The diffusion of electric vehicles: An agent-based microsimulation

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Abstract

We implement an agent-based, threshold model of innovation diffusion to simulate the adoption of electric vehicles among Irish households. We use detailed survey microdata to develop a nationally representative, heterogeneous agent population. We then calibrate our agent population to reflect the aggregate socioeconomic characteristics of a number of geographic areas of interest. Our data allow us to create agents with socioeconomic characteristics and environmental preferences. Agents are placed within social networks through which the diffusion process propagates. We find that even if overall adoption is relatively low, mild peer effects could result in large clusters of adopters forming in certain areas. This may put pressure on electricity distribution networks in these areas.

Keywords Electric vehicles; Agent-based modelling; Spatial microsimulation

JEL Classification C63, D1, O33, Q4, Q55

1. Introduction

Electric vehicles (EVs) have been around since the mid-nineteenth century but have only recently been offered as a mass-market alternative to private cars with petrol and diesel engines. They are considered an important element in de-carbonising the transport sector and a number of governments have introduced initiatives to encourage their adoption. While this may have environmental benefits, both in direct emission reductions and in helping achieve CO_2 reduction targets in electricity generation [1], negative externalities also exist with mass-adoption. A large engineering literature documents the negative effects clustering of electrical load and uncontrolled charging of

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large numbers of EVs could have on low-voltage distribution networks [2; 3] and [4]. At the aggregate network level, high penetrations of these vehicles, when charging, may exacerbate existing peaks in electricity demand [5]. Even if overall adoption levels are very low, this could be concentrated in relatively few areas, due to the heterogeneous spatial distribution of individuals. This effect could be exacerbated if there is spatial dependence in adoption behaviour[1].

To examine this problem we create a tool to simulate how adoption patterns and clustering might develop over time and across space. We use an agent-based methodology to explicitly model the interactions which may give rise to emergent outcomes, not immediately obvious from an aggregation of individual preferences. Adoption is modelled as a binary choice. Agents have a threshold beyond which the benefits to adoption exceed the costs. Their utility is a function of their socioeconomic characteristics, environmental behaviour and attitudes. Their utility from adoption increases as their peers adopt and as the innovation gains popularity within the population. Agents are heterogeneous, drawn from a detailed, nationally representative study connected to an Irish electricity smart-metering trial. Agent populations are spatially explicit; we can generate populations of agents to match any geographic area of interest.

2. Agent-based adoption models

Agent-based models or ABMs are useful when describing systems of interacting agents, that exhibit emergent properties not easily deduced by aggregating the preferences of individual agents. ABMs have been widely used to study the diffusion of new technology. We will mainly focus on the diffusion of "green" technology for the purposes of this work.

Within an ABM framework, the diffusion process can take different forms. Linder [10] uses a Bass diffusion model to simulate adoption profiles for EVs amongst households in Stuttgart in 2020. Based on microdata they construct different adopter types and simulate various scenarios of spatial diffusion. They find that adopters will concentrate in urban areas and that spatial differences will become quite apparent by 2020.

Tran [11] explicitly models social network effects to examine their interaction with individual preferences in innovation diffusion. The author simulates adoption profiles for a variety of competing

[1] This has been shown to occur in the adoption of solar PV panels in California [6], High-voltage air conditioning systems in Chigaco [7]. Also in the adoption of hybrid electric vehicles [8] and [9]

vehicle types; including petrol, diesel, EV and hybrid electric vehicle (HEV). Using heterogeneous agents, it is found that network influence can be an important factor in driving high levels of adoption, even if agents have low individual incentives to adopt. However, he cautions that homophily can account for a lot of what first appears to be contagion. Other work by the same author [12], examines the techno-behavioural aspects of diffusion.

Threshold models are also widely used throughout the literature. Eppstein et al. [13] develop spatially explicit, agent-based consumer choice models of plug-in hybrid electric vehicle (PHEV) adoption to assess the market's sensitivity to various input parameters, such as fuel prices, battery range, purchase price and government subsidies. Agents have characteristics such as age and salary. Social groups are modelled as homophilous networks with fat-tailed degree distributions. An agent's threshold is defined as the proportion of adopters within its social group required for the agent to adopt; this is negatively correlated to their salary - the authors argue that wealthier agents would be less risk averse, thus having a lower threshold.

Hamilton et al. [14] model technology diffusion when consumers are uncertain about the performance of a new technology versus the old one. The agent environment is a square lattice of N cells and agents receive electricity from three potential sources; the grid, solar or CHP. Agent's thresholds are normally distributed and heterogeneous. An interesting aspect of this paper is the emergence of *"punctuated equilibria"*. This is a characteristic of a complex system, in which negligible changes in inputs can induce dramatic shifts in system outputs. This feature is observed empirically when the diffusion process does not follow the textbook S-curve.

Other research [15] simulates the adoption of smart-metering technology. This paper has similar features to others mentioned in that agents have local and random interactions on a grid, allowing for networks which exhibit small-world and scale-free properties. An interesting feature of this paper is the finding that a random and dispersed initial seeding can yield a much higher overall diffusion rate than a controlled centralised one. This has interesting policy implications when one considers government interventions to induce adoption of socially beneficial technologies.

A big problem inhibiting the widespread adoption of green technologies is consumer indifference. This is explicitly modelled by Kowalska-Pyzalska et al. [16], in which the authors examine the diffusion of dynamic electricity tariffs. Again, the environment is modelled as a square lattice. Influence is channelled through nearest-neighbours and media. Indifference is essentially noise in the system and can arise if the product offers both advantages and disadvantages between which the agent is unable to compare. They find that due to high levels of indifference, widespread adoption will be "virtually impossible" in modern societies, highlighting the need for better information in order to overcome this.

The focus of our research broadly follows a number of other papers in which agents have a utility function associated with the adoption of a new product. Agents have a threshold beyond which the benefits of adoption exceed the costs and they adopt. Within this literature thresholds can take various distributional forms, be heterogeneous or be the same for all agents.

Delre et al. [17] use a simple utility function consisting of two terms, individual preference and social influence. Agents are heterogeneous in their preferences and thresholds are uniformly distributed. The authors experiment with regular lattice and preferential attachment networks. An interesting element of this research is the study of so-called VIP effects. This is created using scale-free, non-symmetric adjacency matrices, with heterogenous weights on the edges to represent social networks. This is a more realistic representation of real-life networks where influence is not bi-directional. Certain nodes have a greater number of connections, but they also have a greater magnitude. Interestingly, they find that when modelling influential nodes it is the number of connections, more so than their weight/magnitude that propagates the diffusion process.

McCullen et al. [18] extend this approach to multi-parameter models. Along with peer-effects, they include a term for overall diffusion in the population (the S-curve). Thus, agents are influenced by their personal preferences, peer-effects and social-norms. Various network types are constructed; random, small-world and highly clustered community-based networks. They take a dynamical systems approach, rather than agent based, and run multiple simulations to explore the parameter space. They find that the level of adoption depends strongly on network topology and the relative weightings of parameters.

Palmer et al. [19] employ a similar methodology to simulate the diffusion of photovoltaic (PV) systems in Italy. Each agent has a unique utility which is a function of the payback period of the investment, the environmental benefit to the agent, their income and peer-influence from other agents within the population. Adopter categories are constructed using Sinus-Milieu(R) data for Italy and this information is also used to construct homophilous social groups. The aggregate adoption level is calibrated to past data, then projections are made. The authors find a common threshold for all agents that best fits the data and the model output is very sensitive to changes in this. The relative weightings of preferences vary only with adopter category and these weights are also chosen to calibrate to past data.

In terms of the spatial aspect of adoption, Campbell et al. [20] use a clustering algorithm on Birmingham Census data to determine the areas most likely to have high proportions of early adopters. Others employ a similar methodology using Finnish data [21], but go a little further in that they find the correlation between certain demographic and socio-economic characteristics and early HEV adoption.

We incorporate elements from a range of the above mentioned research in our work, we use clustering algorithms on Census data to determine where we might expect dense concentrations of adopters to form. We then generate agent populations based on the distribution of characteristics within these areas. Following that we employ a version of McCullen's main model equation in our agent-based model. We also include elements of [19] in that we decompose personal preferences into economic and environmental categories.

3. Materials and Methods

3.1. Basic Principles

The basic principle examined by this model is the interaction of individual preferences and peer-effects in the adoption or spread of behaviour, attitudes or new technologies.

3.2. Entities, State Variables and Scales

Entities or agents represent households. Agents are heterogenous and defined by a matrix of static and dynamic characteristics. They are located within a neighbourhood. The neighbourhood is represented as a discrete, homogenous grid. A regular lattice of size $N1*N2$, where $N1*N2 = N$ the total number of agents.

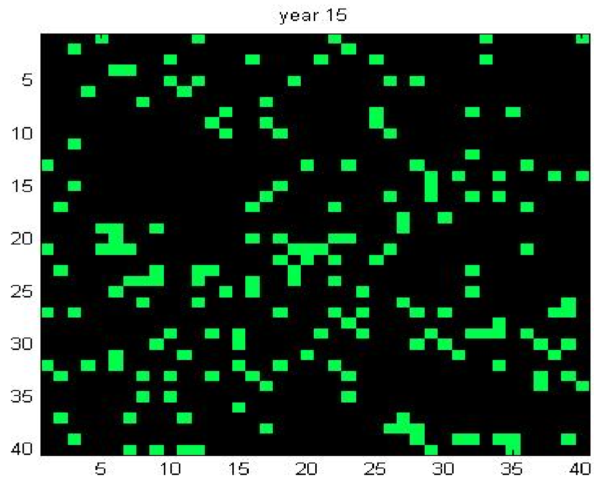

Fig. 1. Agent Environment for $N = 1600$ agents at $t = 15$. Agents are represented as squares on the grid. The green agents have adopted, the black have yet to adopt. Graphics generated using MATLAB code adapted from [22]

The global environment consists of a number of adjacent neighbourhoods based on Irish Census 2011 data. We will mainly work with Electoral Districts (EDs) of about 1,000 households. However, we could easily adapt our environment to cover Small-Areas (approximately 100 households) or much larger regions.

Agents are created using a large, nationally representative micro-data set connected to an electricity metering trial (CER Smart Metering Behavioural Trial 2009). For more information on data used see Appendix 6.1. Agents are described by two attributes, which we call Income Utility (IU) and Environmental Utility (EU).

To create IU, we use the age and social class of the household's chief income earner, combined with the tenure type of the household, $IU \in [0, 1]$. This is an adoption probability which could be considered an implicit budget constraint. Other things being equal, agents with a higher IU are more likely to adopt. We create simple rules; e.g. $\Pr(Adopting \mid of social class AB) > \Pr(Adopting \mid of social class C1) > \Pr(Adopting \mid of social class C2)$ etc. From which we generate these distributions. Further detail on this procedure can be found in Appendix 6.2.

Table 1

Socioeconomic variables

ranking	Age	Social class	Tenure
1	25-59	AB	own outright
2	all other categories	C1	own with mortgage
3		C2	rent private
4		DE	rent from local authority
5		F	other

Agent's EU is based on their attitude toward the environment and previous adoption of energy saving technology within their homes, $EU \in [0, 1]$. Other things being equal, agents with a higher EU are more likely to adopt. Further detail on this procedure can be found in appendix 6.2.

Table 2

Environmental variables-behavioural

ranking	Proportion of Energy Saving Light-bulbs	Proportion of Double-Glazed Windows	Lagging Jacket	Attic Insulated	External Walls Insulated
1	All	All	Yes	Yes, more than 5 years ago	Yes
2	3/4	3/4	No	Yes, less than 5 years ago	No
3	1/2	1/2		Dont know	Don't know
4	1/4	1/4		No	
5	None	None			

Therefore an agent with $IU \geq 0.7$ and $EU \geq 0.7$ for example, is likely to be aged 25-59, a

Table 3

Environmental variables-attitudinal

ranking	Opportunity to sell back electricity	Environmental damage associated with electricity generated	Percentage of electricity generated from renewable sources
1	Very dissatisfied	Very dissatisfied	Very dissatisfied
2			
3			
4			
5	Very Satisfied	Very Satisfied	Very Satisfied

home owner, of social class AB, have strong environmental preferences and already an adopter of a range of energy saving technologies within their home. We have identified these characteristics as being prominent amongst early stage adopters of EVs from the literature [2]. A limit to this work is that we did not have access to econometric estimates of the parameters. We also acknowledge that the weightings we attach to different attitudes or behaviours is problematic as we do not know their relative importance in determining the adoption decision. However, we argue that in reality statistical distributions do exist that describe the range of individual preferences in a population, even if we can't always fully observe them. Also, much research in this space, assumes these distributions to take some or other form, e.g. uniform, normal etc, which can appear quite arbitrary. We base ours on detailed survey data and we argue that this allows us a greater claim to realism.

Fig. 2 below shows the distribution of agent preferences generated from survey data in the full sample of 3099 individuals. IU and EU are weakly positively correlated. We will draw sub-samples from this to create our agent populations.

[2] Early adopters of EVs are expected to share a number of characteristics with early adopters of hybrid electric vehicles. See [23], [24] and [25]

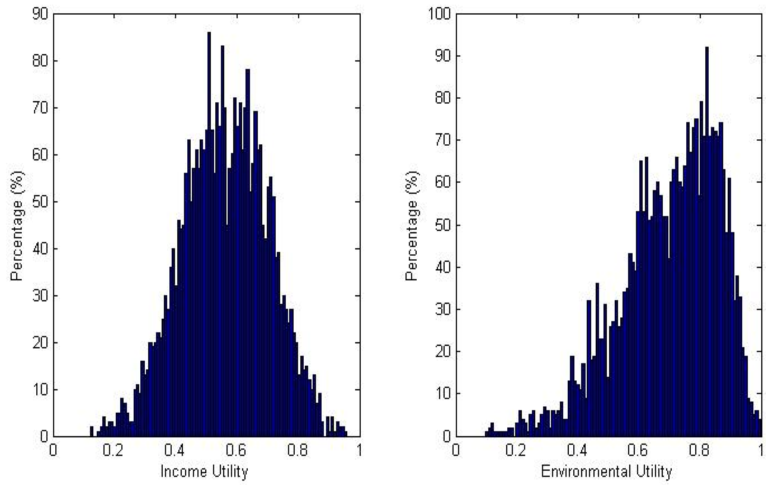

Fig. 2. Distribution of Preferences for full agent population

3.3. Collectives

We will mainly experiment with two different types of social network, that have a number of the characteristics of real-life social networks; small-world and preferential attachment. In order to better describe these, it is first useful to introduce two other network types; regular lattice and random.

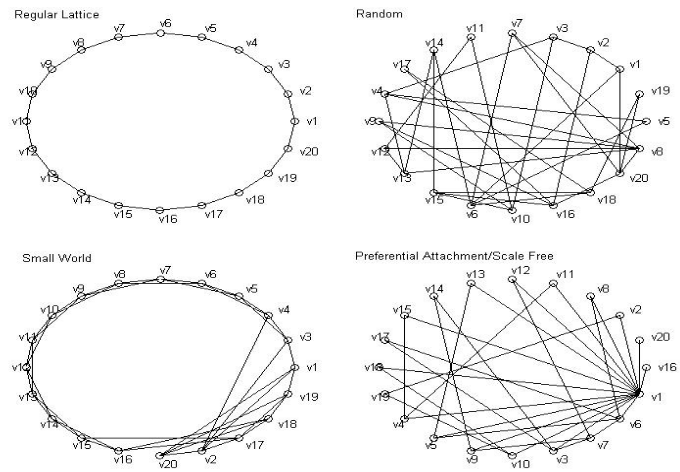

Fig. 3. Social Networks: $N = 20$ nodes or agents in each case. Agents arranged in a circle for illustrative purposes only. Network matrices constructed using CONTEST [26]. Network graphics using "Matlab Tools for Network Analysis" [27]

Starting with the regular lattice in fig. 3.1a, each node is connected to it's k nearest neighbours, with $k = 2$ in this case. This is a very simple network type and not very realistic as nodes can only have local connections. In the next network, a random graph fig. 3.1b, nodes do not necessarily have any local connections but are randomly connected to any other node in the network. Again this is an unrealistic characterisation of a real social network.

A small-world network, fig. 3.1c can be considered something in between a regular lattice and a random graph. They are both highly clustered and have short characteristic path lengths. Small-World networks were originally proposed by [28]. The authors found that by randomly re-wiring a certain proportion of the edges of a regular lattice, they could create a graph which had "small-world" properties. The graph shown has a rewiring probability of 0.1. A wide range of networks in both physical and social systems have this property. Graphs with small-world properties include the neural networks of worms, the electric power grid and collaboration networks in academia and film. For a discussion of their statistical properties, see [29].

Preferential attachment networks fig. 3.1d, exhibit a scale-free property. The connectivity distribution of nodes within these networks decay as a power-law. This essentially means that the majority of nodes have few connections but a small proportion have a very large number of connections, e.g. node v1. As new nodes enter the network, they connect with existing nodes with a probability which is an increasing function of the number of connections these nodes currently have. These highly-influential nodes could be considered opinion leaders in a community. Many real-life networks also exhibit this property.

3.4. Process Overview and Scheduling

The main process in this model is the diffusion of EVs. At every time step, each agent decides to adopt or not. A time step is defined as the length of time it takes to update all agents and thus does not correspond to real time. Agents are updated sequentially on the grid, starting at the top-left corner. Simulations last until all agents are activated or until the model reaches equilibrium. Equilibrium will occur when a gap in either the threshold distribution, or in the agent's individual preferences do not allow any further agents to be activated.

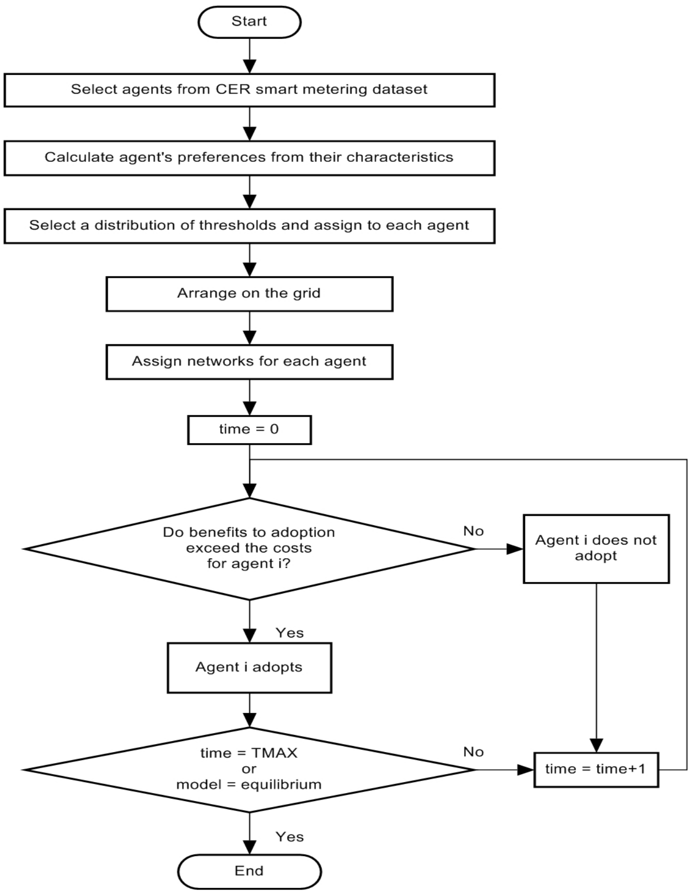

Fig. 4. Flow-chart of agent updates

3.5. The Model

3.5.1. Agent Decision Making

The adoption status of each agent is represented as a binary variable; 1 if $agent_i$ has adopted, 0 otherwise. Adoption is an absorbing state - once an adopter it is not possible to switch back. This model is adapted from the work of [17; 18; 19].

$$x_i(t+1) = \begin{cases} 1, & \text{if } x_i(t) = 1 \\ 1, & \text{if } x_i(t) = 0 \text{ and if equation (2) is true} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The adoption submodel is the main engine of the agent-based model. $Agent_i$ adopts with a certain probability once its utility U_i exceeds its threshold θ_i.

$$U_i(t) \geq \theta_i(t) \text{ and if } t * crit \geq rand(0,1) \tag{2}$$

Utility is a weighted function of individual preferences (IU, EU), peer effects (G) and wider social norms (S).

$$U_i(t) = \alpha_i IU_i + \beta_i EU_i + \gamma_i G_i(t) + \delta_i S(t) \tag{3}$$

With $\alpha_i + \beta_i + \gamma_i + \delta_i = 1$

3.5.2. Individual Preferences

Individual Preferences are determined by an agent's income utility (IU) and an environmental utility (EU). These have been described in detail above.

3.5.3. Peer Influences

Agents are modelled as nodes in a network. Influence between nodes is represented by an adjacency matrix A.

$$A_{i,j} = \begin{cases} 1, & \text{if } n \text{ node i influences node j} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Group influence is the proportion of adopters within each agent's social group.

$$G_i(t) = \frac{1}{k_i} \sum_{j=1}^{N} A_{ij} x_j(t) \tag{5}$$

3.5.4. Social Norms

This is the total number of adopters in the population.

$$S(t) = \frac{1}{N} \sum_{i=1}^{N} x_j(t) \tag{6}$$

3.5.5. Technology/Information Deficiency

This parameter is a decaying stochastic cost term that accounts for poor products or poor information about the product when in its infancy. This is to account for the inertia that can exist in the early stages of technology adoption. For example if the critical value $crit = 0.1$ adoption will be slow in the early periods but by time $t = 10$, $t * crit = 1$ and the product will have reached maturity or agents will be fully informed of its benefits.

3.5.6. Rules/Archetypes

As stated above $\alpha_i + \beta_i + \gamma_i + \delta_i = 1$. We can set fixed weights or allow them to vary depending on the agent or product. This is explained in greater detail in section 4.1.

4. Simulations and Results

4.1. EV adoption for a random sample of agents

Electric vehicles are expensive items and this should be reflected in the decision rule that agents might make when purchasing one. Therefore we feel that peer effects might have a limited impact for certain agents. An individual may be more likely to buy one if a neighbour or friend has one and speaks favourably about it. Or someone with very strong environmental concerns may be more inclined to buy one. However, income will constrain the available options. To initially calibrate the model we create four different consumer groups. We segment agents based on their IU and EU. Table 4 below displays the weights we attach to preferences for each group. We create stochastic weights, within bounds to account for the uncertainty in their estimation.

Table 4

Parameter weightings for EV

Group	Income (α)	Environmental (β)	Social Network (γ)	Population (δ)	Rule 1	Rule 2	Category
1	rand(0.3-0.7)	$(1-\alpha)/3$	$(1-\alpha)/3$	$(1-\alpha)/3$	$IU \leq 0.3$		Low income
2	$(1-\beta)/3$	rand(0.3-0.7)	$(1-\beta)/3$	$(1-\beta)/3$	$IU \geq 0.3$	$EU \geq 0.7$	Mid-high income environmentalists
3	$(1-\gamma)/3$	$(1-\gamma)/3$	rand(0.3-0.7)	$(1-\gamma)/3$	$IU \geq 0.3$	$0.3 \leq EU \leq 0.7$	Mid- high income indifferent
4	$(1-\delta)/3$	$(1-\delta)/3$	$(1-\delta)/3$	rand(0.3-0.7)	$IU \geq 0.3$	$EU \leq 0.3$	Mid-high income non-environmentalists

- Group 1: Low income agents will be income constrained regardless of their environmental preferences and thus will place a high importance on IU. This is an implicit budget constraint. We allow α take a random value between 0.3 and 0.7
- Group 2: Mid-high income environmentalists will place a high importance on environmental factors. We allow β take a random value between 0.3 and 0.7
- Group 3: Mid-high income indifferent agents may be influenced by word of mouth from their peers. We allow γ take a random value between 0.3 and 0.7
- Group 4: Mid-high income non-environmentalists have negative attitudes and behaviour towards environmental issues and will only adopt if a high proportion of the total population adopt. We allow δ take a random value between 0.3 and 0.7

Again we select a random sample of $N = 1600$ agents from our population. We set threshold distribution $\theta \sim N(0.65, 0.15)$ to generate relatively low adoption levels. These results have been verified for a range of threshold distributions. In all simulations thresholds are negatively correlated with IU, as per [13].

4.1.1. The effect of seeding and network type on adoption

With a network model we can examine whether it matters who adopts first within the population. In order to do this we seed different groups of agents, i.e. we initialise them as being EV owners. To seed $agent_i$, we set $x_i = 1$ at time $t = 0$. This may be policy relevant for initiatives which target specific consumer groups in order to encourage the mass adoption of EVs. Three different seeding methods are examined.

1. Seed random: We seed random samples of 5% of the agent population
2. Seed early adopter: We seed the 5% of the agent population with the highest probability of adoption, given their personal preferences
3. Seed most influential nodes: We seed the 5% of the agent population with the greatest number of connections. This can be either a random or early adopter seeding. To do this we place a 5% seeding, then re-arrange the adjacency matrix to make these the most connected nodes in the network

Results are reported in fig. 5 and tables 5 and 6 below. We first connect agents with preferential attachment networks, table 5. Without intervention average adoption after 15 time periods is just over 9%. We then compare seeding a random group of agents with seeding the early adopters. Interestingly a random seeding yields a higher mean adoption level. We suspect this is because the early adopters are likely to adopt anyway. However, by activating a random group of agents, adoption is spreading to agents and groups that would otherwise not have adopted. Zhang and Nuttall [15] found similar results in their ABM of smart-metering technology adoption.

Within a preferential attachment network some nodes have a much greater number of connections than others. We investigate the outcome when the most influential nodes adopt first. We find that seeding is much more effective when the most influential are targeted. Again, a random distribution results in higher adoption than if the high probability agents adopt first. However, in reality it is impossible to fully map the network topology. This simulation is run to illustrate the point that if we aim to encourage high levels of adoption through the targeting of specific consumer groups, we need much better data on the channels through which technology diffuses.

These results also hold for small-world networks as can be seen in table 6. We must be cautious when interpreting these results, due to limitations with the model. In particular, the adjacency matrices we use are symmetrical and we do not place different weights on the links between nodes in the network. In reality, as well as having many connections, some individuals are likely to have a greater weight to their connections.

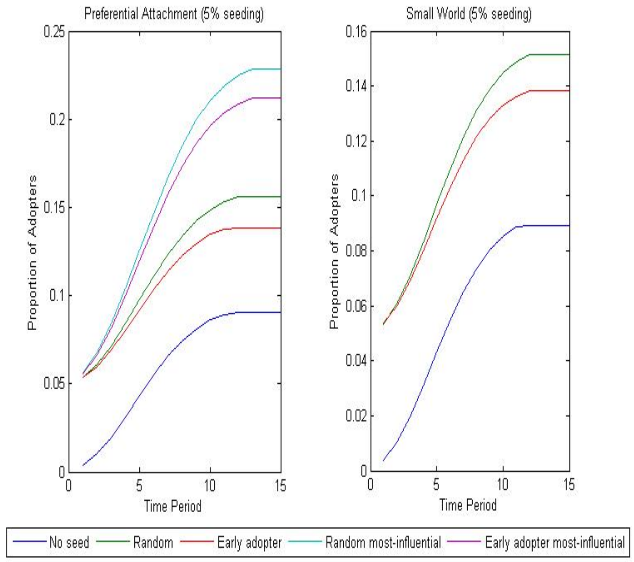

Fig. 5. EV adoption levels. Results reported for average uptake after 100 Simulations of $N = 1600$ Agents. $\theta \sim N(0.65, 0.15)$ for all simulations

Table 5

Preferential Attachment

	Mean	Std. Dev.	Min	Max
No seeding	9.28	1.04	7.00	12.25
Random 5%	15.93	1.04	13.44	18.63
Early Adopter 5%	14.18	0.89	11.50	16.63
Random most connected 5%	23.31	1.51	18.25	26.81
Early Adopter most connected 5%	21.45	1.38	18.19	24.63

Table 6

Small-World

	Mean	Std. Dev.	Min	Max
No seeding	9.25	0.95	7.00	11.44
Random 5%	15.48	1.01	12.69	17.56
Early Adopter 5%	14.04	0.90	11.50	16.25

In reality though, neighbourhood composition is not random and clusters may develop if certain types of individual self-select into particular areas. We will examine this in the next section.

4.2. EV adoption for specific neighbourhoods

To motivate this section we use Census 2011 data to generate a heat map of areas with high proportions of likely early adopters in Dublin, fig. 6. We use Ward's clustering algorithm to rank Small-Areas based on their proportions of individuals of social class AB, who drive a car to work and live in a house. Details on the ranking algorithm can be found in Appendix 6.3

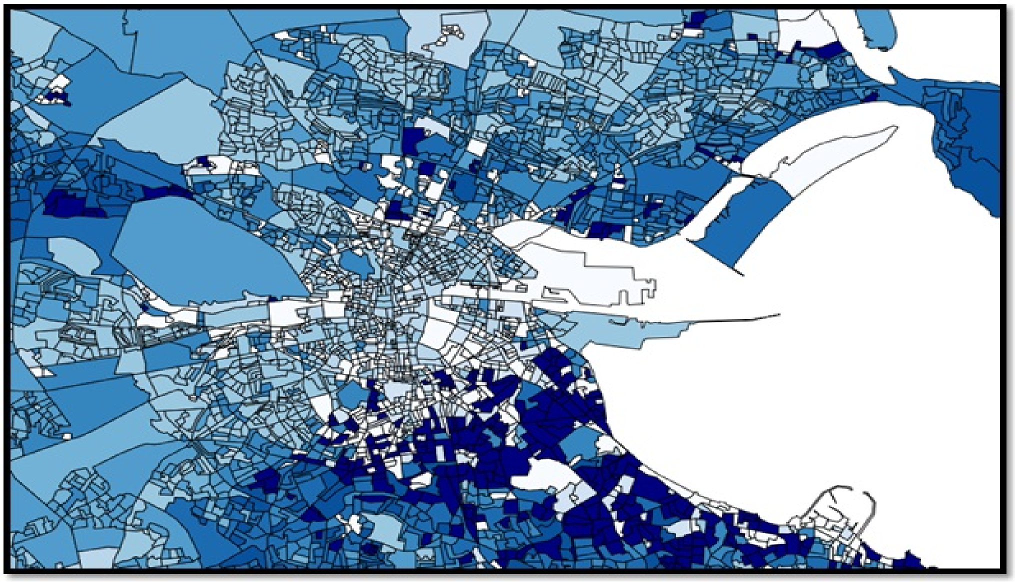

Fig. 6. Spatial distribution of likely early adopters for Census Small-Areas in Dublin (approx 100 households in each area). Areas are ranked 1-10. 1-coloured white indicates a very low proportion, 10-coloured dark blue indicates a very high proportion

There is quite a degree of spatial heterogeneity, as can be seen. This is interesting as positive network externalities may exacerbate clustering in areas with high proportions of adopters. To simulate this process we generate agent populations that represent the distributions of households within these areas.

4.2.1. Adoption levels

In this section we focus on four neighbourhoods, based on Census Electoral Districts (EDs) which vary in their socioeconomic characteristics. The selected EDs are Clonskeagh-Roebuck, Dalkey-Hill, Palmerstown West and Arran Quay C. We select houses based on the social class of their chief income earner and tenure type.

Table 7

Neighbourhoods included in simulations

Number	Electoral District (ED)	Reason for inclusion
1	Clonskeagh-Roebuck	Current location of a electricity distribution test network examining the effect of EV charging
2	Dalkey-Hill	High proportion of social class AB and home-owners
3	Palmerstown West	High proportion of social class DE and local authority renters
4	Arran Quay C	Good mix of social class and high proportion of private renters

Below are the resulting distributions of preferences for each ED.

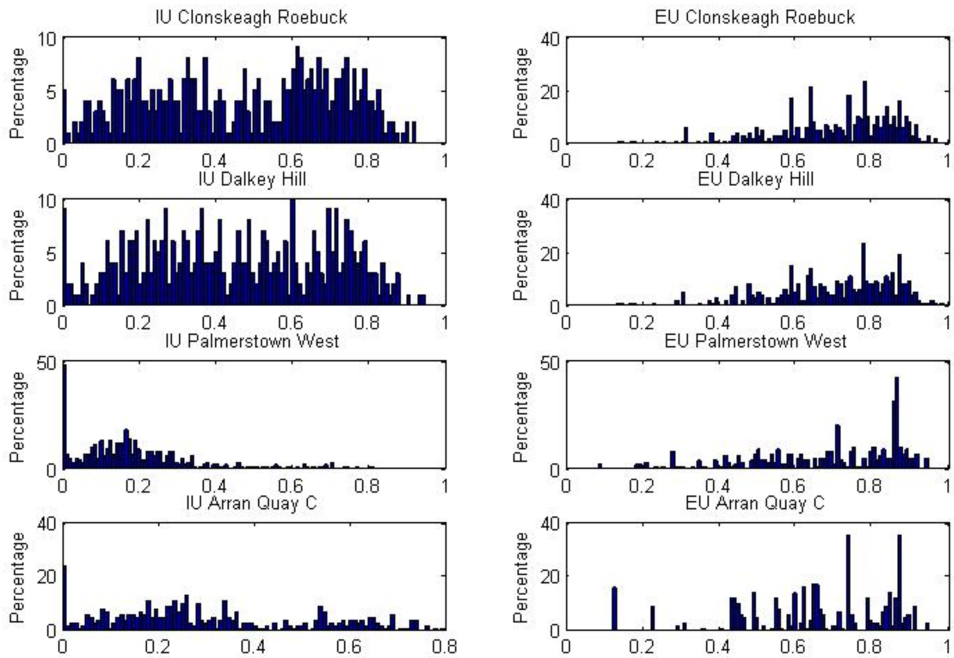

Fig. 7. Distribution of agent preferences for different EDs

We use the previous model specification and parameter set up. We split our grid into four quadrants to represent each ED. This process no longer generates the smooth adoption S-curves previously observed when using a random sample, fig. 8. This is because we now have groups of similar individuals and their preference distribution can take discrete jumps, potentially causing a number of similar agents to adopt within the same time period as each other.

Results are reported below in fig. 8 and tables 8 and 9. The wealthier neighbourhoods (1,2) with a greater proportion of homeowners have much higher adoption levels the the less wealthy (3,4), as expected. Interestingly, the choice of network used to connect agents now begins to have a greater impact on the results.

Preferential attachment networks lead to average adoption levels of 17-18% in the wealthier neighbourhoods and 0.7-3.2% in the less wealthy neighbourhoods.

However, small-world networks generate over 10% higher average adoption levels for the wealthier neighbourhoods than preferential attachment networks. We can easily get to 30% adoption for these areas. This level is very sensitive to changes in threshold distribution and a reduction of threshold mean from 0.65-0.55 can induce uptake of over 50% for these areas. This lowering of threshold is analogous to the cost or barriers to adoption dropping. For instance, if technological developments allowed price to fall or if charging infrastructure improved for a particular area the cost to adoption for agents in that area would fall. This high adoption in certain areas may have an impact on the distribution network in these areas. We will discuss this in the next section.

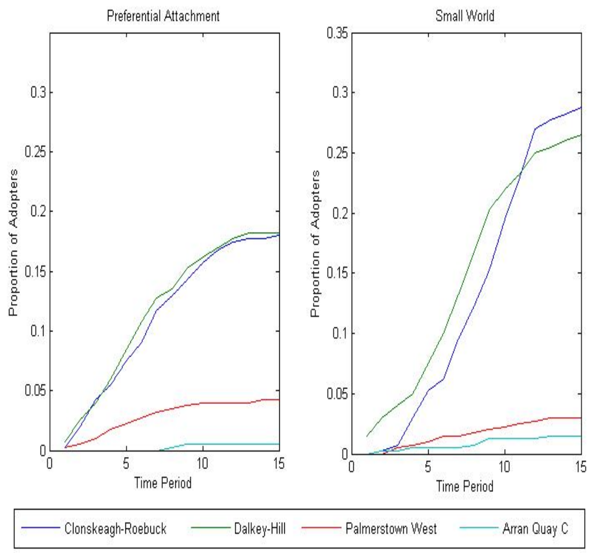

Fig. 8. EV adoption levels. Results reported for average uptake after 100 Simulations of $N = 1600$ Agents. $\theta \sim N(0.65, 0.15)$

Table 8

Preferential attachment network

ED	Mean	Std. Dev	Min	Max
Clonskeagh-Roebuck	18.02	1.02	16	21
Dalkey-Hill	17.61	1.1	15.5	21
Palmerstown West	3.18	0.42	2.5	4.25
Arran Quay C	0.69	0.38	0	1.75

Table 9

Small-world network

ED	Mean	Std. Dev	Min	Max
Clonskeagh-Roebuck	29.77	0.61	27	30.5
Dalkey-Hill	31.79	0.33	30.75	32.5
Palmerstown West	3.97	0.1	3.75	4.25
Arran Quay C	1.99	0.035	1.75	2

4.2.2. Local Clustering

The most interesting results occur when we examine the level of clustering of adopters. We find small-world networks yield a smaller number of clusters than preferential attachment networks.

Table 10

Clustering. Results reported for 100 simulations of $N = 1600$ agents. $\theta \sim N(0.65, 0.15)$

Network type	Number of clusters			Size of clusters		
Small-World	Mean	Max	Min	Mean	Max	Min
$k = 1$	21.06	24	17	12.26	295	2
$k = 2$	21.06	24	17	22.47	242	2
$k = 3$	21.06	24	17	23.78	237	2
$k = 4$	15.32	17	13	33.84	236	2
$k = 5$	21.06	24	17	26.66	249	2
Preferential attachment	23.54	29	16	2.36	9	2

However cluster size increases dramatically if agents are connected locally using small-world networks. If agents are connected to just their two nearest neighbours ($k = 1$), mean cluster size increases from 2 to 12. Cluster size further increases as we increase the number of local connections agents are allowed to have. We can't generalise these results as they may be particular to the areas in question, and our networks are a stylised version of reality. However, we can say that even mild peer-effects could induce dense clusters in areas with high proportions of adopters.

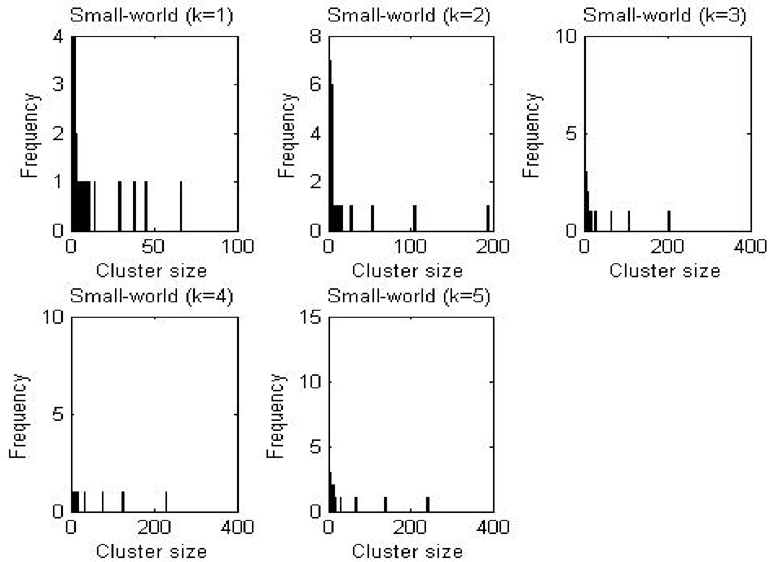

Fig. 9. Distribution of cluster size for small-world networks

In a study of a test network of 134 households in Dublin, Richardson et al. [30] found that severe voltage drop and unsafe thermal loading of components can occur when EV penetration reaches 27-44% of the households. Clusters occurring further from the transformer have a greater impact. From the distribution of cluster size we generate, it is quite possible to observe clusters that in reality would be large enough to cause the network to exceed safe operating limits. This problem would be greater if clusters are located towards the end of network line, away from the substation bus.

5. Conclusion

In this paper we present a simple and stylised agent-based model of EV adoption amongst Irish households. The motivation was to create a tool in order to model;

- The drivers of aggregate adoption levels
- The formation of clusters of adopters at a local level
- Spatially explicit adoption profiles

This is relevant because we know that spatial dependencies do exist in the adoption of ”green” technologies and if this exists for EVs it may cause negative externalities in the form of reduced life for electricity network assets.

We use an agent-based methodology as there is potential for micro-interactions to generate aggregate outcomes that can't be deduced by merely examining the preferences of individuals. We adapt a methodology used by others and apply it to the diffusion of EVs amongst Irish households.

Agents are created based on detailed, nationally representative survey data. We define simple rules that govern their behaviour, link them with other agents, through different network types and place them within an environment. We then use a spatial microsimulation algorithm to generate agent populations that represent specific geographic areas of interest.

We find that it is important who adopts first in determining the overall diffusion level in the population. We demonstrate that in order for policies encouraging the adoption of socially beneficial technologies to succeed, network topology needs to be better understood.

In terms of clustering, we find that mild peer-effects can induce very high adoption levels in certain areas. Even if overall adoption levels are quite low, this could be highly clustered in certain areas and peer-efects within those areas could significantly increase cluster size. This could lead to increased costs for electricity network operators and ultimately for consumers, as the average cost of improvements to the network will be socialised.

There are many limitations to this type of modelling in general and to this model in particular. We do not claim to accurately understand agent preferences; we merely use survey data to generate distributions that should be considered place-holders in order to calibrate this model. Nor do we claim to create realistic social networks; we experiment with different network types, both of which contain some of the characteristics of actual human social networks. We do not suppose to fully describe the various consumer groups that may exist; we use some simple rules to segment the population into different groups to illustrate how heterogenous groups can alter the dynamics of such a system.

Further work will involve collecting survey data to better inform our choice of parameters. As more data on EV adopters becomes available, we will be better able to characterise them. Survey data on early adopters and the factors which influence them to adopt would help inform our network matrices. We could potentially generate adoption profiles for all Census Small-Areas in Dublin to create a ranking of areas in order to inform distribution network upgrades. We also plan to link this model with engineering network-cost models.

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6. Appendices

6.1. Appendix A: Data

(1) CER Smart Metering Customer Behavioural Trial. This is a nationally representative sample of over 5,000 households in the Republic of Ireland. This dataset contains high frequency energy consumption data along with socioeconomic information on the participants. The survey was conducted on Electric Ireland customers who at that time represented 100% of Irish residential electricity demand. Households were randomly assigned to a treatment group or different control groups in order to estimate the effect of different stimuli on residential electricity demand. This is described in detail in [31]. The main questions of interest for this paper are listed below in Appendix 6.2

(2) Census 2011 Small Area Population Statistics. This is a national census, conducted in 2011, based around 46 different tables covering a range of themes, see table 11. This data is disaggregated to Small Area level, of which there are approximately 18,500 across the country; typically these would consist of 80-100 households. We have based our agent populations on Electoral Districts (EDs) of which there are approximately 3400.

Table 11

Census SAPS Themes. Source: Central Statistics Office (CSO), Census 2011 Small Area Population Statistics (SAPS)

Census SAPS Themes	
Theme 1: Sex, age and marital status	Theme 9: Social class and socio-economic group
Theme 2: Migration, ethnicity and religion	Theme 10: Education
Theme 3: Irish language	Theme 11: Commuting
Theme 4: Families	Theme 12: Disability, carers and general health
Theme 5: Private households	Theme 13: Occupation
Theme 6: Housing	Theme 14: Industries
Theme 7: Communal establishments	Theme 15: PC and internet Access
Theme 8:Principal status	

6.2. Appendix B: Weights applied to calculate IU and EU

To create weights we ranked each category from 0-1, summed up the totals and normalised between 0 and 1. We then add a degree of randomness to these distributions. This is to remove the initial lumpiness, allowing them to be more continuous as we would expect to be the case in reality.

In calculating EU, we felt past adoption is a better guide to future adoption than declared environmental attitudes. We allowed the past adoption of energy saving measures within the home have 5 times the weight of the attitudinal data.

Table 12

Calculation of IU and EU

Income utility (IU)		Environmental Utility (EU) - attitudinal		Environmental Utility (EU) - behavioural	
Social Class	Rank	Opportunity to sell back electricity	Rank	Lightbulbs	Rank
AB	1.00	Very dissatisfied	1.00	All	1.00
C	0.25	-	0.50	3/4	0.80
DE	0.20	-	0.33	1/2	0.60
F	0.17	-	0.25	1/4	0.40
No answer	0.14	Very satisfied	0.20	None	0.20
Tenure		Environmental damage with electricity generation	Rank	Windows	Rank
own outright	1.00	Very dissatisfied	1.00	All	1.00
own with mortgage	0.50	-	0.50	3/4	0.80
rent private	0.33	-	0.33	1/2	0.60
rent from local authority	0.25	-	0.25	1/4	0.40
other	0.20	Very satisfied	0.20	None	0.20
Age		Percentage generated from renewables	Rank	Lagging	Rank
25-59	1.00	Very dissatisfied	1.00	Yes	1.00
Other	0.50	-	0.50	No	0.00
		-	0.33		
		-	0.25		
		Very satisfied	0.20		
				Attic	Rank
				Yes, more than 5 years ago	1.00
				Yes, less than 5 years ago	1.00
				Don't no	0.00
				no	0.00
				External Wall insulated	Rank
				Yes	1.00
				No	0.00
				Don't know	0.00

6.3. *Appendix C: Ward's clustering algorithm*

To rank Census small-areas we used Ward's method, a hierarchical clustering algorithm. These results are purely descriptive, do not feed into the simulations and were generated only to graphically represent the level of spatial heterogeneity that may exist. Dublin is divided into over 4000 small-areas. The objective of Ward's method is to minimise within-cluster variance. It starts by considering each individual area/observation as a cluster. It then begins to merge clusters with each other, at each step finding the pair of clusters that leads to lowest within-cluster variance. We decided after trial and error to allow 10 distinct clusters. We merged on:

1. absocial. The proportion of individuals of AB social class in each area
2. carwork. The proportion of individuals who drive to work
3. house. The proportion of individuals who live in a house

This work is informed by [20] who employ this method to determine the spatial location of potential early EV adopters in Birmingham.

Table 13

Clusters generated for Dublin small-areas

wards10		absocial	carwork	house
1	mean	0.255	0.465	0.048
$N = 196$	sd	0.118	0.096	0.047
2	mean	0.392	0.234	0.060
$N = 244$	sd	0.091	0.113	0.072
3	mean	0.130	0.123	0.122
$N = 347$	sd	0.083	0.085	0.095
4	mean	0.202	0.220	0.549
$N = 511$	sd	0.127	0.092	0.139
5	mean	0.332	0.472	0.427
$N = 231$	sd	0.121	0.093	0.136
6	mean	0.202	0.429	0.975
$N = 727$	sd	0.057	0.048	0.025
7	mean	0.345	0.388	0.975
$N = 748$	sd	0.063	0.071	0.031
8	mean	0.334	0.364	0.757
$N = 404$	sd	0.120	0.091	0.074
9	mean	0.120	0.277	0.952
$N = 952$	sd	0.067	0.058	0.044
10	mean	0.519	0.387	0.972
$N = 446$	sd	0.065	0.060	0.041
Total	mean	0.261	0.332	0.734
$N = 4806$	sd	0.150	0.123	0.339