Factors influencing early electric vehicle adoption in Ireland

SANGHAMITRA CHATTOPADHYAY MUKHERJEE & LISA RYAN*, UCD SCHOOL OF ECONOMICS & UCD ENERGY INSTITUTE.

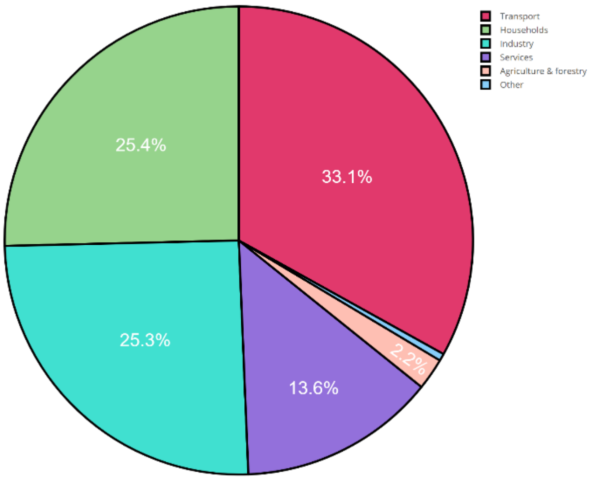
*Corresponding author. *Tel:* +353 1 7168212; *Email address:* lisa.ryan@ucd.ie

Abstract

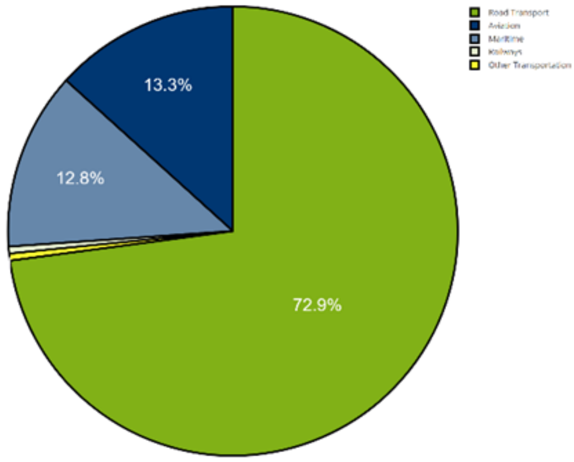
The objective of this work is to analyse the key determinants of electric vehicle uptake amongst early adopters. Transport accounts for about a quarter of Europe's total greenhouse gas emissions and has not achieved similar reductions in emissions as other sectors. However, there is an opportunity to achieve lower emissions through the widespread use of electric vehicles. Due to the rising awareness of the link between emissions and global warming, the European Union has set serious targets for renewable energy and greenhouse gas emissions that member states must achieve by 2020 and 2030. Although considerable progress has been made in reaching targets, efforts in the transport sector have been lagging in many countries, with a significant boost required in electric vehicle roll-out if transport-specific targets are to be met. One reason for this lack of progress is possibly an incomplete understanding of the motivations behind consumer uptake, which in turn, hampers policy design to encourage adoption. Here, for the first time, the case study of Ireland is used to analyse socio-demographic and neighbourhood characteristics such as charging infrastructure, dealers and other EV adopters, to identify the key determinants of electric vehicle adoption in the early phase of technology diffusion. From our exploratory data analysis, social class which represents whether the population consists of skilled, semi-skilled or unskilled workers, appears to be the principal factor affecting EV uptake in Ireland. This variable may proxy for income effects, implying that the average wealth of a neighbourhood matters for EV ownership. There also appears to be clustering in EV adopters, possibly due to unobserved peer effects. The OLS model performs poorly for our dataset. Our future work will help determine the significant predictors of adoption based on a spatial econometric approach that explicitly models relationships between agents in the model such that the restrictive assumptions of OLS models can be relaxed to allow for interdependence between individual actors.

1. Introduction

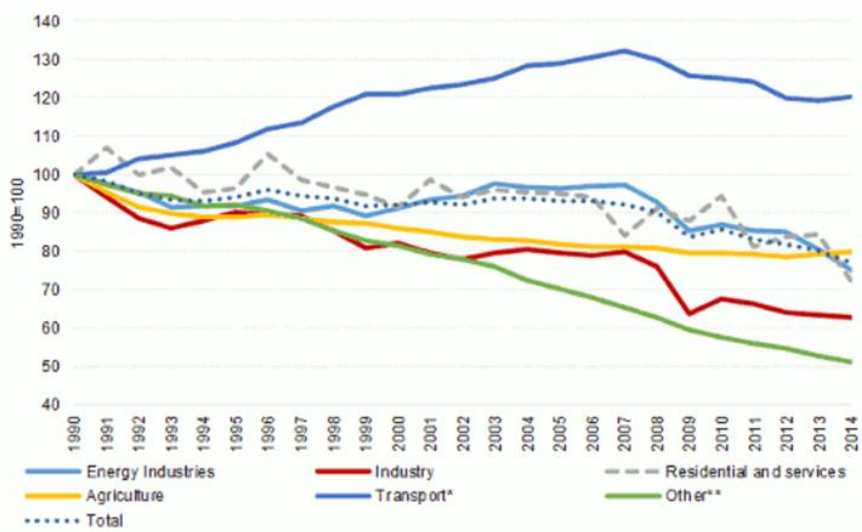
Given the urgency to stop global warming in its tracks and even reverse some of the anthropogenic damages already caused, countries worldwide are striving to reform their domestic energy policies such that future consumption and production processes are more sustainable. As shown in Figure 1 (a), the transport sector accounts for a third of energy consumption in the European Union (EU) and is still heavily reliant on fossil fuels (European Environment Agency, 2017). This sector also accounts for a quarter of greenhouse gas emissions (GHGs) in the EU (European Commission, 2018). Additionally, energy consumption is growing - energy consumption in the EU-28 in 2015 was 25% higher than 1990 levels. Road transport has accounted for a major share of this growth with a 20% increase in passenger car demand over this period. As seen in Figure 1 (b)-(d), GHG emissions from transport have been steadily rising in most countries in Europe, with road transport accounting for 72.9% of total emissions from transport in EU-28 in 2014. In this regard, renewables in the form of liquid biofuels as a transport fuel has seen rapid development. However, the average share of energy from renewable sources has increased only from 1.4% to 7.1% between 2004 and 2016. Moreover, the performance of countries has varied considerably, with the relative share of renewable energy in fuel consumption ranging from over 30% in Sweden to only 2% in Estonia. Electric vehicles (EVs) offer a viable alternative that could help member countries meet the common target that requires at least 10% of their transport fuels to come from renewable sources by 2020.



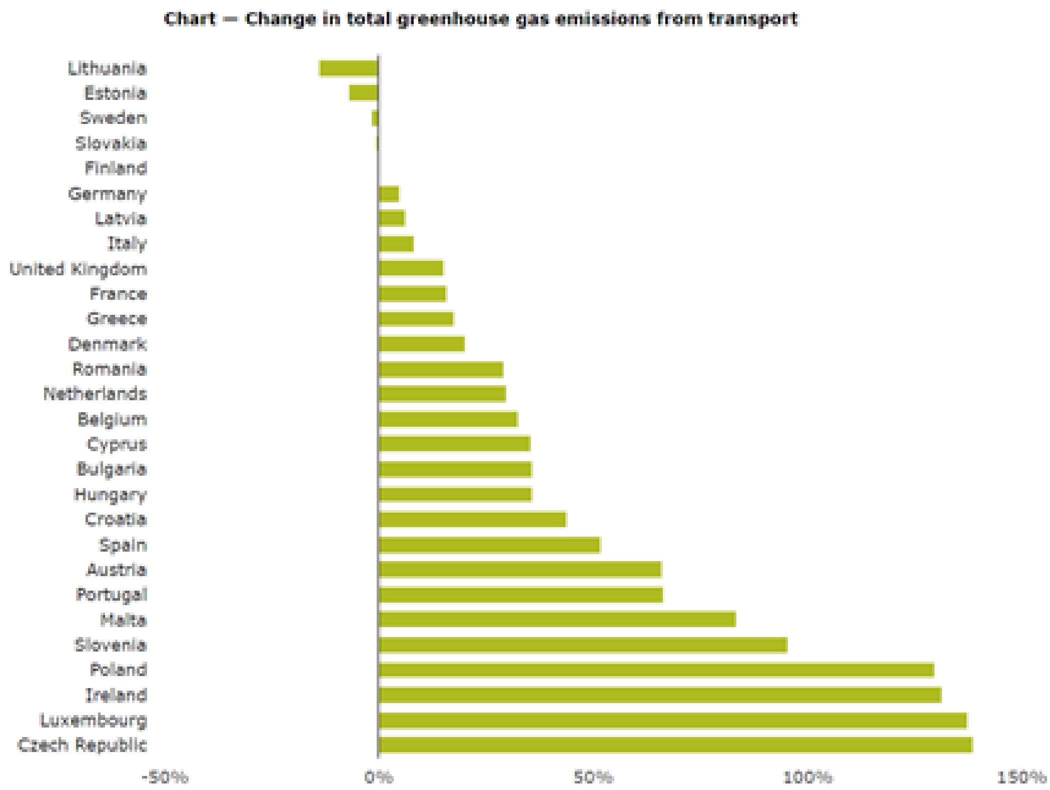
(a) Share of transport in final energy consumption, EU-28, 2015
Source: Eurostat



(b) Share of road transport in total GHG emissions from transport, EU-28, 2015
Source: EEA



(c) GHG emissions from transport over time, EU-28, 2014
Source: EEA



(d) Change in total GHG emissions from transport between 1990-2015, EU-28, 2015

Source: EEA

Figure 1 Contribution of transport to overall consumption and GHG emissions

An EV is a vehicle that uses at least one electric motor for propulsion. A self-contained EV is usually powered by a battery, solar panels or a generator that converts fuel to electricity in the case of hybrids, or alternatively, through a collector system from off-vehicle electricity sources. The idea of an EV has been around from the mid-19th century. However, fossil-fuel based internal combustion engines (ICEs) remained the preferred vehicle propulsion technology until the 21st century, when technological advancements, increasing awareness of climate change and concern for energy security brought on a revival of interest in electricity as a power source for transportation.

The key benefits of EVs are its potential to reduce carbon emissions that contribute to climate change and cause ecological damage. In addition, the resulting reduction in smog and pollution levels have immense public health benefits. Importantly, electrification of transport using renewable electricity reduces dependence on imported fossil fuels and expands the diversity of domestic fuel choices available to consumers since almost all electricity is produced domestically within countries. However, several studies have identified current EV adopters as early adopters, implying that the diffusion of EVs is still in the early stages, with the technology yet to reach the take-off point (Nayum *et al.*, 2016; Plotz *et al.*, 2014; Bockarjova *et al.*, 2013). This is perhaps because the technology for EVs is still developing and EVs are yet to become financially competitive with ICEs. Besides, being a dynamically continuous innovation[1] means that the adoption of EVs involves some behaviour change that may act as an additional barrier to adoption.

Despite the challenges pertaining to EVs, transport must be electrified if countries are to meet their renewable energy targets for the transport sector. It is, therefore, crucial that planners and policy makers understand the diffusion process of EVs and aid in their rapid diffusion. The present research proposes that incentivising localised EV adoption could boost national uptake substantially. This paper aims to apply a spatial econometric approach at a fine geographical scale to the case study of Ireland to explore the causal relationship between charging infrastructure and EV adoption for the first time as well as to identify other neighbourhood characteristics that may determine early EV adoption.

The paper is structured as follows. Section 2 provides an extensive literature review on the characteristics of EV adopters, explains the Irish context and lays out our contribution to the literature. Section 3 describes the data sources used and presents a summary of the exploratory data analysis techniques implemented. It also displays exploratory plots of the spatial dispersion of adopters, infrastructure and dealers. Results are presented in Section 4 with significant determinants of adoption clearly marked and their implications discussed. Section 5 provides some concluding remarks. The appendices provide background information on important concepts and findings. Specifically, Appendix A: Technology diffusion describes the theory of technology diffusion, Appendix B: Determinants of RET uptake tabulates the characteristics of Renewable Energy Technology (RET) adopters identified from the literature, and Appendix C: Data and Methods provides summary statistics for all variables in our dataset, explains terminology and provides the mathematical foundation behind the spatial statistics tools used in the analysis.

2. Overview of the literature

2.1 Drivers and barriers to EV uptake

This paper categorises the main variables, triggers and underlying characteristics that underpin the adoption and diffusion of RETs into seven[2] broad categories: economic, non-economic (but potentially monetisable), socio-demographic, spatial and the built environment, technical, behavioural and psychographic. Key non-spatial barriers and motivations for EV uptake are highlighted in this sub-section. Appendix B: Determinants of RET uptake provides the comprehensive list of characteristics that relate to RET adoption generally with an emphasis on EVs.

There is consensus on the main technical challenges of EVs. Egbue and Long (2012) study technology enthusiasts to identify some socio-technical barriers to EV adoption. Battery range seems to be the biggest concern within this group while sustainability is less important than cost, performance or concerns surrounding charging infrastructure. The prospect of minimal maintenance requirements, potential to eliminate the use of petroleum and reduced GHGs are attractive features of EVs. Bockarjova *et al.* (2013) present results of a stated choice experiment showing that innovators and

[1] See Appendix A: Technology diffusion for a detailed description of the process of technology diffusion and types of innovations.

[2] Eight, if legal factors are considered, such as the need for planning permission to install a residential solar PV system on the roof. This is not included here as it is not applicable to EV uptake.

early adopters value EVs negatively relative to conventional vehicles predominantly due to the long charging times associated with fast charging rather than any inconvenience perceived for slow charging at home or work. Nayum *et al.* (2016) use choice-modelling and psychographic theories of behaviour to reveal that buyers of EVs tend to value convenience and performance less than those of conventional vehicles as EVs are usually second cars, although fuel efficiency is a common concern.

Conversely, there is no definitive evidence on the role of socio-demographic characteristics. Biere *et al.* (2009) demonstrate that early adopters of EVs are likely to be those with a full-time job living in towns with less than 100,000 inhabitants. Plotz *et al.* (2014) further observe that early adopters of EVs have a distinct configuration of socio-economic and attitudinal characteristics. They tend to be middle-aged, male, with high socio-economic status, living in rural areas with several household members, often children, interested in trying out technical innovations, and less concerned with comfort. In contrast, Nayum *et al.* (2016) find that EV owners are significantly younger compared to conventional car owners but concur that they enjoy a significantly different socio-psychological profile from conventional car buyers in that they have more cars and children per household, a larger household size, are more likely to be working, with higher education, higher household income, and higher levels of awareness and acceptance of environmental problems, besides spending less time evaluating car attributes. However, Anable *et al.* (2011) show that socio-demographic factors are less important, with low range anxiety and an EV-friendly social environment being stronger drivers. Curtin *et al.* (2009) suggest that neither gender nor location are clear predictors of uptake.

Certain socio-psychological factors positively influence uptake, including personal capabilities such as openness to innovative technology, high risk tolerance, image consciousness, social and personal norms, and favourable attitudes towards reducing the carbon footprint. Claudy discover that awareness of microgeneration technologies differs significantly amongst Irish consumer segments, with men more likely to have heard of microgeneration technologies than women. Egbue and Long (2012) also show that knowledge and perceptions differ across age, gender and education groups, influencing the level of uptake within different socio-demographic groups. Gardner *et al.*(2011) use the Theory of Planned Behaviour (TPB) model to find that social influence, experience and psychographics such as consumer perceptions and attitudes towards EVs are key factors determining uptake. Anable *et al.* (2011) note that openness to EV technology and a high willingness to pay are characteristics of early adopters. Busic-Sontic and Fuerst (2017) extend Roger's Diffusion of Innovation model with the big five personality dimensions: openness to experience, conscientiousness, extraversion, agreeableness, neuroticism, to confirm that homeowners who are open to experience invest earlier in energy efficiency while agreeable homeowners tend to be laggards. There is no conclusive evidence on whether environmental attitudes matter. Curtin *et al.* (2009) and Ziegler (2012) find that potential EV customers in the US value the environmental benefits offered by EVs and are willing to demonstrate their beliefs through their purchase decisions. In contrast, Hidrue *et al.* (2011) find that economic motives are a more decisive factor than environmental considerations. Moreover, Bockarjova *et al.* (2013) suggest that early adopters tend to value environmental benefits of EVs much less than later adopters.

Overall, the primary advantages of EVs are its zero tailpipe CO_2 emissions[3], lower maintenance needs, and the potential independence it offers from fossil fuel energy (IET, 2011). A key barrier to adoption is its high upfront cost, although continuous technological development is leading to rapidly falling price of batteries, which constitutes roughly a third of the price of an EV (Egbue and Long, 2012). Moreover, EVs could become competitive with conventional vehicles at a sufficiently high gasoline price once uncertainties, such as regarding the standardisation of batteries across manufacturers and suppliers and the resale/scrap value of EVs, are resolved (Becker *et al.*, 2009). Furthermore, non-economic benefits such as exclusive high-occupancy vehicle (HOV) lane access tend to counteract some of the economic concerns (Nath, 2016). However, the limited range of EVs compared to ICEs still present a problem for long-distance journey planning, slowing down uptake. Range anxiety may, however, be less prevalent in the future when battery swapping possibilities become available besides opportunities to purchase the vehicle and battery separately. EVs also require a shift in driving behaviour in terms of charging times and remembering to charge, that may act as 'hassle' factors that discourage adoption (IET, 2011). Electricity tariffs may play a role here. The current payment infrastructure in many countries is a flat tariff rate and therefore rather rigid. However, variable prices for different charge types like full-charge and fast-charge and time-of-use tariffs incentivise charging during off-peak hours and shifts in charging behaviour generally, lowering variable costs to charge.

2.2 The importance of spatial characteristics

Spatial characteristics are key in RET diffusion. Gardner *et al.*(2011) show that people with similar incomes, age profiles and education levels often aggregate, creating pockets across space that are more suitable for technology uptake than others. In contrast, Sierzchula *et al.* (2014) indicate that aggregation of socio-demographic variables such as income and education levels are ambiguous predictors of adoption as non-adopters could also be highly educated and wealthy. Rather, EV-specific characteristics such as charging infrastructure could potentially explain uptake better.

Achtnicht *et al.* (2012) and Tran *et al.* (2013) recognise that a lack of charging availability slows down EV uptake. In Sierzchula *et al.* (2014)'s assessment of the role of financial incentives, charging infrastructure[4] and socio-economic characteristics in EV adoption across 30 countries, charging infrastructure appears to be the best predictor of a country's EV market share. Mersky *et al.* (2016) agree on the importance of charging infrastructure in Norway but remain undecided on whether the correlation of sales with charging stations results from a consumer incentive effect, or if charging stations are being built in response to local EV demand. Coffman *et al.* (2017) provide a helpful review on this topic and point out that although access to charging infrastructure and EV uptake are clearly related, there is no conclusive evidence yet on whether the presence of infrastructure drives adoption or vice-versa. McCoy and Lyons (2014) recognise this gap for Ireland and suggest improving their spatial model by integrating data on the existing charging infrastructure, as although still uncertain, proximity to public charging points likely influences the decision to purchase an EV.

Axsen *et al.* (2009) demonstrate the potential importance of neighbour effects. Intangible social costs decrease with increased market share since the adoption of an innovative technology becomes more desirable when increasing uptake in the neighbourhood shifts cultural norms, changes social

[3] Although the green benefits of EVs are only realised when the fuel mix generating electricity is low carbon.
[4] Calculated as each country's total number of charging stations corrected for population.

concerns, improves credibility, and enhances opportunities to learn from others. Exploiting this observation, Becker *et al.* (2009) build a network externalities model to estimate the maximum market share of EVs as a function of oil prices, possible purchase price incentives, driving habits and the number of other adopters. McCoy and Lyons (2014) implement an agent-based model (ABM) of innovation diffusion to simulate the adoption of EVs among Irish households. They find that mild peer effects[5] could result in large clusters of adopters in certain areas even if overall adoption is low. Nath (2016) uses the TPB model and Rogers' Diffusion of Innovations theory to demonstrate the importance of marketing channels, trusted information sources (e.g. developers or installers) and peer effects in the adoption decision. While innovators tend to decide independently of others, interpersonal interactions with other EV owners seem to have a much more profound impact on later adopters.

There is a general dearth of spatial research in RET adoption, but there has been considerably more work on solar PV uptake than on EVs[6]. Graziano and Gillingham (2015) show that clustering in solar PV adoption does not simply follow the spatial distribution of income or population in Connecticut, US. Contrary to previous findings, smaller centres seem to contribute to PV adoption more than larger urban areas, in a wave-like centrifugal pattern. One new adoption in the previous 6 months increases the number of adoptions in a block group per year-quarter within 0.5 miles of the solar PV system by 0.44 systems on average. This effect diminishes with distance and time, implying that social interaction and visibility are key players in this process. Adoption reduces with housing density and the share of renter-occupied buildings, possibly due to a split incentive problem. Lastly, community engagement programmes such as the Solarize[7] campaign have a significant and positive impact on adoption.

Balta-Ozkan *et al.* (2015) also find significant regional spillover effects in solar PV adoption in the UK. Adoption not only follows patterns of solar irradiation but in addition, households that are smaller, and in highly polluted, less dense areas tend to be early adopters. Electricity demand, the average level of household education and housing type also define regional PV uptake. Local enterprise partnerships or third-sector organisations like charities and non-governmental organisations that coordinate environmental policies at sub-regional levels are other key players in the diffusion process.

Likewise, Dharshing (2017) discovers that significant spatial spillover effects between neighbouring counties in Germany create 'solar clusters' over time. Regional PV uptake is not only determined by the similarities in solar radiation or demographic characteristics, but also by spatial dependence across neighbouring regions, where cross-regional spillovers can be caused by peer effects, clusters of local craftsmen or regional solar initiatives.

[5] Peer effects operate via two main channels: the passive influence from observing the presence or use of the technology in the neighbourhood, and the active influence through interpersonal communication with neighbours. Peer effects have been widely studied in the technology adoption literature and their importance is generally acknowledged.

[6] Both EVs and solar PV systems are visible technologies, i.e. they are in full view of neighbours and therefore, could espouse both passive and active peer effects in their adoption process. They differ technically: solar panel systems generate electricity for domestic use and export the surplus onto the grid, while EVs use electricity from the grid and potentially provide storage services to the electricity system when not in use.

[7] See https://www.nrel.gov/docs/fy12osti/54738.pdf for details.

Rai and McAndrews (2012) identify perceived uncertainty and non-monetary costs as a key metric to explain why social and communication networks are important for technology diffusion. Rai *et al.* (2016) demonstrate that neighbourhood contact increases motivation, confidence, convenience, relevance, and trustworthiness, improving the chances of uptake. Both active and passive peer effects appear to create positive feedback loops that speed decision-making. Similarly, Schelly (2014) establishes that communities of information (e.g. energy fairs) positively influence adoption because they provide the context and perceptions of trustworthiness to potential early adopters before they receive any information relating to the technology. Sigrin *et al.* (2015) find that early adopters are more likely to be influenced by other solar owners as part of a home tour. In addition, trusted sources such as installer advertisements (via radio, TV), direct marketing by solar companies and personal contacts are valuable information channels. Rai *et al.* (2016) also show that direct marketing by a solar company, and either viewing or conversing with a neighbour who installed a solar panel acts as a spark event. However, Robinson and Rai (2015) demonstrate through an ABM that information diffusion alone does not predict technology adoption; information must diffuse to *economically capable* nodes.
Finally, Palm (2017) studies peer effects using qualitative studies - active peer effects tend to be more important and propagate through existing and close social networks rather than through neighbours who do not already know each other. Active contact with peers helps confirm that the technology works as intended and with minimum hassle without necessarily providing any additional information about the technology. Merely noticing a neighbour's PV system does not automatically lead to direct contact and is hence not as helpful in inducing adoption. In an earlier study, Palm (2016) finds that both peer effects and local organisations supporting PV are important determinants of the diffusion of solar PVs in Sweden. Electric utilities are powerful influencers, acting as trusted organisations informing about and promoting solar energy at the initial stages of adoption.

In summary, socio-demographic determinants such as household income, education, employment status and age are often spatially clustered. Neighbourhoods hosting individuals of higher social status, with bigger households and more children and cars in the family are more likely to adopt EVs. The housing stock in a certain locality may act as a barrier. Flats with no secure parking spaces for vehicle charging, for example, may not be suitable for EVs (IET, 2011). Neighbourhood effects may also seep in through interpersonal networks. Interpersonal communication helps in reducing perceived barriers related to low trialability and low observability when adopting an innovative technology. Peers may be able to directly help in decision-making, for instance, in selecting the best procurement mechanism. In addition, mere visibility of EVs in the neighbourhood may spark interest as the proximity of other adopters may indicate a changing social norm in that location. Moreover, suitably located EV dealers may assist in minimising hassle by providing reliable information and lowering transaction costs.

2.3 The Irish context

The transport sector accounted for 35% of primary energy consumption in Ireland in 2015 (SEAI, 2016a). Furthermore, Ireland's transport sector is heavily reliant on imported oil. To reduce its dependence on fossil fuels, Ireland is committed to ensure that 10% of its transport demand is met by renewable sources by 2020 under the EU Renewable Energy Directive (SEAI, 2016b). There are policies in place introduced by the Department of Transport, Tourism and Sport (DTTAS) such as the Biofuels Obligation Scheme that aim to expand the role of renewables in the transport sector (DTTAS, 2017). Studies have also confirmed that the introduction of EVs offer the potential to significantly reduce CO_2 emissions and primary energy requirement on a per-km basis (SEAI, 2016b). Ireland embraces this fact through its commitment to a target of selling only “zero-emissions capable” cars and vans by 2030. However, in contrast to other countries that are aiming to expand their EV fleet by 2020 and banning combustion engines by 2025, Ireland has revised its targets downwards from 230,000 to 20,000 EVs on the road by 2020, due to lower-than-anticipated uptake and an unfavourable fuel price and infrastructure situation (O’Sullivan, 2017).

There are currently around 3,000 EVs in Ireland, including Plug-in hybrid electric vehicles (PHEVs), Battery electric vehicles (BEVs), and Hybrid electric vehicles (HEVs). There are currently 11 unique EV models such as the BMQ i3, Renault Zoe, Hyundai Ioniq, Volkswagen e-Golf, Nissan Leaf and the Tesla model S introduced in 2017 (Irish EV Owners Association, 2018). These EVs are capable of conventional car speed, acceleration and power, and batteries last between six and ten years (ESB, 2018). With rapid advancement in battery technology, the range has significantly improved with, for instance, the Mitsubishi i-MiEV having a range of 150km and the Tesla Model S having a range of 420km. For certain models, the driver can also buy the car and lease the battery. Although prices remain higher than conventional vehicles, with some models costing over a €100,000, public incentives such as a €5,000 purchase grant, a zero rate of Vehicle Registration Tax (VRT) relief of up to €5,000, lower road tax of €120, reduced maintenance costs and significantly lower fuel costs greatly help to reduce overall costs (SEAI, 2017). Furthermore, in addition to free parking while charging, Ireland enjoys modern charging infrastructure financed by the Electricity Supply Board (ESB) with over 1,200 public electric charging points, making seamless travel around the country possible since 2007/08 (ESB, 2018).

Ireland as a case study is particularly interesting given that average commuting distances are short compared to other European countries, with little distinction between urban and rural locations, making a case for adoption even in the absence of an extensive public charging infrastructure. The average Irish commute is under 15 km, with Dublin City, Cork City, and Galway City commuters living within 10 km of their workplace[8] (CSO, 2016). Residents in Laois, a more rural setting, experience the longest commuting distances, at just over 25 km. The cities of Dublin, Cork and Galway jointly represent approximately 659,000 commuters, representing just under 54% of workers who commute by car, and 35% of total commuters. Consequently, Ireland may be highly suited to EV use as short, frequent journeys could largely mitigate concerns with range even as battery packs continue to become more efficient and economical. Most Irish EV users also prefer to charge at home, with the next best alternatives being fast-charging stations at car parks and petrol stations (Morrissey *et al.* 2016). Other types of charging infrastructure and at other locations may, therefore, be necessary solely to provide visibility for potential adopters and reassurance for existing users.

However, although discounted night rate electricity, free access to public infrastructure, and different forms of charging are available, EVs are currently in the “innovator” to “early adopter” stage in Ireland. The availability of charge points and the time to charge are still major barriers. Public charging takes between 2 and 6 hours, home charging between 6 and 8 hours, and fast

[8] According to the Central Statistics Office (CSO) study, where commuting distances are calculated on a straight-line basis from home to workplace.

charging around 25 minutes for an 80% charge (ESB, 2018). Charging infrastructure will likely need to be commercialised to accommodate further infrastructure investments, while battery technology advances further to make EVs fully competitive with conventional vehicles. On a positive note, with the introduction of new car models that keep expanding the choice set for potential consumers and autonomous cars and ride-sharing services equivalent to Uber rising in popularity, the prospects for EVs look more promising.

2.4 Unique contribution

The evidence on EV uptake is often mixed and differs from one context to another. From a socio-demographic perspective, a suitable adopter profile could be a full-time worker in a multi-person household interested in trying out eco-friendly cars. Age, gender and location are more dubious predictors. However, EV adopters tend to be male, middle-aged, and either living in small to medium-sized cities with short commutes, or in rural locations with sufficient garage space for charging and driving longer distances. Government incentives and regulatory and tax policies such as fuel economy standards and fuel and carbon taxes may encourage uptake amongst other adopter profiles.

Additionally, several studies have validated the significance of peer-to-peer neighbourhood effects for RET adoption. However, although there are externalities attached to home and neighbourhood charging infrastructure[9], there is scant literature on the role of charging infrastructure in early EV adoption. There are some cross-country studies suggesting an association between these variables, but further study using country-specific data is needed, given that the distribution of charging infrastructure within countries is heterogenous. Importantly, there are no studies yet that confirm the direction of causality between the availability and distribution of charge points and EV uptake.

Our aim is to examine several socio-demographic and spatial characteristics to identify the significant determinants of regional EV uptake using Irish data at a granular spatial scale of 18-120 households. Further, we would like to establish whether a causal link exists between charging infrastructure and EV uptake using a spatial econometric model that integrates the distance to the nearest charge point as an explanatory variable and explicitly models peer-to-peer interdependence. The present research, therefore, contributes to the literature by studying the EV diffusion process at a finer granular scale than has been carried out to date and incorporating neighbourhood features such as charging infrastructure that is crucially missing from previous research on EV uptake. We also map EV uptake spatially which could help plan for future infrastructure upgrades as well as pinpoint geographical targets for incentivisation. This is because electricity grid systems have geographically variable capacities and although large-scale uptake of EVs is necessary, this will add further loads to the network during charging that could cause a network failure if not planned for.

[9] While localised EV adoption around charging infrastructure may create spatial dependencies that cause negative externalities by overloading stressed electricity network assets, conveniently located charge points could also create positive externalities by reducing range anxiety, thereby improving both perceived and actual utility in owning and using an EV.

3. Data and methodology

3.1 Data sources

The ecars division within ESB collects and maintains a database of all new EV owners in Ireland up to December 2017, as each purchaser of a newly registered EV who qualified for a Sustainable Energy Authority of Ireland (SEAI) grant received a free home charge point from ecars until then. The database contains information on the approximate addresses of adopters, the dealer code of the dealer they purchased from, the car model purchased, installation date of home charge points and whether the installation was confirmed. Using the address information, we successfully geocoded 2050 EV owners who had a home charge point installed between March 2011 and August 2017, out of 2093 addresses in the database. After removing purchasers of plug-in hybrids[10], the final dataset contains the geolocations of 1680 BEV owners.

Ecars also publishes a map for the location and real-time availability status of installed and planned public charge points. There are currently 1,200 public charge points available nationwide in locations such as on-street, shopping centres, and car parks. There is at least one charge point in every town with 1,500 or more inhabitants. Fast charge points are located along main inter-urban routes at service stations and roadside cafés to cater for those on longer journeys. We successfully geocoded 772 charge point locations out of the 865 that had locational information attached on the map. Furthermore, the full list of EV dealers in Ireland with their up-to-date location and contact details is available from the SEAI website. We successfully geocoded 174 out of 177 addresses in that list.

We conduct all analyses at the level of Small Areas[11]. This is the most disaggregated level for which key socio-demographic data are available from the 2016 Census. The Small Area Population Statistics (SAPS)[12] dataset published by the CSO contain data relating to sex, age, marital status, families, housing, education, commuting and occupation, providing an in-depth picture of the socio-economic conditions for each of 18,641 Small Area communities in Ireland. This data was made available for the first time in July 2017. Appendix C: Data and Methods provides summary statistics for our full dataset.

3.2 Exploratory data analysis

Figure 2 shows that despite a dip in adoption rates in 2013, EV ownership has been steadily rising over time, from only 23 EVs on the road in 2010 to 1759 EVs by the end of 2016[13]. Figure 3 demonstrates that out of seven distinct EV models, the Nissan Leaf appears to be by far the most popular in Ireland, constituting over 1200 adoptions by 2016, compared to the second-most popular, the Hyundai Ioniq Electric, at just around 200. This can be expected as the Nissan Leaf has been available longer, with other models entering the market much more recently.

---

[10] We exclude owners of plug-in hybrids as they have the option to only use the on-board combustion engine and seldom or never use the electric powertrain system, which could skew the results in our analysis.

[11] Small Areas are areas of population comprising between 18 and 120 dwellings created by The National Institute of Regional and Spatial Analysis (NIRSA) on behalf of the Ordnance Survey Ireland (OSi) in consultation with the CSO. They were designed as the lowest level of geography for the compilation of statistics in line with data protection and generally comprise either complete or part of townlands or neighbourhoods.

[12] See http://www.cso.ie/en/census/census2016reports/census2016smallareapopulationstatistics/ for details.

[13] Actual numbers may differ slightly from numbers presented here.

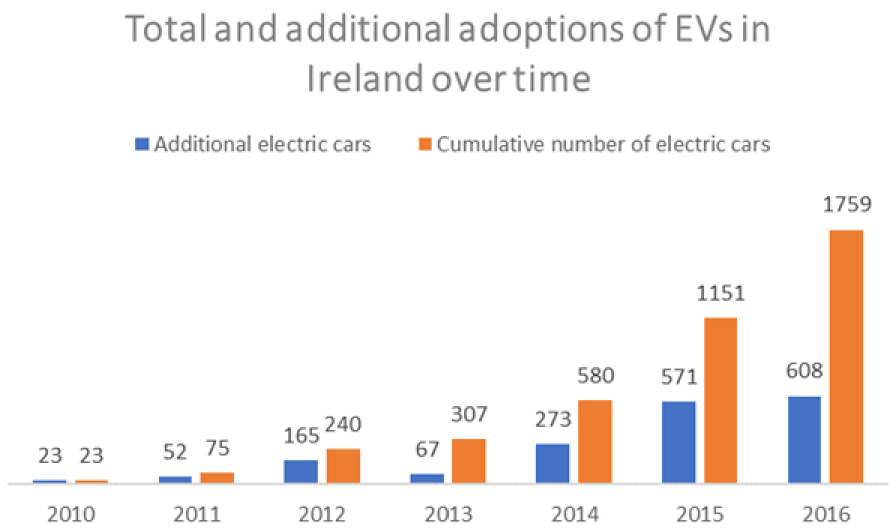


Figure 2 Total and additional adoptions of EVs in Ireland over time

Source: Author's illustration using CSO data

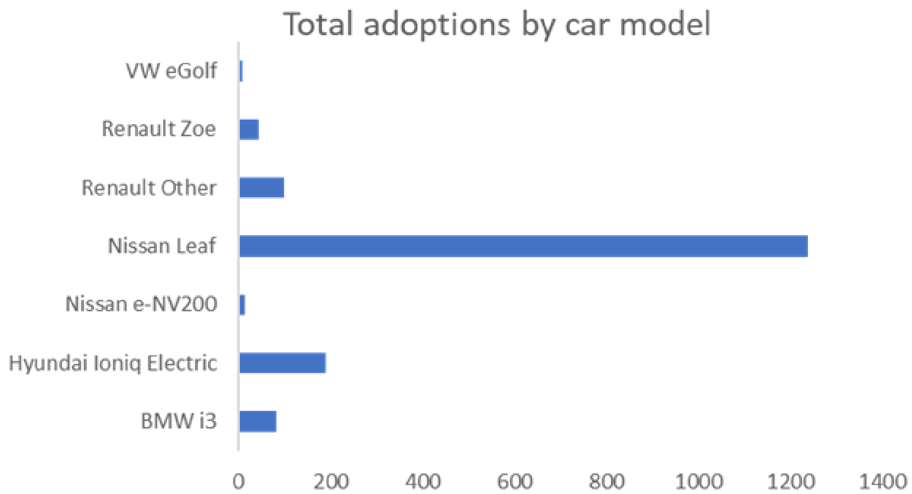


Figure 3 Car models by number of adopters in Ireland

Source: Author's illustration using ESB ecars data

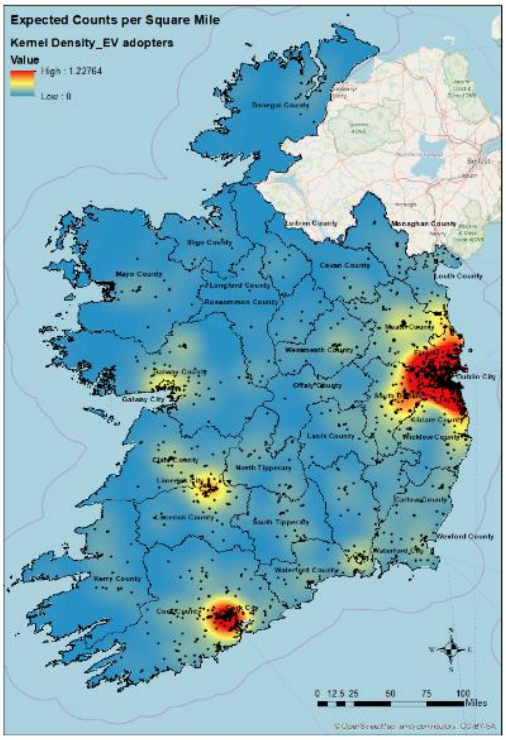
We use Esri's ArcMap 10.4[14] to map our data in various forms, including x-y plots incorporating kernel density maps for EV adopters, charge points and EV dealers in Ireland, maps displaying the distribution of EV owners in and around the Dublin area, hotspot maps of EV adopters, and maps

[14] Esri or the Environmental Systems Research Institute is an international supplier of geographic information system (GIS) software, web GIS and geodatabase management applications. ArcMap is the primary component of Esri's ArcGIS suite of geospatial processing programmes. More information available here: http://www.esri-ireland.ie/.

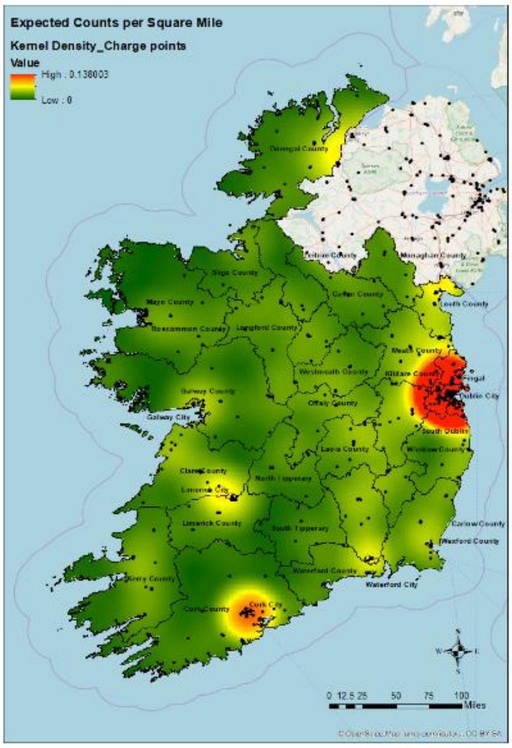
showing EV adoption over time. All data are projected to the IRENET95 Irish Transverse Mercator (ITM) coordinate system for Ireland.

Density Analysis

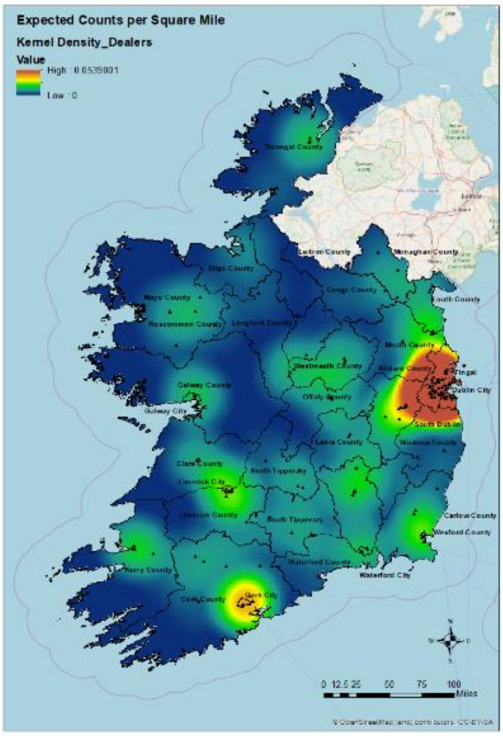
We measure density as the expected counts per square mile. Locations of high density of EV adopters (marked in red) can be clearly differentiated in Figure 4 (a); these align with the areas that host the largest concentration of adopters. The regions of the highest density lie in and around Dublin county and extend to parts of neighbouring border counties of Meath, Kildare and Wicklow. Other regions of high and medium density are Cork city, and Limerick and Galway cities respectively. We also note from Figure 4 (b) and (c) that charge points and dealers also seem to primarily concentrate in and around Dublin and Cork. This can be expected given that these are the two most populous regions in Ireland.



(a) EV adopters



(b) EV charge points



(c) EV dealers

Figure 4 Kernel density plots of expected counts of (a) EV adopters, (b) EV charge points and (c) EV dealers per square mile in Ireland

Source: Author's illustration using ESB ecars and SEAI data

To look at EV adopters more closely, Figure 5 visualises the distribution of EVs in and around Dublin using three different metrics. The large area around Dublin airport seems to have the highest number of EVs when just using counts per small area. When counts are normalised to population, the data looks very different, with more smaller areas showing intense clustering of EV owners. This is clearer when using the shape area of the small areas census boundaries to normalise counts. In that case, many more small neighbourhoods rather than large areas stand out as areas of high density. Although we elaborate this pattern using the example of Dublin, this is probably true of other cities and counties that harbour clustering as well.

Figure 5 Distribution of EVs in and around Dublin city by (a) counts per small area (b) counts normalised to population, and (c) densities per square Km

Source: Author's illustration using ESB ecars and CSO data

Hotspot Analysis

A more objective test of the statistical significance of clustering patterns is the hotspot analysis[15]. A hotspot analysis assumes a null hypothesis of complete spatial randomness and uses the z-scores and p-values it generates to calculate the chances that the observed patterns in the data result from random spatial processes[16]. To run the tool, two parameters need to be specified: a distance band representing a distance at which the data displays significant clustering and a conceptualisation of spatial relationships defining what constitutes a neighbourhood and how neighbouring features might influence each other within a specific research framework. The hotspot analysis then compares whether each neighbourhood is significantly different from the whole study area, yielding a map of statistically significant clusters of high values (hot spots) and low values (cold spots). Hot spots mean that neighbouring features and the study feature are alike while cold spots imply that neighbouring features are dissimilar to the study feature.

A formal method to discover the distance band at which clustering is most pronounced in our data is to calculate the Moran's I statistic for spatial autocorrelation at multiple distances[17]. Moran's I is a measure of spatial autocorrelation iterated over various distances that helps identify the distance at which clustering is most conspicuous. Using this tool, the spatial scale at which spatial processes appear to be most marked for EV adopters is at 2819.05m[18]. We are, however, interested in neighbourhood patterns, so we expect an appropriate radius to be around 1 mile (1609.34m) given that this is a walkable distance, near enough to reach neighbouring adopters, charging facilities or dealers with ease. Consequently, we consider a distance that is somewhere between 1609.34m and 2819.05m to be a more reasonable approximation of the distance at which spatial processes might be active in our data. We rerun the statistic at shorter distances to find that, although not as pronounced, clustering occurs even at 2000m[19]. Hence, we choose to use this distance for the hotspot analysis. We also select the best conceptualisation of spatial relationships which, in our case, is the zone of indifference[20]. Figure 6 displays the results of the analysis at two levels of

---

[15] The hotspot analysis uses the Getis-Ord Gi* statistic. See Appendix C: Data and Methods for details.

[16] A p-value gives the probability that the observed spatial pattern was created by some random process. A low p-value implies it is very unlikely that the observed spatial pattern is the result of random processes. P-values of 0.1, 0.05 and 0.01 mean we can be 90, 95 and 99% confident that a feature belongs to a cluster of either high or low values. Z-scores move inversely with p-values and denote the standard deviations; they are positive for hotspots and negative for cold spots. Both z-scores and p-values are associated with the standard normal distribution. Very high or very low (negative) z-scores, corresponding with very low p-values and are found in the tails of the normal distribution.

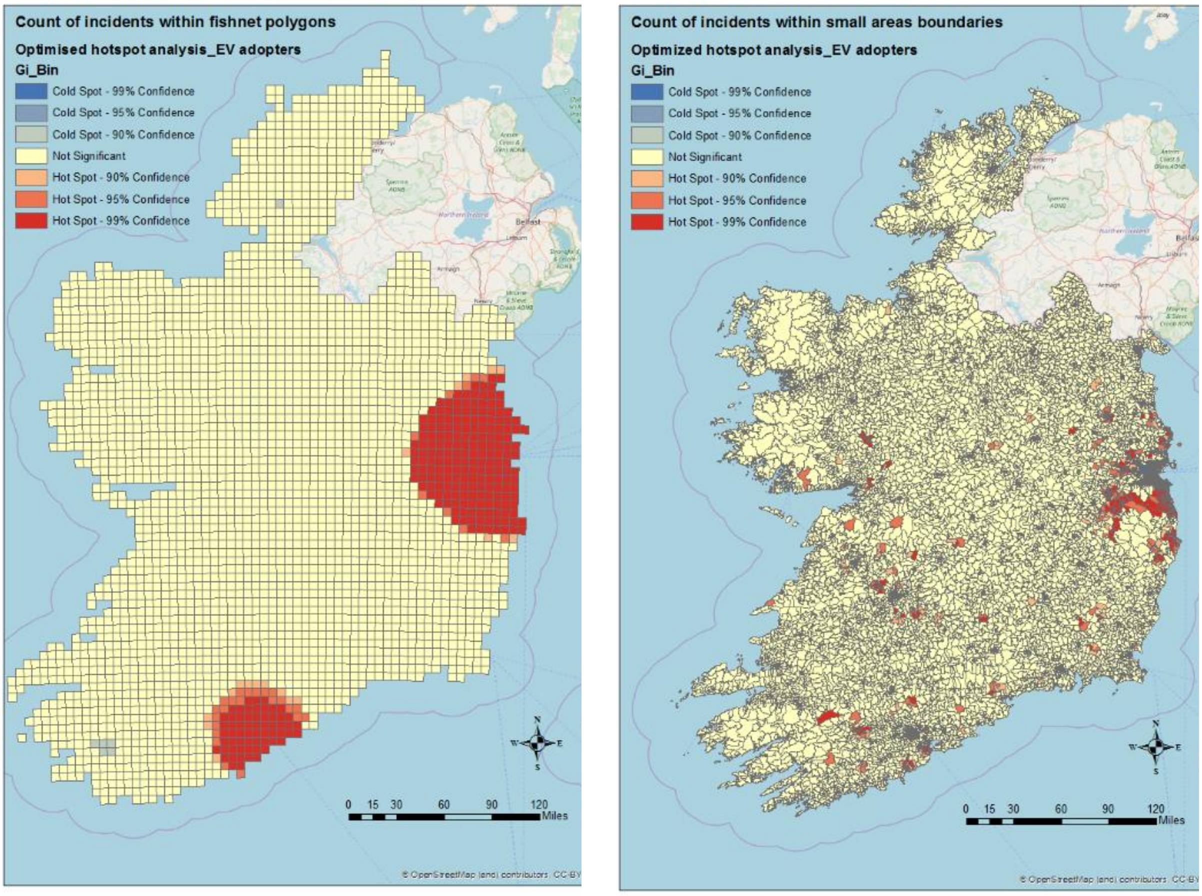
[17] See Appendix C: Data and Methods for the mathematical foundation underlying this test.

[18] The z-score from running the Moran's I statistic at 2819.05m is 2.808 with a corresponding p-value of 0.005.

[19] The Moran's I test at 2000m yields a Moran's Index of 0.051 with a corresponding z-score of 3.457 and a p-value of 0.0005.

[20] In an inverse distance specification, all features influence all other features, but the farther away something is, the smaller the impact. In the case of a fixed distance band, neighbours within a specified distance are weighted equally while features outside the specified distance have a weight of 0. We consider the zone of indifference to be a superior representation of our data as it combines features of both the inverse distance and fixed distance bands. Consequently, it uses a fixed distance band for the target feature, but once the critical distance is exceeded, it does not impose a sharp boundary on neighbouring features included in target feature computations. Instead, the weighting indicating the level of influence tapers off.

geographical granularity. The first panel shows the hot spots for EV adopters using fishnet grids. This calculates densities by dividing up the landscape into equal-sized grid cells, ignoring dissimilarly-sized and arbitrary political boundaries. The second panel recalculates these values for small areas census boundaries.



(a) Fishnet grid (b) Small areas boundaries

Figure 6 Optimised hot spot analysis using (a) fishnet grids and (b) small areas as defined by the CSO

Source: Author's illustration using ESB ecars and CSO data

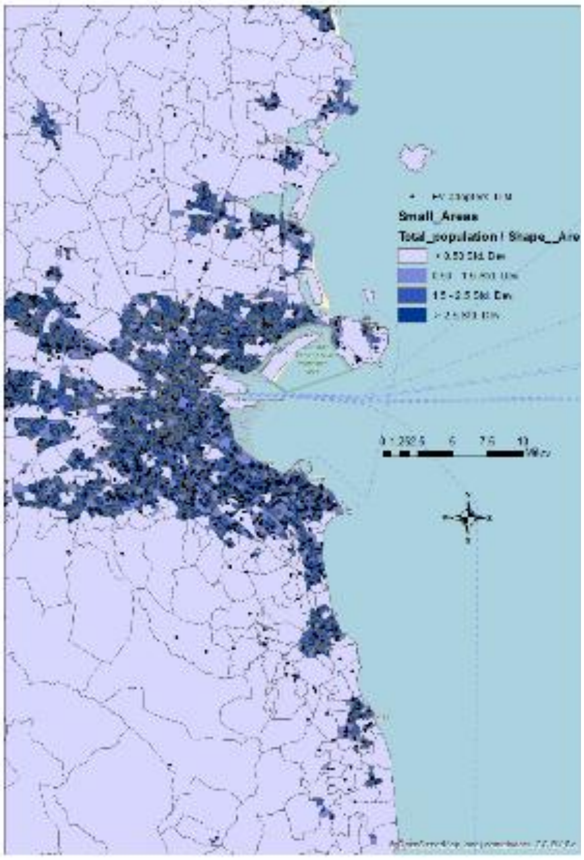
The maps are symbolised, where hot spots are statistically significant clusters of high values shown in red and cold spots are statistically significant clusters of low values shown in blue. Hot spots do not necessarily correspond with the highest values if these values occur in isolation. The values are determined for each neighbourhood rather than for single points in space and are compared to the average for the entire study space, i.e. the Republic of Ireland. As we suspect, we see that Dublin and Cork are intense hot spots for EV adopters[21]. Moreover, running the high-low cluster analysis

[21] An average nearest neighbour analysis at 2000m returns a z-score of -52.098 while a global Moran's I test returns a z-score of 3.632, both implying that there is a less than 1% likelihood that this clustered pattern could be caused by random chance.

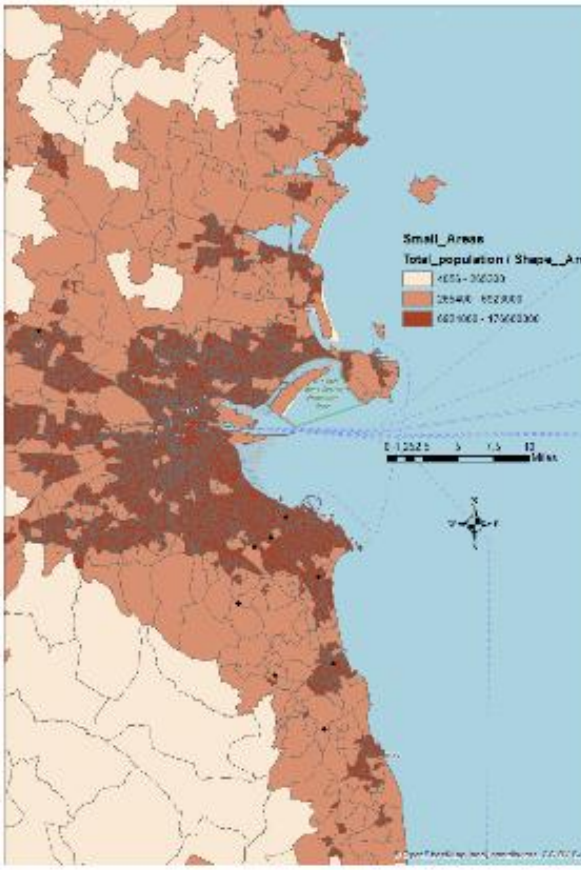
reveals that the clusters are mostly high-clusters[22]. This confirms that there is meaningful aggregation of EV adopters. Although charge points appear to be mildly clustered at a shorter distance of 1000m[23], there does not seem to be any spatial autocorrelation for dealers at any scale. A hotspot analysis of the data (not displayed here), however, reveals some high clustering of dealers and charge points in a small area in and around Dublin city. This might mean that the distribution of charge points and dealers is largely random across space, except in the Dublin city area. This is expected given that charge points and dealers generally need to be evenly distributed over space to reach more customers but there may be more of them in areas of high population density.

Temporal analysis

Figure 7 displays the distribution of EV adopters over time overlaid on population density. It is interesting to note that adoption first began in South Dublin and gradually spread to areas of high population density in the centre and north of Dublin. Since 2012, diffusion appears to have been largely even across space although South Dublin may have a higher concentration of adopters today.



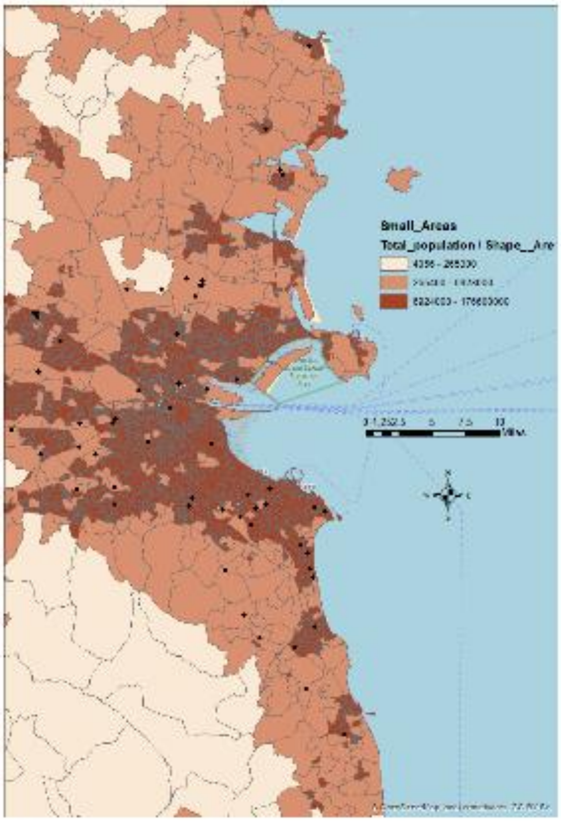
(a) 2011-17



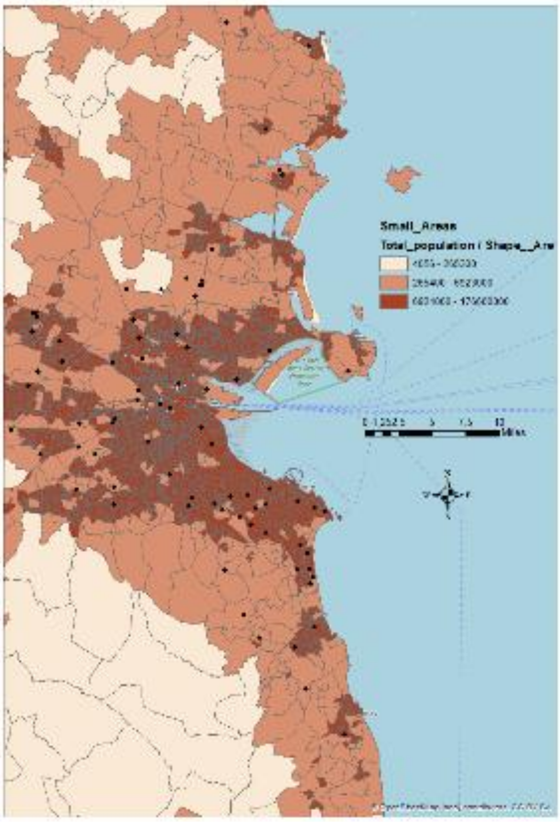
(b) 2011

[22] Given the z-score of 2.005, there is a less than 5% likelihood that this high-clustered pattern could be the result of random chance. The high-low cluster analysis uses the General G statistic. See Appendix C: Data and Methods for details.

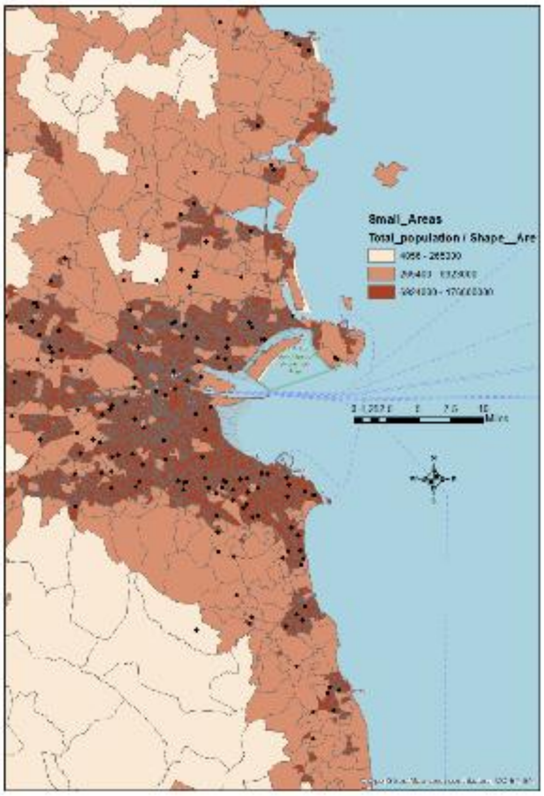
[23] A z-score of 1.744 implies that there is a less than 10% likelihood that this clustered pattern could be the result of random chance.



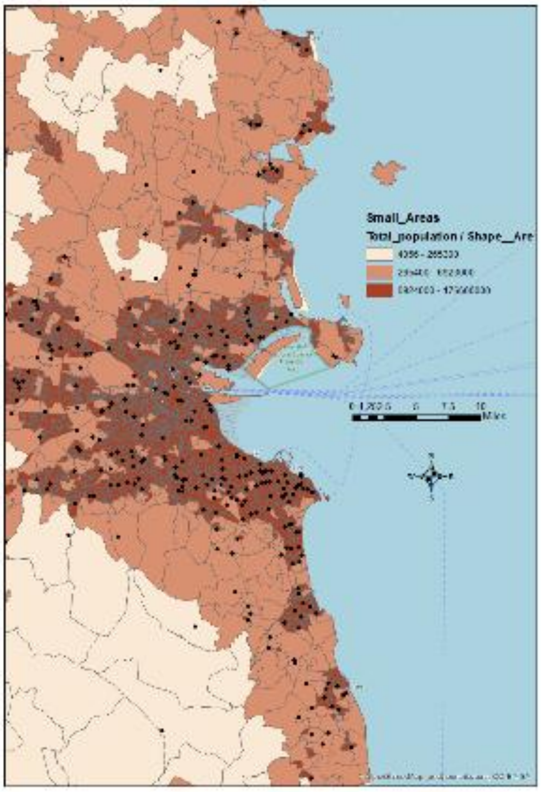
(c) 2012



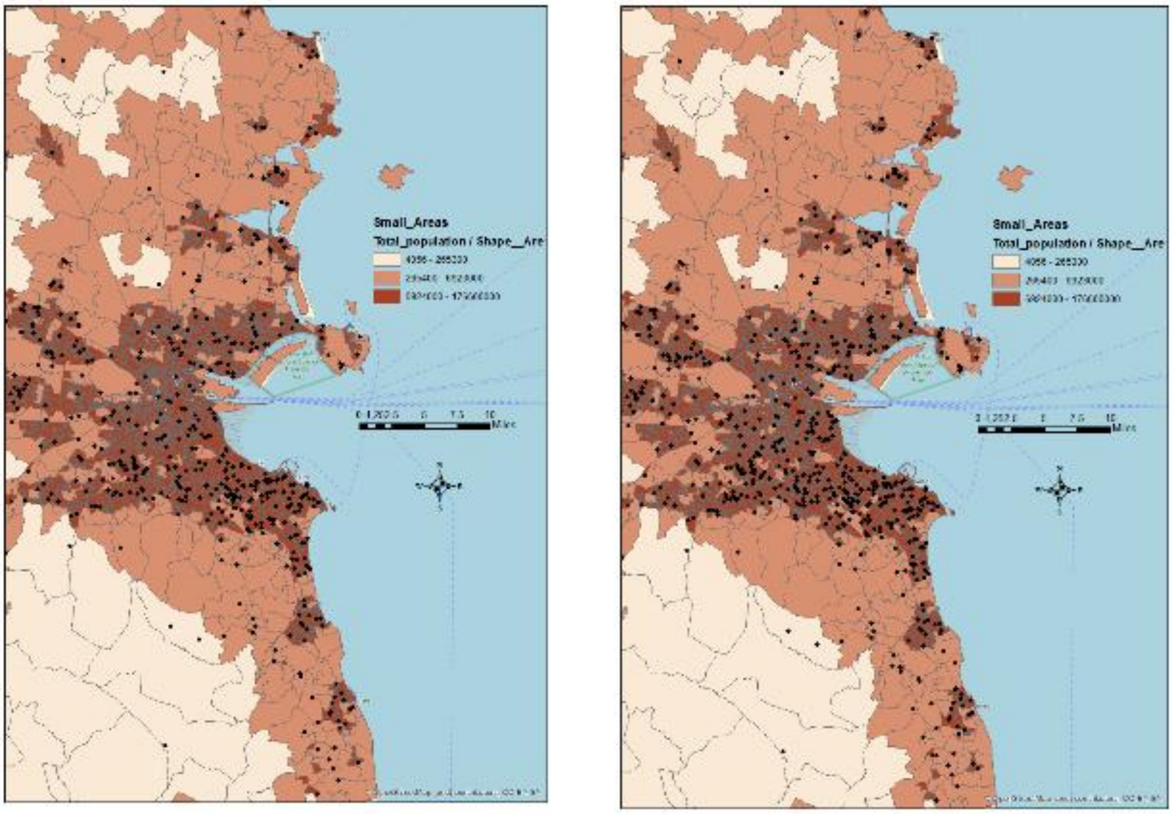
(d) 2013



(e) 2014



(f) 2015



(g) 2016 (h) 2017

Figure 7 EV adoption over time overlaid on population density maps

Source: Author's illustration using ESB ecars and CSO data

Spatial analysis

The clustering in the landscape indicates that there are underlying spatial processes at work. From Figure 5 and Figure 7, we may infer that neighbourhood effects do influence adoption rates, with uptake likely originating in small areas and propagating to larger areas later. It is likely that peer effects play a role in the diffusion process given that new adoptions appear to be situated close to regions of earlier uptake. Further, it may be that adopter clusters are aligned with socio-demographic data, public charging infrastructure or dealers in the area. We, therefore, want to analyse the underlying processes that might cause the clustering in EV adopters at a neighbourhood scale and answer questions such as what it is about Dublin that is leading to hotspots of EV adopters in this area. If there is clustering in some socio-demographic variables in the same locations as the EV adopter data, e.g. if high education and income levels correspond with high adoption rates in Dublin, we could hypothesise possible causal relationships between adoption and these factors. However, this kind of data analysis does not automatically imply any sort of causation.

We will start with a Random Forest classifier[24] and follow up with an Ordinary Least Squares (OLS) regression analysis to test these relationships formally. A random forest classifier fits several decision tree classifiers to different sub-samples of the dataset, leading to higher accuracy and

[24] See https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm for details on the Random Forest Classification approach.

simultaneously avoiding over-fitting. Hyperparameters[25] are optimised by stratified 5-fold cross-validation to split the data into training and test sets. The key predictors identified from this approach are fed into the OLS model to test the relationships via a linear regression approach.

4. Results

Exploratory data analysis

The data analysed comprises relevant socio-demographic variables corresponding to small areas, specifically, gender, age, ethnicity, marital status, employment status, social class, educational level, field of study, type of dwelling, household type, ownership status, building size, family size, family cycle, family type, car ownership, commute time and duration, population distribution, count of EV adopters, count of charge points, and count of dealers. The count of EV adopters is our variable of interest. All variables are normalised by population to aid accurate comparison as population differs across small areas. Any values resulting in division by zeros are replaced by zeros.

Table 1 shows that our dependent variable includes a sizeable proportion of zeros. While there are 16,892 small areas with no adopters, only 1 has an adopter count of 15. Figure 8 displays histograms for all three neighbourhood variables – adopters, charge points and dealers – on the logged scale, showing the same overall pattern for all.

Table 1 Distribution of EV adopters across Small Areas

0	16892
1	1520
2	183
3	34
4	9
5	2
15	1

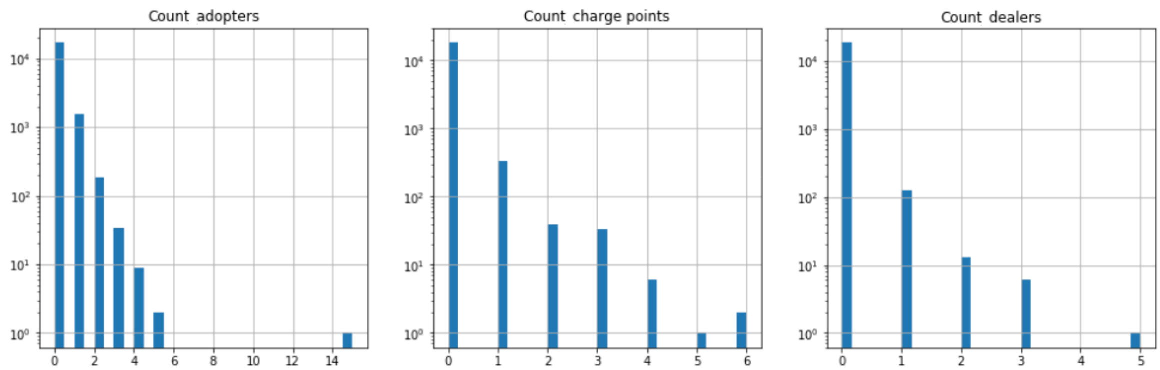


Figure 8 Counts of adopters, charge points and dealers

Source: Author's illustration using ESB ecars and SEAI data

[25] Hyperparameters are parameters of a prior distribution in Bayesian statistics; the term helps distinguish these from standard model parameters. Hyperparameter optimisation is the problem of identifying a set of optimal hyperparameters for a learning algorithm in machine learning.

Given that we expect the count of charge points and dealers to be associated with the count of adopters, we run some scatter plots as shown in Figure 9. However, there does not seem to be any obvious correlation between these variables in the context of small areas. We, therefore, drop counts of dealers and charge points from subsequent analyses.

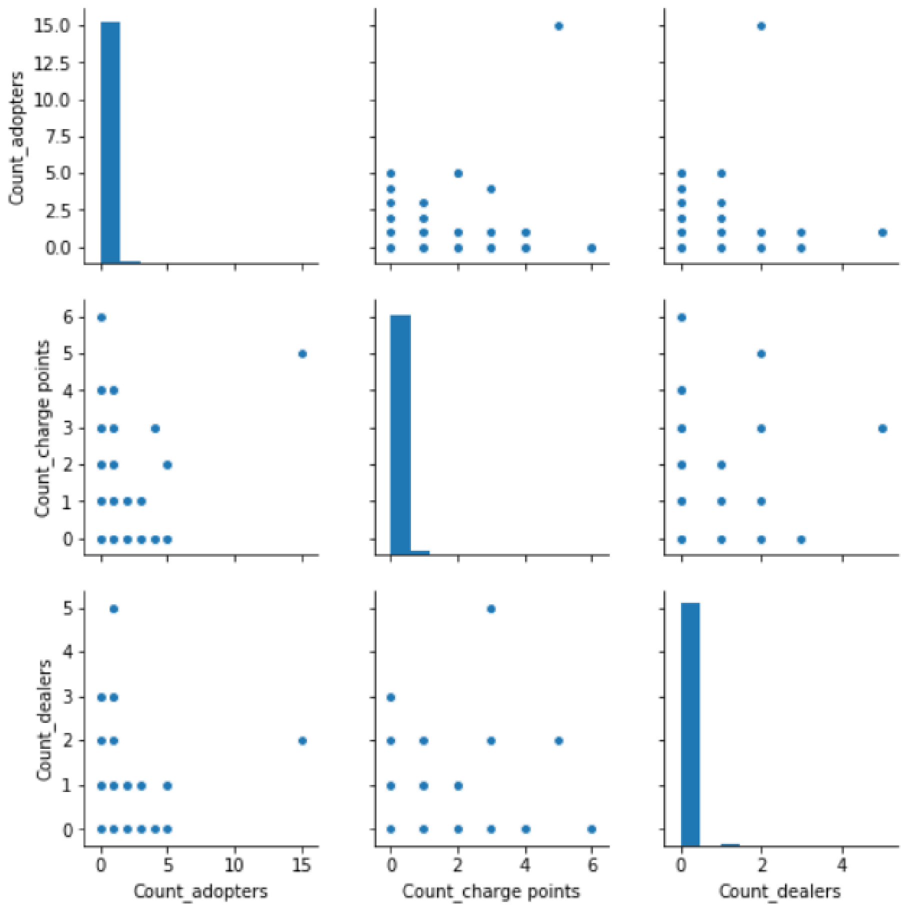


Figure 9 Scatter plots of adopters, charge points and dealers

Source: Author's illustration using ESB ecars and SEAI data

Due to the large imbalances in the outcome variable data, that is, between EV adopters and the non-adopters, a Random Forest classifier is implemented to model the data, with a binary response variable - whether EV was adopted or not in the small area. The performance of the model is assessed using the metrics - Receiver operating characteristic (ROC) and Matthews correlation coefficient (MCC) - which are measures of the quality of binary classifications[26]. Overall ROC area under the curve (AUC) of the model is 0.67[27]. The MCC is 0.166. This considers true and false positives and negatives and can be used even when there are considerable size imbalances among

[26] See http://gim.unmc.edu/dxtests/ROC1.htm and https://lettier.github.io/posts/2016-08-05-matthews-correlation-coefficient.html for details on the interpretation of ROC and MCC curves.

[27] The detailed model results are: Fold 0, ROC AUC: 0.661; fold 1, ROC AUC: 0.644; fold 2, ROC AUC: 0.681; fold 3, ROC AUC: 0.727; fold 4, ROC AUC: 0.655.

various classes. +1 represents a perfect prediction, 0 an average random prediction and -1 an inverse prediction. The folds are obtained by maintaining a percentage of samples in each set. Following parameter optimisation, 28 decision trees are used in the model. The total number of features used to find the best split is the square root of total number of features, and the minimum number of samples for each leaf node is fixed at 30. The model performance is comparatively poor; hence, feature engineering is required to improve future model performance. The overall ROC and MCC curves are shown in Figure 10.

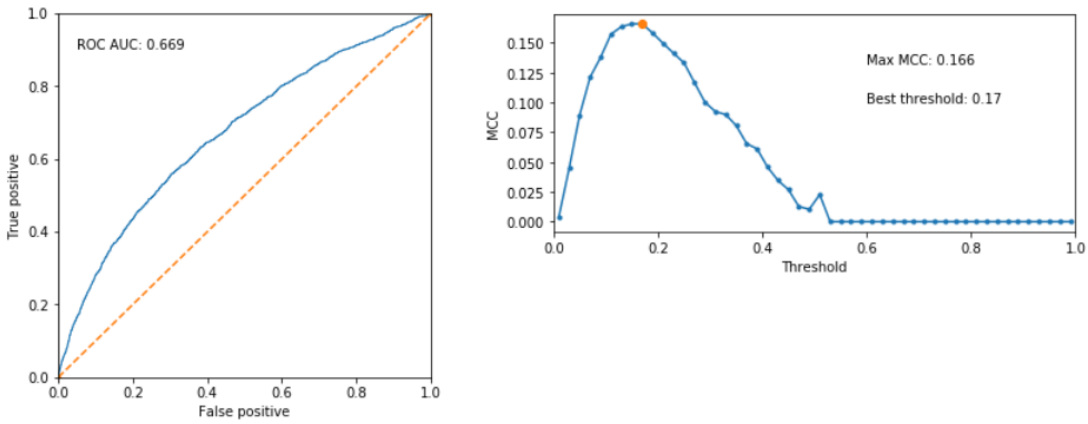


Figure 10 Receiver operating characteristic (ROC) and Matthews correlation coefficient (MCC) curve

Source: Random forest classification model output

Individual variables are grouped under 21 broad categories as in Table 2. Table 2 provides the main results of this analysis and lists the features in order of importance. Social class seems to be the best predictor of EV adoption, while means of commute, duration of commute, commute time, family type, educational level, field of study, and household size in terms of number of rooms are other key variables explaining adoption. Further details of features and relative importance can be found in Appendix C: Data and Methods

Table 2 Relative feature importance of variables determined by the random forest classification model

Variable	Importance
Social class	0.108
Means of commute	0.077
Family type	0.075
Educational level	0.073
Number of rooms	0.067
Commute journey time (duration)	0.066
Field of study	0.066
Commute time (of day)	0.055
Marital status	0.048
Number of motor cars owned	0.045
Home ownership	0.044

Family cycle	0.04
Ethnicity	0.035
Employment status	0.031
Household size	0.03
Population	0.028
Age	0.028
Dwellings	0.025
Family size	0.023
Household type	0.021
Gender	0.012

We run an OLS model using some of the key predictors identified in the random forest classifier. The model is as below:

$$\begin{aligned} &Count\ of\ adopters \\ &\quad = \alpha + \beta_1(Total\ population) + \beta_2(\ 8\ or\ more\ room\ households\ per\ capita) \\ &\quad + \beta_3(Professional\ workers\ per\ capita) \\ &\quad + \beta_4(Managerial\ and\ technical\ workers\ per\ capita) \\ &\quad + \beta_5(Postgraduate\ degree\ or\ diploma\ holders\ per\ capita) + \varepsilon \end{aligned}$$

Table 3 displays the results from the OLS model. All explanatory variables are statistically significant at the 5% level and positively related to the count of adopters, implying that as social status, educational level, household size and total population increase in a small area, so does the level of regional EV uptake. However, the model performs poorly, given an R-squared value of 0.047, a log-likelihood of -8170.2 and low AIC and BIC values of 0.0002. Although the Durbin-Watson test yields a value of 1.945, implying that there is no autocorrelation in the residuals, a significant Jacque-Bera test statistic of 14137153.521 suggests that the residuals are biased possibly because some of the relationships between the variables are non-linear. Any future model will correct for this misspecification by log or power transforming the variables as appropriate.

Table 3 OLS results

Count of adopters	**OLS (N=18640)**
Total Population	0.001*** (0.000)
Eight or more room households	0.255*** (0.028)
Professional workers	0.226** (0.082)
Managerial and technical occupations	0.151*** (0.038)
Postgraduate degree or diploma	0.191** (0.063)
Intercept	-0.144*** (0.011)

Note: Standard error in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Limitations

The results so far are essentially limited. The national EV market is small relative to overall automobile sales. Consequently, EV adopters still represent too small a proportion of the total population to provide conclusive evidence at the level of small areas. Any future work could, therefore, aggregate data to a higher level such as electoral divisions or counties. However, since small areas are strictly nested within these larger areas, the small areas analysis helps counteract the modifiable areal unit problem (MAUP)[28] which is bigger the larger the land area is. The key problem though is that OLS is unsuitable when the outcome variable takes on a limited set of values, including a substantial proportion of zeros, and therefore variations of this model for limited dependent variable data must be used in future analyses.

The OLS is also inappropriate for two forms of underlying spatial processes - spillovers in outcomes and clustering in unobservables. The OLS performs well only when clustering occurs in observed covariates which when included in the model then explain most of the variation in the outcome. Since the OLS model has poor predictive power for our dataset, we can conclude that observed socio-demographic data alone cannot explain the variation in EV uptake at the level of small areas, unobserved variables must play a vital role and, thus, our model is fundamentally incomplete. We, therefore, plan to implement a spatial model for limited dependent variable data that allows for interdependence in unobservables and outcomes besides incorporating the distance to charge points and dealers as explanatory variables rather than their counts in small areas. Specifically, a spatial weights matrix will be defined and combined with a series of relevant fixed effects to model clustering in unobservables and/or interdependencies due to peer effects. However, the geocoding exercise underlying our EV adopter data is essentially approximate. This will still affect the analysis at the fine geographical scale used regardless of the model we choose, which is a risk we must accept. Lastly, to explain how contagion mechanisms operate in this context will benefit from a detailed qualitative study involving focus groups and in-depth interviews that is also planned as future work. The spatial model and the qualitative study will complete this piece of research.

5. Conclusions

Transportation systems are complex socio-technical systems and consumers within them are not always rational decision-makers basing decisions on tangible constraints such as cost and performance metrics. The technology adoption literature unearths a plethora of factors that may determine EV adoption, including intangible characteristics such as peer-to-peer communication, level of trustworthiness, and perceptions of cost. Some individual characteristics such as income levels and age may make someone a suitable adopter. However, these factors are often context specific, and the vast research on adopter characteristics has often produced mixed results. Neighbourhood effects have, on the other hand, only recently gained attention, although they seem to play a significant role in decision-making and may even prove to be more universal. Most of the

[28] The MAUP helps understand the concept of ecological fallacy - the assumption that an individual from a specific group or area will exhibit a trait that is predominant in the group altogether. i.e. that all areas are unified. Aggregating counts to polygons automatically introduces this problem. Changing the pattern and scaling of the zones changes the pattern of aggregated outcomes.

research on neighbour effects have surrounded solar PV adoption. This work is an attempt to extend this field to EVs using the case study of Ireland.

From our exploratory data analysis, social class, which consists of whether the population is comprised of professional workers, managerial and technical staff, non-manual labour, skilled manual workforce, semi-skilled workers, unskilled labour force, or all those who fall in the gainfully occupied but unknown category, appears to be the most important factor affecting EV uptake in Ireland. This variable may proxy for income effects, and as such, the wealthier a community is, the more likely the area may be to host EV owners. Other strong predictors are means of commute, duration of commute and journey time, family type, educational level, field of study, and household size. Variables relating to daily commute are expected to influence EV uptake given that EV owners would generally be car drivers, driving medium distances, and commuting at a time of day that maximises the benefits of owning an EV. Likewise, EV owners are usually highly educated and being trained in certain disciplines might be more favourable for uptake. Finally, family and household size affect adoption given that EVs tend to be second cars in families with children, and a large house is more likely to have garage space for charging than otherwise, facilitating uptake.

Given the limitations of our OLS model, our future work will identify key predictors using a spatial model that relaxes the restrictive assumptions of the OLS approach to allow for underlying spatial processes. This framework will explicitly model relationships between agents, consequently, representing the data more accurately and hopefully yielding more reliable results.

Acknowledgements

The author thanks Dr Lisa Ryan for her help in advising this project and Paul Hayes of ESB networks for helping to procure anonymised geolocation data from ESB ecars Division for all EV adopters who had a home charge point installed in Ireland. The author is also grateful to Dr Igor Romanov for helpful comments on this paper.

References

Achtnicht, M., Bühler, G., & Hermeling, C. (2012). The impact of fuel availability on demand for alternative-fuel vehicles. *Transportation Research Part D: Transport and Environment*, *17*(3), 262–269. https://doi.org/10.1016/j.trd.2011.12.005

Anable, J., Skippon, S., Schuitema, G., & Kinnear, N. (2011). Who will adopt electric vehicles? A sementation approach of UK consumers. Proceedings to ECEEE 2011: Summary Study. *Eceee 2011 Summer Study*, 1015–1026. https://doi.org/978-91-633-4455-8

Axsen, J., Mountain, D. C., & Jaccard, M. (2009). Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid-electric vehicles. *Resource and Energy Economics*, *31*(3), 221–238. https://doi.org/10.1016/j.reseneeco.2009.02.001

Balta-Ozkan, N., Yildirim, J., & Connor, P. M. (2015). Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. *Energy Economics*, *51*, 417–429. https://doi.org/10.1016/j.eneco.2015.08.003

Becker, T., Sidhu, I., & Tenderich, B. (2009). Electric vehicles in the United States: a new model with forecasts to 2030. *Center for …*, 36. Retrieved from http://www.www.odpowiedzialnybiznes.pl/public/files/CET_Technical Brief_EconomicModel2030.pdf

Biere, D., Dallinger, D., & Wietschel, M. (2009). Ökonomische Analyse der Erstnutzer von Elektrofahrzeugen. *ZfE Zeitschrift Für Energiewirtschaft*, *33*(2), 173–181. https://doi.org/10.1007/s12398-009-0020-2

Bockarjova, M., Rietveld, P., & Knockaert, J. S. A. (2013). Adoption of Electric Vehicle in the Netherlands – A Stated Choice Experiment. *TI Discussion Paper*, *100/VIII*. https://doi.org/10.2139/ssrn.2306505

Busic-Sontic, A., & Fuerst, F. (2017). The personality profiles of early adopters of energy-efficient technology The personality profiles of early adopters of energy- efficient technology, (June). https://doi.org/10.13140/RG.2.2.36482.89286

Claudy, M. C., Michelsen, C., Driscoll, A. O., & Mullen, M. R. (2010). Consumer awareness in the adoption of microgeneration technologies An empirical investigation in the Republic of Ireland. *Renewable and Sustainable Energy Reviews*, *14*(7), 2154–2160. https://doi.org/10.1016/j.rser.2010.03.028

Coffman, M., Bernstein, P., & Wee, S. (2017). Electric vehicles revisited: a review of factors that affect adoption. *Transport Reviews*, *37*(1), 79–93. https://doi.org/10.1080/01441647.2016.1217282

CSO. (2016). Census of Population 2016 – Profile 6 Commuting in Ireland. Retrieved from http://www.cso.ie/en/releasesandpublications/ep/p-cp6ci/p6cii/p6td/

Curtin, R., Shrago, Y., & Mikkelsen, J. (2009). Plug in Hybrid Electric Vehicles, 45. Retrieved from http://www.ns.umich.edu/Releases/2009/Oct09/PHEV_Curtin.pdf

Department of Transport Tourism and Sport. (2017). *National Policy Framework*.

Dharshing, S. (2017). Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy Research & Social Science*, *23*, 113–124. https://doi.org/10.1016/j.erss.2016.10.012

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, *48*(2012), 717–729. https://doi.org/10.1016/j.enpol.2012.06.009

ESB. (2018). ecars FAQs. Retrieved from https://www.esb.ie/our-businesses/ecars/ecars-faqs

European Commission. (2018). Climate action - reducing emissions from transport. Retrieved from https://ec.europa.eu/clima/policies/transport_en

European Environment Agency. (2017). Final energy consumption by mode of transport, 12. Retrieved from http://www.eea.europa.eu/data-and-maps/indicators/transport-final- energy-consumption-by-mode/assessment-2

Gardner, J., Quezada, G., & Paevere, P. (2011). Social Study on Attitudes, Drivers and Barriers to the Uptake of Electric Vehicles, Report Number: EP113815, (June). Retrieved from https://publications.csiro.au/rpr/download?pid=csiro:EP113815&dsid=DS3

Goldsmith, R. E., & Foxall, G. R. (2003). The Measurement of Innovativeness. *The International Handbook on Innovation*, 321–330. https://doi.org/10.1016/B978-008044198-6/50022-X

Graziano, M., & Gillingham, K. (2015). Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environmentz. *Journal of Economic Geography*, *15*(4), 815–839. https://doi.org/10.1093/jeg/lbu036

Grubler, A. (1991). *Introduction to Diffusion Theory* (Vol. 3).

Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, *33*(3), 686–705. https://doi.org/10.1016/j.reseneeco.2011.02.002

IET. (2011). The Lifestyle Implications of Electric Vehicle Adoption.

Irish EV Owners Association. (2018). Electric Vehicles (updated 2018 / 181). Retrieved from http://www.irishevowners.ie/electric-vehicles/

McCoy, D., & Lyons, S. (2014). Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. *Energy Research and Social Science*, *3*(C), 89–101. https://doi.org/10.1016/j.erss.2014.07.008

Mersky, A. C., Sprei, F., Samaras, C., & Qian, Z. S. (2016). Effectiveness of incentives on electric vehicle adoption in Norway. *Transportation Research Part D: Transport and Environment*, *46*, 56–68. https://doi.org/10.1016/j.trd.2016.03.011

Morrissey, P., Weldon, P., & O'Mahony, M. (2016). Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. *Energy Policy*, *89*, 257–270. https://doi.org/10.1016/j.enpol.2015.12.001

Nath, V., Rai, V., & Zarnikau, J. (2016). Drivers of environmentally-friendly technology adoption: electric vehicle and residential solar PV adoption in California APPROVED BY SUPERVISING COMMITTEE.

Nayum, A., Klöckner, C. A., & Mehmetoglu, M. (2016). Comparison of socio-psychological characteristics of conventional and battery electric car buyers. *Travel Behaviour and Society*, *3*, 8–20. https://doi.org/10.1016/j.tbs.2015.03.005

O'Sullivan, K. (2017). Ireland leading a weak charge on electric vehicles.

Palm, A. (2016). Local factors driving the diffusion of solar photovoltaics in Sweden: A case study of five municipalities in an early market. *Energy Research and Social Science*, *14*, 1–12. https://doi.org/10.1016/j.erss.2015.12.027

Palm, A. (2017). Peer effects in residential solar photovoltaics adoption—A mixed methods study of Swedish users. *Energy Research and Social Science*, *26*, 1–10. https://doi.org/10.1016/j.erss.2017.01.008

Plotz, P., Schneider, U., Globisch, J., & Dutschke, E. (2014). Who will buy electric vehicles? Identifying early adopters in Germany. *Transportation Research Part A: Policy and Practice*, *67*, 96–109. https://doi.org/10.1016/j.tra.2014.06.006

Rai, V., & McAndrews, K. (2012). Decision-making and behavior change in residential adopters of solar PV. *Proceedings of the World Renewable Energy Forum*. Retrieved from https://ases.conference-services.net/resources/252/2859/pdf/SOLAR2012_0785_full paper.pdf

Rai, V., Reeves, D. C., & Margolis, R. (2016). Overcoming barriers and uncertainties in the adoption of residential solar PV. *Renewable Energy*, *89*, 498–505. https://doi.org/10.1016/j.renene.2015.11.080

Robinson, S. A., & Rai, V. (2015). Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach. *Applied Energy*, *151*, 273–284. https://doi.org/10.1016/j.apenergy.2015.04.071

Rogers, E. M. (1995). Diffusion of Innovation, (1995), 512. https://doi.org/978-0029266717

Schelly, C. (2014). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research and Social Science*, *2*, 183–191. https://doi.org/10.1016/j.erss.2014.01.001

Schirtzinger, W. (2016). Chasm Crossing Confusion – Why Solar Adoption is Unique - Renewable Energy World.

SEAI. (2016a). Energy in Ireland 1990 – 2015, 86. https://doi.org/http://www.seai.ie/Publications/Statistics_Publications/Energy_in_Ireland/Energy-in-Ireland-1990-2015

SEAI. (2016b). Ireland's Energy Targets Progress, Ambition & Impacts - SEAI. Retrieved from https://www.seai.ie/resources/publications/Ireland___s-Energy-Targets-Progress-Ambition-and-Impacts.pdf

SEAI. (2017). Electric Vehicle Grant Scheme. Retrieved from http://www.seai.ie/Grants/Electric_Vehicle_Grant_Scheme/

Sierzchula, W., Bakker, S., Maat, K., & Van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Sigrin, B., Pless, J., & Drury, E. (2015). Diffusion into new markets: evolving customer segments in the solar photovoltaics market. *Environ. Res. Lett.*, *10*(10), 84001. https://doi.org/10.1088/1748-9326/10/8/084001

Sperling, D. (1991). *The rise and fall of infrastructures: dynamics of evolution and technological change in transport*. *Utilities Policy* (Vol. 1). https://doi.org/10.1016/0957-1787(91)90018-Z

Tran, M., Banister, D., Bishop, J. D. K., & McCulloch, M. D. (2013). Simulating early adoption of alternative fuel vehicles for sustainability. *Technological Forecasting and Social Change*, *80*(5), 865–875. https://doi.org/10.1016/j.techfore.2012.09.009

Ziegler, A. (2012). Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. *Transportation Research Part A: Policy and Practice*, *46*(8), 1372–1385. https://doi.org/10.1016/j.tra.2012.05.016

Appendix A: Technology diffusion

Theories of diffusion are the basis for models that help us understand current adoption patterns and predict the rate and pattern of future diffusion of innovations[29]. Technology adoption refers to individual uptake of a new device whereas technology diffusion is an aggregate-level concept concerning the process of the spread of an innovative technology within a group, community or country. Of the many theories of diffusion, the most cited is the one proposed by Rogers that uses a bell-shaped curve to describe the individual decision-making process (Rogers, 1995). Rogers partitioned a bell-shaped curve into its standard deviations from the average time of adoption to form five categories of innovation adopters:

(1) innovators (the first 2.5% to adopt),

(2) early adopters (the next 13.5% of adopters),

(3) the early majority (34%),

(4) the late majority (34%), and

(5) laggards (the last 16% to adopt).

This categorisation simplifies the stages of technology uptake within a heterogenous population by reflecting how the members of a social system learn from the experience and imitate the behaviour of the innovators and earlier adopters to form a new adopter group (Sperling, 1991). Transitions between the different adopter groups, therefore, demarcate the distinct stages or timing of innovation adoption. As consumers make their individual adoption decisions, these aggregate to produce the timing and pattern of innovation diffusion, depicted by an S-shaped curve as in **Erreur ! Source du renvoi introuvable.**Figure 11. The diffusion process is driven largely by interpersonal communication channels such as word-of-mouth and marketing efforts (Grubler, 1991).

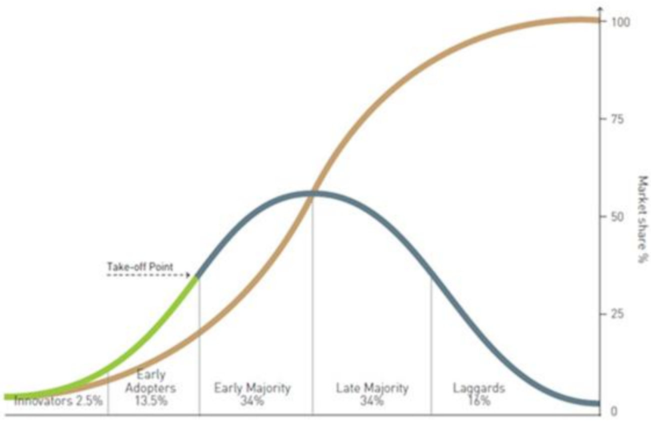


Figure 11 Technology adoption and technology diffusion curves

Source: Everett Rogers, Diffusion of Innovations, 1995

[29] An innovation is a new idea, method or device that is transformative to varying degrees. There are three types of innovations relevant to the pattern and rate of technology diffusion (Goldsmith & Foxall, 2003). A *continuous* innovation makes modest enhancements to existing technologies and has the least disrupting effect on established consumption patterns (e.g. heat pumps). A *dynamically continuous* innovation has somewhat more disrupting effects through the introduction of a previously-unknown version of a product that does not, however, change usage patterns drastically (e.g. electric vehicles). Finally, a *discontinuous* innovation entails the creation of a completely new consumer product that requires the establishment of new consumption patterns (e.g. solar photovoltaics (PVs)).

The different adopter groups vary in their degree of resistance to change due to their diversity in expectations, experience and various socio-demographic and psychological characteristics (Sperling, 1991). While “innovators” tend to be relatively price insensitive, younger, of higher social status, better educated, socially forward and/or more financially lucid people, the general populace may need more certainty about the advantages of an innovation versus the status quo before they consider adopting. Moreover, “innovators” tend to embrace novelty, have a better level of product knowledge, as well as expertise in consumption that other groups may lack, such that their adoption decisions are massively influential on the adoption decisions of the proximate group, the “early adopters”.

Over time, consumers become aware of the innovation, depending on the structure of the social system and the available information channels (Grubler, 1991). On completion of the learning process, consumers may be persuaded to purchase, based on perceived costs and benefits of the technology. They then take a decision based on their beliefs, following which they implement it by adopting new behaviours, and finally, validating their decision and choosing to extend their commitment to change.

To explain why an innovation is adopted requires a close inspection of how the innovation compares with the status quo. In general, five factors matter according to Rogers (Rogers, 1995):

(1) Relative advantage; (2) Compatibility; (3) Complexity; (4) Trialability; and (5) Observability.

Why innovative ideas and technology spread is also predominantly a study of the socio-psychological characteristics of consumers. Innovations penetrate a given user base in stages, corresponding to their psychological and social profiles, viz. their personality, values, opinions, attitudes, interests, and lifestyles (Schirtzinger, 2016). Moreover, consumers need to be aware of technologies before they embark on their decision-making process (Claudy et al., 2010).

Most adoptions take place locally and as measuring localised, psychographic behaviour is particularly challenging, the exact point of market penetration into adopter groups can be difficult to measure. Consequently, transitions from one group to another is far from smooth, implying that the consumer segmentation proposed by Rogers is only an approximation (Schirtzinger, 2016). Additionally, public polices and incentives that may alter consumer risk perceptions serve to blur market dynamics, skewing the proposed psychographic sequence further.

Appendix B: Determinants of RET uptake

RET adoption depends on many factors, as tabulated in Table 4. Drivers and barriers to the adoption of technologies are based on these underlying adopter characteristics. For instance, living in a rural household implies a higher likelihood of owning a garage (hence, a home recharging point), acting as a driver of EV ownership. Not having enough roof space to install a solar panel, on the other hand, may act as a barrier to solar PV adoption. The following table lists the common characteristics that relate to the adoption of RETs generally and highlights some (in red) that are very particular to EVs. The characteristics are categorised as economic, non-economic (potentially monetizable), socio-demographic, spatial and the built environment, technical, behavioural and psychographic. There could be some interaction and overlap between some of these factors.

Table 4 Summary of the determinants of uptake of RETs

Determinants of uptake of RETs	
Economic	Upfront cost (including price of battery), annual operation & maintenance costs (including variable cost to charge), transaction costs, perceived total annual cost, government incentives & policies, fossil fuel inflation, electricity price trajectory, electricity tariff structure, energy cost savings, payment method, resale value of home/car, insurance costs.
Non-economic (monetizable)	Non-financial benefits: comfort & convenience, aesthetics: visual, noise, vibration, emissions reductions, special privileges such as high-occupancy vehicle (HOV) lane access.
Socio-demographic	Homeownership, household size/space, number of children, age, gender, ethnicity, income, unemployment, education, experience with technology, technical competence, political/religious affiliation, personal ties with the non-renewables sector, peer effects, information channels, number of other adopters (network externalities).
Spatial/Building characteristics	Geolocation, housing density, building type, co-adoption of other technology, availability of & distance to local charging points (i.e. available infrastructure), size of city/town/village, commuting distance (including inner city driving).
Technical	Existing home infrastructure, possibility of switching between technologies, fuel economy/energy efficiency, ease of use, reliability, performance expectations, safety, charging time (day/night), recharging time duration, possibility of independent purchase of car and battery, battery swap possibilities, longevity of battery, range, mass, power, MOT service schedule, towing potential.
Psychographic	Environmental concern, preference for energy independence, awareness and knowledge, interest in technology, price sensitivity, risk preference, perception of risk of technology, attitudes towards innovation & uncertainty, openness to experience, agreeableness, leadership tendencies, image, social and personal norms.
Behavioural	Habits/current use behaviour, inertia.

N.B. Points in red are factors that relate specifically to EV adoption while the rest is also applicable to other RETs.

Appendix C: Data and Methods

Data

Table 5 lists the summary statistics for each variable in our dataset.

Table 5 Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Population	255.451	88.167	50	1629
% male	49.52	3.543	24.096	86.135
% female	50.48	3.543	13.865	75.904
% aged ≤ 18	25.302	8.368	0	63.13
% aged 19-34	21.043	10.612	0	98.718
% aged 35-54	28.541	5.34	0	52.597
% aged 55-74	19.24	8.925	0	77
% aged ≥ 75	5.874	5.107	0	60.51
% white Irish	82.064	16.219	.845	100
% other white/ Irish traveller	10.45	9.538	0	71.429
% minorities	7.486	8.923	0	98.873
% single	53.446	8.996	24.918	100
% married	37.389	8.893	0	65.185
% widowed/ separated/divorced	9.165	4.25	0	60.563
% employed	53.294	11.829	.59	93.103
% unemployed	31.921	9.633	5.405	99.115
% retired	14.785	8.637	0	78.947
%, professional technical/managerial	35.678	15.552	0	85.833
% non-manual/ skilled manual	31.699	8.1	0	65.926
% semi-skilled/ unskilled	14.41	6.851	0	50.917
% all others gainfully occupied, unknown	18.212	11.481	.855	100
% only primary/no formal education/unknown	18.904	10.926	0	100
% lower or upper secondary	33.018	9.407	0	100
% technical training	19.702	5.849	0	55.932
% undergraduate	18.318	8.757	0	100
% postgraduate	10.058	8.088	0	76.471
% AHSS, Education	22.521	11.088	0	100
% STEM	13.439	4.999	0	61.765
% Farming/health	10.069	4.708	0	50
% Services/others/unknown	53.971	15.275	0	100
% occupied permanent dwellings	85.562	11.613	12.136	100
% vacant homes	14.438	11.613	0	87.864
% house/bungalow	86.62	24.469	0	100

% other housing	13.38	24.469	0	100
% owned outright, with mortgage or loan	67.857	24.074	0	100
% rented	27.324	22.657	0	100
% occupied free of rent or unknown	4.819	4.193	0	97.5
% 1-3 room households	16.682	17.504	0	96.97
% 4-7 room households	63.585	16.613	0	100
% ≥ 8 room households	14.165	13.055	0	88.764
% unknown sized households	5.567	4.24	0	97.5
% single or 2-person households	52.774	13.835	2.5	100
% 3 or 4-person households	33.877	9.496	0	69.512
% 5 or more-person households	13.35	6.967	0	48.75
% families without children	31.034	12.698	0	100
% families with up to 2 children	52.245	10.151	0	100
% families with 3 or 4 children	15.509	7.53	0	100
% families with 5 or more children	1.212	1.704	0	22.222
% pre-family cycle	10.507	12.461	0	100
% empty nest families	10.203	5.503	0	85.714
% retired families	10.323	7.745	0	75
% pre-school or early school families	21.527	10.221	0	100
% pre-adolescent or adolescent families	22.817	9.323	0	81.034
% adult families	24.622	10.933	0	100
% one-person households	24.093	11.088	.746	98.113
% married or cohabiting couples without children households	19.106	6.925	0	56.667
% married or cohabiting couples with children	34.735	13.486	0	83.784
% one parent family with children with and without others	11.46	6.858	0	58.064
% couple and others with and without children	3.041	2.248	0	20
% two or more non-related persons households, non-family households and relations households, or two or more non-related persons households	7.564	7.671	0	97.5
% no motor car	15.267	15.576	0	93.333
% 1 motor car	41.004	10.604	1.111	72.857
% 2 motor cars	33.33	15.762	0	84.615
% 3 motor cars	5.631	4.423	0	31.746
% 4 or more motor cars or unknown	4.769	3.862	0	97.5
% commute ≤ 15 minutes	33.256	13.108	0	90.206
% commute between 1/4 hour - under 1/2 hour	28.463	9.007	0	81.457
% commute between 1/2 hour - under 3/4	16.892	7.336	0	46.202

hour				
% commute between 3/4 hour - under 1 hour	5.653	3.622	0	25
% commute between 1 hour - under 90 minutes	5.787	3.886	0	30.12
% commute ≥ 90 minutes	2.256	1.863	0	15.663
% unknown commute time	7.693	5.871	0	98.873
% travel on foot or bicycle	17.488	15.253	0	94.466
% travel by bus, minibus or coach	10.136	6.772	0	48.295
% travel by train, DART or LUAS	2.469	5.063	0	48.052
% car driver	38.872	11.079	0	81.538
% car passenger	18.002	8.884	0	55.6
% travel by van	4.37	3.101	0	27.273
% travel by other means (including lorry, motorcycle, scooter, unknown)	5.321	5.241	0	98.873
% work mainly at or from home	3.342	3.29	0	31.482
% commute before 06:30 am	5.674	3.238	0	35.965
% commute between 06:30 - 07:00 am	6.984	3.114	0	25
% commute between 07:01 - 07:30 am	8.93	3.695	0	27.928
% commute between 07:31 - 08:00 am	14.584	5.153	0	42.857
% commute between 08:01 - 08:30 am	20.256	6.807	0	60.14
% commute between 08:31 - 09:00 am	22.105	8.042	0	73.404
% commute between 09:01 - 09:30 am	8.553	6.347	0	52.239
% commute after 09:30	7.571	4.132	0	46.364
% unknown commute start time	5.343	5.472	0	98.873
Count of adopters	.11	.384	0	15
Count of charge points	.03	.229	0	6
Count of dealers	.009	.117	0	5

NB. Minorities include Black/Black Irish, Asian/Asian Irish, others and unknown
Married includes same-sex civil partnership
Unemployed includes those looking for their first job, student, looking after home/family, lost or given up previous job, or unable to work due to permanent sickness or disability or other
Technical training includes higher certificate, advanced certificate/completed apprenticeship, technical or vocational qualification
Undergraduate includes ordinary bachelor's degree, national diploma, honours bachelor's degree and/or professional qualification
Postgraduate includes postgraduate diploma, degree, Doctorate (PhD) or higher
AHSS, Education includes Art, Education and teacher training, Humanities, Social sciences, Business or Law
STEM includes Science, mathematics, computing, engineering, manufacturing or construction
Farming/health includes Agriculture, veterinary, health and welfare
Vacant homes include dwellings representing the temporarily absent, unoccupied holiday homes, others
Other housing includes Flat/Apartment, Bed-sit, Caravan, mobile home or unknown
Rental accommodation can be from private landlord, local authority or voluntary/co-operative housing body

Spatial data analysis tools

Global tools test the existence of overall clustering in the data, i.e. they test whether objects with similar attributes are close to each other. Tools that identify local clusters test the relation between each object's attribute value with that of its neighbours. Both groups of tools operate by comparing the distance between the objects in "attribute space" i.e. how similar objects are (summarised as a Y matrix) with the distance between the objects in spatial space, which may be non-spatial weights such as travel time and not necessarily based on geometric properties such as Euclidean distance (summarised as a W matrix). While Global measures consider the Y and W matrices for the entire study area, local measures of patterns only accounts for the Y and W matrices for neighbours.

The incremental spatial autocorrelation tool runs the Global Moran's I tool for spatial autocorrelation for a series of increasing distances, measuring the intensity of spatial clustering for each distance. The intensity of clustering is determined by the z-score returned. Typically, as the distance increases, so does the z-score, indicating intensification of clustering. At some distance (where the W matrix is set to 0), the z-score peaks, which is the point of the highest positive autocorrelation. There may be multiple peaks in the data.

The mathematics behind the Global Moran's I statistic is set out below:

The Moran's I statistic for spatial autocorrelation is given as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

The z_I-score for the statistic is computed as:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}} \tag{3}$$

where:

$$\mathrm{E}[I] = -1/(n-1) \tag{4}$$

$$\mathrm{V}[I] = \mathrm{E}[I^2] - \mathrm{E}[I]^2 \tag{5}$$

The hot spot analysis, on the other hand, is a local tool that calculates the Getis-Ord Gi* statistic for each feature in the dataset to produce a z-score for the degree of high-low clustering. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values. The local sum for a feature and its neighbours is compared proportionally to the sum of all features. A statistically significant z-score results when the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance.

The Getis-Ord Gi* statistic formula is displayed below:

The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n-1}}} \quad (1)$$

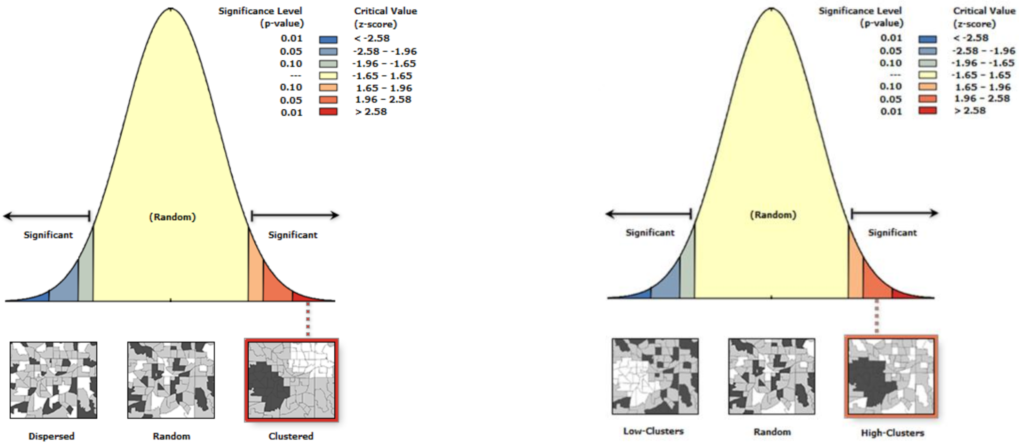
where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \quad (3)$$

The G_i^* statistic is a z-score so no further calculations are required.

The Spatial Autocorrelation test using the Global Moran's I tool for EV adopters in our dataset yields a Moran's Index of 0.051 with a corresponding z-score of 3.456 and a p-value of 0. 0.0005 at a distance threshold of 2000m. The Observed General G statistic for high-low clustering yields an observed general G value of 0.0006 with a corresponding z-score of 2.399 and a p-value of 0.016 at the same distance threshold. All analyses use the zone of indifference as the conceptualisation of spatial relationships. The graphical output of these tests is displayed in Figure 12.



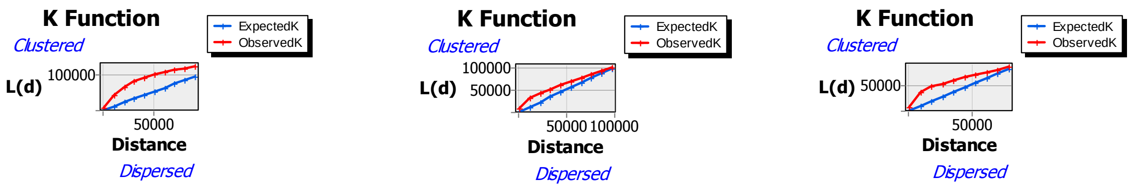
(a) Spatial Autocorrelation Report (b) High-Low Clustering Report

Figure 12 Spatial Autocorrelation and High-Low clustering reports

Source: Spatial analysis GIS model output

The Average Nearest Neighbour tool measures the distance between each feature centroid and its nearest neighbour's centroid location and averages all nearest neighbour distances. If the average distance is less than the average for a hypothetical random distribution, the distribution of the features being analysed is considered clustered, and vice versa. The average nearest neighbour ratio is calculated as the observed average distance divided by the expected average distance based on a hypothetical random distribution with the same number of features covering the same total area. At a ratio of less than 1, the pattern exhibits clustering, while at a ratio of greater than 1, the pattern exhibits dispersion. Our average nearest neighbour analysis corroborates the previous findings of clustering for EV adopters by returning a nearest neighbour ratio of 0.434 and a corresponding z-score and p-value of -43.434 and 0.000 respectively.

Similarly, the Multi-distance spatial cluster analysis (Ripley's K Function) determines whether features, or the values associated with features, exhibit statistically significant clustering or dispersion over a range of distances. When the observed K value is larger than the expected K value for a distance, the distribution is more clustered than a random distribution at that scale of analysis, and vice versa. The graphical output in Figure 13 seems to confirm that although EV adopters clearly cluster in space at multiple distances, this is less likely to be true for charge points or dealers.



(a) EV adopters (b) EV Charge points (c) EV dealers

Figure 13 Multi-distance spatial cluster analysis for EV adopters, charge points and dealers

Source: Spatial analysis GIS model output

Anselin local Moran's I statistic lies at the heart of Cluster and Outlier Analysis. Although like a hotspot analysis, this local tool identifies spatial clusters of features with high or low values as well as spatial outliers. For each feature with a statistically significant p-value, there is an associated z-score that determines whether the feature is part of a cluster or is an outlier. A positive value for I indicates that a feature has neighbouring features with similarly high or low attribute values, i.e. this feature is part of a cluster. A negative value for I indicates that a feature has neighbouring features with dissimilar values, i.e. this feature is an outlier. From our cluster and outlier analysis, we find a few high outliers in and around Dublin. This is useful insight if we were to perform an in-depth analysis of where EV adopters locate in every neighbourhood in Dublin county. High and low clusters may form from neighbourhood spillover effects. However, there are other spatial processes underlying outliers, which may be interesting to explore in future work.

Machine learning model results

Table 6 presents the results from the random forest classification model. The model shows the relative importance of a set of predictors, which informs our OLS model.

Table 6 Top 20 features by importance in Random Forest classification model

Feature	Importance
Managerial and technical occupations	0.037
8 or more room households	0.036
Art, Education and teacher training, Humanities, Social Sciences, Business or Law	0.03
Total population	0.028
Ordinary bachelor's degree, national diploma, honours bachelor's degree and/or professional qualification	0.02
Postgraduate diploma, degree, Doctorate (PhD) or higher	0.017
Semi-skilled workers	0.016
Professional workers	0.016
Total motor cars owned	0.015
Single	0.015
Primary education or no formal education	0.015
Permanent dwellings	0.015
Unskilled workers	0.012
Skilled manual workers	0.012
Married (including same sex civil partnership)	0.012
Commute to work or school between 1 hour – under 1 ½ hours	0.011
Total household - number of persons per household	0.011
Commute to work or school by Train, DART or LUAS	0.011
Field of study - Services, other subjects or not stated	0.01
Science, mathematics, computing, engineering, manufacturing or construction	0.01