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Spatial scenarios of potential electric vehicle adopters in Ireland

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ABSTRACT

Transition to electric vehicles (EVs) is among public policy measures to reduce carbon emissions from the transport sector in Ireland. While EV adoption rates are increasing there is broad scepticism about achieving ambitious national policy targets. We employ microdata on commuting behaviour and different assumptions on the profile of adopters and purpose of vehicle use, based on existing literature, to identify clusters of candidates for transition to EV in Ireland. We estimate that depending on the assumption 17% to 42% of vehicle owners could comfortably switch to EV. High density areas of potential candidates for transition to EVs are identified in specific urban areas such as Cork and Dublin cities. We also find between 2 to 37% reduction in emissions from car owners based on the different set of assumptions we employ. While the per unit emission reduction in rural areas is higher, the aggregate emission reduction that can be achieved is higher in urban areas because of the higher density of candidates for transition in such areas as per our analysis. We show that apart from Dublin, urban areas are lacking when it comes to density of charging infrastructure.

1. Introduction

In Ireland transportation is the largest energy-consuming sector with a 42% share of final energy consumption and it accounts for 41% of energy related emissions. Passenger transportation is the largest polluter in this sector (SEAI, 2020). Electrification of the sector is key in the policy agenda to transit towards a more sustainable economy in Ireland and in many other countries around the world. However, the uptake of this technology has been very slow. Previous literature identifies individual, technological and infrastructure attributes that drive electric vehicle adoption (Plótz et al., 2014; Vassileva and Campillo, 2017; Westin et al., 2018; Zhuge et al., 2019; Chen et al., 2020; Broadbent et al., 2021; Haustein et al., 2021; Featherman et al., 2021). Mukherjee and Ryan (2020) note that the early adopter population in Ireland shows similar characteristics to the ones found elsewhere. Range anxiety and lack of awareness about existing technology and infrastructure can reduce adoption rates of EV technology (Thügersen and Ebsen, 2019; Broadbent et al., 2019; Chen et al., 2020; Haustein et al., 2021). In this study we are specifically concerned with examining range anxiety and understanding the extent to which travel patterns can be easily satisfied using EV technology widely available in the market today without the need for intra-week charging. While concerns surrounding range anxiety are valid issues, this work attempts to quantify the extent to which weekday charging is not necessary to complete weekly travel activities (e.g. commuting, family errands, etc.). The analysis will identify the numbers of households where one of the main non-financial barriers to EV adoption (i.e. range anxiety) should not practically arise in decisions to purchase Battery Electric Vehicles (BEVs)[1].

Our primary objective is, not to identify the numbers of households where range anxiety should not practically arise, but to ascertain the spatial distribution of candidates for switching one of their vehicles to an EV. Namdeo et al. (2014), Morton et al. (2018) and Pucci (2021) note that understanding the spatial patterns of EV potential can help in future planning of EV related infrastructure and directing localised marketing campaigns. Understanding the distribution of potential adopters can also help us anticipate distributional impacts of taxation and subsidies related to electric vehicles. Isik et al. (2021) estimate the emission reduction potential of EV adoption in New York City and note how critical it is to understand emission reduction potential under various scenarios for future plans. We extend our analysis to include estimation of gains through emission reduction from the switch to EVs. Globisch et al. (2019) find that proximity to charging infrastructure can improve

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[1] BEVs are EVs with zero tail pipe emissions unlike hybrid electric vehicles. The focus of the paper is are BEVs and for purpose of the paper the term EV will be synonymous with BEV.

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adoption of EVs among non-traditional adopters. With this aim, we map clusters with close proximity to high density of existing charging infrastructure and in turn identify areas where possible charging network expansion might improve adoption based on the clustering of potential buyers.

While many papers consider the diffusion pathway of EVs and likely early adopters, the current approach differs in two ways. First, we begin from the perspective of households' transport needs and the technical capacity of current technology EVs to deliver such service rather than simply focusing on socio-demographic traits and likelihood of EV adoption. Second, we design the analysis to preclude situations where EV range anxiety may be a concern. Hence, within existing commuting/ driving requirements and using EV technology currently available on the Irish market, we estimate the technical potential for EVs to comfortably satisfy existing transport needs. This provides an estimate of where existing fossil fuel vehicles can be substituted with EVs without compromise or accommodation in travel patterns. As this estimate ignores factors such as budget constraints or behaviour decisions, following the literature on EV adoption, we further drill down to the sub-sample of candidates that are more likely to be early EV adopter based on socio-economic characteristics as well. Emissions reduction achieved by potential adoption can play an important role in marketing campaigns targeting the more environmentally conscious subgroups. Hence our study includes estimates of emission reductions in the scenarios developed. Lastly, charging networks can be critical in the adoption decisions of non-traditional adopters and hence, we study how the clusters of candidates for switching their existing vehicle intersect with good coverage of existing charging infrastructure. By undertaking this case study, we add to the literature on effective planning and design of policy for targeted adoption of EVs and the impact such policies may have on transport emissions. In the coming sections we will review the literature, present data methodology, and scenario results, which are followed by a discussion of policy implications and overall conclusions.

2. Background and literature review

2.1. Factors affecting EV adoption

Vehicle price is one of the main concerns of potential EV adopters (Zhuge et al., 2019; Haustein et al., 2021; Broadbent et al., 2019; Broadbent et al., 2021). Electric Vehicles on average are costlier compared to their conventional vehicle counterparts. Despite the improvements in EV technology and significant increases in range achieved by EVs after a single charging session, range anxiety continues to be a primary concern among potential adopters (Thügersen and Ebsen, 2019; Broadbent et al., 2019; Guerra and Daziano, 2020; Chen et al., 2020; Haustein et al., 2021). Conventional car users are often unaware of the improvements in EV technology and underestimate the existing coverage of EV charging infrastructure (Thügersen and Ebsen, 2019; Haustein et al., 2021). Availability and affordability of charging stations can be important in the purchase decisions based on the location of the potential adopter and their national context (Guerra and Daziano, 2020; Haustein et al., 2021). Chen et al. (2020) note that conventional car users often assess EVs based on their knowledge specifically applicable to conventional cars. Hence, to improve electric vehicle adoption rates it is important to design effective marketing campaigns targeting conventional car users who are 'EV positives '(i.e., those who are next-ready for EV adoption) (Broadbent et al., 2021). Uncertainties and anxieties related to availability of charging infrastructure and governmental support can significantly influence the decision to adopt (Guerra and Daziano, 2020; Haustein et al., 2021; Broadbent et al., 2021). Such anxieties are often expressed by owners of conventional vehicles, not EV users. Zhuge et al. (2019) in their study in China find significant influence of social networks in the decision to adopt EVs. Featherman et al. (2021) find that consumers perception of risk related to post-purchase consequences can be critical in EV purchase decisions and can be reduced by marketing strategies emphasising the trustworthiness and expertise of EV manufacturers.

2.2. Factors affecting EV adoption in Ireland and related regulations

The popularity of EVs in the Irish market is showing an upward trend (McAleer, 2021)[2]. According to the National Transport Survey of Ireland (CSO, 2019), purchase price/ affordability is the main factor influencing the decision to purchase an EV for Irish citizens. The Irish government has already introduced purchase grants, Vehicle Registration Tax relief, toll incentives, home charger installation grants and reduced motor tax rates to encourage adoption of EVs (Kevany, 2019). Availability of more charging points away from home and availability of overnight charging at low cost were also factors influencing decisions to adopt EV technology (CSO, 2019).

2.3. Profile of early adopters in related literature

To identify the candidates for transition to EVs in our study we take into account the profile of early adopters identified by previous studies. In Ireland as elsewhere higher levels of education is a predictor for EV adoption (Vassileva and Campillo, 2017; Haustein and Jensen, 2018; Westin et al., 2018; Zhuge et al., 2019; Mukherjee and Ryan, 2020). Higher income households are typically the early adopters of new technologies such as EVs (Plötz et al., 2014; Haustein and Jensen, 2018; Westin et al., 2018; Zhuge et al., 2019; Mukherjee and Ryan, 2020; Chen et al., 2020; Gehrke and Reardon, 2021). Individuals who work in technical jobs and have technological affinity have a higher likelihood of adopting EVs (Plötz et al., 2014; Brückmann et al., 2021). Younger or middle aged men are more likely to be early adopters of EV technology (Plötz et al., 2014; Haustein and Jensen, 2018; Westin et al., 2018; Zhuge et al., 2019; Chen et al., 2020). However, Westin et al. (2018) note that while some of these socio-economic factors may in isolation be associated with EV ownership, their impact may be conflated with other issues, such as, environmental attitudes. Early adopters of EVs may typically own more than one car and own their home (Haustein and Jensen, 2018; Zhuge et al., 2019; Brückmann et al., 2021; Gehrke and Reardon, 2021). Brückmann et al. (2021) find that Green Party affiliation is associated with EV adoption in German speaking areas of Switzerland. Mukherjee and Ryan (2020) find that EV adopters in Ireland are typically concentrated in urban areas and have socio-demographic characteristics similar to the early adopters elsewhere.

2.4. Identifying spatial distribution of potential adopters

Previous studies have examined the distribution of EV adoption using a variety of data sources (Namdeo et al., 2014; McCoy and Lyons, 2014; Saarenpaa et al., 2016; Gehrke and Reardon, 2021; Mukherjee and Ryan, 2020; Pucci, 2021). Saarenpaa et al. (2016) identify areas favourable for EV adoption in Finland by mining public data. McCoy and Lyons (2014) employ agent-based modelling to study the diffusion of EV technology in Ireland using survey data. Their study emphasises that targeting 'early adopters' for messaging may not result in faster adoption unless detailed network topology is well understood. Mukherjee and Ryan (2020) employs micro-data of EV adopters in Ireland to study the spatial distribution of existing EV owners. Pucci (2021) studies the spatial scenarios for EV adoption employing spatial and demographic data in Milan, while Namdeo et al. (2014) identify hot spots for expanding the charging infrastructure in urban areas in Northeast England through spatial analysis of the socio-economic characteristics and commuter information of urban residents. Our study adds to this literature by attempting to identify spatial clusters where large number of candidates for switching one of their vehicles to an EV without the necessity for intra-weekly recharging of vehicles. As emissions reduction is

[2] For the most recent official EV adoption statistics in Ireland refer Table A.1.

Table 2
Descriptive statistics.

	Mean	SD
Distance to work (km)	17.7	26.5
Charging point count per ED	1.53	0.91
Charging points within 3 KM (per ED)	12.07	13.87
	Count	**Percentage**
SEG: Managers, professionals (Ref. cat: Yes)	535,393	46.3
Education:University degree (Ref. cat: Yes)	656,500	56.8
Cars owned		
No car	2,990	0.003
1 car	315,641	0.27
More than 1 car	838,828	72.6
Age group: 35–54 (Ref. cat: Yes)	648,527	56.1
Dwelling owned (Ref. cat: Yes)	892,348	77.2

Note: Sample size is 1,154,469.

central to debates surrounding EV adoption (Isik et al., 2021), the analysis outlined later will also estimate potential emission reductions associated with EV adoption.

2.5. EV charging infrastructure and its role

When it comes to the role played by charging networks in the adoption of EVs, Globisch et al. (2019), Funke et al. (2019) and Guerra and Daziano (2020) note that proximity to EVSE (Electric Vehicle Supply Equipment) can be critical to a subset of non-traditional adopters especially in metropolitan areas. These groups do not belong to the profile of middle aged, male, high income earning early adopters, but are technophilic, environmentally aware younger individuals, mainly women (Globisch et al., 2019). This sub-group may be residing in apartments or do not own their residences, for example in countries such as Netherlands where proportion of detached houses are lower (Funke et al., 2019). Hence, expansion of charging infrastructure, which includes both fast and slow charging points, may help to speed up the adoption of EVs among non-traditional early adopters. Improved quantity and quality of charging infrastructure along with marketing campaigns which reduce misconceptions of EV technology and existing infrastructure can improve adoption (Thügersen and Ebsen, 2019; Haustein et al., 2021). Guerra and Daziano (2020) argue that future studies should incorporate commuting information and proximity to charging infrastructure to correctly identify a household's potential to buy a PEV. Recent studies, however, question the association between presence of EV charging infrastructure and EV purchases (Kaufmann et al., 2021; Brückmann et al., 2021).

3. Data and methodology

In this section we outline the conceptual framework for the work, which is followed by a detailed description of the methodology.

3.1. Conceptual framework and assumptions

We employ data on commuting distances, car ownership and socio-demographic characteristics to devise the spatial scenarios for potential EV adoption in Ireland. A list of study steps and related assumptions are provided below.

- **Step 1:** Identification of the spatial patterns of candidates for transition to EVs in Ireland.

  We utilise commuting distance from the POWSCAR dataset (CSO, 2018), which is based on population census returns, and Irish travel statistics (CSO, 2019; CSO, 2016b) to calculate the weekly distance travelled by each person in our data sample. The assumptions employed in this case are as follows.

  – **Assumption 1**: Owners of two or more vehicles can transition one of their vehicles to an EV easier than one or non owners of conventional vehicles (Haustein and Jensen, 2018; Zhuge et al., 2019; Brückmann et al., 2021; Gehrke and Reardon, 2021).

  – **Assumption 2**: If the weekly distance travelled by a candidate is lower than the range of typical EVs in Irish market, they are candidates for an easy transition to an EV. This implies they can complete all of their weekly travel distances from a single charging session of an EV and avoid range anxiety (Namdeo et al., 2014; Guerra and Daziano, 2020; Thügersen and Ebsen, 2019; Haustein et al., 2021). [3] We employ two assumptions to calculate the weekly distance travelled.

  * The Euclidean distance between location of work and home is a close approximation of actual commuting distance (Pucci, 2021; Ahrens and Lyons, 2021).

  * The non-work related distance travelled by a candidate in a week is a proportion of the average distance travelled by a private car in Ireland. (CSO, 2016b).

  – **Assumption 3**: In a more restrictive scenario, if the candidates identified by the travel distance filter also fits the socio-economic profile of an early adopter of EV, they can be considered as candidates for transition to EV. A typical EV adopter is a middle aged, highly educated vehicle owner working in higher income professions, who owns their home (Plötz et al., 2014; Westin et al., 2018; Mukherjee and Ryan, 2020; Broadbent et al., 2021; Haustein et al., 2021).

- **Step 2:** Estimation of the emission reduction.

  – **Assumption 4**: We assume that the emissions reduction achieved are equivalent to tailpipe emissions of conventional vehicles (SEAI, 2021b; Isik et al., 2021).

- **Step 3:** Studying the coverage of EV charging infrastructure in Ireland and their proximity to clusters identified by the transition scenarios.

  – **Assumption 5**: We assume that a charging station within the ED makes it easily accessible to a candidate for transition to EV (especially in the case of candidates who do not live in detached homes). EDs with existing infrastructure of one or more charging stations within its boundaries or nearby are more suitable for early transition to EVs (Globisch et al., 2019; Guerra and Daziano, 2020; Funke et al., 2019; Thügersen and Ebsen, 2019) and others.

The following subsections will explain the detailed methodology applied as per the assumptions explained earlier. We include the descriptive statistics of indicators we develop where applicable.

3.2. Data sources

The analysis in this study utilises commuting data from the Census of population of Ireland 2016 (CSO, 2018), the Place of Work, School or College (POWSCAR) data. The unit of analysis in this study is a candidate for switching their second vehicle to a BEV, whom we assume to be a vehicle owner who commutes by car to work and belongs to a certain subsection of population. Over 39% of vehicle owners in the census own at least one car and drive to work. We exclude car commuters who are passengers to avoid double counting within same household. We obtain location data on EV charging points across the Ireland installed by the Electricity Supply Board of Ireland (ESB, 2021). It should be noted that private charging stations, which account for a small proportion of

[3] Most of our candidates are home owners and hence can charge their vehicle overnight. However, we apply a weekly distance filter taking into account the inconvenience of having to charge the vehicle multiple times a week. Hence the estimates obtained are conservative.

charging points across Ireland, are excluded from our analysis. The main variables of interest in this study are geographical location of work and home, socio-economic characteristics and vehicle ownership data obtained from POWSCAR dataset along with location information of EV charging infrastructure in Ireland (descriptive statistics shown in Table 2).

3.3. Estimating weekly distance travelled

The POWSCAR dataset includes location data of work and home at Small Area level[4] for each individual. From this information the distance between work and home is calculated. We follow the method employed by Ahrens and Lyons (2021) and Pucci (2021) calculating the commuting distance as the Euclidean distance between the centroid of Small Area of work and Small Area of home in kilometres.[5] The Euclidean distance, which is the length of a line segment between two points in Euclidean space (Pebesma, 2018), though is usually an underestimate of commuting distance (Sander et al., 2010; Gonçalves et al., 2014). However, Chica-Olmo et al. (2018) notes that Euclidean distances are a reasonable approximation of actual commuting distances. Hence, we follow the methodology by Pucci (2021) and employ the Euclidean distances as our main estimation method and further include alternate calculations to check the robustness of our assumptions.

To estimate the weekly distance travelled by a candidate, commuting distance and non-work related travel are calculated separately. We assume that a typical individual makes 5 round-trips to work in a week and hence, we multiply the euclidean distance to work by 10 for a whole week of commuting distance estimation (Ahrens and Lyons, 2021; Pucci, 2021). To estimate non-work related travel, we consider that the average distance travelled by a private car annually in Ireland is 18,000 km for urban residents and 20,000 km for rural residents (CSO, 2016b). Based on this we assume that urban based private cars travel approximately 350 km per week, on average, and 385 km per week in case of rural based vehicles. CSO (2016b) estimates that only 25% of journeys undertaken by private cars are work related in Ireland. Hence, non-work related travel is assumed to average 250 km/week for urban based vehicle and 285 km/week for rural based vehicles. Thus the total distance travelled in a week by the candidate is estimated as follows.

$$\begin{aligned} \textit{Weekly travelled}_h &= \textit{Distance to work}_h * 10 \\ &+ \textit{Distance travelled for non-work related activity} \end{aligned} \tag{1}$$

3.3.1. Sensitivity analysis for estimating weekly distance travelled

We employ two sensitivity analysis methods to check robustness of our assumptions in the main weekly distance estimation method. The first assumption we make is that the Euclidean distance is a close approximation of actual commuting distance. Since we expect the Euclidean distance to be a lower-bound approximation of real travel distance (Chica-Olmo et al., 2018; Pucci, 2021), we overestimate the distance to work in our first sensitivity analysis. We double the Euclidean distance as commuting distance and assume that the real-life scenario will be somewhere closer to the main estimation method or between the main estimation method and the doubled scenario. Average distance to work in the data (as per this assumption) is 34 km. Hence to keep in line with CSO, Ireland calculations of annual mileage of private cars, we add a smaller distance of 60 km to urban areas and 120 km to rural areas as non-work related travel.

Our second assumption for calculating weekly distance travelled included an assumption about the non-work related travel undertaken by the candidate. Since we do not know the exact non-work related travel undertaken, the distance added in our main calculation does not take into account the heterogeneity in travel patterns. To account for this, we undertake Monte Carlo simulations for estimating the non-work related distance, which centers around the average distance travelled based on CSO data (CSO, 2016b; Schouten et al., 2014). We randomise the non-work related distance travelled by a household from a normal distribution with mean of 250 km (standard deviation of 50 km) for urban area candidates and 285 km (standard deviation of 75 km) for rural area candidates (the distribution of weekly distances travelled as per one of these iterations is shown in Fig. A.1). We undertake 1500 iterations and aggregate the count of potential adopters in each simulation. The average of adopter counts based on all the simulations and emissions calculations based on these are reported. We include the results from both sensitivity analysis in the appendix (A.2 and A.3). The clusters identified are similar to the patterns identified by our main methods, however the Monte Carlo simulations give us higher counts of candidates for transition. This confirms our expectation that our main method is conservative, and our calculations are robust to variations in distance calculations.

3.4. Candidates for transition to EVs: 2 scenarios

We take into account the total distance travelled in a week by potential buyers and classify those distances as above or below the range of a typical BEV. The information on distance ranges that electric cars in the market can travel from a single charging session was gathered from various sources including the Sustainable Energy Authority of Ireland (SEAI, 2021a). To determine a thresholds for potential travel distance based on a single charge we use the 25th percentile range as a lower limit and 75th percentile as the upper range limit based on the technical data from BEVs currently available in Irish market. The 25th percentile is 310 km and 75th percentile is 436 km. Two of the most popular BEVs in Ireland are the Hyundai Kona with a distance range of 449 km and Nissan Leaf with a range of 378 km, sandwiching our upper threshold.

3.4.1. Scenario 1: commuters with two cars

In the first scenario we employ data on weekly distance travelled and car ownership to study the distribution of candidates for switching their second vehicle (shown in Table 1). For identifying the potential buyer population at an ED level, we add the number of car commuters (only drivers counted) in an ED who fulfil the distance criteria and own two or more cars. Both high and low range mileage attained by the EVs in market are used for the analysis to understand how the hotspots will expand with the improvement of battery technology. The results for this analysis is given in Table 3 and the results of the sensitivity analysis is given in Tables A.2 and A.3.

3.4.2. Scenario 2: commuters with two cars who belong to the socio-economic profile of EV purchaser

In the second scenario we additionally consider the socio-economic characteristics of the car driver based on literature related to EV adoption. The socio-economic characteristics considered include education, socio-economic group (SEG), home ownership status and age of candidates for switching to a BEV. As early adopters of electric cars are more likely to be highly educated, have higher income, or be middle aged individuals we concentrate this scenario on such individuals in addition to the travel assumptions applied in scenario 1. Managers, employers,

[4] They are the smallest administrative boundaries in Ireland.

[5] Chica-Olmo et al. (2018) provides a comparison of distance calculation methods when used in commuting distance calculations. The distance calculation and all analysis in our study was undertaken using spatial statistics packages in R language for statistical computing (Rigaux et al., 2001; Wickham et al., 2019).

Table 1
Summary of assumptions employed in the two scenarios of analysis.

Conditions applied		Scenario 1		Scenario 2	
		EV range		EV range	
		Low: 310 km	High: 436 km	Low: 310 km	High: 436 km
Distance related (sum less than EV range)	Weekly work commute				
	Distance to work * 10	✓	✓	✓	✓
	Non-work related commute				
	Urban: 250 km	✓	✓	✓	✓
	Rural: 285 km	✓	✓	✓	✓
SEG based (belongs to)	Own 2 or more cars	✓	✓	✓	✓
	SEG: Managers, professionals			✓	✓
	Education: University degree			✓	✓
	Age group: 35–54			✓	✓
	Dwelling owned			✓	✓

lower and higher professionals are coded as high-income individuals in this study, as the dataset does not include information on income. Vehicle owners with a university degree are considered as highly educated for this study. The assigned age group of candidates for switching to a BEV is 35–54. We do not take gender as a factor in our profile as we assume that the EV purchase decision is a joint decision in a household. Descriptive statistics for categorical variables which are indicators of these socio-economic characteristics which are associated with potential candidates for switching their second vehicle to an EV are given in Table 2. In this scenario, an owner of 2 or more cars (within the household), with weekly travel distance within the battery capability of a typical EV on single charge, belongs to a higher SEG, has higher educational attainment, is middle aged and owns their home, we consider them as a candidate for switching their second vehicle to an EV. This method is much more restrictive than Scenario 1. We count the number of candidates at ED level. The potential number of EV switchers under this scenario is reported in Table 3 and the results of sensitivity analysis is given in Tables A.2 and A.3.

3.5. Emission reduction calculations

The emission reductions from each scenario are calculated using estimates for recorded emissions per km of travel from petrol and electric cars. Tailpipe emissions per km employed in this study is 130 g for petrol/diesel fueled cars and 0 g for electric vehicles.[6] From the weekly commuting distance, the annual emissions estimate for each potential buyer is calculated by aggregating weekly emissions. The aggregate emissions are calculated by taking the sum of emissions from all potential buyers in each scenario and calculated as follows:

$$\begin{aligned}&\textit{Annual aggregate emissions}\\&=\Sigma_h^H(\textit{Weekly commute distance}_h * 52 * \textit{Emissions per km})\end{aligned} \tag{2}$$

where H refers to the total number of candidates in each scenario. Emission estimates for the scenarios are reported in Table 4 and 5. The results of sensitivity analysis are given in Tables A.6, A.7, and A.8.

3.6. Charging point infrastructure

We use geocoded location data on public charging points across Ireland to determine the candidate's proximity to public charging points (ESB, 2021). The majority of Irish households live in detached and semi-detached homes, but in urban areas, such as Dublin city, the share of households living in apartments is as high as 35%(CSO, 2016a). Presence of public charging points or workplace charging infrastructure can be crucial in the decision to buy a BEV for a certain sub-section of population who may not own their homes or live in apartments (Globisch et al., 2019). About 34% of vehicle owners in the dataset work within 3 km of their home, hence we calculate the number of charging points within 3 km of ED centroid to study proximity of candidates to a charging point. We use the topological relations between spatial objects, in this case the number of charging points within 3 km radius of the ED centroid, to estimate the charging point density (see Rigaux et al. (2001), Pebesma (2018), Wickham et al. (2019)). We take snapshots of areas with high density of potential buyers to study how the existing charging networks overlap. Since all these areas are urban areas and hence may include large number of renters and individuals who live in apartments, we map the charging point density within 3 km of the home as well in these plots. These maps highlight areas of high density of potential buyers with or without good charging infrastructure.

4. Results

4.1. Distribution of candidates for switch to a BEV based on the scenarios described

The distribution of candidates for switching to a BEV based on commuting distance and ownership of more than one car is studied in the first scenario. The calculation also considers EV battery capacity concerning the distance covered from a single recharge at two levels. The results for this analysis is given in Table 3 as well as in Figs. 1 and 2. The results of sensitivity analysis are given in Tables A.2 and A.3. We identify hotspots mainly around cities in Ireland where a large concentration of potential buyers is present. Fig. 1 shows the distribution of candidates based on these criteria at two different ranges attained by common EVs in market. Based on the lower EV range, i.e. 310 km, an estimated 194,000 candidates could comfortably complete their weekly car trips on a single charge (refer Table 3). This figure is significantly higher than the number of EVs in the existing car fleet[7]. Based on a high range EV (i.e. 436 km) the number of candidates is 481,000. As mentioned earlier, the calculation is conservative and focuses on vehicle owners with two vehicles so EV range anxiety is not necessarily a factor in occasional longer trips. Table 3 provides the vehicle penetration rate where the base is the total number of vehicle owners who drives to work. Between 17 and 42% of vehicle owners could comfortably satisfy existing weekly transport needs on a single charge of an EV. Table A.4 provides a list of high-density areas which are at the 99th percentile or above for aggregate count of potential adopters as per scenario 1. The higher density of potential adopters are found in Dublin, Cork and Limerick counties. Douglas in Cork and Blanchardstown-Blakestown in Fingal have the highest number of

[6] Electricity generation also has associated emissions but are not considered here but are regulated through the EU Emissions Trading System.

[7] The latest EV registration statistics for Ireland is given in Table A.1. There are 8,473 EVs registered in Ireland as of 2019.

Table 3
Aggregate count of potential buyers.

	Scenario 1		Scenario 2	
	Low range	High range	Low range	High range
Count	194,422	481,077	34,670	94,386
Share (%)	16.8	41.6	3.0	8.1

Note: share out of 1,154,469 (Individuals who own at least 1 car and drive to work).

candidates for switch to a EVs. Our sensitivity analysis scenarios show same patterns of distribution of potential adopters as the main scenario (Table A.2 and A.3). The aggregate counts obtained are within the range of the main estimation as well, which shows that our estimates are robust to changes in distance calculation.

Under scenario 2, where socio-economic characteristics are also considered, we see that the penetration rates for EVs are substantially lower at between 3% and 8% for low and high battery ranges respectively (as per Table 3). Similar to Morton et al. (2018) for the UK and Pucci (2021) for Milan, we identify potential hot spots for EV substitution in both urban and rural areas. Rural areas with pockets of high density of potential candidates are in Meath, Kilkenny and Kerry. Fig. 2 shows the distribution of candidates for EV substitution based on these criteria at two different ranges attained by common EVs in market. The electoral areas with the highest number of candidates for EV substitution are Lucan-Eskar in Dublin, Douglas in Cork and Blanchardtown-Blakestown in Fingal. Table A.2 and A.3 includes the aggregates from sensitivity analysis methods.

4.2. Emission reduction potential from switching

The aggregate emissions associated with each scenario is shown in Table 4. We provide the results across the two proposed scenarios and EV battery ranges. We estimate aggregate and average potential emission savings from a transition to EV. As per scenario 1 for high range EV the emission savings can be as high as 1073 kt if we consider tailpipe emissions. The first set of rows in Table 4 shows that the direct emissions savings range from 2.2% to 36.9% from the emissions generated by vehicle owners who own at least one conventional vehicle. The average emissions in each scenario indicates that improving battery capacity will improve adoption of EVs by drivers of longer distances, which eventually will increase the emission savings further (shown in Table 4). We further differentiate emissions from rural and urban areas as well (shown in Table 5). The emission savings can be as high as 711 kt in the case of urban areas if we consider only direct emissions or 60.2 kt with more restrictive assumptions. This comes up to a substantial reduction of 40.6% of total emissions from vehicles owners in urban areas. Hence targeting just urban areas for expansion of charging network and messaging in the initial stages can yield significant emission reduction as per our estimation. While urban areas can have the largest environmental savings due to the higher aggregate EV adoption potential as per our scenarios, the average emission in rural areas is higher than urban areas[8]. The average emissions in rural areas are 26% higher than in urban ones (shown in Table 5). If we aggregate emission reduction from transition to EV in Dublin county as a whole and Cork county, they jointly account for almost half of the emission reduction which can be achieved (shown in Table A.5). This again shows that targeting the urban areas with hotspots of candidates for messaging can significantly reduce emissions with existing infrastructure. The results based on sensitivity analysis estimates are given in Tables A.6, A.7 and A.8.

4.3. Charging infrastructure around candidate hotspots

Based on the results from previous sections, we focus on urban areas with higher density of candidates for switch to a BEV (shown in Fig. 3). Since the urban area population might be residing in apartments without

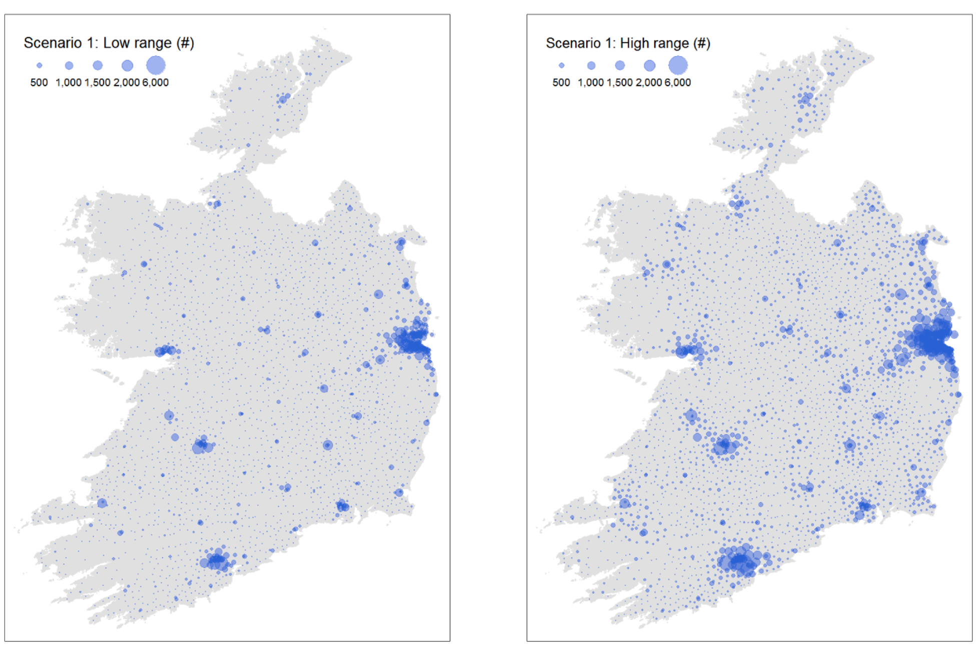

Fig. 1. Candidates for switching their second vehicle to a BEV based on Scenario 1 (weekly distance criteria and car ownership).

[8] The average distance travelled by drivers in rural and urban areas are 359 and 317 km as per our estimation.

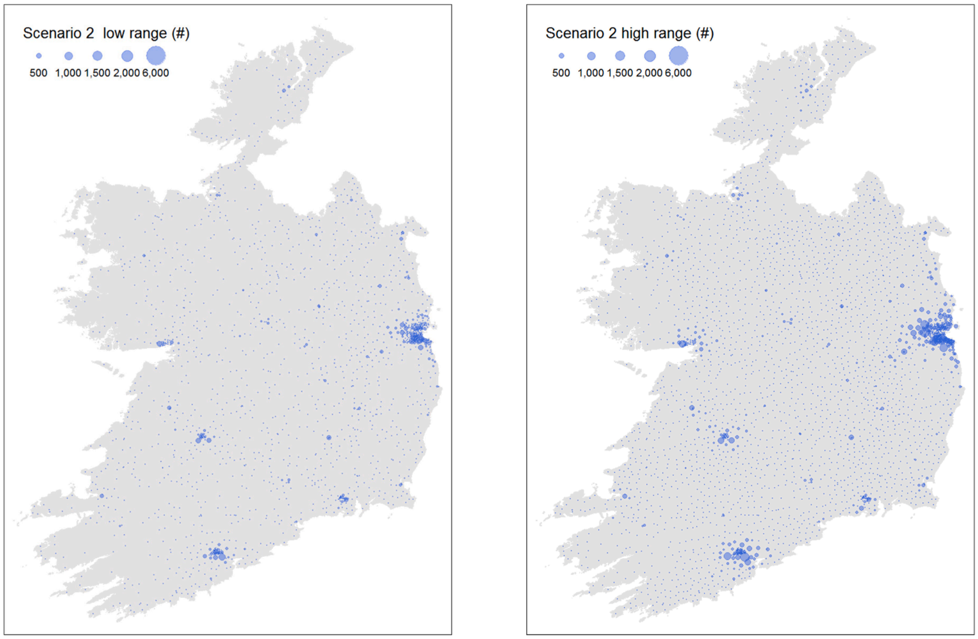

Fig. 2. Candidates for switching their second vehicle to a BEV based on scenario 2 (socio-economic characteristics and commuting patterns based on weekly distance calculations).

Table 4
Reduction in CO_2 emissions and their share out of total emissions in different scenarios. Values in kilo tonnes (kt) and in %.

		Scenario 1		Scenario 2	
		Low range	high range	low range	high range
Direct emission reduction	Emissions (kt)	367	1073	65.8	213.3
	Share (%)	12.6	36.9	2.2	7.3
	Average (t)	1.88	2.23	1.89	2.26

Note: Emission share out of 2906.72 kt emissions (from 1,154,469 car owners who drive in the sample).

adequate charging infrastructure, we chart the density of charging points within 3 kms of EDs within these areas. In Fig. 3 polygons with darker shading show areas with high density of proximate charging points. Overall, the charging network in Dublin is better than other areas in the country. Even within Dublin county, there is significant heterogeneity when it comes to density of public EV charging infrastructure. From panel 1 in plot 3 there are areas with high density of candidates with lower density of charging infrastructure. However, considering the existing infrastructure within Dublin, non-traditional early adopter categories can be targeted for messaging related to EVs. Urban areas other than Dublin lack the density of charging infrastructure compared to Dublin, for example in Cork county as shown in panel 2 of Fig. 3. Overall charger density in Ireland with distribution of candidates for switch to a BEV is shown in Fig. 4. Targeted expansion of public charging networks in Cork, Limerick and Galway can attract non-traditional early adopters of EV.

5. Discussion

In order to bring new insights in the Irish context to increase the uptake of EVs, this paper presents a geospatial analysis exploring the potential for the adoption of EVs. We quantify potential environmental gains and identify areas where infrastructural investment is needed. Our first objective in this paper is to understand the spatial patterns of EV adoption in Ireland. By using microdata on commuting behaviour and EV adopters profiles based on existing literature, we identify potential candidates for the switch to BEVs and compute associated emission savings from such a switch. We find that there are between 194,422 and 481,077 cases where EVs could be substituted for internal combustion engine vehicles and comfortably satisfy weekly driving needs without the need to alter

Table 5
Emission reduction calculation from various scenarios in rural and urban areas.

			Scenario 1		Scenario 2	
		Total emissions (kt)	Low	High	Low	High
Rural	Emissions (kt)	1,156	36.7	362	5.7	67.2
	share (%)		3.2	31.3	0.5	5.8
	Average (t)	2.90	1.98	2.42	1.99	2.45
Urban	Emissions (kt)	1,750	330.4	711.05	60.2	146.2
	share (%)		18.8	40.6	3.4	8.3
	Average (t)	2.30	1.87	2.14	1.88	2.18

behaviour. This shows the large potential for EV adoption without the need for drivers to change their behaviours (e.g. for charging). When the focus is confined to typical ’early adopters’ the number of candidates for substitution falls dramatically to between 35,000 and 94,000 depending on the scenario. This therefore reflect the depth of challenge to reach policy targets. However, this still implies that the EV fleet in Irish market, which is 8,473 BEVs as of 2019, could be significantly larger. Considering commuting patterns and vehicle use there are significant number of potential ‘EV positives ’, in Ireland, a term coined by Broadbent et al. (2021).

The research identifies locations in Dublin, Cork and Limerick as core areas (i.e. hot spots) where there is potential for greater diffusion of EVs. These locations are identified as having a high density of residents that can easily satisfy their weekly travel needs based on a single battery charge, in essence without range anxiety concerns. The analysis focuses on multi-car owners, with the assumption that one car is potentially replaced with an EV. Range anxiety is often associated with occasional longer trips so for longer trips multi-car owners are not constrained to use their EV. In summary, the assumptions underlying the analysis are such that potential EV switchers can continue all their usual travel patterns without any concerns regarding finding public EV charging points or delays while charging. While some of the hotspots are located in urban areas, we find hotspots in rural areas of Ireland as well in line with the findings of Morton et al. (2018) and Pucci (2021).

A significant reduction in transport emissions is feasible from switching to EVs. Many of the hot spots for EV switching in our scenarios are situated in urban areas. Emission savings associated with a single EV are relatively small but aggregate emission savings potential within such areas is substantial. While switching to an EV is a private decision for each vehicle owner and their household, the promotion of the collective emission reduction potential could be used as a motivation for more environmentally conscious groups to consider adoption of EVs.

Availability of charging points away from home and availability of overnight charging at low cost are also factors influencing decision to adopt EV technology (CSO, 2019; Funke et al., 2019). The distribution of current charging stations infrastructure in certain hotspots such as County Dublin is already extensive. Hence such areas can be targeted for

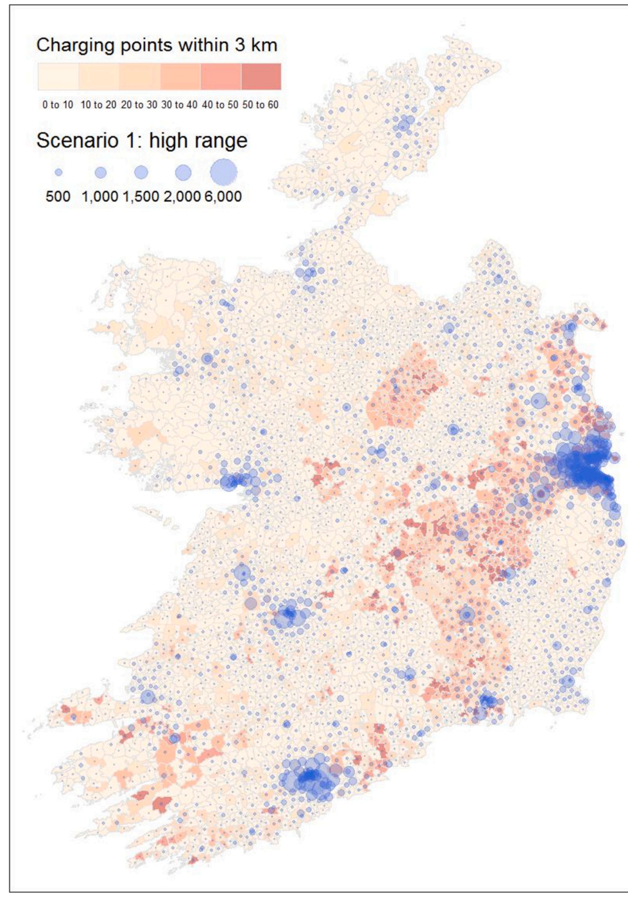

Fig. 4. Distribution of candidates for switching their second vehicle to a BEV as per scenario 1 and proximity to charging points in Ireland.

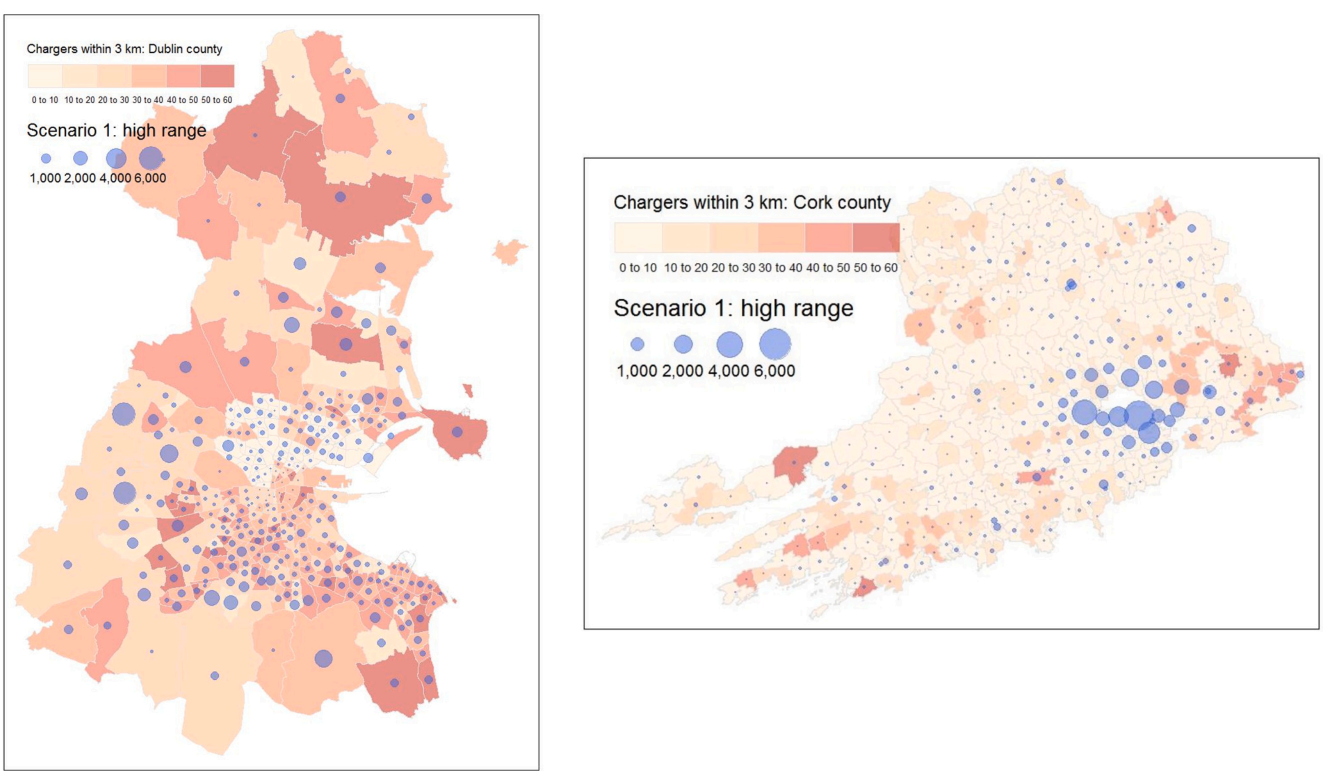

Fig. 3. Distribution of candidates for switching their second vehicle to a BEV as per scenario 1 and proximity to charging points in Dublin and Cork.

campaigns aiming for improving adoption rates among non-traditional adopters of EVs, like environmentally conscious younger individuals or apartment dwellers (Globisch et al., 2019). Other urban areas such as county Cork and some of the rural hotspots could gain from improvements in charging infrastructure especially near areas with clusters of candidates (Broadbent et al., 2018). In areas where there are fewer detached houses, Dutch-style free parking incentives coupled with expanded slow charging network in public parking areas can be an effective policy to accelerate adoption (Funke et al., 2019). The proportion of detached homes in Ireland is relatively high and hence home charging can be a solution for most candidates in our scenarios. As noted by Funke et al. (2019) and Guerra and Daziano (2020), charging infrastructure expansion should be targeted based on the specific needs of a locality, such as hotspots with fewer or no public charging points or areas with fewer detached homes such as Dublin city.

6. Conclusion

The Climate Action Plan of the Government of Ireland sets out ambitious targets for EV adoption (Govt. of Ireland, 2019). However, the current EV adoption figures raise significant scepticism about achieving these targets. Our study provides evidence that such plans are feasible with targeted localised marketing campaigns considering the EV adoption potential of a significant number of Irish households. This research identifies geographical areas with a high density of potential candidates for switching their second vehicle to an EV. Such information is beneficial for targeted or localised promotion of EVs. While high level marketing is necessary for transition to EVs, the identified hotspots if targeted for specialised efforts to encourage EV uptake might be most successful (Morton et al., 2018; Pucci, 2021). Specialised initiatives could be established in these areas in addition to existing incentives. For example, local EV test drive centres, sponsored local EV champions could be organised. Campaigns that target the identified hotspots could create a multiplier effect because drivers are more likely to adopt EVs as EV adoption becomes normalised (Noppers et al., 2019). Mukherjee and Ryan (2020) note that targeting the hotspots, where existing adoption is lower, might help to accelerate EV adoption rates overall.

Affordability is the main factor influencing the decision to purchase an EV for Irish citizens (CSO, 2019). There are already several financial incentives to overcome such barriers, including purchase grants, Vehicle Registration Tax (VRT) relief, toll incentives, home charger installation grants and reduced motor tax rates. However, other measures to raise adoption rates such as an increase in vehicle registration tax rates or increase in fuel prices for conventional vehicles (McAleer, 2021) should be carefully considered because of potential distributional impacts. McCoy and Lyons (2014) notes that certain scenarios of EV adoption can also put pressure on electricity distribution networks in some areas. We identify areas in Ireland where the current infrastructure and vehicle use patterns make transition to EVs more difficult. While the switch to EVs will have an impact on reducing transport emissions, the extend of reduction varies substantially between scenarios, largely related to the profile of EV adopters and their driving patterns. Notwithstanding policies advocating EV adoption, other policies for reducing transport emissions such as promoting cycling and increasing accessibility of public transport are also necessary (Friis, 2020).

This study utilises quite precise commuting data but faces data limitations in other areas (e.g. non-commuting travel), which impacts on the depth of analysis and consequent conclusions for policy. While better data would invariably refine the precision of the analysis, two central conclusions from the analysis are unlikely to change. First, while range anxiety is a genuine fear among motorists, there are many households where petrol/diesel cars could be substituted with EVs without impact on their routine driving patterns. Technological improvement is not necessary to large-scale EV adoption. Second, while EV adoption may be associated with certain socio-demographic profiles, it will also be associated with driving needs that are likely to be clustered spatially. Policy measures advocating EV switching within these spatial hotspots may be more productive than and complementary to general policy incentives targeting EV switching.

CRediT authorship contribution statement

Arya Pillai: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **John Curtis:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Miguel Tovar Reaños:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

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Appendix A

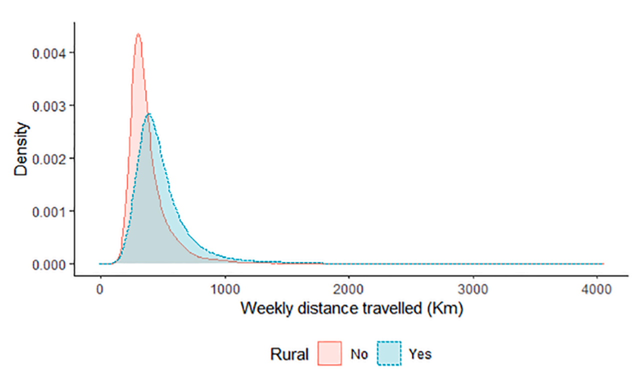

Fig. A.1. Histogram of distances calculated in the Monte Carlo simulations.

Table A.1
Electric vehicle fleet in Ireland as of 2019 (Department of Transport, 2019).

Vehicle type	Total fleet	Private cars
Petrol/ diesel and electric hybrids (HEV)	48,683	45,167
Electric (BEV)	9,120	8,473
Plugin hybrids (PHEV)	6,427	6,305

Table A.2
Aggregate count of potential buyers as per the sensitivity analysis scenario.

	Sensitivity analysis			
	Scenario 1		Scenario 2	
	Low range	High range	Low range	High range
Count	378,269	487,948	71,987	95,865
Share (%)	32.7	42.2	6.2	8.3

Note: share out of 1,154,469.

Table A.3
Aggregate count of potential buyers based on average of Monte Carlo simulations (1500 iterations).

	Sensitivity analysis: Monte Carlo			
	Scenario 1		Scenario 2	
	Low range	High range	Low range	High range
Count	204,040	463,848	37,576	91,482
SD of count	292	225	125	106
Share (%)	17.6	40.1	3.2	7.9

Note: share out of 1,154,469.

Table A.4
EDs with 99 percentile count for potential adopters as per Scenario 1 high range.

	ED	County	Scenario 1 high range
1	Blanchardstown-Blakestown	Fingal	5,553
2	Douglas	Cork County	5,335
3	Lucan-Esker	South Dublin	5,269
4	Ballincollig	Cork County	3,740
5	Castleknock-Knockmaroon	Fingal	3,360
6	Glencullen	Dún Laoghaire-Rathdown	3,126
7	Ballycummin	Limerick City and County	2,954
8	Carrigaline	Cork County	2,808
9	Swords-Forrest	Fingal	2,545
10	Bearna	Galway City	2,495
11	Naas Urban	Kildare	2,482
12	Firhouse Village	South Dublin	2,397
13	Lehenagh	Cork County	2,340
14	Celbridge	Kildare	2,334
15	Leixlip	Kildare	2,287
16	Ennis Rural	Clare	2,242
17	Ballysimon	Limerick City and County	2,221
18	Kilkenny Rural	Kilkenny	2,114
19	Firhouse-Ballycullen	South Dublin	2,037
20	Navan Rural	Meath	2,025
21	Caherlag	Cork County	1,840
22	Rathcooney (Part Rural)	Cork County	1,808
23	Tallaght-Jobstown	South Dublin	1,791
24	Dunboyne	Meath	1,735
25	Kilmacanoge	Wicklow	1,724
26	Tralee Rural	Kerry	1,688
27	Maynooth	Kildare	1,570
28	Lucan-St. Helen's	South Dublin	1,569
29	Ballybaan	Galway City	1,560
30	Swords-Lissenhall	Fingal	1,523
31	Kinsaley	Fingal	1,469
32	Donaghmore	Meath	1,429
33	Tramore	Waterford City and County	1,425
34	Morristownbiller	Kildare	1,423
35	Ashtown A	Dublin City	1,405

Table A.5
County wise tailpipe emission reduction in each scenario considering a high range EV being adopted.

	Emission reduction Direct (kt)	
County	Scenario 1	Scenario 2
Cork County	127.4	26.8
South Dublin	84.7	17.5
Fingal	82.05	18
Dublin City	76.1	15
Dun-Laoghaire Rathdown	61.2	17.6
Kildare	52.9	10.9
Limerick City	45.4	8.9
Galway County	41.8	9.4
Meath	40.1	7
Kerry	32.5	5.7
Tipperary	32.4	5.2
Wexford	31.4	5
Clare	30.3	6
Waterford City	29.2	6.1
Donegal	29.1	5.2
Mayo	28.2	4.7
Wicklow	26.7	5.4
Kilkenny	25.3	4.9
Louth	23.7	4.3
Cork City	23.6	4
Westmeath	17.9	3.3
Galway City	16.5	3.5
Sligo	16.1	3.6
Laois	15.9	2.5
Cavan	15.8	2.3
Roscommon	14.5	2.5
Offaly	14.3	2.2
Monaghan	13.8	1.9
Carlow	10.9	1.8
Longford	7.1	1.1
Leitrim	6.1	1.1

Table A.6
Reduction in CO_2 emissions and their share out of total emissions in different sensitivity analysis scenarios. Values in kilo tonnes (kt) and in %.

		Sensitivity analysis			
		Scenario 1		Scenario 2	
		Low range	high range	low range	high range
Direct emission reduction	Emissions (kt)	452	725	88.8	148.4
	Share (%)	15.5	24.9	3.05	5.1
	Average (t)	1.19	1.48	1.23	1.54

Note: Emission share out of 2,906.72 kt emissions (from 1,154,469 car owners who are drivers in the sample).

Table A.7
Reduction in CO_2 emissions and their share out of total emissions in Monte Carlo sensitivity analysis scenarios. Values in kilo tonnes (kt) and in %.

		Sensitivity analysis: Monte Carlo			
		Scenario 1		Scenario 2	
		Low range	high range	low range	high range
Direct emission reduction	Emissions (kt)	477.45	1085	87.92	214.07

Note: Emission share out of 2,906.72 kt emissions (from 1,154,469 car owners who are drivers in the sample).

Table A.8
Emission reduction calculation from various Monte Carlo scenarios in rural and urban areas.

		Sensitivity analysis: Monte Carlo			
		Scenario 1		Scenario 2	
		Low	High	Low	High
Rural	Emissions (kt)	101.38	325.66	17.59	60.79
Urban	Emissions (kt)	376.06	759.73	70.32	153.28

References

Ahrens, A., Lyons, S., 2021. Do rising rents lead to longer commutes? a gravity model of commuting flows in Ireland. Urban Stud. 58 (2), 264–279. https://doi.org/10.1177/0042098020910698.

Broadbent, G.H., Drozdzewski, D., Metternicht, G., 2018. Electric vehicle adoption: An analysis of best practice and pitfalls for policy making from experiences of europe and the us. Geogr. Compass 12 (2), 1. ISSN 17498198.

Broadbent, G.H., Metternicht, G., Drozdzewski, D., 2019. An analysis of consumer incentives in support of electric vehicle uptake: An australian case study. World Electric Vehicle J. 10 (1) https://doi.org/10.3390/wevj1001001. ISSN 2032–6653.

Broadbent, G.H., Metternicht, G.I., Wiedmann, T.O., 2021. Increasing electric vehicle uptake by updating public policies to shift attitudes and perceptions: Case study of new zealand. Energies 14 (10). https://doi.org/10.3390/en14102920. ISSN 1996–1073.

Brückmann, G., Willibald, F., Blanco, V., 2021. Battery electric vehicle adoption in regions without strong policies. Transp. Res. Part D 90, 102615. https://doi.org/10.1016/j.trd.2020.10261. ISSN 1361–9209.

Chen, C., Zarazua de Rubens, G., Noel, L., Kester, J., Sovacool, B.K., 2020. Assessing the socio-demographic, technical, economic and behavioral factors of nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. Renew. Sustain. Energy Rev. 121, 109692. https://doi.org/10.1016/j.rser.2019.109692. ISSN 1364–0321.

Chica-Olmo, J., Rodríguez-López, C., Chillón, P., 2018. Effect of distance from home to school and spatial dependence between homes on mode of commuting to school. J. Transport Geogr. 72, 1–12. https://doi.org/10.1016/j.jtrangeo.2018.07.013. ISSN 0966–6923.

CSO, 2016. Ireland. Census of population 2016 – profile 1 housing in Ireland. Retrieved from URL: https://www.cso.ie/en/releasesandpublications/ep/p-cp1hii/cp1hii/od/. Accessed on 26/04/2021.

CSO, 2016. Ireland. Road traffic volumes, transport omnibus 2016. Retrieved from URL: https://www.cso.ie/en/releasesandpublications/ep/p-tranom/to2016/rtv/. Accessed on 24/02/2021.

CSO, 2018. Ireland. Census 2016 place of work, school or college - census of anonymised records (powscar). Retrieved from URL: https://www.cso.ie/en/census/census2016reports/powscar/. Accessed on 18/02/2021.

CSO, 2019. Ireland. National travel survey: Electric vehicles, 2019. Retrieved from URL: https://www.cso.ie/en/releasesandpublications/ep/p-nts/nationaltravelsurvey2019/electricvehicles/.

Department of Transport, Tourism and Sport, 2019. Bulletin of vehicle and driver statistics. Retrieved from URL: https://www.gov.ie/en/publication/0f943b-irish-bulletin-of-vehicle-and-driver-statistics-2019/. Accessed on 10/03/2021.

ESB, 2021. Public EV charging points in Ireland. Accessed on 18/02/2021.

Featherman, M., Jia, S.J., Califf, C.B., Hajli, N., 2021. The impact of new technologies on consumers beliefs: Reducing the perceived risks of electric vehicle adoption. Technol. Forecast. Soc. Change 169, 120847. https://doi.org/10.1016/j.techfore.2021.120847. ISSN 0040–1625.

Friis, F., 2020. An alternative explanation of the persistent low ev-uptake: The need for interventions in current norms of mobility demand. J. Transport Geogr. 83, 102635. https://doi.org/10.1016/j.jtrangeo.2020.102635. ISSN 0966–6923.

Funke, S.A., Sprei, F., Gnann, T., Plötz, P., 2019. How much charging infrastructure do electric vehicles need? a review of the evidence and international comparison. Transp. Res. Part D 77, 224–242. https://doi.org/10.1016/j.trd.2019.10.024. ISSN 1361–9209.

Gehrke, S.R., Reardon, T.G., 2021. Patterns and predictors of early electric vehicle adoption in massachusetts. Int. J. Sustain. Transp. 1–29. https://doi.org/10.1080/15568318.2021.1912223.

Globisch, J., Plótz, P., Dütschke, E., Wietschel, M., 2019. Consumer preferences for public charging infrastructure for electric vehicles. Transp. Policy 81, 54–63. https://doi.org/10.1016/j.tranpol.2019.05.017. ISSN 0967–070X.

Gonçalves, D.N.S., de Morais Gonçalves, C., de Assis, T.F., da Silva, M.A., 2014. Analysis of the difference between the euclidean distance and the actual road distance in brazil. Transp. Res. Proc. 3, 876–885. ISSN 2352–1465. doi:10.1016/j.trpro.2014.10.066. 17th Meeting of the EURO Working Group on Transportation, EWGT2014, 2–4 July 2014, Sevilla, Spain.

Govt. of Ireland, 2019. Climate action plan 2019. Retrieved from URL: https://www.gov.ie/pdf/?file=https://assets.gov.ie/25419/c97cdecddf8c49ab976e773d4e11e515.pdf#page=null. Accessed on 15/03/2021.

Guerra, E., Daziano, R.A., 2020. Electric vehicles and residential parking in an urban environment: Results from a stated preference experiment. Transp. Res. Part D 79, 102222. https://doi.org/10.1016/j.trd.2020.102222. ISSN 1361–9209.

Haustein, S., Jensen, A.F., 2018. Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior. Int. J. Sustain. Transp. 12 (7), 484–496. https://doi.org/10.1080/15568318.2017.1398790.

Haustein, S., Jensen, A.F., Cherchi, E., 2021. Battery electric vehicle adoption in Denmark and Sweden: Recent changes, related factors and policy implications. Energy Policy 149, 112096. https://doi.org/10.1016/j.enpol.2020.112096. ISSN 0301–4215.

Isik, M., Dodder, R., Kaplan, P.O., 2021. Transportation emissions scenarios for New York City under different carbon intensities of electricity and electric vehicle adoption rates. Nat. Energy 6 (1), 92–104. https://doi.org/10.1038/s41560-020-00740-2. ISSN 2058–7546.

Kaufmann, R.K., Newberry, D., Xin, C., Gopal, S., 2021. Feedbacks among electric vehicle adoption, charging, and the cost and installation of rooftop solar photovoltaics. Nat. Energy 6 (2), 143–149. https://doi.org/10.1038/s41560-020-00746-w. ISSN 2058–7546.

Kevany, L., 2019. Spending review 2019, incentives for personal electric vehicle purchase. DPER, Gov. of Ireland. Retrieved from URL: https://assets.gov.ie/25107/eb5a541e3b614c94a3e47c8d068e72c9.pdf. Accessed on 15/03/2021.

McAleer, M., 2021. Electrified vehicles see sharp rise in sales under new tax scheme. Irish Times. Retrieved from URL: https://www.irishtimes.com/business/retail-and-services/new-car-sales-up-25-as-demand-for-electric-vehicles-surges-1.4662189. Accessed on 15/10/2021.

McAleer, M., 2021. Tax plan would force up car prices by €1,500, industry group warns. The Irish Times. URL: https://www.irishtimes.com/business/retail-and-services/tax-plan-would-force-up-car-prices-by-1-500-industry-group-warns-1.4684162. Accessed on 05/10/21.

McCoy, D., Lyons, S., 2014. Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. Energy Res. Soc. Sci. 3, 89–101. ISSN 2214–6296. doi:10.1016/j.erss.2014.07.008.

Morton, C., Anable, J., Yeboah, G., Cottrill, C., 2018. The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom. J. Transport Geogr. 72, 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020. ISSN 0966–6923.

Mukherjee, S.C., Ryan, L., 2020. Factors influencing early battery electric vehicle adoption in Ireland. Renew. Sustain. Energy Rev. 118, 109504. https://doi.org/10.1016/j.rser.2019.109504. ISSN 1364–0321.

Namdeo, A., Tiwary, A., Dziurla, R., 2014. Spatial planning of public charging points using multi-dimensional analysis of early adopters of electric vehicles for a city region. Technol. Forecast. Soc. Change 89, 188–200. https://doi.org/10.1016/j.techfore.2013.08.032. ISSN 0040–1625.

Noppers, E., Keizer, K., Milovanovic, M., Steg, L., 2019. The role of adoption norms and perceived product attributes in the adoption of dutch electric vehicles and smart energy systems. Energy Res. Soc. Sci. 57, 101237. https://doi.org/10.1016/j.erss.2019.101237. ISSN 2214–6296.

Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. R J. 10 (1), 439–446. https://doi.org/10.32614/RJ-2018-009.

Plótz, P., Schneider, U., Globisch, J., Dütschke, E., 2014. Who will buy electric vehicles? Identifying early adopters in Germany. Transp. Res. Part A 67, 96–109. https://doi.org/10.1016/j.tra.2014.06.006. ISSN 0965–8564.

Pucci, P., 2021. Spatial dimensions of electric mobility–scenarios for efficient and fair diffusion of electric vehicles in the milan urban region. Cities 110, 103069. https://doi.org/10.1016/j.cities.2020.103069. ISSN 0264–2751.

Rigaux, P., Scholl, M., Voisard, A., 2001. Spatial databases: with application to GIS. Elsevier.

Saarenpää, J., Kolehmainen, M., Niska, H., 2016. Identifying socio-demographically favourable area types for early hybrid electric vehicle adoption through mining of public sector data. Intell. Data Anal. 20 (2), 339–355.

Sander, H.A., Ghosh, D., van Riper, D., Manson, S.M., 2010. How do you measure distance in spatial models? an example using open-space valuation. Environ. Plann. B 37 (5), 874–894. https://doi.org/10.1068/b35126.

Schouten, M., Verwaart, T., Heijman, W., 2014. Comparing two sensitivity analysis approaches for two scenarios with a spatially explicit rural agent-based model. Environ. Model. Software 54, 196–210. https://doi.org/10.1016/j.envsoft.2014.01.003. ISSN 1364–8152.

SEAI, 2020. Energy in Ireland. Retrieved from URL: https://www.seai.ie/publications/Energy-in-Ireland-2020.pdf. Accessed on 30/03/2021.

SEAI, 2021. SEAI grant eligible cars. Retrieved from URL: https://www.seai.ie/grants/electric-vehicle-grants/grant-eligible-cars/. Accessed on 18/02/2021.

SEAI, 2021. CO2 emissions. Retrieved from URL: https://www.seai.ie/technologies/electric-vehicles/why-drive-electric/the-environment/. Accessed on 15/03/2021.

Thügersen, J., Ebsen, J.V., 2019. Perceptual and motivational reasons for the low adoption of electric cars in Denmark. Transp. Res. Part F 65, 89–106. https://doi.org/10.1016/j.trf.2019.07.017. ISSN 1369-8478.

Vassileva, I., Campillo, J., 2017. Adoption barriers for electric vehicles: Experiences from early adopters in Sweden. Energy 120, 632–641. https://doi.org/10.1016/j.energy.2016.11.119. ISSN 0360–5442.

Westin, K., Jansson, J., Nordlund, A., 2018. The importance of socio-demographic characteristics, geographic setting, and attitudes for adoption of electric vehicles in Sweden. Travel Behav. Soc. 13, 118–127. https://doi.org/10.1016/j.tbs.2018.07.004. ISSN 2214–367X.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T.L., Miller, E., Bache, S.M., Müller, K., Ooms, J., Robinson, D., Seidel, D.P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. J. Open Source Software 4 (43), 1686. https://doi.org/10.21105/joss.01686.

Zhuge, C., Shao, C., 2019. Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives. J. Clean. Prod. 213, 199–216. https://doi.org/10.1016/j.jclepro.2018.12.099. ISSN 0959–6526.