Investigating the Importance of Public Charging Infrastructure and Early Adoption Effects on Electric Vehicle Uptake

Mingyue Selena Sheng [a], Le Wen [a*], Basil Sharp [a, b], Ajith Sreenivasan [a], Prakash Ranjitkar [c], Bo Du [d, e]

[a] *Energy Centre, Faculty of Business and Economics, The University of Auckland, New Zealand*

[b] *Department of Economics, Faculty of Business & Economics, The University of Auckland, New Zealand*

[c] *Department of Civil and Environmental Engineering, Faculty of Engineering, The University of Auckland, New Zealand*

[d] *SMART Infrastructure Facility, University of Wollongong, Australia*

[e] *School of Civil, Mining and Environmental Engineering, University of Wollongong, Australia*

Electrification of transport fleet is considered one of the most viable options to reducing the reliance on fossil fuels and carbon emissions. However, there are still significant hurdles associated with electric vehicle (EV) uptake. Electric fleet only make up to less than 1.2% of the total vehicle fleet in New Zealand. Based on spatial negative binomial regression models, the aim of this study is to determine the main factors that influence consumers' EV purchase decisions. Specifically, two hypotheses are tested. First, we test if EV-charging infrastructure has a "neighbourhood effect" on EV uptake. Second, we examine if EV adoption by technology enthusiasts during the early-adopter phase could affect subsequent adoption once the technology becomes more widely spread. Our empirical results suggest that EV-charging infrastructure in the neighbouring areas as well as early adoption have an overall positive effect on subsequent technology adoption. Other variables such as driving range, driving mode, and car ownership also play a significant role on EV uptake. A robustness check using alternative weights matrix has been applied to the regressions. Results suggest that the inverse distance spatial weights matrix is more appropriate for analysing the spillovers in the EV context due to its specific driving range requirement. To cope with future challenges, government and transport planners need to consider launching more attractive battery/charging schemes to attract consumers. Additionally, more public promotion of EVs are also required to eliminate potential consumers' misperceptions and increase social acceptance of EVs.

Key words:

Electric vehicle uptake; public charging infrastructure; early adoption effects; driving range; driving mode; car ownership

1. Introduction

For the past few decades, the transport sector has been a major contributor to carbon dioxide (CO_2) emissions. Around 17% of the global CO_2 emissions has been attributed to the transport sector (IEA, 2015) while more than 70% of these emissions came from road transport. Moreover, transportation sector is responsible for the second highest global energy related CO_2 emissions (IEA, 2016). This provides strong motivation for targeting transportation in abating emissions and thereby reducing the reliance on fossil fuels for energy. Among all other possible pathways, electrification of the transport fleet, is considered as one of the most viable options for reducing reliance on fossil fuels. Electric vehicles (EVs) mainly refer to plug-in hybrids electric vehicles (PHEVs) and battery electric vehicles (BEVs). PHEVs are defined as vehicles that are powered by two sources – fossils fuel and electricity. For low speed application, the vehicle runs on electric power supplied by the battery in the vehicles and for higher speed requirements, the diesel-powered engine is used. The power from the battery pack is used to run the electric motor and the conventional engine is run on diesel. There are two separate refuelling facilities for charging the battery from the electricity grid by a wired or wireless charger and diesel from conventional gas stations. Although PHEVs still produce negative environmental impacts as they are reliant on fossil fuels to run the engine at high speed, the emissions generated from this type of vehicle are significantly less when compared to conventional vehicles mainly powered by diesel.

On the other hand, BEVs which run completely on the battery pack mounted on the vehicle can be recharged from the electricity grid. The main advantage of EVs is that they produce zero tailpipe emissions and may only produce indirect emission from electricity generators for charging the batteries. The vehicle motor generates almost-instant torque, thus providing smooth driving experience compared to conventional vehicles. Furthermore, since there is no piston system for powering the vehicle, the vehicle produces almost zero noise and lesser wear and tear requiring low maintenance. It also eliminates the reliance on fossil fuels for powering the vehicle and hence is considered the future of transportation. The total stock of electric cars surpassed 3 million units in 2017 and grew by more than 50% from the previous year. China leads the global market in the sales of EVs, accounting to 40% of the global EV sale and Norway leads the market in terms of sales share (39%) (IEA, 2018). There is a large body of literature on the study of future growth and a number of mathematical models in predicting the future sales of EVs. According to Al-Alawi and Bradley (2013), three of the most common models used to project the uptake levels of EVs were agent-based models, discrete choice models and diffusion rate models. Based on the New Policies Scenario of IEA (2018), EVs are expected to exceed 150 million units by 2040. While under the 450 scenarios (limiting the CO_2 in the atmosphere to 450 ppm), EVs are expected to make up 50% of the total vehicle sales by 2040. This projects a positive future for the transportation sector, but the pace of the progress falls short of the emission targets set in the Paris Climate Accord.

Turning into the case of New Zealand, EV sales are gaining momentum at quite a staggering pace. The number of EVs running in New Zealand was up by 90% in 2017-2018 (Vehicle Fleet Statistics, 2019). As seen in Fig. 1, pure EVs have the largest share in the vehicle market, followed by PHEVs and then heavy EVs. There were about 8791 pure EVs, 2834 PHEVs and 132 heavy EV in 2018, making up 75%, 24% and 1% the total EV fleet in New Zealand, respectively. In addition, used EVs are popular compared to new EVs possibility due to a lower cost, thereby increasing the overall age of the vehicle fleet.

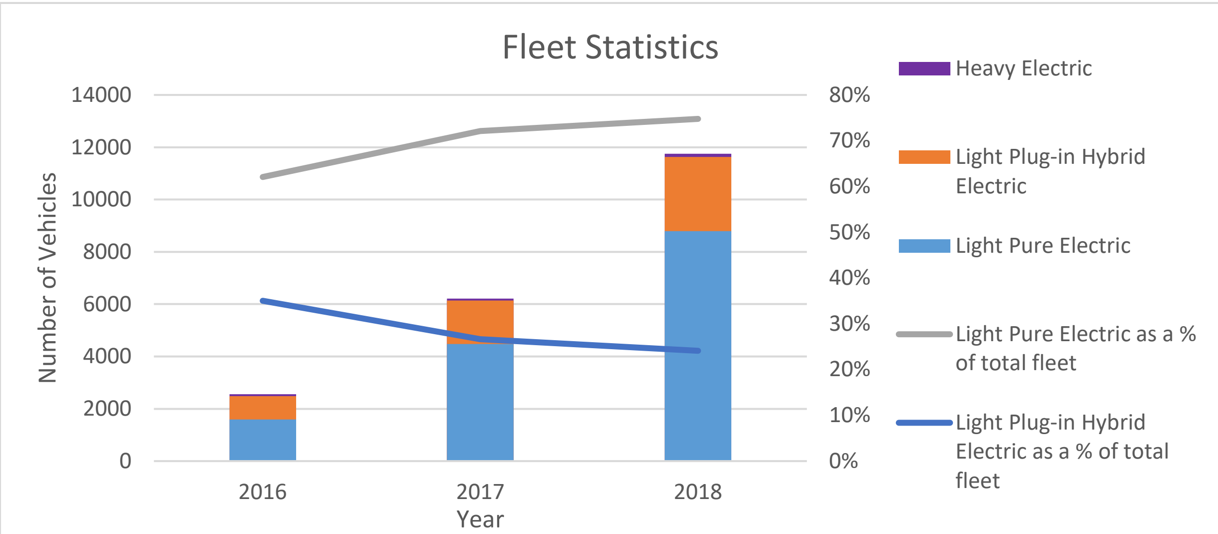

Figure 1. Electric Vehicle Fleet Statistics, 2016 – 2018 (Vehicle Fleet Statistics, 2019)

Apart from the home-based charging facilities, public charging infrastructure is regarded another important factor when consumers make decisions to switch to EVs (Illmann and Kluge, 2020). As of now, there are around 175 public direct current (DC) fast chargers and more than 300 public alternating current (AC) chargers in New Zealand (Leading the Charge, 2019). Public slow charging is generally free, however, public fast charging costs about $10 per 100 km nominal range (EECA, 2018). The New Zealand government has a target of installing DC fast chargers every 75 km along highway (NZTA, 2019a). It also trailed special EV lanes in March 2017 to get a better understanding of the consumer behaviour and providing future incentives (NZTA, 2019b). Despite all these non-financial initiatives taken up by the government to stimulate the EV uptake, the overall percentage of EVs is still miniscule as they only make around 1% of the total vehicle fleet in New Zealand. Apart from the economic barriers associated with the purchase of EVs, including upfront vehicle cost, vehicle type and fuel economy (Musti and Kockelman, 2011), this slow uptake could also been attributed to consumer characteristics, range anxiety due to a lack of public charging infrastructure, and and public visibility/social norms (Sierzchula *et al.*, 2014; Kihm and Trommer, 2014) .

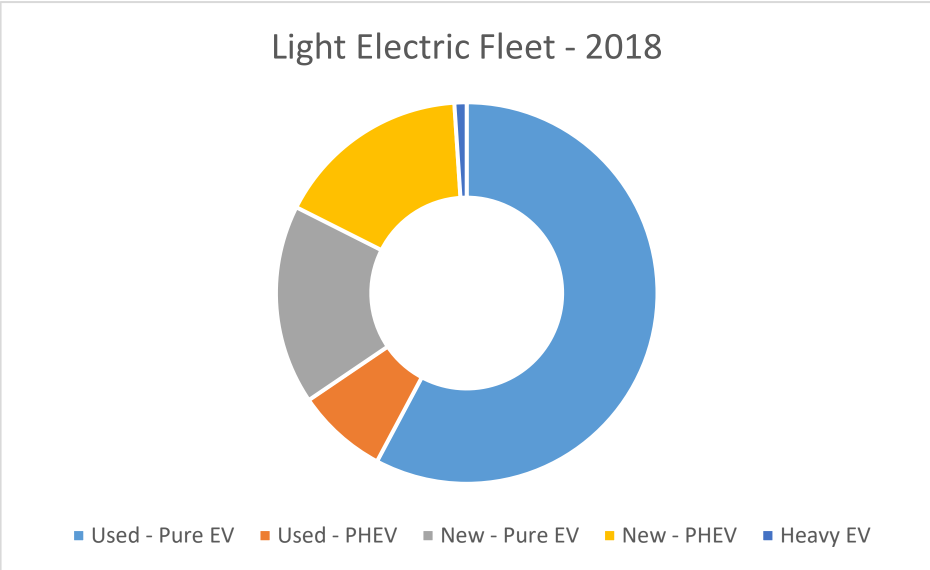

Figure 2. Fleet Composition - 2018 (Vehicle Fleet Statistics, 2019)

It is commonly recognised and accepted that consumer behaviour could be affected by others, which means one's decision on adopting an EV could be affected by others' EV adoption behaviour. However, most of previous literature assume that car consumers make vehicle adoption decision individually. For example, China's leading market share in the sales of EVs is mainly accredited to the policies and incentives centred on economic factors like license fee exemption, tax exemption and technical EV support policies like no charging restriction, provided for purchase of EVs (e.g. Wang *et al.*, 2017; Ma *et al.*, 2017). A number of studies also discusses the social and demographic factors influencing EV adoption in various locations through geographic clustering (Javid and Nejat, 2017, Dimatulac and Maoh, 2017). However, the major limitation from these previous research is that spatial spillover effects and peer effects are largely ignored. The aim of this paper, therefore, is to examine the effect of the public charging infrastructure on people's choice behaviour and analyse how early adoptions affect latter adoptions in a spatial context. To the best of our knowledge, this is the first paper to address these two issues in the context of New Zealand. The rest of the paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data used in this study. Section 4 elaborates the methodology. Section 5 discusses the empirical results. The last section concludes and for future research.

2. Literature Review

2.1 Public chargers and EV uptake

Rokicki and Stępniak (2018) conducted a study on Poland between the year 2004 and 2014 to verify the impact of improving accessibility in terms of land use and transportation on regional economic development. The results showed a positive correlation between the improving accessibility and economic development and the study also showed a weak correlation with regional employment rate. Another study by Pereira and Andraz (2004) used a Vector Auto-Regression (VAR) model to show that a large aggregate effects on regional improvement was due to spillovers from improved infrastructure and investment. Lakshmanan (2011) explain about the three analytical approaches used to find the contribution of transport infrastructure to the wider economy. They conclude that transportation improvement help open up markets, influencing economic structure and interaction between firms. The results from these papers indicate the importance of investment in infrastructure in facilitating economic growth in a wider context and development of new technologies for adoption.

Morton *et al*. (2018) studied the UK market for analysing the spatial pattern in the EV uptake based on a number of socioeconomic, household and transportation parameters. The study uses 2016 Department of Transport on UK vehicle statistics to conduct Ordinary Least Square (OLS) regression tests to find the effects of the parameters on EV registration. Moran's *I* test was used in determine if the values were spatially associated. The results indicated that transition towards EV was occurring in a spatially heterogeneous manner with a number of socioeconomic factors indicating a clustering effect of EV adoption with a few areas ahead in adoption than others. The study also sheds light on the impact of charging infrastructure on EV uptake levels. The level of charging point infrastructure present in an area was found to be positively associated with EV demand. Zhuge *et al.* (2019) developed an agent based integrated urban model (SelfSim EV) to project the EV uptake level and forecast the effects of EV uptake on the transport facilities and electricity grid between 2016 and 2020. The results confirmed the presence of neighbour effect on purchase decision and the uptake level of EV had a strong effect on the charging facilities indicating the importance of charger units in accelerating and facilitating the uptake of EV.

Neaimeh *et al*. (2017) studied the relation between daily driving distance and standard and fast charging infrastructure available. The paper measured the real-world usage of EV fast chargers in UK and the US and the impact of the infrastructure on driving behaviour. A multiple regression analysis showed that fast chargers were more influential than slow chargers in terms of driving behaviour at a 95% confident level. The paper found that quantitatively, fast charging energy was 2.5 times more influential than standard charging energy in predicting driving behaviour. Gnann *et al.* (2018) analysed the current public charging infrastructure for estimating the future needs of the infrastructure by developing a queuing model. The study is done on Norway and Sweden where the uptake levels of EVs are one of the highest. The paper estimates the number of charging events per charging point and the ratio of number of vehicles to the number of refuelling stations (VRI – Vehicle to Refuelling station Index). The paper suggests that additional cost of installing a fast charger with respect to a standard charger was less if a 'demand driven approach' was used to set up fast charging stations based of driving behaviour. But these two papers only study the effect of charging infrastructure, not taking into account the demographics and social factors.

2.2 Early adoption and EV uptake

Several literatures mention the time-lagged effect showing the effect of previous EV adoption on subsequent EV adoption. This trend follows the market diffusion curve developed by Bass (1969) which categorizes consumers broadly as innovators who choose to use the technology irrespective of other individuals and imitators who are influenced by pressures of the society. In order to accelerate the use of any technology, innovators must be targeted to develop a wider influence on the society. El Zarwi, Vij & Walker (2017) develop a Latent Class Choice Model (LCCM) to analyse the car sharing service 2.5 years into service. The results from the paper suggest that individuals may adopt a certain service which can be highly influenced by social influences, network effect, socio-demographics and level-of-service attribute. Similar results were found by a study in USA. Choi (2018) uses time-series Vector Auto Regression (VAR) and Vector Error Correction (VEC) models on USA data to show that technology development precedes demand and that influence of new technology is not dominant in its early stages but has a strong influence later.

Focusing on Hybrid Electric Vehicles (HEVs), Liu *et al*. (2017) found that previous vehicle adoption has an overall positive effect on current market share indicating that people get influenced by peer decisions in the USA. The paper uses a general spatial model and conduct a time series analysis on US census data which shows a statistically significant positive value in all three time-lagged SAR, SE and GWR modes. This HEV study can be used as a proxy for other vehicle types as well because of similar technology dynamics. Another study by Soltani-Sobh *et al*., (2017) developed an aggregated binomial logit share model and conducted a cross-sectional/time-series panel analysis to show that the major factors in adoption of new technologies are time, awareness and knowledge. The study analysed EV sales data from 2003 to 2011 demonstrated that over time people will be ready to accept new technology provided there is strong peer effect. The results are similar to a singular spectrum analysis (SSA) as a univariate time-series model and vector autoregressive model (VAR) as a multivariate model developed by Zhang et al., (2017) to show that diffusion of EVs in China is greatly influenced by increasing awareness and strong peer effects.

Graziano *et al*. (2019) studied the peer effect in the adoption of PV in Hartford Capital Region. The study found spatial spillover effects from blocks of neighbourhood on PV purchase decision and found it to be quite significant leading to the suggestion that ignoring spatial effects will produce biased results. Chen, Wang and Kockelman (2015) found similar spatial spillover effects in EV adoption. The paper uses a trivariate Poisson-lognormal conditional autoregressive model (CAR) model to study the zone level spatial effects and land use factors on EV purchase behaviour in Philadelphia region. Similarly, the spatial model here is used to study the discrete count data, like vehicle ownership. The spatial correlation results show the presence of neighbour effects on purchase decisions and geographical clustering effects. One other important finding from the paper was the provision of public charging infrastructure on purchase decision. Although this research lacks a formal consideration of the effects of public charging infrastructure, the authors have suggested that it should have a positive effect on EV purchase decision.

Dimatulac and Maoh (2017) studied the spatial distribution effects of Hybrid Electric Vehicle (HEV) in Windsor Census metropolitan area (CMA), Ontario, Canada. The study was conducted on the 2010 vehicle registration data. Multinomial Logit model (MNL) model was used to study the spatial effects, which revealed key findings on the spatial pattern. The result suggested that education, gender, income, profession, and urban form had the most significant effects on EV adoption. But the study did not take peer effects into account. Liu, Roberts and

Sioshansi (2017), also examined the spatial effects on HEV adoption. Furthermore, the paper also took into account the neighbour/peer effect on the purchase decisions of the consumers along with other demographic and social features like education, annual income and mode of transportation in the state of Ohio. The paper used three models for the analysis – Spatial Autoregressive (SAR), Spatial Error (SE) and Geographically Weighted Regression (GWR) model. The study showed a positive correlation between neighbours' HEV purchase decision and one's own purchase decision. In addition, marginal analysis showed a relation between previous purchase levels of HEV and present decision. Since the above two models only examined the effects on HEV adoption, they did not take into account the effect of the presence of the charging infrastructure on purchase decision. Hence the model cannot be directly translated for the study of BEVs or PHEVs. Another study by Zhuang and Shao (2019) on EV uptake in Beijing, China, showed that vehicle price and usage accounted for 32.3% and 28.1% of the final purchase decision, highlighting the importance of these factors in EV purchase. The results suggested that people with similar attitude towards EV tend to live closer to each other. The paper used a Multinomial Logit (MNL) models to find the weightage of each factor on decision making and K means clustering algorithm to aggregate them based on weights. Also, the paper accounted for peer effects on purchase decision, thus highlighting the importance of social interaction on purchase decision. However, it did not take into account the influence of charging infrastructure uptake level.

3. Data

Similar to previous studies, this paper divides the following independent variables into three broad categories: main factors, transport mode, vehicle ownership, and social and economic factors. As shown in both Fig. 3 and the upper section in Table 1, the unconditional mean of the dependent variable EV uptake is much lower than its variance. This indicates the existence of over-dispersion and suggests the application of a negative binomial model to EV adoption.

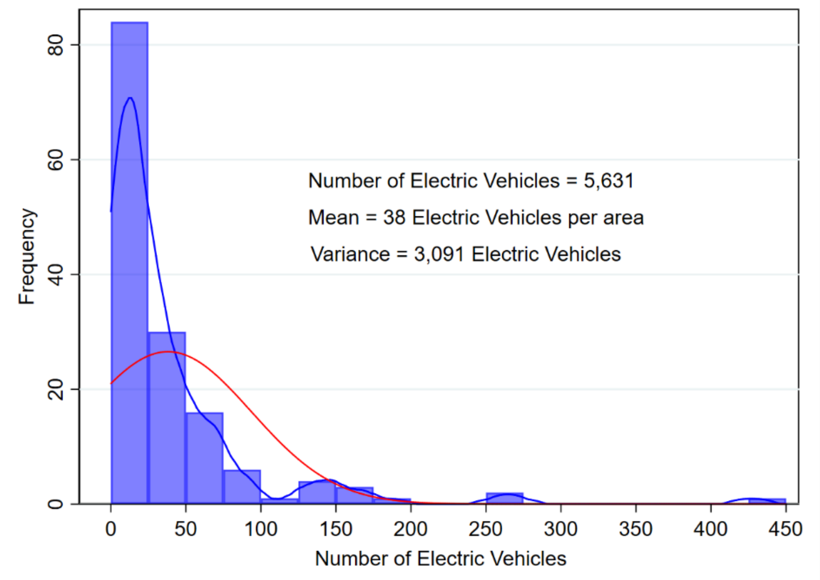

Figure 3. Number of Electric Vehicles adoption

Table 1. Summary Statistics

Variables	Mean	Std. Dev.	Min	Max	Observations
Dependent variable					
Total EV 2020	38.047	55.599	1	427	148
Explanatory variables					
Main factors					
Total EV 2018	16.757	28.096	1	200	148
Public chargers	.216	.77	0	8	148
Distance to CBD (km)	15.176	13.577	.673	132.557	148
Transport mode					
Drive alone	1609.054	1055.026	84	5757	148
Public transport	187.784	218.069	3	2052	148
Bicycle, walk, or jog	163.986	509.326	3	6066	148
Vehicle ownership					
No vehicle	152.777	458.196	3	5469	148
One vehicle	634.845	549.981	60	4344	148
Two vehicles	710.473	447.874	42	2175	148
Three or more vehicles	313.804	192.913	6	1107	148
Social and economic factors					
High qualification (%)	19.034	9.148	2.273	40.59	148
Income (kNZ$)	122.847	63.74	31.8	298.5	148
# of household	1918.764	1472.847	144	12033	148
Male (%)	.486	.017	.397	.569	148
Female (%)	.514	.017	.431	.603	148
Kids (%)	.799	.052	.621	.938	148
Unemployment	223.135	229.238	12	1812	148

4. Methodology

4.1. Spatial Durbin – Negative binomial model

Prior spatial studies are mainly concerned with models that contain only one type of spatial interaction effect *viz*. the spatial lag model (SAR) and the spatial error model (SEM) to address the issue of spatial autocorrelation. The former contains a spatially lagged dependent variable on the right-hand-side of a regression whereas the latter incorporates a spatial autoregressive process in the error term.

In practice, however, a "mixed" spatial Durbin model (SDM) introduced by Anselin (1998) offers a more flexible alternative and might be more appropriate to apply by including the "inherent spatial autocorrelation" and the "induced spatial dependence" simultaneously. The SDM is specified as follows:

$$y = \rho Wy + X\beta + WX\gamma + u \qquad (1)$$

The reduced form of (1) is:

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} WX\gamma + (I_n - \rho W)^{-1} u \qquad (2)$$

Based on the above equations, an additional term $WX\gamma$ must be included in the model to capture the $k \times 1$ autoregression coefficient vector γ of the spatially lagged explanatory variables WX, which measures the marginal impact of the independent variables from adjacent observations on the dependent variable.

Furthermore, Osland (2010) argues that this SDM could be developed from either an SEM or from an SAR, and this "mixed" model can be viewed as an unrestricted model of either SEM or SAR. Fig. 4 illustrates the theoretical relationship between SDM, SAR and SEM in a cross-sectional case.

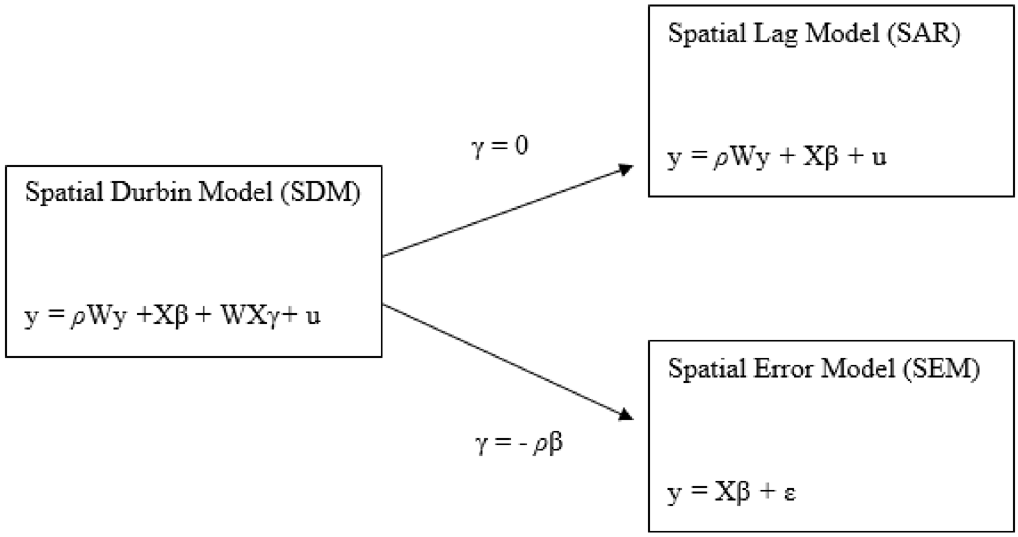

Figure 4. Relationship between SDM, SAR and SEM

Therefore, as seen from Fig.4, SDM is advantageous in producing unbiased estimates regardless of the true data-generation process (i.e. whether it is a spatial lag or a spatial error). In addition, as the dependent variable consists of a number of occurrences (i.e. EV sales counts) when the event has extra-Poisson variation, that is, when it has overdispersion. Negative binomial regression models have to be used to describe the distribution of count data.

4.2. Hypothesis Testing

We have proposed two hypotheses to be tested. One is the public charging infrastructure effect and the other is the early adoption effect.

Hypothesis 1: EV-charging infrastructure in the neighbouring areas have a positive and significant impact on EV uptake.

- <u>Spatial autocorrelation</u>: to test if EVs may appear in more dense clusters. This is important for planning the location of EV-charging infrastructure and upgrades to electricity-distribution infrastructure for EV charging, by using current EV adoption as a proxy for future EV adoption.

Hypothesis 2: Early adoption has an overall positive effect on subsequent technology adoption: the lagged EV adoption having a statistically significant positive value in all time-lagged spatial models.

- Early adoption effects: to examine if EV adoption by technology enthusiasts during the early-adopter phase could affect subsequent adoption once the technology becomes more widely spread. Hypothesis: early adoption has an overall positive effect on subsequent technology adoption: the lagged EV adoption having a statistically significant positive value in all time-lagged spatial models. Transport planners could tailor incentive programs to increase the uptakes of EVs by early adopters. Furthermore, incentive programs can be tailored toward early adopters that exhibit the greatest spatial spillover effect on subsequent technology adoption.

5. Empirical Results

Table 2 reports estimation results from two models based on negative binomial regression. Model 1 does not take any neighbourhood effects into account. In our hypotheses, we expect that improving public EV-charging infrastructure in the neighbouring areas is more likely to increase the confidence of potential EV purchasers and therefore increase EV uptake. This will be tested in Model 2 based on a row-standardised inverse distance weights matrix.

Table 2. The impact of EV adoption and EV-charging infrastructure on EV uptake

	Model 1		Model 2	
VARIABLES	Coefficient	*Incidence rate*	Coefficient	*Incidence rate*
Main factors				
Total EV 2018	0.034***	*1.034*	0.033***	*1.034*
	(0.005)		(0.009)	
WX-Total EV 2018	/		-0.060*	*0.942*
	/		(0.034)	
Public chargers	0.133	*1.143*	0.215	*1.240*
	(0.179)		(0.184)	
WX-Public chargers	/		2.706**	*14.977*
	/		(1.380)	
Distance to CBD	-0.013***	*0.987*	-0.028***	*0.972*
	(0.005)		(0.010)	
Transport mode				
Drive alone	-0.001***	*0.999*	-0.001***	*0.999*
	(0.000)		(0.000)	
Public transport	0.001	*1.001*	0.001	*1.001*
	(0.001)		(0.001)	
Bicycle, walk, or jog	-0.001	*0.999*	-0.001	*0.999*
	(0.001)		(0.001)	

Vehicle ownership				
No vehicle	0.003	*1.003*	0.002	*1.002*
	(0.002)		(0.002)	
One vehicle	0.003	*1.003*	0.002	*1.002*
	(0.002)		(0.002)	
Two vehicles	0.005**	*1.005*	0.004**	*1.004*
	(0.002)		(0.002)	
Three or more vehicles	0.003	*1.003*	0.002	*1.002*
	(0.003)		(0.002)	
Social and economic factors				
High qualification	0.030*	*1.031*	0.031**	*1.031*
	(0.017)		(0.015)	
Income (kNZ$)	0.002	*1.002*	0.002	*1.002*
	(0.003)		(0.003)	
Income x high qualification	-0.000	*0.999*	-0.000	*0.999*
	(0.000)		(0.000)	
# of household	-0.003	*0.997*	-0.002	*0.998*
	(0.002)		(0.002)	
Male percentage	11.347	*84675.79*	-9.601	*0.000*
	(65.007)		(53.009)	
Female percentage	15.758	*6975968*	-4.730	*0.009*
	(64.398)		(52.119)	
Having Kids (%)	-1.208	*0.299*	-0.925	*0.397*
	(1.450)		(1.328)	
Unemployment	0.002	*1.002*	0.001	*1.001*
	(0.001)		(0.001)	
Constant	-10.630	*0.000*	10.575	*39146.37*
	(64.746)		(52.810)	
Log likelihood	-607.05		-605.23	
Wald Chi2	155.5		1603	
p-value for model test	0		0	
LR test of alpha=0: Chi2(01)	1327.83***		1245.01***	
LR test of M1 versus Model 2			3.63*	
Sample size	148		148	

Notes: Model 1: Negative binomial regressions. Model 2: Spatial negative binomial regressions based on a row-standardized inverse distance weights matrix. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.

In each model, we report both coefficient and incidence rate. In a negative binomial model, the log of the expected count, i.e. # of EV uptake in our case, is a function of the explanatory variables. Thus, the coefficient can be interpreted as the difference in the logs of expected # of EV uptake in response to one-unit change in the explanatory variable holding the other explanatory variables constant. For example, if we assume μ_{xo} is # of EV at xo and μ_{xo+1} is # of EV at $xo+1$, a unit change in variable x given others constant, the coefficient on variable x, β can be written as $\beta = \log(\mu_{xo+1}) - \log(\mu_{xo}) = \log(\mu_{xo+1} / \mu_{xo})$ and it is the log of the incidence rate ratio. Thus, the incidence rate (IRR) is the exponential function of β. That is $IRR = \mu_{xo+1} / \mu_{xo} = \exp(\beta)$. The IRR represents the estimated rate ratio for one unit increase in the explanatory variable, given the other variables holding constant.

We also found that alpha as the dispersion parameter is significantly greater than zero, indicating the data is over dispersed and a negative binomial model, rather than a passion model is applied. The LR test results confirm that Model 2 incorporating spatial effects performs better than Model 1.

If the "Total EV 2018" increases by one unit, holding the other variables constant, the log of # of EV uptake would increase by 0.033. This effect is statistically significant. The IRR results suggest that one unit increasing in EV early adoption would expect to increase the current # of EV uptake by a factor of 1.034. This finding is consistent with our hypothesis. Early adoption has an overall positive effect on subsequent technology adoption. Transport planners could tailor incentive programs to increase the uptakes of EVs by early adopters. The coefficient of "WX total EV origin adoption" is negative and significant, indicating that earlier EV adoption in the neighbouring area reduces current EV uptake. Early EV technology limitation may result in less satisfaction among the EV users who then discourage the potential EV purchasers.

In particular, we found a significant positive effect of "WX-Public chargers" on EV uptake in Model 2. Results show that EV-charging infrastructure has no significant effect on EV uptake in the same area. But EV-charging infrastructure in the neighbouring areas does have a positive and significant impact on EV uptake. A one unit increase in charger installation would increase log of # of EV uptake by 2.706. The IRR reports that a one unit increase in EV charger installation would increase by a factor of 15. It is reasonable. Suppose you are an EV owner or potential EV purchaser, you would care more about EV-charging infrastructure in a distant area than the local charging facility due to the limited EV driving range.

The driving range significantly affects EV uptake. It can be seen the distance to CBD has a significant negative effect on EV uptake. The shorter distance to CBD, the larger counts for EV uptake. Moreover, the effect of car ownership on the EV uptake depends on how many vehicles he or she owed. A household that owns two vehicles has a significant positive impact on EV uptake. This is because two cars increase flexibility. One car is for short distance travel, and EV is an ideal choice. The other vehicle is for a long journey, and a traditional car is ideal. Additionally, educated people are more likely to buy and adopt EV than other groups due to their environmental awareness. Driving alone also has a significant negative impact on EV uptake.

Table 3 below reports robustness check results by using different spatial weights matrix. Models 3 and Model 4 use weight matrices that contain 5 and 75 nearest neighbours, respectively. Model 5 employs an inverse economic distance spatial weights matrix using income as the economic variable. Except for coefficients of "WX-Total EV 2018" and "WX Public chargers", the rest of the coefficients' significance and magnitude are consistent with those obtained in Table 2. The empirical findings suggest that the inverse distance spatial weights matrix seems more appropriate for analysing the spillovers in the EV context due to its specific driving range requirement.

Table 3. Robustness check: alternative weights matrix

VARIABLES	Model 3 5-nearest neighbour W	Model 4 75-nearest neighbour W	Model 5 Economic W
Main factors			
Total EV 2018	0.034***	0.034***	0.032***
	(0.010)	(0.009)	(0.009)
WX-EV 2018	-0.005	0.033	-0.003
	(0.004)	(0.049)	(0.004)
Public chargers	0.151	0.138	0.102
	(0.186)	(0.177)	(0.195)
WX-Public chargers	0.194	0.728	0.092
	(0.240)	(2.475)	(0.107)
Distance to CBD	-0.015**	-0.012*	-0.015**
	(0.006)	(0.007)	(0.006)
Transport mode			
Drive alone	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Public transport	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Bicycle, walk, or jog	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Vehicle ownership			
No vehicle	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)
One vehicle	0.003	0.003	0.004
	(0.002)	(0.002)	(0.002)
Two vehicle	0.005**	0.005**	0.005**

	(0.002)	(0.002)	(0.002)
Three or more vehicle	0.003	0.003	0.004
	(0.002)	(0.002)	(0.003)
Social and economic factors			
High qualification	0.033**	0.028*	0.035**
	(0.014)	(0.015)	(0.015)
Income (kNZ$)	0.003	0.003	0.002
	(0.003)	(0.003)	(0.003)
Income x high qualification	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
# of household	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Male percentage	1.936	8.067	12.329
	(52.775)	(48.846)	(42.705)
Female percentage	6.822	11.847	17.846
	(51.797)	(48.026)	(41.208)
Having Kids (%)	-1.167	-0.845	-2.282*
	(1.293)	(1.378)	(1.265)
Unemployment	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)
Constant	-1.499	-8.224	-11.314
	(52.335)	(48.428)	(42.140)
Log likelihood	-606.6	-606.5	-545.9
Wald Chi2	1478	1348	1677
p-value for model test	0	0	0
LR test of alpha=0: Chi2(01)	1258.19***	1302.15***	1086.33***
Sample size	148	148	133

Notes: Models 3-5: Spatial negative binomial regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Conclusion and Discussion

The global EV industry is developing rapidly due to their significant advantages in emission reduction and energy conservation. However, the majority of prior studies focused on analysing the economic, social and demographic factors of the adoption of this new transport mode in a non-spatial context, where they simply assumed that there are no spatial interactions in the EV market. This study, in contrast, explores the main factors that influence consumers' EV purchase decisions using New Zealand centric data, by applying spatial negative binomial regression models. Our empirical results suggest that public EV-charging infrastructure in the neighbouring areas as well as early adoption have an overall positive effect on subsequent technology adoption. It is also revealed that variables such as driving range, driving mode, and car ownership also play a significant role on EV uptake.

The research outcomes hence provide some insightful suggestions for government interventions and policymaking in a New Zealand context or any other countries at the early stage of the development of the EV industry. For instance, the increasing investment in public charging infrastructure, alongside launching more attractive battery/charging schemes over the years would help in eliminating the range anxiety. With adequate charging infrastructure, BEVs may be preferred by consumers over PHEVs. Furthermore, there is also an urgent need for future studies to disentangle the right types of government incentives with EV adoption, whether financial or non-financial, concentrating on matters such as the optimal timing around early adopters and/or to encourage mass adoption, as well as the magnitude of the benefits these incentives could deliver. Lastly, it is also evident that social/network/peer effects are important in the uptake of new vehicle technology. EV promotion should not solely target individuals, but rather social networks alike in smaller communities.

Acknowledgement

Funding for this research was provided by the Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund 2017 (Research Project 3714101).

References

Al-Alawi, B. M., and Bradley, T. H. (2013). Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. *Renewable and Sustainable Energy Reviews*, *21*, 190-203.

Anselin, L. (1998). *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Pereira, A. M., and Andraz, J. M. (2004). Public highway spending and state spillovers in the USA. *Applied Economics Letters*, *11*(12), 785-788.

Chen, T. D., Wang, Y., and Kockelman, K. M. (2015). Where are the electric vehicles? A spatial model for vehicle-choice count data. *Journal of Transport Geography*, *43*, 181-188.

Choi, H. (2018). Technology-push and demand-pull factors in emerging sectors: evidence from the electric vehicle market. *Industry and Innovation*, 25(7), 655-674.

Dimatulac, T., and Maoh, H. (2017). The spatial distribution of hybrid electric vehicles in a sprawled mid-size Canadian city: Evidence from Windsor, Canada. *Journal of Transport Geography*, *60*, 59-67.

EECA. (2018). *Charging Electric Vehicles.* Energy Efficiency and Conservation Authority, New Zealand Government. Retrieved on March 14, 2019 from https://www.energywise.govt.nz/assets/Resources-Energywise/on-the-road/EV-Charging-Brochure-30-Jan-2019.pdf

El Zarwi, F., Vij, A., & Walker, J. L. (2017). A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. *Transportation Research Part C: Emerging Technologies*, 79, 207-223.

Gnann, T., Funke, S., Jakobsson, N., Plötz, P., Sprei, F., and Bennehag, A. (2018). Fast charging infrastructure for electric vehicles: Today's situation and future needs. *Transportation Research Part D: Transport and Environment*, *62*, 314-329.

Graziano, M., Fiaschetti, M., and Atkinson-Palombo, C. (2019). Peer effects in the adoption of solar energy technologies in the United States: An urban case study. *Energy Research and Social Science*, *48*, 75-84.

IEA (2015). World Energy Outlook 2015. International Energy Agency.

IEA (2016). World Energy Outlook 2016. International Energy Agency.

IEA (2018). Global EV Outlook 2018. International Energy Agency.

Illmann, U. and Kluge, J. (2020). Public charging infrastructure and the market diffusion of electric vehicles. *Transportation Research Part D, Transport and Environment, 86, 102413.*

Javid, R. J., and Nejat, A. (2017). A comprehensive model of regional electric vehicle adoption and penetration. *Transport Policy*, *54*, 30-42.

Kihm, A. and Trommer, S. (2014). The new car market for electric vehicles and the potential for fuel substitution. *Energy Policy*, 73, 147-157.

Lakshmanan, T. R. (2011). The broader economic consequences of transport infrastructure investments. *Journal of transport geography*, *19*(1), 1-12.

Leading the Charge. (2018). Electric Vehicle Charging Sites around New Zealand. Leading the Charge. Retrieved on March 14, 2019 from: https://www.leadingthecharge.org.nz/charging-sites

Liu, X., Roberts, M. C., and Sioshansi, R. (2017). Spatial effects on hybrid electric vehicle adoption. *Transportation Research Part D: Transport and Environment*, *52*, 85-97.

Ma, S. C., Fan, Y., and Feng, L. (2017). An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions. *Energy Policy*, *110*, 609-618.

Morton, C., Anable, J., Yeboah, G., and Cottrill, C. (2018). The spatial pattern of demand in the early market for electric vehicles: Evidence from the United Kingdom. *Journal of Transport Geography*, *72*(C), 119-130.

Musti, S., Kockelman, K.M. (2011). Evolution of the household vehicle fleet: anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. *Transportation Research. Part A*: Pol. Pract. 45 (October), 707–720.

Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., and Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, *108*, 474-486.

NZTA. (2019a). Enabling a nationwide network of public charging infrastructure. New Zealand Transport Authority. Retrieved on March 14, 2018 from https://www.nzta.govt.nz/planning-and-investment/planning/transport-planning/planning-for-electric-vehicles/national-guidance-for-public-electric-vehicle-charging-infrastructure/enabling-a-nationwide-network-of-public-charging-infrastructure/

NZTA. (2019b). Auckland EV trial survey feedback. New Zealand Transport Authority. Retrieved on March 14, 2018 from https://www.nzta.govt.nz/roads-and-rail/electric-vehicles-special-vehicle-lanes/auckland-ev-trial-survey-feedback/

Osland, L. (2010). An application of spatial econometrics in relation to hedonic house price modelling. *Journal of Real Estate Society*, 32, 289-320.

Rokicki, B., and Stępniak, M. (2018). Major transport infrastructure investment and regional economic development–An accessibility-based approach. *Journal of Transport Geography*, *72*, 36-49.

Schmidt, O., Hawkes, A., Gambhir, A., and Staffell, I. (2017). The future cost of electrical energy storage based on experience rates. *Nature Energy*, 2(8), 17110.

Sierzchula, W., Bakker, S., Maat, K., van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194.

Soltani-Sobh, A., Heaslip, K., Stevanovic, A., Bosworth, R., & Radivojevic, D. (2017). Analysis of the electric vehicles adoption over the United States. *Transportation research procedia*, 22, 203-212.

Tolonen, K. T., Vilmi, A., Karjalainen, S. M., Hellsten, S., Sutela, T., and Heino, J. (2017). Ignoring spatial effects results in inadequate models for variation in littoral macroinvertebrate diversity. *Oikos*, *126*(6), 852-862.

Vehicle Fleet Statistics. (2019). Monthly electric and hybrid light vehicle registrations. Ministry of Transport. Retrieved on 14 March 2019, from https://www.transport.govt.nz/mot-resources/vehicle-fleet-statistics/monthly-electric-and-hybrid-light-vehicle-registrations/

Wang, N., Pan, H., and Zheng, W. (2017). Assessment of the incentives on electric vehicle promotion in China. *Transportation Research Part A: Policy and Practice*, *101*, 177-189.

Wang, N., Tang, L., and Pan, H. (2017). Effectiveness of policy incentives on electric vehicle acceptance in China: A discrete choice analysis. *Transportation Research Part A: Policy and Practice*, *105*, 210-218.

Zhang, Y., Zhong, M., Geng, N., & Jiang, Y. (2017). Forecasting electric vehicles sales with univariate and multivariate time series models: The case of China. PloS one, 12(5), e0176729.

Zhuge, C., & Shao, C. (2019). Investigating the factors influencing the uptake of Electric Vehicles in Beijing, China: Statistical and spatial perspectives. *Journal of Cleaner Production*, *213*, 199-216.

Zhuge, C., Wei, B., Dong, C., Shao, C., and Shan, Y. (2019). Exploring the future Electric Vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. *Journal of Cleaner Production*.