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Simulating electric vehicle policy in the Australian capital territory

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ABSTRACT

Increased use of electric vehicles (EVs) has the potential to reduce carbon emissions. Therefore, predicting the impact of governments' EV incentive policies on the future uptake of EVs is important. This study estimates the impact of incentive policies introduced in the Australian Capital Territory. This estimation is conducted through constructing a microsimulation model and using it to assess the impact of the incentive policies on the purchase of EVs for households in different income quintiles. In the model, the decision about purchasing an EV is based largely on the total cost of ownership of an EV compared to the vehicle already owned and the additional utility of having a new vehicle. The application of the model shows that, regardless of incentives, a drop in the price of EVs will play the most important role in uptake. Incentives will help lower to middle income households, although EV demand is dominated by those in the highest income quintile. Importantly, however, incentives can increase uptake in locations with previously low uptake. Future work needs to focus on the reliability of data on EV's, and how to incorporate the rapid change in the market (eg, rapid uptake of EV's in the ACT) seen in the last few years.

1. Introduction

As the transition to low carbon energy production accelerates, greater attention has focused on addressing decarbonisation of the transport sector, the next largest contributor of carbon emissions after power generation. As the energy production sector increasingly decarbonises, increased use of electric vehicles (EVs) has the potential to reduce carbon emissions (Caulfield et al., 2010; de Haan et al., 2009; Plötz et al., 2014). Further, EVs effectively eliminate local pollution that would otherwise come from vehicle tailpipe emissions, as well as leading to reductions in particulate matter (PM). While there is the possibility of a small increase in PM from tyre wear due to potentially heavier vehicles, this is likely more than offset by large reductions in PM derived from conventional brake wearing through the use of regenerative braking (OECD 2020). With household-based domestic transport contributing a significant proportion of global carbon emissions, there is growing interest in increasing the household-level adoption of EVs to reduce greenhouse gas emissions (Märtz et al., 2021) and lessen reliance on non-renewable resources, with EVs able to use renewable energy sources like solar or wind (Carley et al., 2013; Ozaki and Sevastyanova 2011; Smith et al., 2017). With the capacity for vehicle to grid (or home) charging, EVs can assist households to capture renewable energy from their domestic solar systems (Oates 2023).

The uptake of EVs by households varies widely across different countries and regions (Märtz et al., 2021). Predicting the impact of policies on future uptake of EVs is important for governments as the transition to EVs occurs. Modelling that predicts the effects of different policies on uptake, as well as identifying how changes in price signals more broadly are likely to affect uptake, can enable governments to plan for and invest in actions that enable a smooth transition to EVs. For example, being able to predict change in uptake can enable identification of changed infrastructure needs, such as likely increases in electricity demand from the grid, greater need for charging stations, and changes in tax revenue from fossil fuel powered vehicles.

Research seeking to estimate future demand for EVs remains limited, especially in relation to the impact of government policy. This paper aims to address this gap by using the Australian Capital Territory (ACT) government's Zero Emissions Vehicles (ZEV) policy as a case study. The paper demonstrates how microsimulation modelling can be used to predict the effect of policy incentives, such as those introduced in the ACT, on the future demand for EVs.

2. Government policies and the uptake of EVs by households

The impact of government policies is affected by the wide range of factors that influence a household's decision-making process when

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considering whether and when to purchase an EV. Some studies have examined the role of availability of information and test driving (Brückmann 2022), the provision of charging infrastructure (Sheng et al., 2022), and the influence of early adopters in encouraging subsequent adoption (Sheng et al., 2022). In a review of 239 articles examining factors influencing adoption of EVs, Kumar and Alok (2020) found that dealership experience, resilience of charging infrastructure, total costs of ownership (in addition to initial purchase cost) and marketing/information are all important. However, while the evidence points to many factors influencing adoption, it also suggests that some are more influential and have a greater overall effect than others. In particular, the sales price of EVs and the availability of charging points are especially influential (Broadbent et al., 2022).

In multiple studies, financial considerations have been found to be significant in the decision to purchase an EV, including both the purchase price of the vehicle and the subsequent running costs (de Haan et al., 2009; Heffner et al., 2007; Ozaki and Sevastyanova 2011). While reduced running costs is a common motivation for purchase, factors such as high initial cost of purchase, range limitations and recharging time reduce the likelihood of purchasing an EV (Carley et al., 2013; Caulfield et al., 2010; Smith et al., 2017). Hidrue et al. (2011) found that attitudes related to lifestyle, the willingness to buy a new product, fuel price expectation and length of driving also contribute to the purchasing decision. The ongoing take-up of EVs will lead to improvements in both battery and charging technology, which could help incentivise EV purchasing in terms of financial and practical considerations (Cano et al., 2018; Huang and Zhang 2023).

Some studies have also examined whether adoption varies based on socio-economic characteristics, typically finding variation in adoption likelihood based on factors such as age, gender and education (Carley et al., 2013; Hidrue et al., 2011). However, these studies found that income level had an insignificant impact (Carley et al., 2013; Hidrue et al., 2011). Instead, individual environmental concerns and subjective norms are important for many (Smith et al., 2017). For example, Ozaki and Sevastyanova (2011) found that adoption was more likely amongst those concerned about preserving the environment and eager to reduce their household's ecological footprint.

The discussion above suggests that perceived financial benefits are a major factor in deciding to purchase an EV, and that financial benefits will depend both on the upfront cost of purchase and ongoing running costs of an EV relative to a fossil fuel powered vehicle. In addition, other socio-economic and demographic factors may influence the decision.

This understanding allows a model of the decision-making process to be developed based on the different financial costs incurred for different choices. However, effective modelling requires access to information about consumer views regarding financial benefits, as well as data on price changes, and on the other factors likely to contribute to the adoption decision – such as a person's values regarding the environment and the importance of taking personal action to reduce greenhouse gas emissions, their lifestyle and how it affects transportation needs, and socio-demographic information such as age and gender.

These types of information typically exist in separate datasets; some, such as availability of charging points or running costs of EVs, are available as administrative datasets, while others require direct surveys of users.

3. Application: the Australian capital territory (ACT)

The ACT is a territory of Australia and is home to the capital city of Canberra. It has it's own Territory Government, that develops policy for its 454,000 residents (Australian Bureau of Statistics, 2021a; Vidyattama et al., 2023). This paper uses a microsimulation model to assess the impact of the ACT's incentive policies on EV uptake. This model (described fully in the next section) is applied to policies currently in place in the ACT. Historically, Australia has had a low uptake of EVs. Given this low base, the development of policies to encourage take-up of EVs is important. Only a very small number of EVs are on the road in Australia. In 2014, the EV market share was 0.04 %. In 2020, there were 15,688 EVs in Australia which is equivalent to around only 0.07 % of all vehicles in Australia. This number increased to 24,602 in 2021 or 0.1 % of all vehicles. The ACT led this increase, with the proportion of EVs rising from 0.13 % in 2020 to 1.6 % in August 2023 (Australian Electric Vehicle Association, 2023). This proportion is still below the take-up of European countries. For comparison, in Germany, the proportion of EVs in vehicle sales increased from 1.9 % to 3 % and then to 13.5 % over the 2018–2020 period. This meant that EVs represented 1.2 % of all vehicles used in Germany in 2020. This figure rose to 2.5 % in 2021, which is only slightly higher than the average European Union proportion of 2.2 %; globally, the proportion has reached 1.4 % (International Energy Agency 2022).

In Australia, some states and territories have invested in a range of policies seeking to encourage uptake of EVs. While in 2022 the Australian Federal Government announced a renewed focus on encouraging EVs, the ACT Government acted relatively early. This was an important step for the government of a predominantly car-dependent city (Nakanishi and Black 2016; Tranter and Whitelegg 1994). The policies implemented by the ACT Government aim to encourage the uptake of EVs through the ZEV program, in conjunction with other carbon reduction transport policy measures that promote active travel and public transport.

Two key EV policy approaches have been introduced by the ACT Government. One of these was to increase infrastructure to support EV take-up. This is mainly related to increasing the charging stations around Canberra, as well as requiring new housing developments to install fast charging facilities. The other approach was to provide incentives to purchase EVs. These include full stamp duty exemption, free registration for two years and a zero-interest $15,000 loan. More recently, the ACT Government has announced its intention to phase out the sale of new light internal combustion engine (fossil fuel) vehicles by 2035 (ACT Government 2022).

The model we use in this paper simulates the impact of the incentive policies on the purchase of EVs especially in terms of the income distribution of new purchasers, as previous research has suggested that such policies may favour higher socio-economic groups (Sovacool et al., 2019). Importantly, the application of the model to the ACT policy context also demonstrates the broader potential for using microsimulation modelling to predict likely changes in EV uptake. While applied here to the incentives being implemented in the ACT, the modelling can be applied to evaluate other incentives. This is important given the wide range of financial incentives being offered in different jurisdictions to encourage EV uptake. For example, within Australia, another jurisdiction (New South Wales), in September 2021 introduced rebates of $3000 for the first 25,000 EVs sold that cost under $68,750 and the removal of stamp duty for EVs costing under $78,000. However, the New South Wales government introduced road user charging at the same time.

4. Methodology

The assessment of the ACT ZEV policy impact is conducted using a microsimulation model that operates at the household level. While other modelling approaches have been used to predict EV uptake (see, for example, Broadbent et al., 2022), these have predominantly used macroeconomic simulation. This means that household behaviour is typically included as an exogenous element of the model, rather than as an endogenous element that changes in response to the types of incentives offered. Therefore, this paper provides an approach that enables dynamic simulation of household decision-making to be incorporated into modelling of future household demand for EVs. In doing so, this approach tries to capture the decision to purchase an EV to estimate the proportion of EVs owned and the income quintile of households owning EVs.

In the simulation, the decision to purchase an EV is based on the household's comparison of the cost of alternative vehicles (similar to Mueller and de Haan 2009; Plötz et al., 2014). The main reason for this choice was the flexibility of looking at the impact of a policy on different households (Li et al., 2022). This approach can identify which types of households are more likely or less likely to adopt EVs under different scenarios and with different incentives, and thus enables assessment of which households are likely to be able to achieve benefits from different EV incentives – and, conversely, which are less likely to adopt EVs in response to different types of incentive. For this study, the impact is disaggregated by income range and location, because the distribution of the impact is as important as the overall impact on the take-up of EVs.

The problem of conducting the assessment using microsimulation in Australia is the data requirements. Making a decision about purchasing an EV will be partly based on the total cost of ownership (TCO) of the vehicle compared to the vehicle already owned and the additional utility of having a new vehicle, with preference toward buying EV also playing a role. This follows the TCO concept used by Plötz et al. (2014) who examined the investment based on purchase price of the vehicle and operating costs such as the cost to cover the kilometres the vehicle is driven. In TCO, the total cost consists of the cost of investment, which is mainly the value of vehicle, and the operational costs, which include fuel, service and repair. In addition, other data for each household, such as household income, need to be linked with the TCO data. This means the data need to contain information on the vehicles owned by households as well as information on the costs of the vehicles. As there is no publicly available data in Australia that connect household characteristics with vehicle characteristics, we used a database that links these characteristics in a single dataset (Vidyattama et al., 2021).

4.1. Data on households and their vehicles

In Australia, the data availability challenge identified above relates to relevant data only being available in separate datasets. Data are available on individual households and on vehicles, but these datasets are not linked to each other. Therefore, the main dataset for this model is a synthetic dataset. The dataset was constructed by Vidyattama et al. (2021) and primarily uses the confidentialised unit record file from the Australian Bureau of Statistics (ABS) 2015–16 Household Expenditure Survey (HES) and data from the ABS Motor Vehicle Census (see Australian Bureau of Statistics, 2019). This combination creates synthetic households with information on their characteristics (such as household type, tenure-landlord type, age of persons in the household, their income both gross and disposable, and their various expenditure including expenditure on various fuel types) as well as information about their vehicle/s and vehicle efficiency. The availability of fuel expenditure and vehicle efficiency data means the distance travelled with the vehicle can be estimated.

The linking process was facilitated by location. The ABS Motor Vehicle Census has information on different types of motor vehicles in households based on vehicle registration data at the start of the year. While this census does not include any household information, it does include location. The HES contains information on fuel expenditure that allows estimation of kilometres travelled using the households' vehicles.

As explained in Vidyattama et al. (2021), the synthetic database was constructed using a spatial microsimulation technique (Tanton et al., 2011) involving two initial steps before the households are matched to a vehicle. The technique reweights the survey observations to the benchmarks for each small area across Australia. In the first step, the households were distributed across ABS Statistical Area Level 4 (SA4) regions. The SA4 is a standard geographical unit that is part of the ABS Australian Statistical Geography Standard (ASGS) (Australian Bureau of Statistics, 2016). It is the largest sub-state and territory region available using information from the Australian Bureau of Statistics, 2016 Census of Population and Housing and, more importantly, the smallest geographical level where information about fuel expenditure is available from Bureau of Infrastructure, Transport and Regional Economics research on fuel economy and vehicle kilometres travelled by Australian households. The next step was to use these data from each SA4 and distribute them to the ABS Statistical Area Level 2 (SA2) level using the Australian Bureau of Statistics, 2016 Census of Population and Housing data as benchmarks. The SA2 is another standard geographical unit, smaller than an SA4. In most capital cities, SA2s are suburbs.

The database was then linked to the vehicles in the ABS Motor Vehicle Census. The linking was conducted in each SA2 to ensure accuracy. This linking of other household information with vehicle data was further enhanced by incorporating estimated preferences for different vehicles for different types of households, using a regression model to estimate the relationship between household characteristics and the type(s) of vehicle a household owns. The household characteristics included occupation and age of the household reference person, household income, household type, tenure-landlord type and household location. The income for the results came from this linked dataset, with the income estimated using the Census income benchmarks at the SA2 level. Although the benchmarking of incomes to Census data was done based on gross household income (see the method section), the existence of disposable income data and household information on the HES has enabled us to use equivalised disposable income.

Given the huge variety in types of motor vehicle, these vehicles were classified based on whether they were passenger vehicles or motorcycles, year of production, engine size, and type of fuel. These classifications were also used to estimate the vehicles' fuel efficiency and to validate their current value. Vidyattama et al. (2021) conducted several types of validation of this database; these showed that, although not perfect, the data could estimate the average vehicle owned by a household at the SA4 level with 91 % accuracy (using a modified R-square measure). Accuracy dropped to 81 % when the type of household was included, despite increasing the aggregation of area to capital cities and the rest of each state and territory. Finally, most of the data were adjusted to reflect the 2018/19 situation relevant to this study.

Having this data for households and their vehicles was crucial but not sufficient for the model. The other important information is the households' utility and likeliness of having a new vehicle and for purchasing an EV. To understand and incorporate this information to a particular household, survey data about household vehicle preferences was collected and used, as described in the next section.

4.2. Survey on EV preference

The authors conducted a survey of ACT adult residents in 2020. The sample was drawn from an existing database of approx. 3800 adults living in the ACT and nearby parts of NSW, developed based on mailed invitations sent to randomly selected households across the ACT inviting them to participate in previous surveys. The previous surveys completed were omnibus surveys asking about experiences of liveability, wellbeing, and resilience in the region (see Schirmer, 2020). Of the database, 2900 lived in the ACT. This 2900 was compared to characteristics of ACT adults in the 2016 ABS Census of Population and Housing, and found to have good coverage of the population. However, the database had slight over-representation of women, under-representation of those aged under 35, and over-representation of those aged 65 and older, and slight over-representation of some inner suburbs of the city of Canberra. Given this, a stratified sample was selected from the database to ensure those invited to complete the survey were representative of the adult population. Participants were sent either an email inviting them to complete the survey, or a posted letter, depending on the preference they had specified when participating in previous surveys. All participants could opt to complete the survey online or using a paper form, and a free phone line number was provided for those requiring assistance completing the survey due to issues such as literacy, vision or other difficulties. To reduce potential for salience bias, in which responses are biased to those with a specific interest in the topic, the survey was not made open to the general population to complete, and no advertisement was used. This meant that recruitment used only a database containing participants who had previously completed surveys discussing their views about overall liveability and wellbeing in the ACT region, a topic unlikely to have generated bias in the database towards or against those with an interest in EVs. A total of 850 valid survey responses were received by October 15, 2020 (including 847 surveys completed online and three surveys completed on paper forms).

Not all participants completed all survey questions. Depending on the question, between 20 and 60 participants eligible to complete an item did not complete it. The survey dataset provided information used in the model to understand the perceptions and intentions of the adults in the synthetic database based on age, gender, household income (14 income ranges), household type (six types) and the 10 districts of the ACT.

All surveys have potential for bias in response. Potential response bias was assessed by examining the respondents for indication of high rates of participation by those who were early adopters of EVs. In total, three respondents indicated their household currently or previously had an EV – consistent with known adoption rates of EV in the ACT at the time the survey was conducted. Non-response bias assessment was also conducted: 200 of those who did not respond to the invitation to complete the survey were asked why they did not complete it. Of the 70 who provided a response, 32 had not noticed the initial invitation, 34 reported being too busy, and four disliking the survey topic, while four provided responses indicating unique circumstances such as illness occurred. None indicated that lack of interest in the survey was a reason for non-participation. Overall, the approach to sampling reduced risk of salience bias, and the non-response bias assessment indicated that it was unlikely the survey respondents were biased towards those with a strong interest in EVs, given that non-response was not due to lack of interest, and that the database used for recruitment was recruited separately to this survey.

Respondent characteristics were examined to identify how representative they were of the ACT adult population (Table 1). While responses were highly representative by gender, this was not the case for age, with an under-representation of younger age groups and an over-representation of older age groups. However, a sufficiently large sample of younger age groups was achieved to enable weighting to correct for this bias. This was addressed by weighting the sample based on age, gender and district of the ACT using data from the 2016 ABS Census of Population and Housing. This weighting was conducted in an iterative way, where the sample was adjusted to match each of the demographic benchmarks sequentially.

The survey examined multiple dimensions of the likely adoption of EVs. Not all dimensions were applied to the model used here. The main dimensions used were existing vehicle use and plans to purchase new vehicles, as well as current views about EVs. The survey contained information about other factors that may be affecting intention to purchase an EV such as respondents' views about the potential for different types of policy action to achieve higher adoption of EVs.

Table 1
Survey representation of ACT adult population.

	Benchmark (2016 Census of Population and Housing)	Electric vehicle survey respondents
	%	%
Gender		
Female	51.5 %	50.4 %
Male	48.5 %	48.5 %
Other or prefer not to answer		1.0 %
Age		
18–34	34.9 %	15.0 %
35–54	35.3 %	26.8 %
55–74	23.0 %	46.9 %
75–100	6.7 %	11.2 %

The "current vehicle use and replacement intentions" section of the survey examined current patterns of vehicle use and intended vehicle replacement. This provides an understanding of the time period and price range in which the ACT's private residential vehicle fleet is likely to be replaced over a one-, two- or five-year period, providing opportunities for EVs to be purchased. This was a crucial section for the model as it captures the possible additional utility from buying a new vehicle reflected by the difference in the price participants were willing to pay compared with the price of their current vehicle. Further, this section also provided information about participants' time frame for replacing their current vehicle, as people may want to utilise the capacity of their current vehicle before buying a new one.

The "current EV adoption interest, experience and intention" section of the survey examined current intentions regarding the purchase of EVs. This captures survey respondents' views about the idea of purchasing an EV without considering any specific incentives or other information. It reflects their current impressions about EVs (for example, EV price, availability, driving range and performance) and their current awareness of existing incentives to purchase an EV. This provides the "starting point" for EV adoption, by identifying what EV adoption intentions are under current circumstances with no specific intervention to increase adoption. Given the availability of this data, the model only allocated the possibility of buying an EV to the type of person who indicated any intention to buy an EV.

Although this survey was an important source of information for the model, there are issues in trying to capture EV purchasing intentions through surveys (Coffman et al., 2017). The main issue is the gap between preference and action, meaning that using respondents' views on their intention to purchase an EV is likely to overstate the actual purchase of such vehicles. Eppstein et al. (2011), who created an agent-based model, noted that their model might have over-predicted EV take-up due to reliance on survey data. Therefore, the simulation process in our model further restricted purchasing behaviour. This means the proportion of those who purchase an EV has been reduced from those who had stated their intention to replace their current vehicle and who had indicated a preference towards EVs by also considering that they also need to have the financial benefits of EV purchase (the discussion about operational costs in the next section explains this further). This approach will not only reduce potential overestimation but also provides a threshold that can be used to model incentives, similar to Eppstein et al.'s (2011) suggestion.

4.3. Simulation process

The model assumes that households purchase EVs based on various factors, including whether the household plans to replace its vehicle, financial considerations or incentives, and the household's preferences for an EV. As discussed earlier, the decision-making process in the model was built based on notable work from Mueller and de Haan (2009) and Plötz et al. (2014). Following Plötz et al. (2014), two main considerations in terms of financial benefit formed the basis for this simulation – investment and operational costs – while also considering the likelihood of replacing the current vehicle and the willingness to adopt EVs. This required the spatial microsimulation synthetic database described above to be merged with the survey as the first step of the simulation depicted in Fig. 1.

While there are other options for merging such data (e.g., probabilistic matching), the merge was conducted between the synthetic household data with the link to the household's vehicle/s and the weighted cross-tabulation of the survey. This means the survey information was aggregated based on several criteria, which were district, type of household, age of the household reference person and household

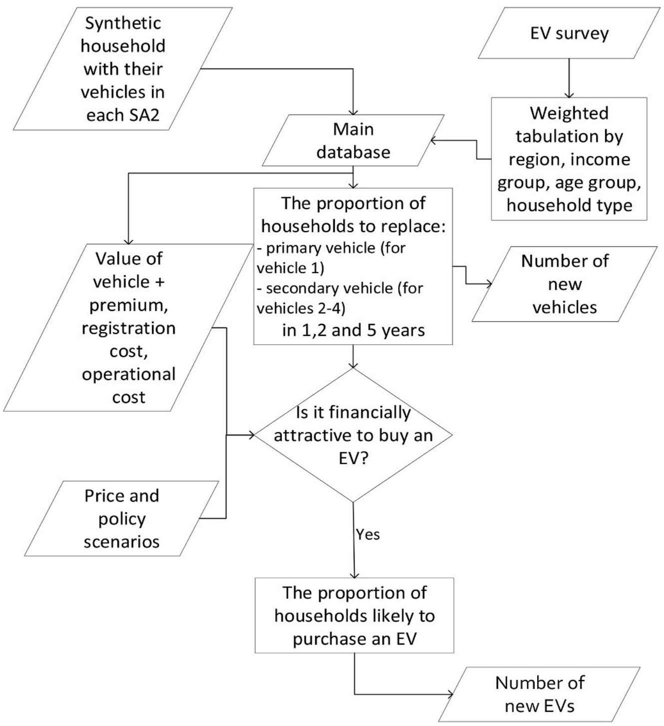

Fig. 1. The electric vehicle (EV) take-up decision model.

income. Due to the number of observations, location, age and income were reclassified to become seven, six and three groups, respectively. The classifications were then used to attach the survey information to the different households in the synthetic dataset. As a result, each household observation had a probability of replacing their primary and secondary vehicles in one, two and five years based on the weighted proportion from the survey. By applying the proportion for the primary vehicle to the first vehicle and the proportion for the secondary vehicle to the second, third and fourth vehicles, when available, this simulation produced the estimate of new vehicles purchased in those time frames.

Another piece of information captured from the survey was the average additional utility or premium of having a new vehicle for each household. This was estimated using the value of the household's current vehicle and what they were willing to spend on a new vehicle. This premium or additional utility was added to the current vehicle value obtained from the HES and validated using the trading price of the five most popular vehicles from each year range and cylinder numbers in 2016. The simulation used the difference between the set EV price and the value of the current vehicles plus the premium for having a new vehicle as the loan that needs to be financed. The weekly repayment of that loan based on five-year loan terms and a 6.5 % interest rate was the investment cost component of the TCO.

The second consideration, operational cost, was mainly but not entirely based on cost of fuel and level of fuel consumption. The synthetic data contained the fuel expenditure information from the HES, and the kilometres travelled for each vehicle in the household was estimated based on the proportion of specific fuel expenditure, the vehicle efficiency and the price of fuel. This was compared to the cost of electricity for the same number of kilometres travelled, which was estimated based on the average price for electricity per kilowatt hour (kWh). In Australia in 2019, it cost about $0.25 and took around 18 kWh to travel 100 km in an average EV, which equates to approximately $4.50 in electricity charges. This is a conservative assumption and does not take into account electricity generated from the growing use of solar panels among households in Canberra (Brown 2021).

The operational cost consideration can also include maintenance costs. While the maintenance cost of the current vehicle was available in the HES, the maintenance cost of an EV had to be estimated. For consistency, we used the estimates from Consumer Reports (consumerreports.org) based on the frequency of repairs on vehicles from its 2019 and 2020 reliability surveys of electric and petrol vehicles, as discussed in Hanley (2020). The results indicated that the average maintenance cost for EVs and plug-in hybrid EVs were $0.048 and $0.050 per kilometre while internal combustion engine vehicle maintenance costs were $0.098 per kilometre on average.

The base scenario for the modelling estimated EV take-up without any incentives. For this scenario, if the reduction of the weekly operational cost from using EVs was bigger than the weekly repayment of the higher EV price then the proportion of those who were willing to adopt EVs from the survey's weighted cross-tabulation was used to estimate the number of EVs purchased as new vehicles. This proportion was incorporated to reduce overestimation.

4.4. Scenarios

The final stage in the modelling was to implement the changes into the model from three chosen policy scenarios. These scenarios, as outlined below, represented two elements of the current ACT ZEV program, and well as an additional policy option not currently in place. Each scenario was applied to each vehicle in the synthetic household database. The three policy scenarios added incentives progressively to the base scenario. The first scenario provided the zero-interest loan of $15,000 as an incentive. This incentive reduced the weekly repayment component by separating the loan into the $15,000 that had no interest and the rest of the loan, which attracts 6.5 % interest. This meant that if the difference was less than $15,000 then there would be no interest on loan repayments.

The second scenario is the primary focus of this study as it is the closest scenario to the actual policy in the ACT. This scenario includes free annual vehicle registration as well as the zero-interest loan. This scenario added a benefit in terms of operational costs, as the new EV owner pays no registration costs while the owner of an internal combustion engine vehicle pays a weekly registration cost as a pro rata of the annual cost. As an additional comparison, the third scenario changed the $15,000 loan into a subsidy, so no repayments for loans of any amount up to $15,000 were included in weekly repayment costs. This scenario is not part of the existing policy. Instead, it was introduced to understand the impact of taking further action.

One element of the current policy settings could not be included in the scenarios. This was the eligibility rule for both current policies (registration and loan) that the unimproved value of the householder's property must be below $750,000 for non-unit-titled dwellings, and below $200,000 for unit-titled dwellings. This could not be included in the model due to lack of data about this unimproved value of property.

5. Results

The first estimate examined was the predicted overall take-up of EVs in the next five years (the longest time available in the survey for replacing current vehicles) under the base model and the three scenarios. Table 2 shows that if the price of the average EV stays at around

Table 2
Simulated electric vehicle take-up for various prices and scenarios as a proportion of all new vehicles bought in a five-year period.

EV price	Base model	Scenario 1	Scenario 2 – ACT ZEV policies	Scenario 3
	(% ownership)	(% ownership)	(% ownership)	(% ownership)
$100,000	0.16	0.44	0.77	1.39
$50,000	8.93	9.88	11.26	17.25
$25,000	23.54	25.27	27.36	30.30

$100,000 then without any policy incentives the market share of EVs would stay at 0.16 %. The early adopters of EVs should be captured by the database since although Vidyattama et al. (2021) used a category of "other" for vehicle types owned by households that did not spend on fuel (petrol, diesel or LPG), their vehicle value in the data was relatively high and so they are likely to immediately convert their vehicle to an EV. Therefore, even if the price of the average EV is $100,000, there are an estimated 0.10 % of vehicles in the ACT that are EVs in the simulated first year. In addition, there are three samples in the survey that are early adapters. The market share increases significantly if the price of the average EV is reduced to $50,000 and even more so if it can be reduced to $25,000, with EV sales increasing by a multiple of 50 to a market share of nearly 9 % and 23.5 % of new vehicles sales in five years, respectively.

Looking at the impact of the policies, at a $50,000 price tag the government incentives assessed in the model have a considerable impact given the higher EV sales compared to the base model. The third scenario examined provided a $15,000 subsidy rather than a zero-interest loan. As noted above, this is not part of current ACT policies, and was assessed as a theoretical incentive that could be offered. As can be seen in Table 2, this incentive increased the take-up much more than the combined current ACT ZEV policies (Scenario 2) because it had a direct effect on the real price for the consumer, changing the average price of an EV to $35,000. This is consistent with Ghasri et al.'s (2019) finding that consumers were more sensitive towards reduction in the purchase price than to higher rebates. Table 2 also illustrates how much financial benefits affect purchasing behaviour. Scenario 3, where a household need pays only $10,000 for an EV, results in 30 % EVs purchased among new vehicles in 5 years. The higher price of $50,000 in the base model reduced the financial gain so that the take-up reduced to only around 9 %.

A preference for owning an EV will not automatically mean that the vehicle pool in the ACT will become predominantly EVs. Based on the survey, only around 7 % of respondents planned to replace their vehicle in the following two years and 17 % planned to do so in five years. This means that the Scenario 2 estimate of 11.3 % EVs among new vehicles in five years at a price of $50,000 would increase the proportion of EVs to just below 2 % (Table 3). This number is much higher than the 2019 proportion of EVs in the ACT, which was still below 0.1 %. This indicates that although the demand for fuel and the related infrastructure will still dominate ACT private transport, the government needs to prepare the infrastructure for the increasing number of EVs when prices continue to go down.

Besides looking at the overall impact, another important assessment of EV policy is to analyse its distributional impact. This is where microsimulation modelling has particular utility, as it enables disaggregation of impacts on different types of households. Here, we examined impacts of the different scenarios on households with different income levels, disaggregating model outputs based on quintile of household income. The household income measure used was equivalised disposable household income, which assumes that income coming into a household is shared across all people in the household. The equivalising factor is the OECD Modified version, which provides a weight of one to the first adult, 0.5 to each additional person aged 15 years and over, and 0.3 to each child under the age of 15. (Buhmann et al., 1988). To simplify the results, only one price for EVs was used in this simulation, which was $50,000.

Table 4 indicates that people living in households with income in the highest quintile are much more likely to buy EVs – with or without the availability of government incentives. For this group, such incentives do not result in significant differences in rates of EV uptake. The much higher take-up of households in the highest income quintile without government incentives was also estimated in a UK model (Lee and Brown 2021), but the difference in that study was not as great as shown in Table 4. Incentives were most effective in increasing EV take-up amongst those in the second lowest income quintile, while those in the lowest income quintile were not able to buy an EV even with incentives. At $50,000, only a subsidy of $15,000 (Scenario 3) would increase the demand for EVs amongst this lowest quintile income group. In general, changing the incentive from a loan to a $15,000 subsidy increased EV demand substantially across almost all income quintiles.

The model results suggest that ownership of EVs will reach 5.8 % among the highest income quintile households in the ACT within five years even in the absence of government incentives encouraging uptake (see Table 5). This is because higher income households tend to replace their vehicles faster and benefit the most from vehicle-related benefits (Vidyattama et al., 2021; West, 2005). The model estimates that one-third of the highest income quintile households will replace their car in five years while those in the bottom quintile only replace their cars every 10 years on average. In contrast, providing incentives could increase the ownership of EVs in the second lowest quintile almost threefold, from only 0.2 % to nearly 0.6 %. Despite this, the much higher probability of higher income households replacing their vehicles and buying EVs means a reduction in EVs purchased could be substantial if the incentives were restricted to low-income households (Quintiles 1–3).

The location of different household types is also important in the discussion of which type of household will take up an EV. The availability of location also helps policy makers to plan priority areas for EV infrastructure, such as charging stations or access for households to install fast charging power points. Fig. 2 suggests that the highest take-up in EV's will be concentrated near the inner north of Canberra by a big margin compared to the inner south, which had the next highest take-up. However, this increased take-up in the south of the ACT shows how incentive policies could be important in the future. Not only will this help increase interest in EVs in this area, but it will also help justify the distribution of the development of EV infrastructure to the south. This will have a multiplier effect since the survey indicated that people are more willing to buy EVs when the infrastructure is available.

6. Calibration and issues with the simulation

This section tries to understand the performance of the simulation and the possible issues by comparing the results to actual data. The availability of data to be compared is the main issue in this calibration. Although the survey was conducted in October 2020, the synthetic data was constructed to represent the 2019/2020 financial year. The disaggregated data at postcode level are available for the year 2021

Table 3
Simulated electric vehicle take-up for various prices and scenarios as a proportion of total vehicles after five years.

EV price	Base model	Scenario 1	Scenario 2 – ACT ZEV policies	Scenario 3
	(% vehicles)	(% vehicles)	(% vehicles)	(% vehicles)
$100,000	0.03	0.08	0.13	0.24
$50,000	1.57	1.73	1.98	3.03
$25,000	4.13	4.43	4.80	5.32

Table 4
Simulated electric vehicle take-up by quintile of household income as a proportion of new vehicles purchased in a five-year period.

Household equivalised disposable income quintile	Base model (% of new vehicles)	Scenario 1 (% of new vehicles)	Scenario 2 – ACT ZEV policies (% of new vehicles)	Scenario 3 (% of new vehicles)
1	0.82	0.82	0.82	13.07
2	1.45	3.19	4.15	14.45
3	3.00	3.42	4.53	8.77
4	0.75	0.92	1.11	4.21
5	17.43	18.74	21.07	26.06

Table 5
Simulated electric vehicle take-up by quintile of household income as a proportion of total vehicles after five years.

Household equivalised disposable income quintile	Base model (% vehicles)	Scenario 1 (% vehicles)	Scenario 2 – ACT ZEV policies (% vehicles)	Scenario 3 (% vehicles)
1	0.08	0.08	0.08	1.24
2	0.20	0.43	0.57	1.97
3	0.35	0.40	0.52	1.01
4	0.10	0.12	0.15	0.57
5	5.81	6.24	7.02	8.68

(Australian Bureau of Statistics, 2021b) while there is some information about the overall progress reported by media in 2023. By comparing this information, there are some dynamics that are not captured by the model. The changes and variation of prices can be used as an example. A $50,000 price resulted in EVs making up 0.7 % and 0.8 % of all vehicles in the ACT in the simulation of the second year using the base model and Scenario 2, respectively, while the 2021 data shows 0.6 % of all passenger vehicles registered were EVs with an average price of $66,900. Therefore, the model's estimated proportion of EVs in five years could be an overestimation if the price is maintained at the higher level indicated by the 2021 data.

There is also a change in preferences as the proportion of EVs surged to 1.6 % in 2023 (four years after 2019) at an average price of $62,000 while Table 3 shows simulated EV take-up as a proportion of total vehicles after five years is at 1.6 % and 2.0 % for the base model and Scenario 2 at the price of $50,000, respectively. Given that there was only one year of policy implementation between 2019 and 2023, the simulation has no longer overestimated the take up even when the lower price is used. Unfortunately, further calibration based on household characteristics such as income is not possible since, as discussed before, the vehicle data in Australia is not linked to household data.

The calibration that is possible is based on location (postcode). This calibration reveals another issue which is related to the dynamics of the city (such as population, infrastructure, or housing composition). This calibration of postcode estimation using the 2021 Motor Vehicle Census data showed that the model overestimates the very high EV take-up in the Inner North. One possible explanation for this is the increase in the proportion of apartments between 2016 (the basis of the small area distribution used in the simulation) and 2021 in these areas. In addition, the model underestimates the EV take-up in the new housing development area to the west of the city. The use of district (such as Inner North) as one of the tabulation criteria exacerbated this issue, as a district's dynamics could change as new residents come in. Fig. 3 illustrates how one postcode (which is bigger than SA2 in ACT) in the Inner North Area is extremely overestimated by the model while the data shows a more

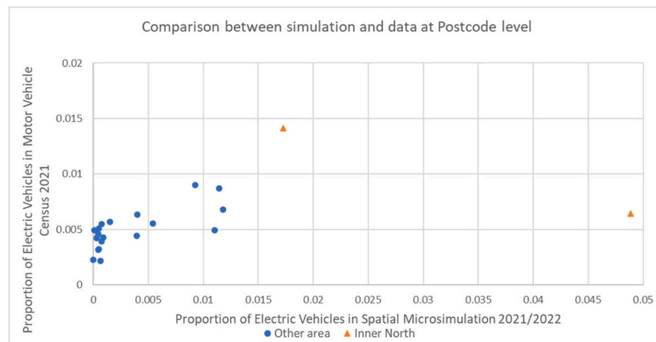

Fig. 3. Comparison between estimated proportion of electric vehicles (EVs) among all vehicle in a two-year period and 2021 Motor Vehicle Census data at Postcode level, Canberra.

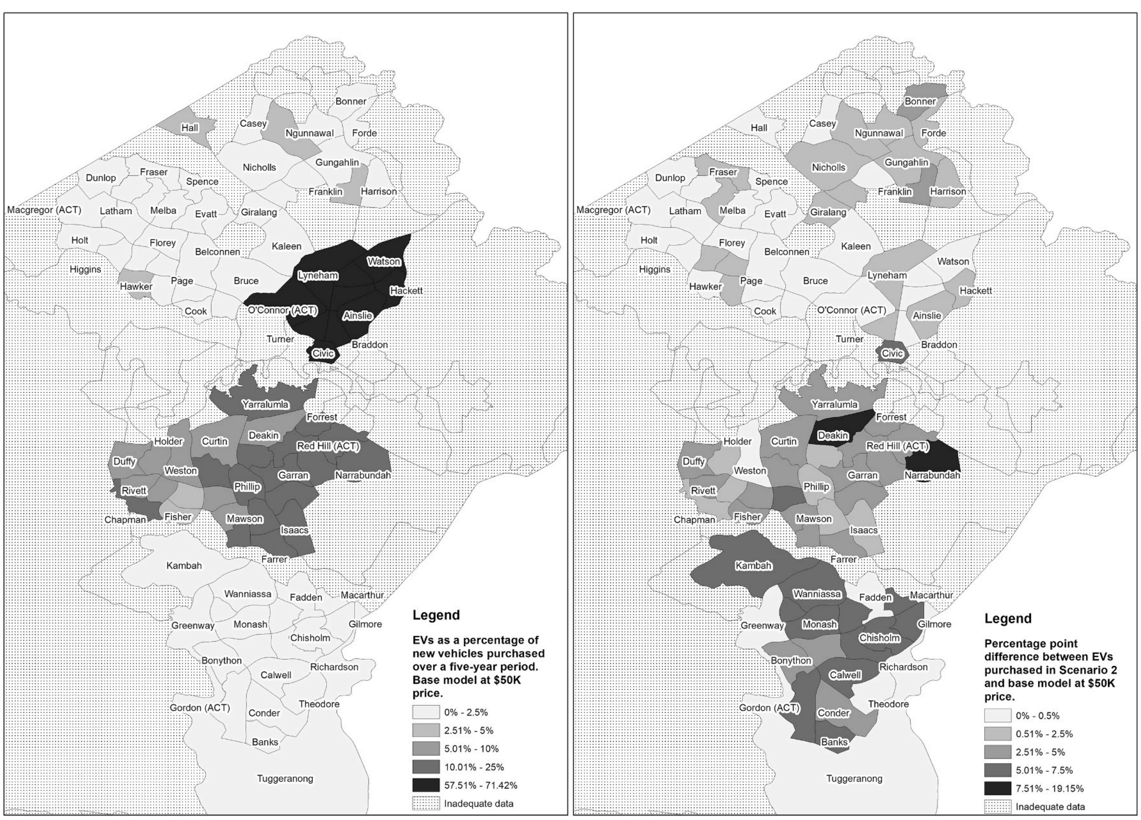

Fig. 2. Proportion of electric vehicles (EVs) among new vehicles purchased in a five-year period and estimates of ACT ZEV policy (Scenario 2) impact by SA2, Canberra.

even spread of take up in other postcodes. Despite this, the simulation was able to capture the higher take-up of EVs in the south and further estimated this increase as a result of the incentives.

The application of the model further identified some issues with the input data in the simulation. The simulations show very low take-up from households in the second highest income quintile. This take-up was low before any policy changes, and the policy incentives did not appear to increase take-up by much. Further investigation into the raw dataset revealed a very low take-up among couples aged 15–34 years with no children. The results may thus be affected by a low sample size for this group of people rather than reflecting their actual preferences. As Table 1 showed, people aged below 35 were under-represented in the survey. This highlights the importance of having data available for all disaggregated household types when conducting microsimulation modelling. Another input data issue, previously noted, was the inability to incorporate the incentive eligibility criteria relating to property values. Unfortunately, no data or proxy exists to check these criteria.

7. Conclusion

This study demonstrates the assessment of government policies designed to increase EV uptake using microsimulation modelling based on a synthetically linked dataset. The study provides useful policy insights, both within the ACT and beyond. EV purchasing incentives are likely to be most effective if the average purchase price of EVs is close to the $50,000 price point. Incentives may be less effective at higher and lower price points. This suggests that incentives are more effective at accelerating uptake during the phasing in of EV adoption when prices are falling but have not yet reached the levels where uptake of EVs is likely to occur amongst a wide range of households, even in the absence of government incentives. This is the phase that Australia is likely entering, with several new EV models coming onto the market in the second half of 2023 with prices between $39,000 and $55,000 (Misoyannis 2023). This coincides with some states and territories introducing (larger) EV purchasing incentives; for example, Queensland has doubled its rebate from $3,000 to $6,000 for EVs that are below $68,000 (including GST) from July 2023 (Queensland Rural and Industry Development Authority 2023). Conversely, the Victorian government recently announced that it is cutting its EV subsidy of $3,000 nearly a year earlier than originally planned, effective from June 30, 2023 (AAP 2023).

Another policy insight is that targeting EV purchasing incentives at low-income households (especially those in the second lowest income quintile) is likely to make the incentives have a larger impact on the spread of EV uptake than on the total number of purchases. This is because high-income households are more likely to be planning EV purchases and these households update their vehicles more regularly. Nevertheless, targeting incentives at low-income households has additional policy benefits because such households tend to live in outer suburbs, are more dependent on private vehicles for work and other travel, and travel longer distances overall. Therefore, increased EV uptake by low-income households will lead to a larger overall reduction in carbon emissions (as well as other tailpipe pollutants) because they are more car dependent and drive greater distances. It will also generate greater financial savings for this group (and positive distribution impacts) through lower EV running costs. Further, those living in outer suburbs are more likely to have off-street parking, making it easier to charge EVs at home.

The modelling can help policy makers plan for the rollout of EV infrastructure, including the installation of public charging stations and assistance for households to install fast charging power points. Initially, at least, it may be argued that public charging should be concentrated in those locations with the highest uptake. However, further policy nuance is warranted. The provision of public charging infrastructure could focus on higher density locations with less access to off-street charging, while outer suburbs (as noted above) with greater access to off-street parking could be targeted for government assistance in the installation of private fast charging.

Finally, we found some issues with the application of the model. For example, in applying it to the ACT, it slightly overestimated EV take-up in the first two years. This study also could not check the eligibility of high-income households to obtain zero-interest EV loans due to an inability to check the relevant assets test. A comparison of the estimates with real data from 2021 indicates the model could be improved in the future by integrating information on the development of the city, including changes in housing composition, especially the development of new housing areas, while reducing the use of certain criteria, such as location-based preferences, in the model.

Data availability

Code is provided while data can be partially made available upon request

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2024.01.018.

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