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**A habit persistence model of multiple discrete/continuous demand for evaluating charging behaviour of Australian electric vehicle owners**

**By**

**Andrea Pellegrini<sup>a</sup>, John Rose<sup>a</sup>**

<sup>a</sup>

Institute of Transport and Logistics Studies (ITLS),  
The University of Sydney, Australia

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**TITLE:** A habit persistence model of multiple discrete/continuous demand for evaluating charging behaviour of Australian electric vehicle owners

**ABSTRACT:** This paper introduces a novel habit persistence model of discrete/continuous demand that allows the joint evaluation of the spatial (i.e., location) and temporal (i.e., time of day) dimensions of the charging decision-making process. The model's habit persistence structure further captures established recharging routines that influence both when and where charging occurs. The proposed model is applied to data capturing weekly charging activities collected using an online survey disseminated to a sample of EV owners recruited from across Australia between February and March 2024. Results show that charging at home is the most prevalent behaviour, with a strong tendency towards daytime charging largely driven by households with access to residential solar panels. Workplace charging emerges as a viable alternative to home charging when employers provide free charging and commuting frequency is high. The model also reveals the presence of state dependencies in charging behaviour, indicating that past choices are likely to influence current charging patterns. The empirical findings are subsequently used to demonstrate how changes in electricity prices can shift charging demand and impact grid load, corroborating the importance of targeted policy interventions to manage the growing energy demand for EVs.

**KEY WORDS:** *Charging preference behaviour, charging location choices, time of day preferences, habit persistence effects, impact on grid load*

**AUTHORS:** Pellegrini, Rose

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**CONTACT:** INSTITUTE OF TRANSPORT AND LOGISTICS STUDIES (H04)  
The Australian Key Centre in Transport and Logistics Management  
The University of Sydney NSW 2006 Australia  
Telephone: +612 9114 1813  
E-mail: [business.itlsinfo@sydney.edu.au](mailto:business.itlsinfo@sydney.edu.au)  
Internet: <http://sydney.edu.au/business/itls>

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## 1. Introduction

Decarbonisation of the transportation sector is widely regarded as one of the most urgent areas requiring intervention if net-zero targets are to be met by 2050 (Frankie and Krems, 2013; Rezvani et al., 2015; Nanaki and Koroneos, 2016; Liao et al., 2017; Harrison and Thiel, 2017; Yu and Stuart, 2017; Jang and Choi, 2021; Pellegrini and Rose, 2023; Cincotta and Thomassen, 2025). In 2023, the global carbon footprint of transport activities reached nearly eight billion metric tons of CO<sub>2</sub>, a four percent increase on emissions from the previous year, with road based services (passenger cars and light vehicles) representing the primary contributor, followed by aviation and shipping (International Energy Agency (IEA), 2023). Given that transport-related emissions are projected to continue rising until 2030 (Thiel et al., 2016), accelerating the transition to electromobility represents an imperative area of policy action requiring immediate attention (Campello-Vicente et al., 2017). In this regard, electric vehicles (EVs) are seen by many political authorities as the most viable emissions free, or low emission alternative to equivalent conventional vehicles (Sierzchula et al., 2014). In addition to lowering reliance on fossil fuels, the diffusion of cleaner energy vehicles holds the potential to improve urban air quality (Sioshani and Denholm, 2009; Thompson, Webber and Allen, 2009; Nichols et al., 2015; Pellegrini et al., 2025), reduce noise pollution (Campello-Vicente et al., 2017), and enhance energy independence (Raugei, Hutchinson and Morrey, 2018).

In spite of the many societal benefits, the pathway to transport electrification continues to face numerous implementation challenges, including concerns over cost-effectiveness, distributive justice, charging accessibility and political acceptability, among others (Hawkins, Gausen and Strømman, 2012; Lucas and Pangbourne, 2014; Contestabile, Alajaji and Almubarak, 2017; Sovacool et al., 2019; Hasan, Chapman and Frame, 2020; Henderson, 2020; Carlton and Sultana, 2023; Malabanan, Lavieri and Mateo-Babiano, 2025). Governments both at national and local levels continue to struggle with allocating the substantial economic resources necessary to match EV market growth, partially due to uncertainty surrounding the long-term financial viability of EV related infrastructure (Geels et al., 2012; Nesterova, MuConsult and van der Waard, 2018; Li et al., 2021; Haghani, Ghaderi and Hensher, 2024; Hensher, 2024; Dall-Orsoletta et al., 2025;). These obstacles have, in part, given rise to the current fragmented EV take-up rate, with China, Europe and the United States accounting for approximately 90 percent of the total sales worldwide (IEA, 2024). Because the penetration of EVs is expected to become more geographically widespread in the coming years, it becomes essential to understand not only what drives the decision to move away from internal combustion engine vehicles, but also the factors that dictate the charging behaviour of EV owners, namely, when, where, and how EV drivers choose to charge their vehicles.

Early efforts to assess EV users' travel behaviour primarily involved the analyse of the driving patterns of traditional vehicle owners, either to infer potential charging locations for optimizing public infrastructure provision, or to examine how variations in charging facilities and battery capacities

influence vehicle usage (Nie and Ghhamami, 2013; Dong et. al, 2014; Tal et al., 2014; Gnan et al. 2014; Liu and Lin, 2015; Guo et al., 2016). The initial reliance on mobility data from conventional vehicles was mostly due to the fragmented nature of the information on EV ownership and use. In doing so, however, preliminary methodological approaches disregard the important role that socio-demographic and economic characteristics of EV drivers play in shaping travel decisions, especially with regards to where and how frequently individuals choose to charge. Consequently, numerous studies have adopted discrete choice experiments (DCEs) to elicit the charging preferences of EV owners (Daina, Sivakumar and Polak, 2017; Wolbertus et al., 2018; Ashkrof, Homem de Almeida Correia, and van Arem, 2020). For example, Jabeen et al., (2013) conducted a DCE as part of the Western Australia Electric Vehicle initiatives, revealing that home is the most preferred charging location among battery electric owners. Wen, MacKenzie and Keith (2016) find that respondents hold strong preferences for fast charging technology over slower alternatives at public infrastructure. Latinopoulos, Sivakumar and Polak (2017) demonstrate that dynamic changes in parking and charging prices result in individuals delaying charging activities in order to benefit from more affordable charging bundles.

While DCEs can help overcome challenges that are typically associated with revealed preference (RP) data, such as missing observations or limited sample sizes, they may lack realism because respondents are often asked to make choices of a hypothetical nature that may not accurately reflect actual real life decision-making contexts (Rose and Pellegrini, 2025). The growing availability of real-world data however, has prompted the use of a RP data to understand the determinants impacting the charging-decision making process of EV users (Xu et al., 2017; Lee et al., 2018; Anderson et al., 2018; Hardman et al., 2018). For instance, Wolbertus, Van den Hoed and Maase (2016) report a higher dependency on public charging stations at night among Dutch EV users relative to daytime, attributing this pattern to a lack of access to charging infrastructure within private dwellings of EV owners. Chakraborty et al. (2019) assert that the ownership of Level 2 (L2) chargers positively influences the likelihood of plug-in hybrid electric vehicle owners charging at home. The authors also find that access to free charging at a place of work can trigger excessive charging events, thus causing potential congestion issues around the charging stations provided. Lee et al. (2020) identify a wide range of factors that can possibly affect the location of charging, including residential electricity costs, availability of private home chargers, and type of dwelling, amongst others. Crozier, Morstyn and McCulloch (2021) report that the timing of charging decisions made by EV users is primarily impacted by the distance and duration of their trips. In addition to these factors, Anderson et al. (2022) report that charging costs and convenience or charging related level of service (e.g., waiting time and queuing) are crucial when making charging decisions. Based upon a nationwide case study undertaken in Switzerland, Gellrich, Block, and Leikert-Böhm (2022) conclude that most charging activities occur during work hours. Similar findings are also reported in Boarlaug et al. (2023), who further highlight that both the take up rate of EVs and the size of the network matter in terms of public charging infrastructure availability.

A key limitation of the studies that have analysed RP data on EV adoption and charging to date, is that charging locations are often modelled as mutually exclusive options. That is, drivers are implicitly assumed to charge their vehicle at only one location over the course of a fixed time period, for example, a day or a week. However, it is plausible that charging events may occur at multiple locations over a given timeframe, such as work and supermarkets or home and supermarkets, depending on individuals' travel habits and infrastructure availability (e.g., private home chargers). When multiple locations are observed to be chosen for charging over time, it is common to aggregate them into a single category, sometimes labelled as *multiple locations* (see e.g., Chakraborty et al., 2019). Whilst this approach can be effective in reducing the choice set size to be modelled in order to facilitate analytical computations, it can impair the ability of the analyst to empirically identify the determinants affecting the choice to charge at each specific location within the composite alternative. Further, charging location decisions are often intertwined with the time of day. For instance, EV owners belonging to households with solar panels may be more inclined to charge at home during daylight rather than later in the day in order to benefit from solar generated electricity. Similarly, commuting to work by car can lead EV drivers to charge during the day when they are more likely to be at work. Assessing the interplay between charging location and charging time is therefore critical for designing targeted strategies to ensure that the charging ecosystem keeps up with the increasing demand for greener energy vehicles.

The aim of this study is to contribute to the literature on charging behaviour. We do this by developing an error component based habit persistence multiple discrete continuous extreme value (MDCEV) (Bhat, 2005; 2008) model that allows for evaluating behavioural decisions resulting in EV users charging at multiple locations. In addition to examining charging location choices, the model proposed also jointly investigates the factors that drive time-period decisions regarding when an EV is charged. To this end, three distinct timeslots are considered: a) overnight (12 am to 8 am), b) during the day (8 am to 5pm), and c) evenings (5pm to 12 am). A further feature of the model is its ability to account for potential habit persistence effects in charging routines. Specifically, the underlying assumption is that past charging behaviour may influence current charging decision-making, giving rise to repeated charging patterns over time in terms of timing and location choices. Moreover, the error-component structure imposed allows for capturing unobserved substitution patterns that may exist between charging location and time-period alternatives. As a proof of concept, the econometric specification that we formalize is applied to RP charging data collected via an online survey administered to EV users sampled from all Australia between February and March 2024. The data collection represents a collective effort of the Institute of Transport and Logistics Studies at the University of Sydney and the Australian Vehicle Council and is designed to bridge the current knowledge gap on EV ownership and usage experience in Australia.

The remainder of the paper is structured as follows. In the next section, we present the data collection phase in detail, followed by a description of the dynamic MDCEV model used to assess

charging preference behaviour. Section 4 then goes on to illustrate the empirical findings, followed by a discussion of the results in the form of a prediction exercise that explores how charging location choices vary with changes in electricity prices at both private and public charging locations, as well as how a reduction in residential electricity prices could affect grid load in Section 5. Section 6 then provides concluding remarks.

## 2. DATA

The Institute of Transport and Logistics Studies partnered with the Australian Electric Vehicle Council (EVC) to launch a series of nationwide surveys aimed at uncovering EV ownership experiences across Australia. An EV ownership survey was administered to 1,600 EV owners recruited from all Australian states and territories between February and March 2024 through a web-based questionnaire programmed in Qualtrics (<https://www.qualtrics.com>). The sample was drawn from the EVC membership base. Whilst participants were not directly reimbursed, they had the opportunity to separately enter into a draw to win a prize, such as a home EV charger valued at approximately AUD \$2,000 RRP. A data cleaning process was implemented to exclude respondents who returned incomplete questionnaires (missing socio-economic information), resulting in responses from a sample of 1,440 eligible EV owners being available for analysis. Note that, in this paper, the term *electric vehicles* encompasses both battery electric vehicles and plug-in hybrid electric vehicles, with owners of the latter making up only three percent of the sample.

The survey consisted of five main sections. In section one, EV owners were first required to indicate the size of the household fleet, after which they had to provide details for each automobile, including vehicle age, manufacture year, driving range, annual kilometre travelled, body type, and fuel type, including battery capacity (expressed in kWh) for EVs. Detailed information about the vehicles fuel type was only collected from households with two or more vehicles, as the vehicle type for single vehicle households had to be an EV, by study design. Attention was restricted to the two primary household vehicles so as to reduce the burden on survey participants when recalling the characteristics of each vehicle within the fleet. Next, respondents were asked whether it was possible for them to charge their EV at home and work, and if so, what charging setup was currently in place. For each available charging setting, information was collected on charger technology, parking location, charging cost, and charging duration. Section three of the survey focused on information related to the use of public charging outlets. Specifically, participants were asked to report the distance from their home and workplace to the nearest public charging site, the charging networks (i.e., brand) typically used if any, the average charging cost, the usual charging time, the typical frequency of queuing experienced, and the importance that public infrastructure network played on their decision to purchase an EV. In section four, respondents were required to state whether they had charged their primary vehicle in the week preceding the survey. Note that primary vehicle was defined as the electric car that was mainly used by most family members for daily activities such as commuting to work, school, running errands, etc.

Upon sharing travel information, respondents were given the possibility of selecting one or more options from the following set of charging sites:

- Home;
- Workplace;
- Supermarkets / shopping centres;
- Destination Chargers (e.g., hotels, restaurants, recreational areas, or tourist attractions where charging facilities are provided as an amenity); and/or
- Other Public Charging Stations (located along travel routes or in public areas, specifically for charging needs and not part of a destination like supermarkets or hotels).

The list of charging locations was compiled following a series of meetings with industry members of the Electric Vehicle Council of Australia. Participants with two or more EVs were required to report charging patterns for the automobile that was mainly used by most family members for daily activities such as commuting to work, school, running errands, etc. Finally, the last section of the survey asked respondents a series of questions in which they were asked to provide socio-demographic and economic data, such as gender, employment status, household composition, type of dwelling, area of residence (urban vs. regional/rural areas), income, etc.

## 2.1 Charging behaviour

Table 1 presents the descriptive statistics of charging location choices among respondents who report charging the household’s primary vehicle during the preceding seven days before completing the survey. As shown in the table, nearly 87 percent of respondents reported charging their vehicles at their private dwellings, 9.65 percent at work, 13.68 percent at supermarkets and shopping centres, and 6.74 percent at destination chargers. Approximately 18 percent of survey participants used charging stations located along routes travelled or in public areas.

**Table 1: Charging location**

Charging location	% of EV owners charging in each location
Home	86.67%
Workplace	9.65%
Supermarkets / shopping centres	13.68%
Destination Chargers	6.74%
Other Public Charging Stations	17.43%

Table 2 displays the distribution of weekly charging instances by location. The table shows that most respondents charged their vehicles multiple times, with about six in ten EV drivers reporting at least four charging sessions in the week before being surveyed. In contrast, only 12.15 percent in the sample

charged their EVs only once. Of further note is that respondents tended to predominantly use a single charging location, regardless of the total number of charging sessions they report throughout the week.

**Table 2: Charging frequency distribution**

Number of Weekly charging instances	Proportion of EV drivers	Single Charging location	Multiple Charging locations
1	12.15%	100.00%	0.00%
2	17.43%	90.04%	9.96%
3	13.13%	75.66%	24.34%
4	12.15%	65.71%	34.29%
5	7.36%	59.43%	40.57%
6	6.11%	63.64%	36.36%
7	10.90%	79.62%	20.38%
8	4.86%	42.86%	57.14%
9	2.64%	44.74%	55.26%
>=10	13.26%	76.44%	23.56%

For each selected charging location, respondents were also required to indicate how often the primary vehicle was charged during the week (i.e., weekdays versus weekends) and the time of day the charging events occurred. An example of a charging schedule included in the survey is shown in Table 3. For example, a value of three was reported in the *Evening - Monday* cell for the charging location *Home*, indicates that three charging events occurred at home between 5pm and 12am on Monday. Additionally, if respondents charged the vehicle for ten hours between 12am and 10am, they were instructed to enter one in both the *overnight* and *during the day* cells of the table.

**Table 3: Example of charging schedule**

Time period	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Overnight (12am to 8am)							
During the day (8am to 5pm)							
Evening (5pm to 12am)							

Upon cleaning the data, it was noticed that very few charging events were reported to have taken place at *Work*, *Supermarkets/shopping centres* or using *Destination chargers* during the overnight and evening timeframes. Consequently, the latter timeslots were combined into a single timeframe, namely *Evening/Overnight*, resulting in a total of twelve non-mutually exclusive combinations of charging locations and time slots:

- 1) Home-During the day;
- 2) Home-Overnight ;
- 3) Home-Evening;

- 4) Work-During the day;
- 5) Work-Evening/Overnight;
- 6) Supermarkets/Shopping centres-During the day;
- 7) Supermarkets/Shopping centres -Evening/Overnight;
- 8) Destination chargers-During the day;
- 9) Destination chargers-Evening/Overnight;
- 10) Other public chargers- During the day;
- 11) Other public chargers-Evening; and
- 12) Other public chargers-Overnight.

The above twelve time/location combinations represent the decision variables that stand at the core of our empirical analysis. Table 4 outlines the descriptive statistics of weekly charging patterns for those EV owners who indicated charging their vehicles during the week before participating in the survey at each of the twelve time/location combinations. Specifically, 60 percent of respondents report charging at home between 8am and 5pm, 23.61 percent between 5pm and 12am, and nearly 40 percent overnight. Daylight hours accounted for most charging activities recorded at *Other public charging stations* (12.71 percent), *Supermarkets/ Shopping centres* (9.31 percent), *Work* (9.24 percent), and *Destination charging* (4.51 percent). In contrast, *Work-Evening/Overnight* and *Other public chargers-Overnight* are the least chosen location/time combinations. The highest weekly average charging frequency is associated with the alternative *Home-During the day* (4.33), succeeded by *Home-Overnight* (3.65) and *Work-During the day* (3.06). On the other hand, *Supermarkets/ Shopping centres* and *Other public chargers-Overnight* have the lowest average charging frequencies with values of 1.69 and 1.33, respectively.

**Table 4: Weekly charging patterns**

Charging location/ time slot combinations	% of EV owner charging in each location-time slot combination	Descriptive statistics among those who charge the vehicle in each location-time slot combination		
		Mean	Std. Dev	Median
Home-During the day	58.13%	4.33	5.01	3
Home-Evening	23.61%	2.91	2.72	2
Home-Overnight	39.38%	3.65	4.28	2
Work-During the day	9.24%	3.09	2.74	2
Work-Evening/Overnight	1.25%	3.06	2.84	1.5
Supermarkets/ Shopping centres-During the day	9.31%	1.69	1.37	1
Supermarkets/ Shopping centres-Evening/Overnight	5.49%	1.73	1.59	1
Destination chargers-During the day	4.51%	1.48	1.06	1
Destination chargers-Evening/Overnight	2.78%	2.48	3.31	1
Other public chargers-During the day	12.71%	1.92	1.46	1

Other public chargers-Evening	5.07%	1.79	1.34	1
Other public chargers-Overnight	1.67%	1.33	0.87	1

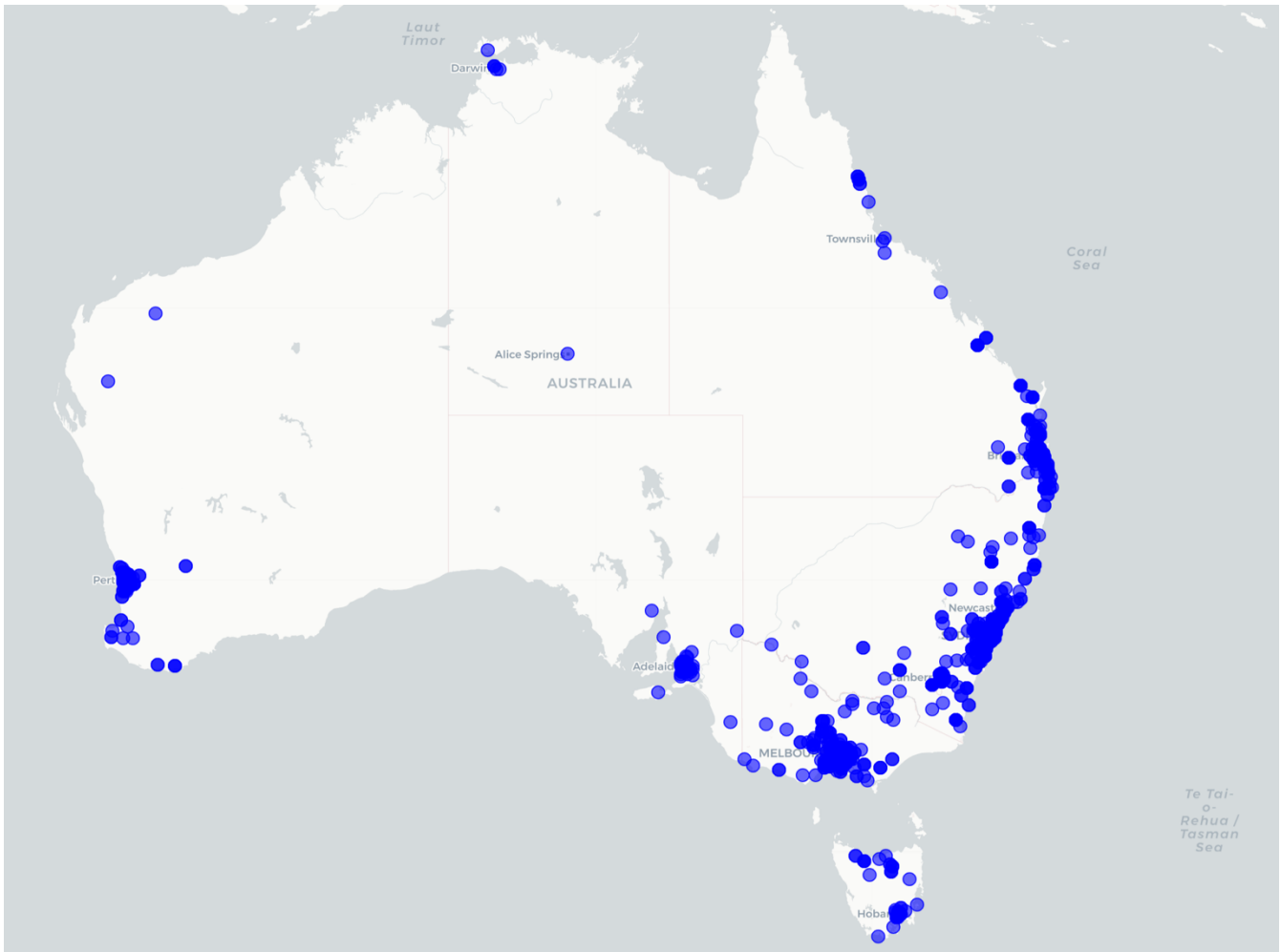
Table 5 further breaks down charging patterns by days of the week. It is clear from the table that respondents in the sample primarily charged their vehicles on weekdays, independent of location or time of day. For example, nearly 78 percent of those who charged overnight at home did so on weekdays, while 68.11 percent of daytime home charging occurred between Monday and Friday. The majority of workplace charging events were observed on weekdays, with 93.38 percent of the sample preferring to charge the vehicle between 8am and 5pm. Among those using public chargers along travel routes or in public areas, approximately three in ten charged over the weekend, with the highest proportion choosing to charge overnight (note that only 1.67 percent of the sample indicated to use public charging stations overnight in the week before the survey enrolment).

**Table 5: Charging patterns weekdays vs weekend**

Charging location/ time slot combinations	% of EV owner charging in each location-time slot combination		
	Week	Monday to Friday	Saturday and Sunday
Home-During the day	58.13%	68.95%	31.05%
Home-Evening	23.61%	75.11%	24.89%
Home-Overnight	39.38%	77.86%	22.14%
Work-During the day	9.24%	93.38%	6.62%
Work-Evening/Overnight	1.25%	89.74%	10.26%
Supermarkets/ Shopping centres-During the day	9.31%	71.50%	28.50%
Supermarkets/ Shopping centres-Evening/Overnight	5.49%	76.80%	23.20%
Destination chargers-During the day	4.51%	73.33%	26.67%
Destination chargers-Evening/Overnight	2.78%	74.63%	25.37%
Other public chargers-During the day	12.71%	68.36%	31.64%
Other public chargers-Evening	5.07%	64.35%	35.65%
Other public chargers-Overnight	1.67%	62.50%	37.50%

## 2.2 Sample

Figure 1 displays the geographical distribution of the respondents who agreed to participate in the survey. As shown in the heatmap, EV owners are predominantly concentrated along the east coast of Australia, with 75 percent of the sample residing in the three most populous states, namely New South Wales, Victoria, and Queensland. The remaining twenty-five percent of respondents are distributed across Western Australia (11.04 percent), South Australia (5.56 percent), The Australian Capital Territory (3.96 percent), Tasmania (3.68 percent) and Northern Territory (0.49 percent).



<i>Australian states and territories</i>	<i>% of sample</i>
The Australian Capital Territory	3.96%
New South Wales	36.46%
Northern Territory	0.49%
Queensland	13.89%
South Australia	5.56%
Tasmania	3.68%
Victoria	24.93%
Western Australia	11.04%

**Figure 1: Geographical location of the sample**

The descriptive statistics of the sample are embedded within Table 6. From the table, we can see that 25 percent of respondents are in the 50-59 age group, 23.13 percent in the age group 40-49, whilst only 1.46 percent are 29 years of age or younger. The households sampled are predominately childless, with the majority of family members being ably employed (nearly 70 percent). Retirees and students on the

other hand, make up approximately 26 percent of the sample. Around three in ten respondents report having a weekly household income greater than or equal to \$3,000 and reside in a freestanding home. More than half of the sample own at least two vehicles, live within 17 kilometres (kms) from the nearest public charging bay, and drive more than 30 kms per day. Lastly, the average cost at public charging outlets stands at \$0.28 per kWh, with a median and a standard deviation of \$0.24 and \$0.23, respectively.

**Table 6: Descriptive statistics of the sample**

<i>Explanatory variables</i>	<i>% of sample</i>		
<b>Age</b>			
18-29		1.46%	
30-39		13.13%	
40-49		23.13%	
50-59		25.28%	
60-69		22.64%	
70 or older		14.38%	
<b>Presence of children under 18 years of age</b>			
Yes		36.67%	
No		63.33%	
<b>Employment status</b>			
Full time employed		51.46%	
Part time employed		6.32%	
Self-employed		10.76%	
Casually employed		2.08%	
Volunteer work		0.97%	
Unemployed but looking		0.90%	
Unemployed but not looking		0.97%	
Full time student		0.21%	
Retired		25.42%	
Other (none of the above)		0.90%	
<b>Weekly Household income &gt;=\$3,000</b>			
Yes		31.18%	
No		68.82%	
<b>Type of dwelling</b>			
Flat		7.22%	
Freestanding house		80.76%	
Semi-detached		12.01%	
<b>Daily VKT &lt;=30km</b>			
Yes		18.75%	
No		81.25%	
<b>Household vehicle fleet</b>			
1 vehicle		29.51%	
2 vehicles		47.50%	
2 or more vehicles		22.99%	
<b>Distance to public charging outlets from home &gt;=17kms</b>			
Yes		8.40%	
No		91.60%	
	Mean	Median	Std. Dev
<b>Electricity price at public outlets (\$/kWh)</b>	\$0.28	\$0.24	\$0.23

Table 7 shows that 44.17 percent did not incur any equipment costs to support home charging such as the installation of a smart meter or a dedicated charger, 33 percent spent between \$1 and \$1,000, whilst 20 percent invested at least \$1,000 to install charging infrastructure at their place of residence. Further, seven out of ten EV drivers had no need to upgrade the electrical system before purchasing an EV, whilst four out of five respondents report having solar panels located at their normal place of residence. Only 25 percent of respondents report being able to benefit from a flexible electricity plan. Finally, on average, EV owners report paying approximately \$0.20 per kWh, with the corresponding standard deviation value of \$0.14 per kWh.

**Table 7: Home charging set-up**

	% of sample		
<b>Installation costs to support charging at home (e.g., a smart meter or a dedicated charger)</b>			
\$0	44.17%		
\$1-\$1000	35.14%		
Greater or equal than \$1000	20.69%		
<b>Upgrade of the electrical system</b>			
Yes	28.47%		
No	71.53%		
<b>Solar panels accessibility</b>			
Yes	75.07%		
No	24.93%		
<b>Flexible electricity plan</b>			
Yes	25.28%		
No	74.72%		
	Mean	Median	Std. Dev
<b>Electricity price (\$/kWh)</b>	\$0.19	0.20	0.14

In total, 1,037 (72 percent) out of the 1,440 respondents reported being in some form of employment arrangement. For those employed, as shown in Table 8, 312 (29.89%) respondents reported being able to charge their vehicle at work. Of these respondents, 66 or 21.14 percent of workers who can charge at work (6.34 percent of all workers) indicated working at locations where they have to pay for charging their vehicles, whereas 12 (3.86 percent or 1.16 percent of all workers) have access to fast charging technology. On average, workers commute by EV one day per week with a standard deviation of 1.79 days.

**Table 8: Work charging set-up and commuting information**

	% of sample		
<b>Free charging at work</b>			
Yes	21.14%		
No	78.86%		
<b>Availability of fast charging bays</b>			
Yes	3.86%		
No	96.14%		
	Mean	Median	Std. Dev
<b>Days travelled to work by EVs</b>	0.92	0.00	1.79

### 3. METHODOLOGY

The econometric model used for analysing charging preference behaviour is built upon the multiple discrete continuous extreme value (MDCEV) model developed by Bhat (2005; 2008). To understand the model, consider an EV driver,  $i$ , who is assumed to maximize their utility subject to some budgetary constraint. The utility function can be written as

$$U_i(\mathbf{x}) = \sum_{s=1}^7 \sum_{k=1}^{12} \psi_{isk} \gamma_{isk} \ln \left( \frac{f_{isk}}{\gamma_{isk}} + 1 \right) \quad (1)$$

s.t.  $\sum_{s=1}^7 \sum_{k=1}^{12} f_{isk} p_{sk} = 1,$

where  $f_{isk}$  is the fraction of the total frequency count allocated to the  $k^{th}$  charging location/time-slot at time  $s$ , with the latter representing the day of the week the charging event took place ( $s=1, \dots, 7$ ). Specifically,  $f_{isk}$  is calculated as the number of charging instances performed by respondent  $i$  on day  $s$  at the  $k^{th}$  location/time-slot combination,  $x_{isk}$ , divided by the total number of charging events across all location/time-slot combinations,  $\sum_{k=1}^{12} x_{isk}$ , with  $0 \leq f_{isk} = \frac{x_{isk}}{\sum_{k=1}^{12} x_{isk}} \leq 1$ . In addition,  $p_{sk}$  refers to the unit price and hence is assumed to be  $p_{sk} = 1 \forall k = 1, \dots, 12$  across  $s$  (Bhat, Sen and Uluru, 2009; Bhat, Castro and Pujari, 2015; Pellegrini, Sarman and Maggi, 2021; Pellegrini and Rose, 2025).  $\psi_{isk}$  are the marginal utility for the  $k^{th}$  location-time slot combination at time  $s$ , whilst  $\gamma_{isk}$  allow for corner solutions as well as govern the rate at which the marginal utility for location-time at  $s$  diminishes. Both  $\psi_{isk}$  and  $\gamma_{isk}$  can be further parametrized to capture heterogeneity among consumers as well as habit persistence effects such that

$$\begin{aligned} \psi_{isk} &= \exp(\theta' q_{ik} + \alpha' I_{is-1k} + \eta_{ib} + \epsilon_k) \\ \gamma_{isk} &= \exp(r' d_{ik} + \lambda' I_{is-1k} + \delta' I_{is-2k}). \end{aligned} \quad (2)$$

In the above equation, the use of the exponential ensures that the utility shown in Equation (1) is valid. Next,  $q_{ik}$  and  $d_{ik}$  are time-invariant explanatory variables that describe charging settings (e.g., access to solar panels, dwelling type, charger technology at work and at home, etc.) and socio-economic characteristics of the EV owners, whilst  $I_{is-1k}$  are time-variant variables (i.e., state dependent covariates) which equal one if a charging event is observed to take place on the previous day at the  $k^{th}$  charging location/time-slot, or 0 otherwise. Unlike previous studies (Roy et al., 1996; Luo, Ratchford and Yang, 2013), the novelty here is that  $I_{is-1k}$  measures the joint effect of habit persistence on both the discrete (i.e., location-time slot) and continuous (i.e., charging frequency) components of the model. An autoregressive specification of order two was imposed to quantify temporal habit persistence variations in satiation (i.e., charging frequency) (Hasegawa, Terui, and

Allenby, 2012).  $\theta$ ,  $\alpha$ ,  $r$ ,  $\lambda$ , and  $\delta$  are on the other hand vectors of parameters to be estimated. Further,  $\eta_{ik}$  are error components which are assumed to be normally distributed with mean zero and standard deviation  $\phi_k$ . The role of  $\eta_{ik \in B\{1, \dots, K\}}$  is to unravel unobserved correlation effects between charging location/time-slot combinations that would be otherwise omitted by standard MDCEV models. In contrast to nested MDCEV models (Pinjari and Bhat, 2010), the proposed econometric model constrains no alternative to belong to only one nest (nets are mutually exclusive within the nested MDCEV), resulting in a flexible analytical specification. In the current application context, four distinct error components are estimated so as to capture unobserved substitution patterns across locations/time slots combinations. The first error component accounts for unobserved substitution patterns between evening and overnight charging at home whilst the second accommodates potential substitution among public daytime charging locations, including *Supermarkets/Shopping centres*, *Destination chargers* and *Other public chargers*. The third error component measures substitution effects between *Home* and *Other public chargers* specifically during the evening time slot. Finally, the fourth error component is employed to quantify unobserved substitution patterns between home charging overnight and workplace charging during the day. Next,  $\epsilon_k$  ( $k = 1, \dots, K$ ) are error terms that acknowledge the presence of unobserved factors that influence charging frequency behaviour of EV drivers. The optimal proportions of location-time slot combinations are obtained by constructing the Karush-Kuhn-Tucker (KKT) conditions for optimality and by solving the Lagrangian function. Denoting Home-evening as a charging location/time-slot combination to which EV owners allot some non-zero fraction of the total frequency count (i.e., the base reference category), the probability expression for the fractional allocation patterns where the first  $M$  combinations of charging location/time-slot are reported to have occurred at time  $s$ ,  $f_{isk}^*$  ( $k = 2, \dots, M$ ), and  $f_{isk}^* = 1 - \sum_{k=2}^{12} f_{isk}^*$  is given by

$$P_{is} = \int_{\eta} \frac{1}{\sigma^{M_{is}-1}} [\prod_{l=1}^M c_{isl}] \left[ \sum_{l=1}^M \frac{1}{c_{isl}} \right] \left[ \frac{\prod_{l=1}^M \exp \frac{V_{isl}}{\sigma}}{\left( \sum_{k=1}^{12} \exp \frac{V_{isk}}{\sigma} \right)^{M_{is}}} \right] (M_{is} - 1)! dF(\eta), \quad (3)$$

where  $V_{isl} = \theta' q_{ik} + \alpha' I_{is-1k} + \eta_{ik} - \ln \left( \frac{f_{isk}^*}{\gamma_{isk}} + 1 \right)$ , and  $c_{isl} = \frac{1}{f_{isl}^* + \gamma_{isl}}$ .

Given that EV owners were recorded charging their vehicles multiple days of the week, the probability function shown in Equation (3) can be further specified as:

$$P_i^* = \prod_{s=1}^7 P_{is}. \quad (4)$$

Note the panel is unbalanced in nature, insofar as most of the respondents did not charge the vehicle daily, meaning the index  $s$  may not run from 1 to 7 for all individuals in the sample. Next, the log-likelihood function of the model over all decision-makers then simply becomes

$$LL = \sum_{i=1}^N P_i^*. \quad (5)$$

#### 4. RESULTS

Numerous model structures were tested using different combinations of consumer socio-economic and charging related variables, with the final specification shown in Table 10 providing the best fit for the data. In addition to the proposed habit persistence based MDCEV model (henceforth, HB-MDCEV), we also estimate a traditional MDCEV without state dependent covariates entering Equation (2). A set of 500 MHLS random draws were utilized to simulate the integral in Equation (3) so that the probability function derived in Equation (5) could be computed. In terms of model fit, Table 9 shows that the log-likelihood at convergence for the HB-MDCEV with 112 parameters is  $-8,542.50$  relative to  $-8,817.35$  with 98 parameters recorded for the standard MDCEV (the model parameter estimates for the latter specification are included in the Web Appendix). The corresponding Bayesian Information Criterion (BIC) values are 18,044.71 and 18,474.44, respectively, thus indicating a superior fit for the dynamic specification. Because the standard MDCEV can be seen as a restricted version of the HB-MDCEV model with habit persistence variables constrained to zero, it is also possible to compare the performance of the two models by the means of the log-likelihood ratio test. The resulting test statistic is equal to 547.57 which exceeds the critical value of  $\chi_{14, \alpha=0.01}^2 = 29.14$ , corroborating the importance of accounting for habit persistence patterns upon evaluating the charging decision-mechanism of EV owners.

**Table 9: Goodness of fit model**

	HB-MDCEV	MDCEV
Initial log-likelihood		-18,658.103
Log-likelihood at convergence	-8,542.501	-8,817.349
BIC	18,044.713	18,474.44
$\rho^2$	0.542	0.527
Adj. $\rho^2$	0.536	0.522
Number of estimated parameters	112	98
Number of respondents		1440
Number of draws		500 MLHS

In the sections that follow, attention is given to the estimates of the HB-MDCEV model, as this specification outperforms its non-dynamic counterpart. The interpretation of the results is structured as follows. Firstly, we examine the influence of the explanatory variables on the joint decision-making process involving both the location and time dimensions of charging preferences. This is followed by a

discussion of the determinants influencing the choice of charging locations, with home being the base reference location. Then, focus is placed on the component of the model related to time of day charging choices. Lastly, substitution patterns obtained from the estimation of four error components are outlined.

#### **4.1 Charging decisions by time of day and location**

We begin by illustrating the results pertaining to the alternative specific constants (ASCs) for the combinations of location/time decisions. To ensure model identification, we normalize the ASC for *Home-evening* to zero such that this location/time slot combination serves as base reference category against which all other combinations are compared. Of the eleven ASCs estimated, nine are found to be highly statistically significant, with the largest positive value (3.717, *t*-ratio of 11.71) observed for *Home-During the day*. This suggests that EV owners are more likely to charge at home during daytime hours relative to all the other charging location/time-slot combinations, *all else being held constant*. This is unsurprising given that approximately three quarters of the sample has access to solar panels (see Table 7). Conversely, the most negative ASC value is associated with *Work-During the day* (-1.651 with a *t*-ratio of -3.05), pointing to a lower likelihood of workplace charging during the day, *ceteris paribus*.

A dummy variable was created to indicate whether the reported charging event took place on a weekend or a weekday. The highest positive coefficients across all timeframes associated with the alternative *Other public chargers* indicate that EV owners are more likely to use public charging infrastructure on weekends compared to weekdays. Similarly, respondents show a higher tendency to charge at *Supermarkets/shopping centres* on weekends, perhaps combining charging with shopping or other leisure activities. By contrast, and as expected, respondents are less likely to charge at *Work* between 8am and 5pm on weekends, reflecting typical work-related travel patterns. Having a flexible electricity plan significantly reduces the probability of daytime charging at home, suggesting that EV owners may defer charging to periods when electricity providers offer off-peak rates. The likelihood of daytime home charging decreases significantly as the residential electricity price increases, revealing the presence of price sensitivity among EV drivers. Employed EV owners are less likely to charge during the day at home, at supermarkets and shopping centres and at other public charging facilities, suggesting that work commitments may reduce opportunities for daytime charging at such locations. On the other hand, charging activities at workplaces are more likely to occur during the day when the employer offers free charging. The parameter associated with the proximity to the nearest public charging infrastructure from home is positive but statistically insignificant, suggesting daytime home charging activities seem not to be influenced when the nearest public station is located 17 km or more away.

With respect to the continuous component of the model, i.e., the proportion of charging instances attributed to each alternative relative to the total number of charging events, the estimated satiation

constants suggest that EV owners tend to charge more frequently at home during the day, at supermarkets or shopping centres irrespective of the time period, and at public infrastructure during daytime hours. These patterns suggest the presence of two distinct user segments within the sample. The first consists of EV owners who charge at home during the day, likely taking advantage of electricity supplied by rooftop solar panels, whilst the second segment comprises users who rely more heavily on the public charging network, likely due to a lack of access to charging facilities either at home or at work. An autoregressive process of order 2 (AR(2)) is employed to capture potential temporal dependencies (i.e., state dependence) in EV charging patterns. In so doing, we seek to account for how past behaviour (charging activities undertaken up to days prior) influences the number of charging instances performed at time  $t$ . All of the estimated coefficients for the first lag are negative and highly statistically significant, indicating that recent charging activity leads to a reduced probability of repeated charging in the immediate future. That is to say that users are inclined to space out their charging events especially when it comes to charging at workplace and at *Supermarkets/shopping centres*. The second lag variables are also negative but smaller in magnitude. This points to a decaying pattern of earlier charging behaviour among EV users impacting current charging behaviour. Overall, these findings reveal the existence of a short-term negative state dependency in EV charging routines.

**Table 10: Model results by time of day and location choices**

	<b>Parameter</b>	<b>(t-ratio)</b>
<i>Baseline component</i>		
Home-Evening	-	-
Home-Overnight	1.488	(8.16)
Home-During the day	3.717	(11.71)
Work-During the day	-2.037	(-3.44)
Work-Evening/Overnight	-2.025	(-3.94)
Supermarkets/ Shopping centres-During the day	1.094	(2.53)
Supermarkets/ Shopping centres-Evening/Overnight	0.863	(2.97)
Destination chargers-During the day	-0.400	(-0.93)
Destination chargers-Evening/Overnight	-0.037	(-0.11)
Other public chargers-During the day	0.910	(1.87)
Other public chargers-Evening	-1.485	(-4.16)
Other public chargers-Overnight	-1.040	(-2.53)
Weekends (weekdays is base)		
Home-During the day	0.982	(9.40)
Work-During the day	-1.698	(-5.22)
Supermarkets/ Shopping centres-During the day	1.030	(5.05)
Supermarkets/ Shopping centres-Evening/Overnight	0.614	(2.57)
Destination chargers-During the day	0.862	(3.15)
Destination chargers-Evening/Overnight	0.703	(2.34)
Other public chargers-During the day	1.070	(5.87)
Other public chargers-Evening	1.091	(4.22)
Other public chargers-Overnight	1.395	(3.71)
Flexible electricity plan (no is base)		
Home-During the day	-0.569	(-4.00)
Electricity price at private dwellings (\$/kWh)		
Home-During the day	-1.014	(-2.43)
Other public chargers-During the day	0.707	(1.17)
Employed (non-employed is base)		
Home-During the day	-0.763	(-4.48)
Work-During the day	-0.254	(-0.51)
Supermarkets/ Shopping centres-During the day	-0.597	(-2.41)
Other public chargers-During the day	-0.465	(-1.97)
Free charging at work		
Work-During the day	2.718	(4.83)
Other public chargers-During the day	-0.032	(-0.08)
Distance to public charging outlets from home $\geq 17$ kms		
Home-During the day	0.183	(0.68)
<i>Satiation component</i>		
Home-Evening	0.061	(0.36)
Home-Overnight	0.502	(2.75)
Home-During the day	1.839	(5.90)
Work-During the day	1.202	(3.22)
Work-Evening/Overnight	0.803	(1.48)
Supermarkets/ Shopping centres-During the day	1.320	(4.39)
Supermarkets/ Shopping centres-Evening/Overnight	2.035	(4.21)
Destination chargers-During the day	0.544	(1.81)
Destination chargers-Evening/Overnight	0.609	(1.72)
Other public chargers-During the day	1.406	(3.76)
Other public chargers-Evening	1.003	(2.48)
Other public chargers-Overnight	1.015	(1.72)
Habit persistence effects		
Home-Evening at $t - 1$	-0.795	(-4.06)
Home-Evening at $t - 2$	-0.246	(-1.26)
Home-Overnight at $t - 1$	-0.771	(-4.04)
Home-Overnight at $t - 2$	-0.564	(-3.17)

Home-During the day at $t - 1$	-0.846	(-2.78)
Home-During the day at $t - 2$	-0.522	(-2.13)
Work-During the day at $t - 1$	-1.123	(-2.52)
Work-During the day at $t - 2$	-0.774	(-1.92)
Supermarkets/ Shopping centres-During the day at $t - 1$	-0.855	(-1.78)

## 4.2 Charging decisions by location

Results for charging location decisions are presented in Table 11. For model identification purposes, we assume that *Home* serves as the base reference category and, as such, unless otherwise stated, the impact of covariates on the other locations are interpreted relative to this alternative. Having solar panels at the respondent's residential location is measured via a dummy variable, which equates to one if the household has such infrastructure, or zero otherwise. The corresponding estimates are all negative and highly statistically significant, confirming the appeal of using solar-powered electricity for charging activities. The type of dwelling also plays a pivotal role in charging location choices. Living in an apartment significantly increases the probability of using public charging infrastructure, particularly for *Other public chargers* (2.30) and chargers located at *Supermarkets/shopping centres* (1.72). One possible cause for this outcome is the existence of barriers to installing private charging infrastructure in apartment buildings in Australia resulting from a reluctance by owners corporations (known as Strata committees in Australia) to grant approval of such infrastructure due to safety and cost concerns, as well as concerns surrounding the capability of the buildings existing electrical system to cope with the increased needs associated with EV charging (Pellegrini, Borriello and Rose, 2023). In contrast, individuals living in stand-alone residential buildings are more likely to charge at public stations compared to semi-detached/townhouse owners. Two dummy variables are included to quantify the effect of investment in home charging equipment. The first relates to an investment between \$1-\$1,000 and the other representing an expense of \$1,000 or more, such that the base is no expenditure. The corresponding estimated coefficients are negative and statistically significant, suggesting that EV owners who invest in home charging infrastructure have a lower likelihood of charging at alternative locations.

The more frequently EV owners commute to work by car, the higher the probability of charging at their workplace, and to a lesser extent, at *Supermarkets/shopping centres*, and restaurants or leisure sites. This suggests that work-related travel routines are crucial in shaping where charging events take place for employed individuals. In addition to this, access to free charging at work significantly increases the likelihood of choosing the person's workplace as a charging location, whilst showing no notable effect on the use of other charging alternatives. As expected, an increased in charging costs associated with the alternative *Other public chargers* leads to a higher propensity for users to choose different charging sites. It further appears that respondents have a higher inclination of using public charging facilities, especially at *Other public chargers* and at *Supermarkets/shopping centres*, when the

daily travel distance is  $\leq 30$  km per day). This perhaps reflects the convenience of top-up charging whilst running errands or participating in non-work-related activities.

Next, the explanatory variables age and geographical location enter the utility function for the charging location *Home*, meaning the corresponding estimated parameters should be interpreted relative to the other four charging location sites. The results indicate that older adults (aged 60 years and above) are more likely to charge at *Home* relative to their younger counterparts, whilst respondents who live in NSW are significantly less likely to charge their vehicles at their private dwellings, potentially due to the scarcity of off-street parking in urban areas.

Five state dependent variables are included in the discrete component of the model to measure the effect of habit persistence on charging location preferences. All parameters are reported to be highly statistically significant and positive, suggesting that EV owners tend to repeat their past charging location decisions indicating a form of habitual behaviour (similar habit patterns were observed within the context of time-use decisions by Luo, Ratchford and Yang, 2013). Notably, the largest values are observed for charging locations other than home. This likely reflects stronger habit formation among users who rely primarily on public charging network, often consisting of slower Level 1 (L1) chargers. Consequently, such users may exhibit more greater temporal dependency due to the need for more frequent top-up chargers.

With regards to the explanatory variables impacting the satiation parameters for charging locations, we observe that the availability of fast chargers (Level 3) at work decreases the proportion of daily charging instances occurring at *Home* and at *Supermarkets/shopping centres*. In contrast, accessing to fast chargers at work has no influence on the charging instances reported at *Destination chargers*, at workplace itself and at other public charging stations. Upgrading the electrical system at the persons place of residence is associated with a decreased in the frequency of charging at *Supermarkets/shopping centres* and *Destination chargers*, while increasing the charging frequency at *Home* (despite this latter finding being statistically significant at the 15 percent level). Compared to residents of semi-detached/townhouses and flats, those living in stand-alone houses appear to charge less frequently at *Supermarkets/shopping centres* and at *Work*, with the latter being marginally statistically significant at the 17 percent level. Lastly, the number of home charging instances diminishes as the size of the household fleet increases, suggesting that households with multiple vehicles are potentially more likely to use non-efficient cars for some trips.

**Table 11: Model results by location choices**

	Parameter	(t-ratio)
<i>Baseline component</i>		
Accessibility to solar panels (no is base)		
Work	-0.507	(-1.77)
Supermarkets/ Shopping centres	-1.136	(-6.18)
Destination chargers	-0.888	(-3.57)
Other public chargers	-1.297	(-6.67)
Flat (semi-detached/townhouse is base)		
Work	1.333	(2.26)
Supermarkets/ Shopping centres	1.723	(6.17)
Destination chargers	1.506	(4.00)
Other public chargers	2.301	(6.89)
Separate house (semi-detached/townhouse is base)		
Other public chargers	0.657	(2.85)
Installation costs to support charging at home \$1-\$1000 (0\$ is base)		
Work	-0.888	(-3.02)
Supermarkets/ Shopping centres	-0.655	(-3.92)
Destination chargers	-0.474	(-2.15)
Other public chargers	-0.606	(-3.53)
Installation costs to support charging at home $\geq$ \$1000 (0\$ is base)		
Work	-0.706	(-2.02)
Supermarkets/ Shopping centres	-0.930	(-4.22)
Destination chargers	-0.234	(-0.93)
Other public chargers	-0.800	(-3.71)
Days travelled to work by EVs		
Work	0.401	(5.66)
Supermarkets/ Shopping centres	0.138	(2.35)
Destination chargers	0.142	(2.81)
Free charging at work (1/0)		
Work	1.615	(3.25)
Supermarkets/ Shopping centres	-0.249	(-0.92)
Other public chargers	-0.055	(-0.17)
Electricity price at public outlets (\$/kWh)		
Other public chargers	-0.718	(-1.84)
Daily VKT $\leq$ 30km		
Work	0.185	(0.66)
Supermarkets/ Shopping centres	0.646	(3.68)
Destination chargers	0.153	(0.63)
Other public chargers	0.898	(5.19)
Habit persistence effects		
Home at $t - 1$	0.934	(9.63)
Work at $t - 1$	1.548	(7.06)
Supermarkets/ Shopping centres at $t - 1$	1.763	(10.34)
Destination chargers at $t - 1$	2.582	(11.72)
Other public chargers at $t - 1$	1.529	(9.54)
Age 60 and above (1/0)		
Home	0.695	(4.03)

Geographical location (remaining states and territories are base)		
Home:		
NSW	-0.428	(-2.84)
Western Australia	0.162	(0.45)
Victoria	-0.195	(-1.17)
<i>Satiation component</i>		
Availability of fast charging bays at workplace		
Home	-0.578	(-2.41)
Work	-0.360	(-0.82)
Supermarkets/ Shopping centres	-1.091	(-1.82)
Destination chargers	-0.987	(-1.42)
Other public chargers	-0.280	(-0.32)
Upgrade of home electrical system (no is base)		
Home	0.168	(1.44)
Work	0.147	(0.33)
Supermarkets/ Shopping centres	-0.749	(-1.78)
Destination chargers	-0.663	(-1.69)
Other public chargers	-0.472	(-1.48)
Separate house (semi-detached/townhouse is base)		
Home	0.141	(1.16)
Work	-0.609	(-1.38)
Supermarkets/ Shopping centres	-0.914	(-2.25)
Household vehicle fleet		
Home	-0.071	(-1.55)
Other public chargers	-0.113	(-0.89)

### 4.3 Charging decisions by time of day

The effect of covariates on time of day charging decisions is assessed by setting evening and overnight as the reference timeframe and are shown in Table 12. Specifically, high-income households (earning \$3,000 or more per week) are more inclined to charge their vehicles during the day compared to respondents from a lower-income household, suggesting that this segment is likely to be less sensitive to electricity prices. The presence of children under the age of 18 living in the household appears to increase the likelihood of undertaking daytime charging, possibly because parents may charge their vehicles whilst being involved in grocery shopping or pick up/drop off activities. Finally, Queenslanders prefer charging during the day whilst the opposite is true for Victorians (the latter is statistically significant at the 11 percent).

**Table12: Model results by time-of-day choices**

	Parameter	(t-ratio)
<i>Baseline component</i>		
Weekly Household income $\geq$ \$3000		
During the day	0.304	(2.27)
Presence of children under 18 years of age		
During the day	0.269	(2.03)
Geographical location (remaining states and territories are base)		
During the day:		
NSW	-0.179	(-0.93)
Queensland	0.472	(1.90)
Victoria	-0.332	(-1.60)

#### 4.4 Substitution patterns

Four error components are incorporated into the baseline utility functions to capture unobserved correlation patterns across alternatives (shown in Table 13). Specifically, *Home-Evening* and *Home-Overnight* are found to be highly substitutable charging location/time-slot alternatives, likely due to convenience and cost-effectiveness. There is also a moderate substitution effect across public charging locations, indicating that there exist EV owners who may use multiple public charging sites depending on their travel needs or possibly because they are not able to charge their cars at home. Further, the error component that links *Home-Evening* and *Other public chargers-Evening* suggests that these two locations are likely to be substitutes. Finally, respondents who charge overnight at *Home* are less likely to do it again at *Work* during the day.

**Table 13: Error component estimates**

	Parameter	(t-ratio)
<i>Baseline component</i>		
Error components		
Home-Evening & Home-Overnight	3.487	(15.59)
Supermarkets/ Shopping centres-During the day & Destination chargers-During the day & Other public chargers-During the day	1.623	(11.25)
Home-Evening & Other public chargers-Evening	2.484	(12.49)
Home-Overnight & Work-During the day	3.470	(18.39)

## 5. MODEL APPLICATION

In this section, we present results from a forecasting exercise undertaken to evaluate changes in charging preferences in response to variations in a) electricity prices at public outlets (i.e., *Other public charging locations*), and b) electricity prices at private dwellings. We begin by forecasting the individual-level fraction of total charging occurrences across the twelve location/timeframe alternatives using the prediction algorithm formalized in Pinjari and Bhat (2022) (see also, Pellegrini, Rose and Scarpa, 2022), after averaging the resulting charging shares over 500 MLHS draws and aggregate at the location level.

Finally, elasticity values are calculated as the ratio of the change in predicted charging demand under scenarios (a) and (b) relative to the baseline scenario where electricity prices remain unchanged.

The forecasting framework is grounded on the premise that EV owners exhibit habitual behaviour with regards to where, when and how frequently they charge their vehicles. The model specification proposed reveals evidence of entrenched routines that characterize EV users' charging decisions that are expected to be retained in the absence of *external stimuli*. Within this application context, variations in electricity prices, both at public infrastructure and private settings, can be seen as exogenous stimuli resulting from, for example, government policy initiatives, inflation induced adjustments by electricity providers, or household budgetary decisions. The latter refers to situations wherein households may opt to switch to a different provider to reduce their energy costs in the light of more competitive electricity rates (per kWh). Thus, these stimuli are likely to influence both the spatial (i.e., location of charging) and the temporal dimension (i.e., time of day) of EV users' charging behaviour.

Table 14 presents elasticity estimates of charging location preferences due to percentage changes in electricity prices at *Other public charging locations*. The table columns correspond to relative price variations in \$/kWh at public bays from -15 percent to +15 percent, whereas each cell refers to the charging demand change at a given location relative to the base case. The elasticity measures are further disaggregated by weekdays and weekends, in order to provide a comprehensive view as to how EV charging preferences evolve throughout the week due to price variations at public stations.

**Table 14: Price elasticities due to variations in \$/kWh at public outlets**

	<i>Weekdays</i>					
	<b>-15%</b>	<b>-10%</b>	<b>-5%</b>	<b>+5%</b>	<b>+10%</b>	<b>+15%</b>
Home	-0.17%	-0.12%	-0.06%	0.06%	0.11%	0.15%
Workplace	-0.17%	-0.17%	-0.06%	0.01%	0.12%	0.16%
Supermarkets / shopping centres	-0.49%	-0.29%	-0.17%	0.14%	0.30%	0.45%
Destination Chargers	-0.43%	-0.28%	-0.16%	0.16%	0.28%	0.42%
Other Public Charging Stations	1.71%	1.15%	0.59%	-0.55%	-1.08%	-1.59%
	<i>Weekend</i>					
	<b>-15%</b>	<b>-10%</b>	<b>-5%</b>	<b>+5%</b>	<b>+10%</b>	<b>+15%</b>
Home	-0.21%	-0.13%	-0.07%	0.07%	0.14%	0.20%
Workplace	-0.26%	-0.24%	-0.07%	0.13%	0.25%	0.25%
Supermarkets / shopping centres	-0.56%	-0.38%	-0.17%	0.21%	0.36%	0.56%
Destination Chargers	-0.54%	-0.34%	-0.18%	0.15%	0.34%	0.51%
Other Public Charging Stations	1.56%	1.01%	0.50%	-0.51%	-1.03%	-1.50%

From the table, we can observe that electricity price changes at public infrastructure lead to notable variations in charging behaviour decisions, both across locations and between weekdays and weekends. The estimated elasticities for *Other Public Charging Stations* reveal that the demand for public chargers

fluctuates between +1.71 percent to -1.59 percent on weekdays, and between +1.56 percent to -1.50 percent, on weekends, in response to a  $\pm 15$  percent change in electricity prices. These results highlight the high price sensitivity associated with public charging, suggesting that users are clearly more responsive to electricity rate changes when using non-private charging alternatives. In contrast, home charging exhibits consistently low elasticity, with maximum variations estimated to fall between  $\pm 0.21$  percent across all scenarios. This is unsurprising, in the sense that EV users with access to private chargers are generally less responsive to marginal cost variations in the public charging network. An additional insight is that home charging appears to be slightly more elastic on weekends, possibly reflecting behavioural adaptations following longer trips typically performed during the weekend. In such cases, EV users may be keen to delay charging their vehicles until returning home, thereby avoiding having to rely on public charging infrastructure, which may be perceived as more costly (as per the current scenario), less convenient or less reliable due to factors such as queuing, limited bays availability or equipment malfunction. In a similar vein, workplace charging elasticities tend to be lower on weekdays due to limited alternative charging opportunities during workday, and slightly higher on weekends, albeit such changes arising from a small base of usage. *Supermarkets/shopping centres* and *Destination chargers* show moderate elasticities with higher values reported for weekends. Specifically, demand for chargers located at supermarkets and shopping centres is foreseen to grow by up to 0.42 percent on weekdays and up to 0.56 percent on weekends. A similar pattern emerges at charging facilities situated at restaurants, cinemas, or hotels, where the likelihood of charging increases by up to 0.51 percent. These findings indicate that *Supermarkets/shopping centres* and *Destination chargers* can, in all likelihood, act as substitute locations within EV users' charging strategies, especially during the weekend when travel purposes tend to be more flexible.

Table 15 presents the estimated own and cross price elasticities obtained from simulating changes in the electricity rate at private dwellings, segmented by weekdays and weekend. Because the electricity price parameter enters the utility function of the alternative *Home – During the day*, it is possible to examine how charging demand varies not only across different locations (e.g., home versus workplace), but, more importantly, across different time periods (daytime, evening and overnight) within the home setting. On weekdays, a 15 percent decrease in electricity price generates a 1.03 percent increase in home daytime charging, whereas a 15 percent increment results in 1.03 drop in charging demand, suggesting that EV drivers are highly responsive to cost changes during daylight hours. On weekends, the response to price variations is slightly less elastic with +0.84 percent and -0.87 percent demand changes due to a  $\pm 15$  percent change in electricity prices. In contrast, overnight and evening home charging exhibit much smaller changes, suggesting that these two time periods are less elastic, and, perhaps, more routine-driven. Notably, overnight charging appears to be a substitute for daytime when prices rise, indicating the potential inclination among EV drivers to shift charging activities to off-peak hours so as to alleviate the impact of increasing costs on the household budget.

**Table 15: Price elasticities due to variations in \$/kWh at private dwellings**

		<i>Weekdays</i>					
		<b>-15%</b>	<b>-10%</b>	<b>-5%</b>	<b>+5%</b>	<b>+10%</b>	<b>+15%</b>
Home		0.73%	0.45%	0.24%	-0.23%	-0.50%	-0.78%
	<i>Overnight</i>	-0.17%	-0.13%	-0.04%	0.08%	0.13%	0.17%
	<i>Evening</i>	-0.13%	-0.10%	-0.05%	0.03%	0.05%	0.08%
	<i>During the day</i>	1.03%	0.67%	0.34%	-0.34%	-0.67%	-1.03%
Workplace		-0.17%	-0.12%	-0.04%	0.08%	0.12%	0.17%
Supermarkets / shopping centres		-0.28%	-0.18%	-0.12%	0.07%	0.16%	0.25%
Destination Chargers		-0.29%	-0.20%	-0.08%	0.10%	0.17%	0.26%
Other Public Charging Stations		-1.19%	-0.78%	-0.37%	0.42%	0.88%	1.31%
		<i>Weekend</i>					
		<b>-15%</b>	<b>-10%</b>	<b>-5%</b>	<b>+5%</b>	<b>+10%</b>	<b>+15%</b>
Home		0.49%	0.34%	0.17%	-0.15%	-0.37%	-0.57%
	<i>Overnight</i>	-0.21%	-0.10%	-0.05%	0.10%	0.16%	0.21%
	<i>Evening</i>	-0.12%	-0.09%	-0.06%	0.03%	0.06%	0.09%
	<i>During the day</i>	0.84%	0.55%	0.28%	-0.28%	-0.58%	-0.87%
Workplace		-0.15%	-0.16%	0.03%	0.09%	0.18%	0.17%
Supermarkets / shopping centres		-0.14%	-0.08%	-0.06%	0.06%	0.12%	0.19%
Destination Chargers		-0.24%	-0.15%	-0.08%	0.06%	0.14%	0.21%
Other Public Charging Stations		-1.04%	-0.73%	-0.36%	0.34%	0.69%	1.03%

Charging at *Other Public Charging Stations* show significant responsiveness to price changes with demand shifts ranging between -1.04 percent and 1.03 percent at  $\pm 15$  percent variation in home electricity prices. This indicates that EV users may tend to replace home charging with public charging when home electricity becomes more costly. Moderate elasticity values are estimated for charging at workplace, especially on weekends due to reduced commuting or availability of alternative charging opportunities. *Supermarkets/shopping centres* and *Destination chargers* seem to become feasible alternative charging solutions when home electricity price increases by 15 percent, possibly because charging at these locations can be paired with other activities, such as running errands, dining or entertainment.

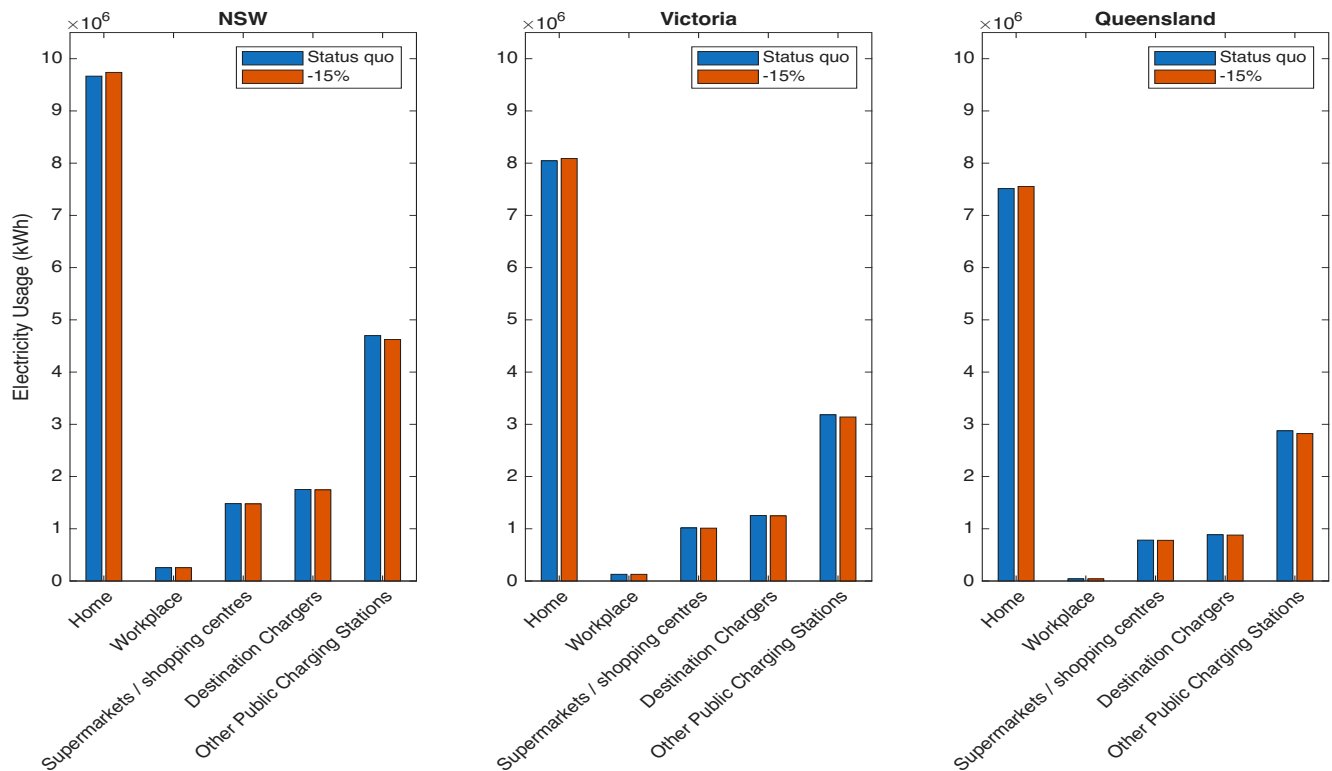
In addition to estimating charging demand elasticities, the model proposed can also be used to predict the impact of electricity price reduction on grid load. In what follows, we simulate the effects of a 15 percent reduction in home electricity prices on the weekly electricity grid demand for three of the most represented states within the sample, namely NSW, Victoria and Queensland. The assumptions that we make for this simulation are reported in Table 2. The first three rows of the table reports the average length of charging activities obtained from the sample of respondents. Specifically, it is possible to note that a typical home charging session in NSW lasts, on average, 6.24 hours compared to 6.00 hours in Victoria, and 5.86 hours in Queensland. At workplaces, charging sessions are longest in Victoria at 4.75 hour, followed by NSW at 4.36 hours and Queensland at 3.18 hours. Further, the average typical charging session at public outlets amounts to 47.88 minutes in NSW, 52.92 minutes in Victoria and 39.12 minutes in Queensland.

**Table 16: Prediction assumptions**

	NSW	Victoria	Queensland
Typical average home charging duration (hours)	6.24	6.00	5.86
Typical average work Charging duration (hours)	4.35	4.75	3.18
Typical average public charging duration (minutes)	47.88	52.92	39.12
Home charging technology	7.20 kWh		
Work charging technology	12.71 kWh		
Supermarkets/shopping centres	7.20 kWh		
Destination chargers	7.20 kWh		
Public charging technology	22.00 kWh		
Home charging accessibility	92.92%		
Work charging accessibility	27.89%		
Workforce distribution	33.95%	23.16%	11.67%
# of BEV on roads	49,768.00	41,546.00	34,495.00
# of PHEV on roads	3,239.60	830.92	1,913.94
Total number of EVs	53,007.60	42,376.92	36,408.94
Drivers with home charging access	49,252.90	39,375.22	33,829.97
Drivers with work charging access	5,019.57	2,737.48	1,184.89

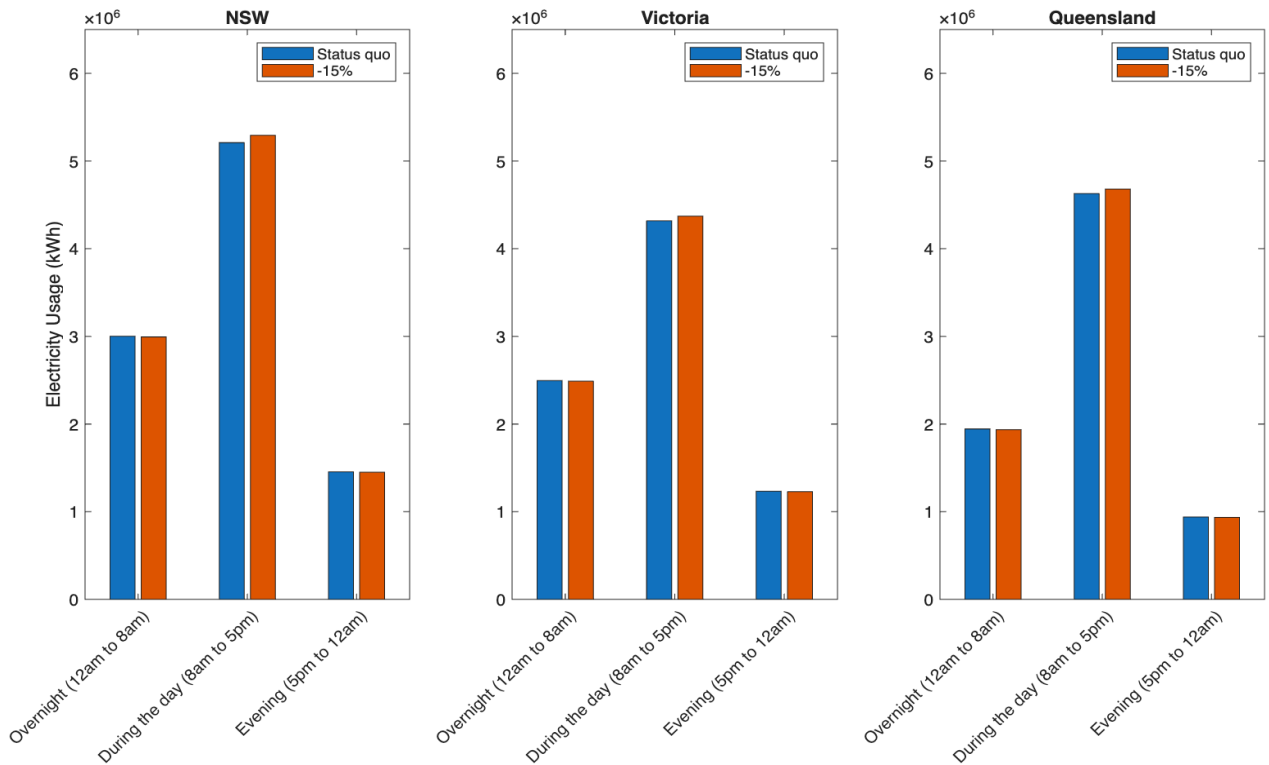
In terms of charging technology, home chargers are assumed to operate at 7.20 kWh, similar to the power levels typically used at public chargers located at *Supermarkets/shopping centres* or at *Destination chargers*. The average charging rate at workplaces is derived by weighting the proportion of slow and fast chargers, with fast chargers accounting for only three percent of the available workplace charging infrastructure. On the other hand, the charging rate for public charging outlets is assumed to be 22.00 kWh, with this value representing the typical power level of the public charging stations used by respondents. Next, we calculate from the sample the fraction of EV drivers who have access to home and work charging facilities, finding that nine in ten respondents report being able to charge their vehicles at home. Alongside home and work charging accessibility, we also compute the distribution of workers across the three states, with NSW accounting for 39 percent followed by Victoria (23.2 percent) and Queensland (11.7). For each state, we obtain the EV take up as of January 2024 from the Australian Automobile Association website (<https://www.aaa.asn.au/research-data/electric-vehicle/>), which we then use to determine the number of EV owners with access to home and work charging infrastructure. Figure 2 presents electricity usage (expressed in kilowatt-hours) across the five charging locations for NSW, Victoria and Queensland. The status quo is compared against the above-mentioned scenario (b), in which the electricity price at private dwellings drops by 15 percent. Under both scenarios, it can be observed that home charging accounts for the largest electricity share across the three states. When

residential electricity costs are reduced by 15 percent, weekly home charging usage increases in all states, reaching 9.7 million kWh (+0.74 percent) in NSW, 8.09 million kWh (+0.54 percent) in Victoria, and 7.55 million in kWh (+0.53 percent) in Queensland. This suggests that even a small reduction in residential electricity prices can translate into substantial additional load on the grid due to the scale of home charging uptake.



**Figure 2: Simulated charging grid load**

On the other hand, grid load from workplace charging shows relatively little variation. In NSW, usage decreases marginally from 255,707 kWh to 254,863 kWh, whilst in Victoria it drops from 128,325 kWh to 127,997 kWh, and in Queensland from 40,052 kWh to 39,865 kWh. A similar pattern can be observed for charging at all public facilities thus suggesting that lowering home electricity costs has a negligible effect on usage at these sites. In summary, the overall grid load from non-residential locations remains predominately stable, with home charging being the primary impacted alternative. Next, in Figure 3, we break down the impact of residential cost changes on charging patterns by time of day. From the figure, it appears that the grid load from home charging is primarily attributable to daytime, where electricity usage is at its highest across all states due to a 15 percent reduction in electricity costs. Indeed, while electricity demand remains relatively stable during evening and overnight periods across states, a substantial increase can be observed between 8am and 5pm. From grid management perspective, these findings indicate that low residential tariffs may lead to substantial change in home charging frequency patterns, which without effective load balancing measures, could exacerbate the demand for electricity in residential areas.



**Figure 3: Simulated home charging grid load by time of day**

## 6. CONCLUDING REMARKS

This study reveals a distinct pattern of EV charging behaviour marked by habitual routines and a strong preference for home-based charging. To account for habit persistence, we develop a model of discrete/continuous demand that investigates the complexity of real-world charging decisions. Unlike previous studies, the model proposed jointly evaluates both the spatial and temporal dimensions of charging behaviour, capturing the determinants affecting location and time of day charging choices made by Australian EV owners over a one-week period. Doing so allows for a more realistic representation of charging routines, in the sense that it explicitly recognises that EV users may charge at multiples locations and at different times. By incorporating a state dependent based structure, the model also unveils the presence of time dependencies, showing that past charging activities are likely to affect current decision-making process. The data suggest that users tend to establish consistent patterns, charging at predictable times and locations, which underscores the role of personal routine in shaping energy consumption.

Empirical results highlight the prevalence of home charging, especially during daylight hours where EV users can benefit from electricity originated from solar panels. Investing in technology equipment (e.g., smart meter) significantly increases the likelihood of home charging, whilst flexible electricity plans seem to encourage off-peak charging. Further, public and workplace remain secondary

options, with the former being more sensitive to price changes whilst the latter being mostly underutilized due to limited infrastructure availability. The prediction exercise allows for identifying distinct user segments: those who rely mostly on home charging and those dependent on public infrastructure. In this regard, price elasticity simulations outline that public charging is more sensitive to electricity price variations than home charging, and that daytime charging at home augments substantially when residential electricity prices drop, thus potentially causing load on the grid.

Given that private dwellings remain the most chosen charging location, policies should be designed to support the installation of dedicated charges, especially for households residing in apartment blocks. To the latter case, it becomes essential to update building codes in new developments so as to make dwellings ready for EVs. Incentives for endowing properties with smart meters and rooftop solar system can further trigger sustainable charging habits and reduce grid dependency. Lastly, charging at work may become a feasible alternative for many without access to private home chargers. This can be facilitated by offering subsidies or tax incentives to encourage businesses to upgrade the existing infrastructure to allow for charging activities at the workplace.

Behavioural insights from the paper carry several policy implications. First, the predominance of home charging implies a need to bolster residential charging infrastructure, including incentives for home charger installations and grid upgrades to support increased localized demand. Second, the habitual nature of charging highlights the importance of designing interventions, such as time-of-use pricing or smart charging programs, that align with and subtly influence established user routines, rather than seeking to disrupt them. Third, given that a potential increase of electricity prices may shift charging to off-peak periods, policymakers could explore flexible demand strategies to further optimize grid efficiency and integrate renewable energy sources. Ultimately, a nuanced understanding of user behaviour must inform EV policy design. By recognizing and working with ingrained charging habits rather than against them, governments and energy providers can craft targeted strategies that support the continued growth of EV adoption while safeguarding grid reliability and sustainability.

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