption (β = -0.027), although to a slightly lower magnitude. The independent variables which produce strong positive correlations and significant beta coefficients of regression for PVs were: dwelling in houses (β = 1.064) and age (β = 0.379). A strong significant negative effect of living in a unit (β = -1.140) was also identified. House value (β = -7.023) and income (β = -0.313) have been identified as important negative predictors of PV adoption, whilst education status (β = 0.183/0.178), commute to work (β = 0.888) exert a less strong, but still significant, positive influence over PV adoption. Gas heating and population density are unanimously identified as poor determinants of BEV and PV adoption due to their weak and often insignificant conflicting regression and correlation results (tables 6 and 7). Renting a property is the one significant common determinant of both BEV and PV adoption, quantified by the negative beta and correlation coefficients (BEV: β = -0.021; PV: β = -0.253), with this study detecting tenancy as a notable barrier to adoption. Adoption of one ETT does not appear to increase the likelihood of adopting another, with the beta coefficient for BEV and PV adoption both showing insignificant low negative values (-0.096 and -0.058).

The multiple linear regression consistently calculates higher r^2 values for PVs than BEVs, suggesting the variables selected in this study are more appropriate for predicting PV adoption than BEV adoption. The built environment variables produce the highest r^2 value for PVs (0.504), whilst lifestyle variables produce the lowest r^2 value of 0.202. Economic variables are the greatest predictor of BEV adoption (r^2 = 0.031) but this is relatively weaker than for PVs, exemplified by the 10-fold larger r^2 (0.290). The cumulative adjusted r^2 value, calculated when assimilating the independent variables, is greater for PV adoption (r^2 = 0.642) than BEV adoption (r^2 = 0.034), suggesting that the local characteristics in this study are better determinants of PV adoption.

Variable	PV				BEV			
	Beta Coefficient	Std. Error	R^2 (adjusted)	F-value	Beta Coefficient	Std. Error	R^2 (adjusted)	F-value
SOCIAL			**0.438**	**40.810****			**0.009**	**3.71***
Median Age	0.379**	0.028			-0.049	0.027		
Education								
1. None	0.040	0.028			-0.083**	0.021		
2. Level 1 & 2	0.183**	0.024			-0.037**	0.020		
3. Level 3 & Apprenticeship.	0.178**	0.019			-0.056**	0.017		
4. Level 4	-0.394**	0.058			0.173**	0.047		
Household Size	0.007**	0.003			-0.003	0.002		
ECONOMIC			**0.290**	**42.551****			**0.031**	**4.354****
Income	-0.313**	0.038			0.068*	0.032		
House value	-7.023**	0.929			2.547**	0.772		
Renter occupied dwellings	-0.253**	0.040			-0.021	0.033		
BUILT ENVIRONMENT			**0.504**	**63.362****			**0.015**	**1.908****
Pop Dens	-0.006	0.018			0.007	0.014		
Dwelling type								
- House	1.064**	0.066			-0.027	0.070		
	0.067	0.084			-0.128*	0.064		
	-1.140**	0.090			0.153	0.086		

- Duplex - Unit								
Charging points	-0.011**	0.003			0.008**	0.003		
LIFESTYLE			**0.202**	**78.421****			**0.001**	**0.633**
Gas Heating	0.196**	0.069			0.082	0.054		
Cars per household	0.011**	0.003			0.024**	0.001		
Car driver or passenger to work	0.888*	0.080			-0.189*	0.073		
BEV adoption	-0.096	0.074						
PV adoption					-0.058	0.044		
R2 (adjusted)			**0.642**				**0.034**	
F Value				**30.010****				**11.920****

** p-value < 0.01
* p-value < 0.05

Table 7. Regression model results with domestic battery electric vehicle registrations and residential solar panel installations per 1000 people as the dependent variable. The collective multiple regressions results are marked in bold.

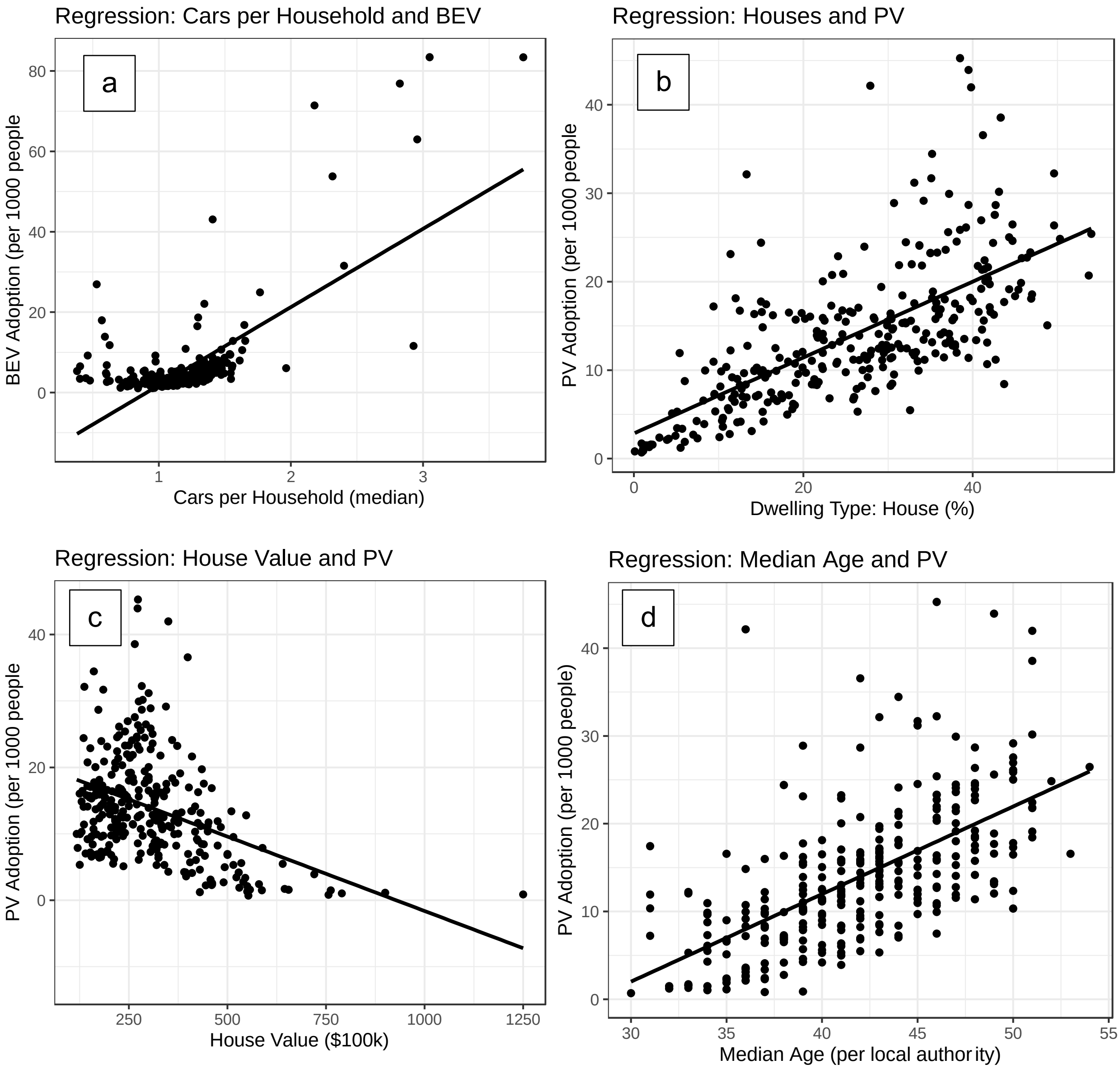

Figure 12. Regression plots from each of the categories with the independent variables marked on the x-axis and dependent variable marked on the y-axis: (a) lifestyle: cars per household and BEV, (b) built environment: houses and PV, (c) economic: house value and PV, and (d) social: age and PV.

5. Discussion

5.1. RQ 1.

The rapid transition of PVs and BEVs from the initial ‘innovators’, to early adopters into aspirational majority markets (Rogers, 2003) is fundamental for meeting the UK Government’s climate obligations (Balcombe et al., 2014). Whilst accelerating patterns of BEV and PV adoption observed in figure 4 is warranted given the 85% decrease in the cost of both EV batteries and PV units (IEA, 2020; IRENA, 2021), literature emphasises the complex network of other factors which are also responsible for determining the trajectories and spatial distribution of ETT adoption.

Growth in residential PV adoption irregularly slowed since 2011, seemingly plateauing from 2019 to 2021 (figure 4b). The peak in PV adoption in 2019, increasing on average in England by 93.89 PVs per 1000 people, coincides with the announced revocation of the FiT which literature suggested sparked a rush on PV instalments (Castenda et al., 2020)., highlighting the role incentives play in determining PV adoption in England. The subsequent decline in cumulative PV adoption in 2020 by -50.58 units per 1000 people aligns with revocation of FiT and the outbreak of Covid-19, possibly representing the dip in PV adoption due to government restrictions imposed during the pandemic (Lempriere, 2020). With the PV markets plateauing at the end of the study period, the trajectory of installation appears uncertain. However recent studies identify a successful restimulation of domestic PV markets, with record breaking growth in the PV industry, doubling small-scale installations in 2022 (Simkins, 2023).

Conversely, BEV adoption accelerated year-on-year from 2011 to 2021, growing by 150,011% over the period, illustrated in figure 4a. Given that the rapid development of the BEV market was undeterred by weakening financial support from government incentives, contrasting to PV adoption (Section 5.1), this potentially places BEVs on a trajectory to catch up with the more mature, larger PV markets in England. Like PVs, BEV markets have also continued to grow, with BEV stocks increasing by 20% in 2022 (Edwards, 2023). The fast-paced, dynamic nature of ETT markets reinforces the importance of this study and of further research in understanding the geographies of the green transition.

PV and BEV adoption is also regionally distinct, with the possible explanations for these spatial differences discussed later in Section 5. Whilst BEV adoption rates were more regular through time on a national scale, geographically BEV distribution was more sporadic than PVs (Section 4). Like Morton et al. (2018), this dissertation suggests the influence of local characteristics change as ETT markets evolve; attributing the regional variability in BEV adoption to changing determinants of adoption as markets mature. Understanding these dynamic determinants of adoption through time and space is useful in shaping effective policies to stimulate the necessary timely and just transition of BEVs and PVs to majority markets across all of England (Lan et al., 2020).

5.2. RQ 2.

The local Moran's analysis (figure 11) emphasises the geographical misfit between BEVs and PVs, with their respective regions of clustering appearing almost inverse. Van der Kam et al. (2018) observed a similar misfit in the Netherlands, stressing the negative implications for the smart integration of energy and mobility systems. PVs predominantly cluster in the South-West, East, East-Midlands, Yorkshire and the Humber and the North-East particularly in the coastal regions, generally distant from major towns and cities. This seriously contrasts to the distribution of BEVs, which are located in closer proximity to urban areas, especially in and around London, the South-East and West-Midlands. Literature commonly recognises the distribution of EVs clustered in more densely populated urban areas, with range anxieties less prevalent due to shorter driving distances and higher density charging infrastructure (e.g., Sierzchula et al., 2014). Conversely literature frequently detects PVs to cluster in rural areas with greater space easing installations and generating more electricity potential (e.g., van der Kam et al., 2018; Kwan, 2012). Although this study detects no significant global effect of population density in the correlation and regression analysis in this study, Section 4.2. highlights specific regions where BEV and PV diffusion follows the expected inverse relationship with urban areas. The disparity between the global regression and local spatial autocorrelation analyses highlights the importance of conducting multiple statistical tests to decompose global statistics. The localised relationship with urbanism either suggests that the urban divide between PVs and BEVs is less severe in England than in literature, or it could infer that the divide will widen and solidify once full market maturity is reached. This dissertation therefore advocates regular monitoring of ETT diffusion to understand pathways of adoption.

Additionally, like van der Kam et al. (2018), this dissertation also finds a similar temporal lag of BEVs behind PVs, contributing to their misaligned diffusion patterns. As adoption rates increased throughout the period, this study also suggests the relative spatial distribution of BEVs and PVs seem to become more pronounced (figures 9 and 10). The current geographical and temporal misfit of BEV and PV adoption in England has serious implications for the smart energy transition (van der Kam et al., 2018), bringing the viability of the smart energy grid into question for the near future. Although the government are focused on developing smart energy technology, notably V2G systems, arguably the implementation of this infrastructure is limited not by innovation, but instead by the conflicting geographies of the green transition. Unless the distinct spatial variance in BEVs and PVs is addressed, the integration of local energy and mobility systems is unfeasible in the near future. This dissertation therefore advocates a re-evaluation of ETT policy, arguing more attention should be paid to the local diffusion patterns of BEVs and PVs, working to stimulate a uniform clean energy transition.

5.3. RQ 3.

The results of the statistical analyses are helpful in constructing BEV and PV adopter profiles, identifying the characteristics of adopters and their respective barriers and motivators for ETT adoption which help determine their distinct spatial diffusion patterns. However, with this dissertation observing BEV and PV at a local authority scale, interpretation of results must be careful of 'ecological fallacy' (Robinson, 1950), whereby relationships identified on a smaller scale are applied to wider groups. The effect of local characteristics quantified in the regression analysis are subject to considerable uncertainty, ranging from 0.001 to 0.929, often similar values to the beta coefficients themselves. The complex, diverse range of potential factors determining BEV and PV adoption contributes to this uncertainty, emphasising the speculative role this dissertation holds when discussing determinants of adoption.

This study observes that PV adopters typically live in houses rather than units, in bigger households with a lower income and lower house value. They are typically older in age, have obtained a mid-tier education level, own more cars and are a driver/passenger to work. Generally, this aligns well with literature, seemingly embodying the 'early adopter' profile identified by Rogers (2003). Although, studies typically find PV adoption to be motivated by the highest education levels, like Balta-Ozkan et al. (2021) this dissertation observes that vocational qualifications (Level 2 and 3 shown in Section 4.3) are more likely to stimulate PV installation due to greater knowledge on the practical construction and instalment process. Three themes of PV adoption have been identified in this dissertation, the importance of house/roof space, the importance of accumulated wealth rather than absolute income and the positive influence of high household energy consumption.

The strong positive effect of living in a house and negative influence of living in a unit, identified in Section 4.3, has been previously identified in literature (e.g., Van der Kam et al., 2018). It is generally acknowledged that households with their own roof space are more likely to adopt PVs (Briguglio and Formosa, 2017). The importance of roof space is logical, the larger the PV, the more electricity generated thus energy bills offset, so the more quickly installation costs are ‘paid back’ (Araújo et al., 2019). Likewise, as multiple units compose one building, residents who dwell in units are therefore less likely to have any access to private roof space, leaving these residents unable to install PVs. The cluster of units and significant absence of houses concentrated in London, depicted in figure 11a and 11g, could therefore explain the consistent significant PV cold spot in London (figure 5) with PV installation less feasible in this dense urban area.

The influence of economic factors, including household income and property value, over PV adoption is heavily contested in literature (table 3). Although it might be expected that the high costs associated with PV installation present a fiscal serious barrier to adoption, this dissertation observes house value and household income to negatively influence PV adoption. This study argues, in line with previous literature, that high income and house value do not disincentivise adoption, but instead suggests that accumulated wealth is relatively more important in motivating PV adoption (e.g., Balta-Ozkan et al., 2021; Lan et al., 2020). As PV installation is a long-term capital investment, households need to be in a strong financial position to invest, highlighting the importance of a disposable income (Balta-Ozkan et al., 2021). Although Balta-Ozkan et al. (2021) suggest a positive effect of renting and PV adoption due to the evasion of mortgages, the strong negative influence of renting a property outlined in Section 4.3, generally aligns well with observations from literature (e.g., Balcombe et al., 2013; Davidson et al., 2014). This also complements the observed importance of accumulated wealth, with tenants found to have a lower disposable income than homeowners (ONS, 2023b), possibly explaining the lower adoption rates in rented accommodation. The same study observed a similar phenomenon for middle aged people, suggesting they have the highest disposable income of all age groups. The positive relationship between PV adoption and age indicates that households older than the average, around 41.94 for England (table 2), essentially middle-aged households, are more likely to install PVs. These findings both aid the conclusion that higher accumulated wealth is an important motivator of PV adoption by overcoming the serious fiscal barrier to adoption, rather than gross household income and house value.

Although not necessarily strong, Section 4.3. observes a positive relationship between household size, living in a house, gas heating, owning more cars and commuting to work. These variables are associated with higher energy consumption and subsequently higher electricity costs (Balta-Ozkan et al., 2021). Given that PVs facilitate savings on energy bills (Capstick, 2023), it is possible that the positive effect of these variables suggest that higher energy consumption acts as a motivator for PV installation. As this dissertation has already identified that these households are not the highest earners and do not live in the highest value dwellings, there might be even more of a drive for them to save on energy bills (Araujo et al., 2019).

The BEV adopter profile differs. Adopters appear to live in smaller households with a higher income and house value, nearer more EV charging points. These early adopters are well educated, property owners with more cars, but do not typically travel in a car to work. This adopter profile generally aligns well with literature (table 3). Three themes of BEV adoption have been identified from this study, the importance of higher economic status, the presence of range anxieties and the identification of a more diverse group of adopters.

Firstly, Section 4.3. shows economic variables to hold the greatest significance for BEV adoption, mirroring the findings in Araujo et al.'s (2019) study. The significant positive relationship between income and house value over BEV adoption detected, aligning with literature (e.g., Kwan, 2012), suggests economic variables are useful predictors of BEV adoption. However, given the consistent removal of most financial aid from the government in reducing costs associated with BEV adoption, it is unsurprising that higher income motivated adoption. This starkly contrasts to PV adoption which instead emphasises the importance of accumulated wealth. Income and house value have a stronger effect over determining PV adoption (-0.313 and -7.023 respectively), with the beta coefficients of the regression at least an order of magnitude greater for PVs than BEVs (0.068 and 2.547), suggesting that accumulated wealth is a more important characteristic for PV adoption than high income/house value is for BEV adoption. The distinct unique determinants of PV and BEV adoption likely explains their spatially inverse patterns of diffusion.

Additionally, the negative relationship between driving to work, and the positive effect of cars per household and charge points (tables 6 and 7) suggests evidence of concerns over range anxiety in England – a potential barrier to BEV adoption (Plotz et al., 2014;

Skippon and Garwood, 2011). The positive effect of owning more cars could be due to BEVs being more popular as a second car, as found in previous studies (Skippon and Garwood, 2011; van Haaren, 2012; Haugneland and Kvisle, 2015). Literature implies that BEVs are therefore designed for local driving rather than for long commutes due to concerns over the battery range (Nayum et al., 2016) hence the negative influence of commuting observed in this dissertation. The positive effect of charging infrastructure complements the detection of range anxieties as adopters appear more confident to make the investment in BEVs knowing they have greater accessibility to charging networks. However, literature identifies a weaker relationship with charging infrastructure than observed in previous literature. When comparing the correlation coefficients with Morton et al.'s (2018) 2015 study in England they appear similar to this dissertation (0.304 and 0.252 respectively). However, given that this study recorded charge points per 1000 people rather than per person, the vastly different scale suggests a weaker correlation between charge points and BEV adoption in 2021 than in 2015. Like Plotz et al. (2014), this dissertation argues that the seemingly lowering dependence on charging infrastructure may be due to the accelerating growth of home charging. The Energy Savings Trust (2019) finds 80% of EV charging to take place in the home, a phenomenon observed as BEVs move into majority markets. Again, highlighting the turbulence associated with ETT markets.

Finally, this study identifies a more diverse group of BEV adopters than PV adopters with the regression and spatial autocorrelation models explaining less of the variance in BEV adoption, aligning with the findings from Araujo et al.'s (2019) study in New York. The higher combined r^2 value for PVs presented in Section 4.3. indicates that the independent variables offer more predictive power over the adoption of PVs than BEVs. However, the r^2 for PVs is more uncertain, quantified by the higher significant f-value of 30.010, reinforcing the limits of this study in defining the absolute determinants of ETT adoption. Van der Kam et al. (2018) observes a very similar phenomenon in the Netherlands, calculating an r^2 of 0.452 and 0.053 for PV and BEV adoption respectively. Like this study, they attribute the lower r^2 value for BEVs to the adopter group being more diverse, with adoption determined by a network of wide-ranging variables beyond the scope of their study. Section 4 identifies an increasingly spatially uneven BEV distribution, with diffusion becoming more sporadic. This dissertation calculates r^2 values of 0.642 and 0.034 for PV and BEV adoption, accounting for ~64% and 3.4% of the variance in spatial distribution respectively. This suggests that a broader or different range of variables determine patterns of BEV adoption

than the local characteristics identified in this study, explaining the geographically sporadic pattern of BEV adoption identified in Section 4.
Given that the independent variables in this study successfully account for the majority of variance in PV instalment, BEV and PV adoption are clearly influenced by very different factors. The distinct adopter profiles for these two ETTs, helps explain inverse patterns of BEV and PV adoption observed figure 2.

Although the distribution of PVs is well explained by the local characteristics, 36% of variance is unexplained by this study. Section 5.1. highlights the important predictive power of incentives over PV adoption in England. Additionally, literature emphasises the significance of differing spatial solar irradiance levels in PV adoption. Balta-Ozkan et al. (2021) find a strong positive effect of high solar irradiance levels in the South-West over PV adoption due to the high electricity generation potential. With this study also consistently identifying the highest concentration and growth rate of PVs in the South-West throughout the period (figure 4), this could be attributed to higher solar irradiance levels.

Local characteristics have been identified as significant determinants of BEV, but particularly PV, adoption. Similar to Lan et al. (2020), this dissertation therefore also advocates a reconsideration of ETT incentives, suggesting that policy making should become more localised to account for these diverse local characteristics, enabling the transition of both BEV and PV adoption from early adopter to majority markets (Rogers, 2003). Furthermore, given the divergence in determinants of BEV and PV adoption and subsequent inverse spatial distribution patterns in England, incentives must encourage adoption of BEVs and PVs in synergy, narrowing the regional imbalance particularly between rural and urban areas. This will help facilitate the aspirational integration of energy and transport sectors (House of Commons Library, 2023).

5.4. Study Limitations and Further Research.

The complex interrelating network of local characteristics collectively responsible for determining BEV and PV adoption, limits this study to merely speculating the influence of the independent variables in this study, exemplified by the notable uncertainty associated with the regression analysis. Whilst useful for assessing diffusion nationally, the local authority scale limits analysis of more local forces determining ETT adoption. To uncover unexplored determinants of adoption, particularly for BEVs where very little variance is explained in this study, this report advocates conducting further smaller scale, qualitative studies within English neighbourhoods. Additionally, given the dynamic nature of ETT markets detected in Section 5.1., this dissertation advocates regular monitoring of BEV and PV diffusion, to better understand the pathways of anticipated rapid market growth.

6. Conclusion

Using a variety of analytical techniques, this study explored the characteristics and determinants of BEV and PV adoption through time and space. The major contribution of this paper is the temporal and geographical misfit in the distribution of BEVs and PVs in England, a phenomenon only previously observed elsewhere. This has serious implications for the UK Government's aspirational development of smart charging infrastructure, intending to integrate energy and transport sectors. PV markets were observed to be more mature, but the accelerating growth of BEV adoption arouses uncertainty over the future composition of ETT markets. The spatial variance in PV and BEV diffusion, appearing almost inverse, has been attributed to their unique determinants of adoption. Generally, the local characteristics in this study exerted conflicting control over determining PV and BEV adoption and were more effective at determining PV than BEV adoption, with the regression models accounting for 64% compared to only 3.4% variance in adoption. Therefore, this dissertation suggests that the BEV adopter group are more diverse and sporadically distributed in England.

Given the observed variance within global statistics, this dissertation emphasised the importance of applying both global and local analytical techniques to better understand the regional nuances of BEV and PV diffusion. Although subject to considerable uncertainties, wider contextual complexities and data resolution limitations, this does not detract from the valuable conclusions drawn from this study. Given the dynamic nature of BEV and PV markets, this study stresses the importance of consistently monitoring adoption. This is useful for shaping relevant and effective policy to stimulate uniform ETT diffusion. This has relevance both within England, but also for the rest of the UK and other nations undergoing a similar decarbonisation process. To promote the necessary adoption of BEVs and PVs in synergy, this study advocates more localised ETT incentives which reduce local barriers to adoption. However, further smaller scale and qualitative research is crucial to understand the forces behind identified determinants of adoption, particularly in understanding the variance in BEV and PV diffusion not explained by this study.

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