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From New to Second-Hand: Consumer Trade-offs Between Price, Range and Vehicle Condition for BEVs and Hybrids in Australia

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ABSTRACT: Most empirical work on vehicle choice has focused on new-vehicle purchase decisions, even though households often acquire vehicles through the second-hand market and face a different set of constraints and information conditions. This paper addresses that gap by estimating a single choice framework that spans new and second-hand passenger vehicle markets, allowing direct comparison of how consumers value vehicle attributes and how substitution patterns differ across the two segments. We use a discrete choice experiment administered to a New South Wales sample, with alternatives that include new and second-hand vehicles and an opt-out, and attributes that reflect both markets, including purchase price, body type, vehicle size, powertrain, range, delivery availability for new vehicles, and odometer and condition for second-hand vehicles. Preferences are estimated using a two-class latent class model with error components to capture correlation in unobserved utility and segment-specific substitution within new and second-hand markets. The results show substantial heterogeneity in valuations and clear differences between new and second-hand decision processes, with second-hand quality signals exerting economically meaningful effects and price sensitivity being stronger for second-hand choices. Powertrain attributes matter, but their implications vary by market segment and by class, indicating that technology preferences interact with the institutional and informational features of the market in which the vehicle is acquired. Applying the estimated class-membership model to population microdata, we generate conditional parameter and willingness-to-pay distributions for a large synthetic population and predict market shares for simulated vehicle profiles. The simulation results underscore that secondary-market dynamics materially shape predicted demand patterns, which has implications for policies and market designs that aim to influence fleet composition through interventions that operate in, or propagate through, the second-hand market.

KEY WORDS: ***New and second-hand vehicle markets, discrete choice experiment, latent class model, error components logit, willingness to pay***

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1.0 INTRODUCTION

Decarbonising passenger transport requires not only the diffusion of low-emission vehicle technologies but also the establishment of market conditions that make those technologies broadly accessible and practically usable. Battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs), including plug-in hybrid electric vehicles (PHEVs), have become central to transport decarbonisation strategies because they offer substantial tailpipe emissions reductions relative to conventional internal combustion engine (ICE) vehicles. Yet, the transition is constrained by well-documented barriers, including high upfront purchase prices, concerns about driving range and charging convenience, and uncertainty regarding operating performance and resale values (Rezvani et al., 2015; Liao et al., 2017). These barriers are not merely "new-car" issues. They interact with the functioning of the second-hand vehicle market, which is the dominant channel through which many households acquire cars and a critical pathway through which new technologies become affordable over time.

The used-car market is also where information and transaction frictions are most consequential. Classic economic theory shows that when quality is imperfectly observed by buyers, an inherent feature of used durable goods, trade can be distorted by adverse selection, with lower-quality vehicles disproportionately offered for sale unless institutions such as warranties, certification, inspections, and reputation systems mitigate the information gap (Akerlof, 1970). Empirical work on used-car wholesale and retail settings has repeatedly highlighted how trading mechanisms and information structure shape price formation and allocations (Genesove, 1993, 1995; Emons and Sheldon, 2009). These market characteristics matter directly for electrified vehicles because used BEVs embed additional latent-quality components, most notably battery state-of-health and degradation trajectories, that are difficult for typical consumers to verify. Consequently, consumer willingness to purchase a used BEV may depend on quality signals and risk mitigants (e.g., condition ratings, warranties) at least as much as on conventional depreciation proxies such as age and mileage.

A further motivation for explicitly studying secondary markets for electrified vehicles is that resale values and depreciation patterns influence both private adoption decisions and the policy effectiveness of incentives. If BEVs depreciate faster than comparable ICE vehicles, potentially due to rapid technological improvements and shifting perceptions of obsolescence, then the total cost of ownership, leasing conditions, and the distribution of benefits from purchase subsidies may differ materially from standard assumptions (Schloter, 2022). These dynamics imply that policy interventions aimed at accelerating electrification (e.g., purchase rebates, charging infrastructure investments, information disclosure standards) should be evaluated with explicit attention to how they operate through *both* new and used markets, and how they affect different consumer segments.

Within this context, discrete choice experiments (DCEs) have become a primary empirical tool for quantifying the trade-offs consumers make among vehicle attributes and technology types, and for forecasting market shares under counterfactual policy scenarios. DCEs grounded in random utility maximisation allow researchers to infer marginal utilities for price, range, and other attributes, and to translate these estimates into willingness-to-pay measures and simulated uptake under alternative policy designs (McFadden, 1974; Ben-Akiva and Lerman, 1985). Contemporary practice in transport demand modelling also emphasises accounting for taste heterogeneity, particularly salient in vehicle markets where constraints such as home charging access, trip patterns, and risk attitudes vary widely, through flexible model structures such as mixed logit and latent class models (Train, 2009; McFadden and Train, 2000; Hensher et al., 2015).

Although the stated-preference literature on BEV and hybrid adoption is extensive, most studies focus on new-vehicle choices and emphasise the "core EV bundle" of purchase price, operating costs, driving range, charging time, and charging availability (e.g., Hidrue et al., 2011; Hoen and Koetse, 2014; Tanaka et al., 2014; Ardeshiri and Rashidi, 2020; Pellegrini and Rose, 2026). Australia-focused evidence similarly demonstrates that price and perceived relative advantages are central to adoption intentions and preferences (Ghasri et al., 2019). However, comparatively fewer studies integrate these electrification-specific attributes with the defining characteristics of used-vehicle markets, age, odometer, condition, and acquisition frictions, within a unified choice framework that permits substitution across ICE, BEV, PHEV, and HEV technologies. This is a significant gap due to the fact that the behavioural decision that many households face is not "new BEV versus new ICE," but rather a broader choice among new and used vehicles across multiple powertrains, subject to budget constraints, perceived risk, and supply/availability conditions.

This paper addresses that gap using a discrete choice experiment implemented in Australia that jointly represents (i) technology choice among petrol, diesel, BEV, PHEV, and HEV options, and (ii) new versus used acquisition contexts. The experimental design includes attributes that reflect both electrification constraints and second-hand market frictions: engine type, body type, vehicle size, vehicle age, driving range, odometer reading, purchase price, availability/waiting time, and vehicle condition. This structure enables direct estimation of how consumers trade off price and convenience against used-market quality signals, and whether these trade-offs differ systematically across powertrain technologies. The results are intended to inform policy analysis and market design questions central to transport planning and evaluation, such as how incentives, infrastructure provision, and information disclosure (e.g., certification of condition or battery health) might alter uptake trajectories and the distribution of benefits across consumer groups.

The remainder of the paper is organised as follows. The next section reviews research on used-car market functioning and the role of information frictions and transaction costs, and then synthesises stated-preference evidence on consumer preferences for BEVs and hybrid vehicles, with particular attention to discrete choice methods and heterogeneity. The subsequent sections describe the experimental design and econometric framework, present estimation results and policy simulations, and discuss implications for transport policy and the development of second-hand markets for electrified vehicles.

2.0 LITERATURE REVIEW

The decarbonisation of the passenger vehicle fleet will depend not only on the supply and uptake of new battery electric and hybrid electric vehicles (BEVs and HEVs/PHEVs), but also on the extent to which these technologies diffuse through the *second-hand* vehicle market. Taking Australia as an example, household vehicle ownership is high and used-vehicle transactions are large relative to new sales[1] . Consequently, the second-hand market is a primary channel through which lower- and middle-income households access vehicle technologies, and where distributional consequences of transport decarbonisation will ultimately be realised. Yet, compared with the extensive literature on new-vehicle demand and policy incentives, evidence on how consumers value electrified powertrains *when vehicles are used* remains comparatively limited.

A core reason for this is that the second-hand market is not simply a scaled version of the new-vehicle market. It has distinct informational frictions, quality uncertainty, and institutional

[1] The Australian Automotive Dealer Association (AADA), using AutoGrab data, reports 2,324,805 used vehicle sales in 2024, whilst the Federal Chamber of Automotive Industries reports 1,220,607 new vehicle sales during the same year

features (e.g., inspections, warranties, auction mechanisms, dealer intermediation) that shape prices and matching. The foundational economics of quality uncertainty in used goods markets traces to Akerlof's "lemons" model, which uses used cars as the motivating example and highlights how asymmetric information can degrade market quality and reduce trade (Akerlof, 1970). Building on this insight, subsequent work emphasises that durable goods markets exhibit dynamic interactions between primary and secondary markets, with resale opportunities influencing new-car demand, product positioning, and welfare (Hendel and Lizzeri, 1999; Gavazza et al., 2014).

At a micro-institutional level, wholesale auctions and dealer behaviour provide a rich setting to test theories of adverse selection and search. Genesove (1993) studies adverse selection in the wholesale used-car market and finds only weak evidence of the canonical lemons' mechanism in that setting, suggesting that market institutions may partially mitigate information problems. Genesove (1995) models seller reserve decisions in wholesale used-car auctions as a search problem, leveraging the fact that offers are observed whether or not a sale occurs. These studies are influential because they underscore that "used-car quality" is multidimensional and only imperfectly summarised by readily observable signals such as age and mileage, an issue that becomes even more salient for electrified vehicles when battery condition is uncertain to buyers.

Beyond auction settings, a substantial literature models vehicle replacement and the joint determination of new and used demand. Structural approaches treat consumers as making dynamic decisions under transaction costs and depreciation, recognising that a used vehicle may be both a substitute for and a stepping-stone toward a new purchase. Schiraldi (2011), for example, estimates a dynamic model of demand for new and used cars and highlights the importance of transaction costs in shaping replacement behaviour and secondary-market turnover. In related work on oligopoly with secondary markets, Esteban and Shum (2007) analyse how secondary markets affect firms' incentives and equilibrium outcomes in the automobile context. Together, these contributions motivate the view that electrification policies that focus narrowly on new-vehicle sales can have delayed or uneven impacts if secondary-market dynamics are ignored.

Unlike the new vehicle market, the used-car market is also characterised by frictions that can impede rapid reallocation from low-valuation to high-valuation owners. Gavazza et al. (2014) quantify the welfare and allocative implications of secondary markets, highlighting that gains from trade arise from heterogeneity in willingness to pay for vehicle quality (e.g., newer vintages), while transaction costs slow adjustment. This perspective is directly relevant to electrified powertrains as some consumers may place a high value on BEV attributes (e.g., low running costs, environmental benefits) whilst others may be deterred by range or charging constraints, such that then the second-hand market can in principle facilitate sorting, provided that information and perceived risks do not prevent trade.

A practical implication of information frictions is that used markets rely heavily on *signals* of latent quality and future costs. Observable attributes such as age (model year), odometer (mileage), and condition summaries are routinely used by buyers as proxies for remaining durability and maintenance risk. The academic literature similarly treats used prices as an outcome of both physical depreciation and information/uncertainty about reliability. Hedonic approaches are common in this space because they decompose observed prices into implicit valuations of characteristics. For example, Prieto et al. (2015) study reliability information and demonstrate asymmetric effects consistent with behavioural valuation patterns in used-car pricing. While not BEV-specific, such findings generalise to contexts where reliability perceptions and risk are salient, an issue that is likely heightened for electrified vehicles when buyers face uncertainty about battery degradation, replacement costs, and future technological obsolescence.

A complementary mechanism is technological progress such that when newer vintages embody substantial quality improvements, older vintages may experience faster value decline even absent "physical" deterioration. Using detailed second-hand market data from Norway, a mature EV market, Andreassen and Lind (2024) provide evidence consistent with faster value decline for electric vehicles relative to gasoline vehicles, linking this to the economics of rapid technological change in low-carbon technologies. This emerging depreciation literature is important for preference studies because it suggests that consumers may interpret "vehicle age" differently across powertrains: for BEVs, age can proxy not only general wear-and-tear but also *vintage technology* (range, charging, software, battery management) and perceived obsolescence. In a discrete choice experiment (DCE), including both *vehicle age* and BEV-relevant performance attributes (e.g., range) therefore has a clear behavioural rationale.

A further distinguishing feature of BEVs and (to a lesser extent) PHEVs is therefore the central role of battery performance, technological progress, and policy incentives in determining residual values. Rapid improvements in range and charging performance for new models can depress the value of earlier vintages, while consumer concerns about degradation and replacement costs may amplify depreciation. Recent empirical evidence suggests that BEV depreciation patterns can differ materially from conventional vehicles, suggesting that as we move towards more mature EV markets, that technological obsolescence can be a first-order determinant of used BEV values. For example, Andreassen and Lind (2024) use extensive Norwegian second-hand listings data and find faster price decline for electric vehicles than for gasoline vehicles, with the difference concentrated among lower-range models, consistent with rapid improvements in new-model range reducing the relative attractiveness of older vintages. Indeed, for BEVs in particular, depreciation may differ from ICE vehicles because rapid technological progress shifts the performance frontier (notably driving range, charging capability, and model variety). Complementing this, Schloter (2022), analysing large multi-country samples of used sales, found higher depreciation rates for electric vehicles than for gasoline vehicles, concluding that stakeholders (including insurers, lessors, and policymakers) should not assume common depreciation schedules across propulsion types, reinforcing the view that residual value risk is material in electrified-vehicle diffusion. These findings matter for policy because residual values influence leasing, financing, and household cost-of-ownership calculations; they also point to the importance of explicitly representing range (and, by extension, battery condition) when studying used BEV demand.

Despite increasing attention to BEV depreciation, comparatively fewer peer-reviewed studies focus on *buyer-side acceptance* of second-hand electrified vehicles. Pedrosa and Nobre (2018) provide an early, targeted look at consumer reception of second-hand electric vehicles, explicitly identifying the secondary market as under-studied relative to new EV adoption. More recently, Meisel et al. (2024) analyse consumer preferences for pre-owned electric vehicles and show that second-hand EV demand is shaped by a distinct bundle of concerns compared with new purchases. This emerging literature supports the premise that modelling used BEV choices cannot simply transpose determinants from new EV studies, due to the fact that secondary-market buyers evaluate a different risk set (battery health uncertainty, warranty remainder, charging compatibility for older models, and accelerated obsolescence) and operate under tighter budget constraints.

2.1 What do consumers value in BEVs, PHEVs, and HEVs in general?

A large peer-reviewed literature examines consumer preferences for electrified powertrains, with consistent evidence that purchase price and total cost are dominant, while range, charging time, charging access, and risk perceptions also remaining key barriers for BEV uptake. Two influential reviews synthesise this evidence and identify recurring gaps. Rezvani et al. (2015) review drivers and barriers to plug-in EV adoption and emphasise the role of perceived attributes, psychological factors, and heterogeneity across population segments. Liao et al. (2017) similarly review the stated-preference and revealed-preference evidence on EV preferences and propose frameworks to organise findings across economic and psychological approaches.

Within this literature, DCEs are particularly prominent because they allow researchers to evaluate trade-offs across a bundle of vehicle attributes and to simulate uptake under counterfactual policy scenarios. Hidrue et al. (2011) is a widely cited early example. Using stated choice data, they quantify willingness to pay (WTP) for key EV attributes and show that driving range and charging time are central drivers of valuation. The salience of range is also consistent with the idea that, in used markets, range may be interpreted as both *capability* and *signal* of battery condition, particularly when direct battery health information is unavailable. Indeed, much research evidence repeatedly finds that *range* is a pivotal BEV attribute, often interpreted as both functional capability and an anxiety-reducing signal. Studies also show that *hybrid* and *plug-in hybrid* options can serve as "bridge technologies," valued by consumers who desire electrification benefits while retaining flexibility under imperfect charging infrastructure. For instance, Hoen and Koetse (2014) and Tanaka et al. (2014) use choice experiments to quantify willingness to pay for alternative fuel vehicle attributes, including trade-offs among purchase price, operating features, and powertrain type. These analyses underscore that consumers do not adopt "electrification" in the abstract. Rather they adopt specific vehicle configurations whose desirability depends on body type, size/class, and the household's travel patterns and constraints, factors that are particularly salient for Transport Policy–oriented interpretation.

Importantly, preferences for electrified powertrains interact with broader vehicle attributes such as body type and size. Higgins et al. (2017) show that body type shapes EV preferences, implying that electrification uptake is intertwined with household needs (space, practicality) and market segmentation. This is highly relevant for DCEs (including the present study) that include *vehicle body type* and *vehicle size*, since these attributes can moderate the attractiveness of BEVs and PHEVs relative to conventional options.

A related strand compares behavioural decision paradigms and illustrates how policy implications can depend on the assumed choice process. Chorus et al. (2013) estimate both random utility maximisation and random regret minimisation models using stated choice data for alternative fuel vehicles and show that, despite similar fit, predicted responses to policy levers can differ. This matters for transport policy analysis because it allows for a behavioural representation in addition to predicted uptake under subsidies, fuel taxes, or charging investments, then model choice becomes consequential rather than purely technical.

Cross-national evidence also indicates that WTP for electrified powertrains depends on context, fuel prices, infrastructure, and cultural norms. Tanaka et al. (2014) compare consumer WTP for alternative fuel vehicles across the United States and Japan using a discrete choice framework, illustrating how valuations differ across national settings. While Australia differs from both contexts, such comparative work reinforces the need for country-specific evidence rather than transferring parameters from European or North American studies.

2.2 Australia-specific evidence and modelling of perceptions

Australian evidence on EV preferences has expanded over the past few decades, often emphasising the role of perceptions, attitudes, and latent constructs in addition to observable attributes. Across this literature, up-front purchase price, operating costs, driving range and charging access, and latent attitudes/perceptions (e.g., environmental concern, safety, design appeal, technology uncertainty) consistently emerge as key drivers of adoption intention and choice, with strong preference heterogeneity by socio-demographics and attitudinal segments. A prominent strand of research links EV choice to environmental attitudes and policy instruments. Beck et al. (2013) show how environmental attitudes condition vehicle choice responses under an emissions-charging policy scenario, illustrating that pricing instruments and "green" dispositions interact in policy-relevant ways. Building on this, Beck et al. (2017) integrate best–worst scaling measures of attitudes directly into EV choice, estimating attitudes and choice jointly to mitigate biases that can arise when attitudes are simply inserted as exogenous covariates. Their results reinforce that conventional "tangible" barriers remain central (notably purchase price and range), but that attitudinal orientations materially shift the probability of choosing an EV.

A closely related methodological contribution is the Australian work on response behaviour and potential biases in EV stated-choice data. Smith et al. (2017), using a best–worst stated choice survey of households in Perth, demonstrate the risk of "environmental enthusiast bias", i.e., the presence of a respondent subgroup that repeatedly selects EVs as the most preferred option across tasks, alongside evidence of non-trading and other decision heuristics that can distort willingness-to-pay inference if not handled carefully. This paper is frequently cited in subsequent Australian and international work as a cautionary example that EV preference estimates can be sensitive to sample composition and choice-task engagement, especially when EV familiarity is low and symbolic/identity motivations are salient.

More recent Australian studies increasingly model perceptions as latent constructs that shape preference formation. Ghasri et al. (2019) explicitly frame EV uptake through "perceived advantage" channels and estimate an integrated choice and latent variable specification, with latent constructs such as perceptions of vehicle design, environmental impact and safety influencing EV choice. Importantly for policy, this framing implies that interventions can operate not only through cost and infrastructure, but also by shifting underlying beliefs about EV suitability and quality attributes, effects that are likely to vary across cohorts and market segments. Heterogeneity and segmentation are also central in work examining policy incentives. Gong et al. (2020) use a stated-choice survey of New South Wales residents and estimate a latent class structure, identifying multiple consumer segments that differ systematically in their responsiveness to incentives and in their baseline propensity to choose EVs. Although the specific mix of incentives evaluated varies across studies and jurisdictions, the broader implication is consistent: incentive effectiveness is not uniform, and policy packages should be designed with segment targeting in mind rather than assuming a representative "average" buyer.

A further consideration, sometimes overlooked in EV adoption modelling, is who the decision maker is. Beck and Rose (2019) show (in the context of household vehicle choice) that group decisions can diverge meaningfully from isolated individual responses, underscoring the importance of intra-household preference aggregation when studying high-cost durable goods like vehicles. For EVs and hybrids, this is particularly relevant because charging access, trip-chaining constraints, and risk perceptions are often shared or negotiated within households.

Alongside choice models, Australian studies also provide constraint-based and behavioural context for interpreting stated preferences. Rafique and Town (2019) analyse NSW household travel survey data to characterise trip distances and infer the technical feasibility of EV substitution for routine travel. They report that a large share of trips are short trips (e.g., under typical urban-range thresholds), supporting the view that perceived (rather than purely technical) range constraints may loom large in adoption decisions. Complementing this, Broadbent et al. (2019) examine barriers and incentives among Australian motorists (with an experimental information component) and find that respondents frequently emphasise charging availability and purchase price, while information provision can shift stated attitudes and reduce uncertainty around the technology, again highlighting the role of perceptions and knowledge in addition to costs. Pellegrini and Rose (2026) analyse vehicle purchase and driving decisions in New South Wales, showing that whilst there is a clear appetite for fuel-efficient vehicles, consumers continue to allocate a substantial share of travel budgets to vehicles already present in the fleet. At the same time, battery electric vehicles attract a relatively larger share of travel budgets compared to conventional vehicles, indicating heterogeneity in driving allocation patterns across vehicle technologies.

2.3 Implications for attribute design in new-and-used vehicle DCEs, and Modelling approaches for DCEs in transport policy applications

The literature on EV preferences provides direct grounding for the attribute set commonly used in vehicle DCEs, while also indicating why second-hand contexts require additional design attention. Price remains central, both because it dominates stated trade-offs and because second-hand purchase decisions are typically more price sensitive. Reviews of EV adoption repeatedly emphasise the centrality of purchase price and total cost (Rezvani et al., 2015; Liao et al., 2017). Range is a pivotal EV attribute, consistently valued in stated preference studies (Hidrue et al., 2011) and plausibly even more important for used BEVs, where consumers may treat reduced range as a proxy for battery ageing. Age and odometer readings are canonical second-hand signals and are also central to depreciation analyses. For BEVs, the empirical depreciation evidence (e.g., Schloter, 2022) suggests that age may capture both physical depreciation and rapid technological obsolescence.

Condition measures, including inspections, ratings, and warranty proxies, play an outsized role in second-hand markets because they partially mitigate information asymmetry (Akerlof, 1970) and complement observable proxies like age and mileage. Availability/waiting time is also policy-relevant, as it represents a market outcome influenced by supply constraints, which has been incorporated in various transport choice contexts. In the electrification context, short-run supply constraints for new BEVs can push consumers toward used options or toward hybrids, suggesting that including availability is useful for capturing substitution channels, particularly in markets where delivery lead times vary. Body type and size matter for electrification because they reflect household constraints and moderate EV adoption (Higgins et al., 2017). A DCE that jointly varies body type/size and powertrain can therefore capture whether consumers treat electrified technologies as close substitutes across segments or as niche products concentrated in particular body categories.

A policy-relevant extension of the literature recognises that market conditions such as supply constraints and delivery delays can alter effective choice sets. Waiting times (availability) can be conceptualised as a non-monetary cost that may differentially penalise BEVs during periods of constrained production or high demand. While many DCEs treat availability implicitly, incorporating an explicit “availability/wait time” attribute can better represent real-world frictions and improve the realism of counterfactual simulations relevant to policy timing and supply-side interventions.

Taken together, the literature supports DCE designs that combine (i) classic market attributes (price, age, mileage/odometer, condition), (ii) EV-specific capability attributes (range and, where feasible, charging characteristics), and (iii) segmentation attributes (body type/size) that connect preferences to household needs.

In terms of modelling, methodological credibility is typically evaluated in terms of behavioural consistency, treatment of heterogeneity, and policy interpretability (e.g., WTP, scenario simulation). Latent class and Mixed logit models are widely used to capture random taste heterogeneity and relax the restrictive substitution patterns of the standard multinomial logit. A foundational reference is McFadden and Train (2000), who formalise Mixed Multinomial logit (MNNL) for discrete response and demonstrate its flexibility for capturing heterogeneity. In EV choice contexts, heterogeneity is empirically important because consumers differ sharply in driving needs, home charging feasibility, environmental preferences, and technology attitudes, factors repeatedly emphasised in the adoption reviews (Rezvani et al., 2015; Liao et al., 2017).

For second-hand markets, modelling considerations also include how respondents process quality signals and risk. Theoretical work on adverse selection and transaction costs suggests that observed attributes may act as imperfect signals of unobserved quality (e.g., Akerlof, 1970; Schiraldi, 2011), which can motivate approaches that allow for correlated unobservable or latent constructs when data permit. Even when latent variable models are not implemented, careful attribute design (e.g., explicit condition ratings) can reduce reliance on respondents' idiosyncratic interpretations of "quality".

2.5 Research gap

To summarise, the peer-reviewed literature provides strong foundations for analysing electrified vehicle adoption, but it also reveals a gap that is central for transport policy. That is, the diffusion of BEVs and hybrids depends on how consumers value these technologies *in the second-hand market*, where informational frictions and distinct depreciation dynamics apply. Economic analyses of used-car markets highlight quality uncertainty, transaction costs, and the tight coupling between primary and secondary markets (Akerlof, 1970; Gavazza et al., 2014; Schiraldi, 2011). Emerging empirical evidence indicates that BEVs can depreciate differently from conventional vehicles and that technological progress may accelerate value decline (Schloter, 2022; Andreassen and Lind, 2024). Meanwhile, DCE studies consistently show that range and price dominate EV trade-offs and that preferences are heterogeneous and shaped by vehicle segment and perceptions (Hidrue et al., 2011; Higgins et al., 2017; Ghasri et al., 2019).

The recent used-EV literature suggests at least three mechanisms that may differentiate second-hand BEV/HEV demand from new-vehicle demand. First, *technology obsolescence* may be more salient because buyers compare older BEVs against rapidly improving new BEVs (Andreassen and Lind, 2024). Second, *battery-related uncertainty* (state-of-health, expected degradation, replacement cost, warranty remainder) can be more consequential than for ICEVs because it concentrates risk into a high-cost component and because battery condition is not fully observable without diagnostics. Third, *financing and resale expectations* may be distinct, particularly if lenders and insurers price residual value risk differently for BEVs (Schloter, 2022). These mechanisms align closely with the selection of attributes commonly used to describe used vehicles, such as age, mileage, and condition, and motivate explicitly incorporating them when modelling preferences across powertrains.

Against this backdrop, a DCE that jointly represents (a) new and used vehicles, (b) multiple powertrains (including BEV, HEV, and PHEV), and (c) both BEV-specific performance (range) and used-market quality signals (age, mileage, condition) can address a clear gap: estimating substitution and valuation patterns that govern whether electrified vehicles diffuse through the second-hand market, and identifying which policy levers (price incentives, information disclosure, supply/availability improvements) are most likely to accelerate that diffusion. Such a framing supports direct translation from preference estimates to policy-relevant counterfactuals and welfare comparisons (McFadden and Train, 2000; Train, 2015). A such, an preference research that explicitly spans new and used vehicles and contrasts petrol/diesel with BEV, PHEV, and HEV powertrains, while incorporating both used-market signals (age, odometer, condition, availability) and EV-salient capability attributes (range), is therefore well positioned to contribute to the literature by connecting consumer preference measurement to the policy problem of second-hand electrification and its distributional implications.

3.0 SURVEY INSTRUMENT AND DATA

Data from 797 respondents drawn from across the state of New South Wales (NSW) Australia were collected between the 20th and 31st May 2024. Prior to this, a pilot study consisting of 91 respondents was undertaken on the 17th and 18th of March 2024 to test the survey instrument and provide informative priors that could be used to optimise the DCE experimental design used in the main field phase of the study. Both main field phase and pilot studies were collected using a web-based questionnaire, with the sample drawn from an online panel, Qualtrics (https://www.qualtrics.com/en-au/). To be eligible to complete the survey questionnaire, respondents had to reside in NSW and be 18 years or older.

Data from the pilot study was discarded from the final analysis and after data cleaning, data from a further 163 respondents were removed from the final estimation sample due to exhibiting non-trading behaviour in the DCE task (n = 77), straight lining behaviour when responding to several attitudinal questions asked as part of the survey (n = 84), and completing the survey in an unreasonably quick manner (n = 54). With respect to this last data cleaning criteria, the median time to complete the survey was eight minutes and 50 seconds, with respondents completing the survey in under three minutes deemed to have not taken the time to respond to all the survey questions in a meaningful manner. Note that the reasons for excluding data are not mutually exclusive meaning that data from respondents could be removed from the analysis for more than one reason. The final data set after data cleaning consists of observations from a total of 634 respondents.

The survey began with a consent request, followed by the assessment of respondents' eligibility to participate. Next, data about the respondents' household vehicle fleet were collected including number of vehicles, the makes and models of the vehicles, the vehicle body type, when the vehicles were acquired, how much the vehicle was purchased for, and the technical specifications of the vehicle such as the number of seats, powertrain, and usage. Respondents were subsequently introduced to the DCE task, including a detailed description of attributes, followed by a practice exercise. After being instructed on how to interpret and answer the DCE questions, respondents were asked to complete eight DCE tasks.

Each DCE task consisted of four choice alternatives, three unlabelled vehicles, and a no choice option. Each vehicle shown was described by nine attributes, including the powertrain of the vehicle, the vehicle body type and size, as well as the vehicles age and physical condition (based on a five-star rating, with one being poor condition, and five being perfect condition). The vehicles odometer reading (zero if a new car), price, and when the vehicle will be available (now, 3 months from now, or six months from now) to the respondent were also used to describe the vehicles. An example of a DCE task is shown in Figure 1.

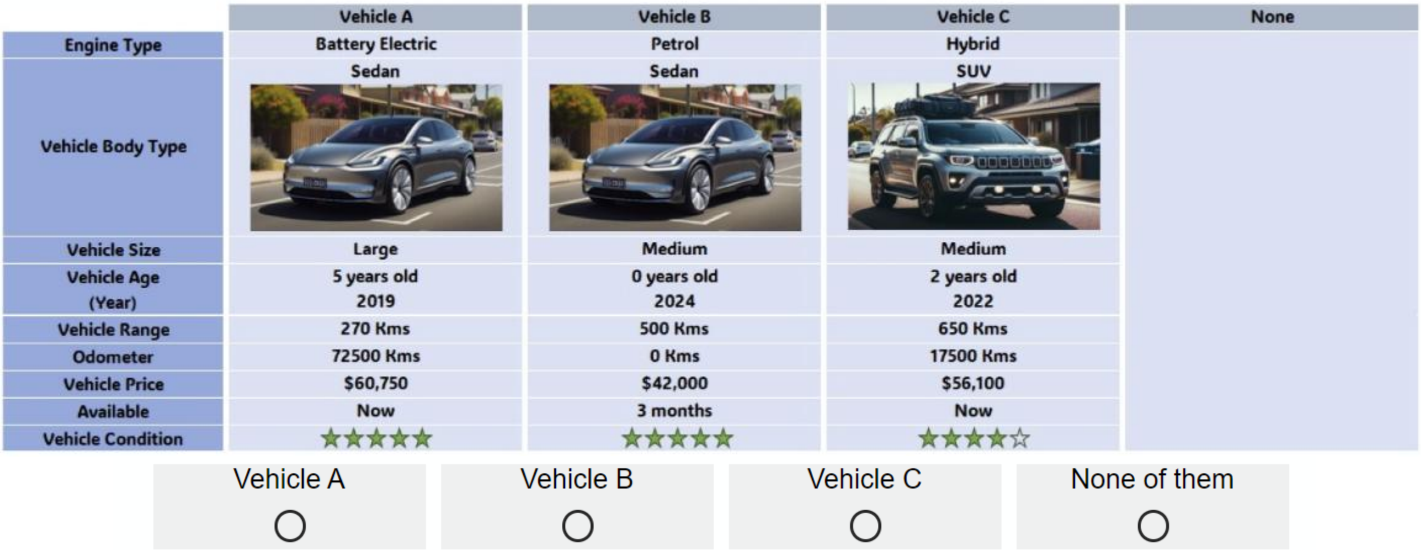


Figure 1: Example choice task

Five powertrain types were included as part of the DCE, consisting of petrol, diesel, HEV, PHEV and BEVs, alongside three vehicle sizes, small, median and large. Five vehicle body types were also accounted for, including hatchbacks, liftback sedans, sedans, station wagons and SUVs. Next, to generate the experimental design, base new vehicle purchase prices were determined for different powertrain, body type and vehicle size combination, as shown in Table 1. Next, the vehicle age was determined based on one of 11 levels, from 0 representing a new vehicle to 10, representing a 10-year-old used vehicle.

Table 1: Body type, vehicle size, powertrain and base new vehicle purchase price

Body type	Vehicle size	Petrol	Diesel	HEV	PHEV	BEV
Hatchback	Small	$36,000	$38,250	$38,250	$40,500	$45,000
Hatchback	Medium	$40,000	$42,500	$42,500	$45,000	$50,000
Liftback Sedan	Small	$52,000	$55,250	$55,250	$58,500	$65,000
Liftback Sedan	Medium	$56,000	$59,500	$59,500	$63,000	$70,000
Liftback Sedan	Large	$60,000	$63,750	$63,750	$67,500	$75,000
Sedan	Medium	$56,000	$59,500	$59,500	$63,000	$70,000
Sedan	Large	$72,000	$76,500	$76,500	$81,000	$90,000
Station wagon	Large	$88,000	$93,500	$93,500	$99,000	$110,000
SUV	Small	$80,000	$85,000	$85,000	$90,000	$100,000
SUV	Medium	$88,000	$93,500	$93,500	$99,000	$110,000
SUV	Large	$96,000	$102,000	$102,000	$108,000	$120,000

For the remaining vehicle attributes, in order to generate realistic hypothetical vehicle alternatives that could be used to populate the DCE tasks of the survey, the experimental design relied on a series of nested attributes. Based on the vehicle age, a yearly discount factor was applied to the base new vehicle price (from Table 1), which was assumed to be similar for non-BEVs, but greater for BEV types (see Table 2, columns 2 to 6). This discount factor is used to determine the base vehicle purchase price. Next, the actual vehicle price shown to respondents was experimentally varied between 0.75 and 1.125 of the computed base vehicle price, with six levels incrementing by 0.075. Five levels were used to generate the vehicle odometer reading, with the actual level determined by the vehicle age (columns 7 to 11 of Table 2).

Table 2: Age vehicle price adjustment and odometer reading

	Year discount					Odometer				
Vehicle age	Petrol	Diesel	HEV	PHEV	BEV	1	2	3	4	5
0	1.000	1.000	1.000	1.000	1.000	**0**	**0**	**0**	**0**	**0**
1	0.900	0.900	0.900	0.900	0.850	5,000	7,500	12,500	17,500	22,500
2	0.850	0.850	0.850	0.850	0.800	17,500	20,000	25,000	30,000	35,000
3	0.800	0.80	0.800	0.800	0.750	30,000	32,500	37,500	42,500	47,500
4	0.725	0.725	0.725	0.725	0.675	42,500	45,000	50,000	55,000	60,000
5	0.650	0.650	0.650	0.650	0.600	55,000	57,500	62,500	67,500	72,500
6	0.575	0.575	0.575	0.575	0.525	67,500	70,000	75,000	80,000	85,000
7	0.500	0.500	0.500	0.500	0.450	80,000	82,500	87,500	92,500	97,500
8	0.425	0.425	0.425	0.425	0.375	92,500	95,000	100,000	105,000	110,000
9	0.350	0.350	0.350	0.350	0.300	105,000	107,500	112,500	117,500	122,500
10	0.275	0.275	0.275	0.275	0.225	117,500	120,000	125,000	130,000	135,000

Finally, the vehicle range was determined based on the powertrain, with PHEV and BEVs having the lowest ranges, and ICEs the largest. The vehicle ranges were also made lower for older vehicles to reflect technological improvements over time.

For each powertrain type, 1,815 different hypothetical vehicles were constructed, forming unique alternative specific candidature sets. A Bayesian efficient D-optimal design was then generated in NGENE (ChoiceMetrics, 2025) using a modified Fedorov algorithm drawing from the five powertrain specific candidature sets. Priors for the design were obtained from the earlier pilot study undertaken in March of 2024, with 1,000 Sobol draws to simulate the Bayesian prior parameter distributions. The final design had 56 choice tasks, blocked into seven blocks of size eight, such that each respondent was assigned to one block in the survey.

After answering the eight DCE tasks, respondents were next asked to answer several attitudinal scales designed to capture attitudes towards technology, vehicle ownership, government policies related to road usage, and sustainable purchasing practices. Once the attitude questions were completed, respondents were required to provide socio-economic data about themselves and the household they reside in. Finally, respondents were offered the opportunity to provide qualitative responses about the survey questionnaire as well as the topic of vehicle choice in general.

Table 3 outlines the key socio-demographic profile of the final sample of 634 respondents. Overall, the sample broadly mirrors the NSW population across several dimensions, whilst exhibiting some expected differences that are common for field studies. The average age of respondents in the sample is 43.4 years, which is lower than the NSW population average of 48.3 years, indicating a modest under-representation of older individuals. Gender composition is closely aligned with the NSW population, with 52.0 percent of respondents identifying as female, as opposed to 50.6 percent reported in the 2021 Census. Average reported weekly household income in the sample is AUD 1,651, which is somewhat lower than the NSW average of AUD 1,829. Employment status distributions are broadly comparable, although the sample exhibits a slightly higher share of full-time employment (58.2 percent) relative to the NSW average (55.2 percent), and a lower share of part-time employment (19.6 percent against 29.7 percent). This suggests a mild over-representation of full-time workers, which may reflect greater survey participation among individuals with stable employment. Geographic representation closely represents population patterns. Approximately 65.1 percent of respondents reside in metropolitan areas, as opposed to 64.8 percent in the NSW population, while the remainder reside in regional and non-metropolitan areas. In terms of household characteristics, the average household size in the sample is 2.25, slightly smaller than the NSW average of 2.60, consistent with the younger age profile of respondents. Vehicle ownership levels are also marginally lower in the sample, with an average of 1.69 vehicles per household, compared with 1.78 vehicles in the NSW population.

Table 3: Sample versus population socio-demographic characteristic profiles

Variable	Sample	NSW (2021)
Age	43.43	48.32
Female	52.02	50.60
Income	$1,651.21	$1,829.00
Employed Full time	58.23%	55.20%
Employed Part time	19.64%	29.70%
Metropolitan	65.14%	64.76%
Rest of NSW	34.86%	35.24%
Average Household size	2.25	2.60
Number of vehicles	1.69	1.78

4.0 ECOMONETRIC MODEL

In this paper, we make use of a Latent Class Model (LCM) estimated on the DCE data described in Section 3.0. Typically, latent class analysis is used to explore and identify the existence of different discrete preference segments within the population (see Kamakura and Russell 1989 or Scarpa et al. 2003). The LCM allows one to link taste heterogeneity to socio-demographic and other contextual variables rather than having to rely on unattributable preference variation common with the use of continuous random parameter distributions associated with Mixed Multinomial Logit (MMNL) models. Unlike other statistical segmentation approaches, such as cluster analysis, individual decision makers are not assigned to a specific preference segment but rather belong to each preference group up to different probabilities. As such, segment or class assignment to a specific set of preferences is probabilistic as opposed to deterministic.

To estimate the model, the analyst assumes the existence of *C* latent classes, each with its own unique utility function, such that the probability that respondent *n* belongs to preference class, c is given by

$$P_{nc} = \frac{\exp\left(V_{nc}\right)}{1+\sum_{c=1}^{C-1}\exp\left(V_{nc}\right)}, \tag{1}$$

where $V_{nc} = \sum_{l}^{L} \theta_{cl} z_{ncl}$ represents the observed utility assocated with class *c* described by *l* covariates terms, z_{ncl}, with attendent parameter weights θ_{cl}. For model identification, it is comment to normalise the parameters for one entire class to zero.

Conditional on belonging to class *c*, the probability that respondent *n* chooses alternative *j* in choice situation *s* is given by

$$P_{nsj|c} = \frac{\exp\left(V_{nsj|c}\right)}{\sum_{j=1}^{J}\exp\left(V_{nsj|c}\right)}, \tag{2}$$

where $V_{nsj|c}$ is the observed component of utility, typically assumed to be a linear relationship of observed attribute levels, *x*, of each alternative *j* and their corresponding weights (parameters), β. Specifying the conditional class utility functions as separable in both cost and non-cost attributes, we obtain

$$V_{nsj|c} = \sum_{k=1}^{K} \beta_{k|c} x_{nsjk|c} - \alpha_c c_{nsj|c}, \tag{3}$$

where $\beta_{k|c}$ is a parameter weight conditional on belonging to class *c*, linked to the k^{th} attribute, associated with alternative *j* as seen by decision maker *n* in choice situation *s*. α_c in equation (3) is a cost parameter associated with the vehicle cost of alternative *j*, $c_{nsj|c}$. As well as containing information on the levels of the attributes, *x,* in Equation (3) may also contain up to *J*-1 alternative specific constants (ASCs) capturing the residual mean influences of the unobserved effects on choice associated with their respective alternatives, where *x* takes the value 1 for the alternative under consideration or zero otherwise.

In order to better understand preferences for both new and second-hand vehicles, rather than assume generic estimates for each of the vehicle attributes independent of the age of the vehicle, we further separate the utility functions into two further components. That is, we specify the utility function such that we estimate unique parameters for new and second hand vehicles, where $\beta_{k,new|c}$ represent the preference weights conditional to belonging to class *c* associated with vehicle k^{th} attribute if vehicle *j* in choice situation *s* is a new vehicle, and $\beta_{k,2hand|c}$ represent similar preference weights if the vehicle is second hand.

In addition to allowing for different preference weights associated with attributes of new and previously owned vehicles, we further estimate a series of error components which are designed to capture different substitution pattern effects within the data. To do so, we create three dummy variables. The first dummy variable equals one for alternative *j* if two or more vehicles in choice situation *s* are new vehicles, or zero otherwise. Mathematically, this can be specified as

$$d_{ns,new} = \begin{cases} 1, \text{ if vehicle } j \text{ is new, and } \sum_{j=1}^{J} 1\left\{M_{ns}\left(j\right)\right\} \geq 2, \\ 0, \text{ otherwise.} \end{cases} \tag{4}$$

The second dummy variable, $d_{ns,2hand}$, is constructed for second hand vehicles when two or more such vehicles are present in a given choice situation. The final dummy variable is designed to capture any additional covariance in the error term between the hypothetical vehicle options relative to the no choice alternative (see e.g., Scarpa, et al.2005 and Ferrini and Scarpa, 2007). As such, the third dummy variable, $d_{nsj,\forall j=1,2,3}$, takes the value of one for alternatives one, two and three, and zero for the fourth no choice alternative in the DCE. For each of these dummy variables, for each set of class specific conditional utility functions, we estimate normally distributed random coefficients with zero means, such that $\eta_{g|c} = \sigma_{g|c} z_{g|c}$, where for dummy variable *g* = 1, 2, or 3, $z_{g|c}$ are independent standard normal distributions, resulting in $\eta_{new|c} \sim N\left(0, \sigma_{new|c}\right)$, $\eta_{2ndhand|c} \sim N\left(0, \sigma_{2ndhand|c}\right)$ and $\eta_{Vehicle|c} \sim N\left(0, \sigma_{Vehicle|c}\right)$. The final conditional utility specification used for the model is given in Equation (5).

$$\begin{aligned} V_{nsj|c} = & \left(\sum_{k=1}^{K} \beta_{k,new|c} x_{nsjk,new|c} - \alpha_{c,new} c_{nsj,new|c} + \eta_{new|c} d_{ns,new,} \right) \\ & + \left(\sum_{k=1}^{K} \beta_{k,2hand|c} x_{nsjk,2ndhand|c} - \alpha_{c,2hand} c_{nsj,2ndhand|c} + \eta_{2hand|c} d_{ns,2ndhand} \right) + \eta_{Vehicle|c} d_{nsj,\forall j=1,2,3}. \end{aligned} \tag{5}$$

Assuming preferences vary between individuals but not within given a sequence of observed choices, given observed choices, y_{nsj}, the probability, conditional to belonging to class *c*, that decision maker *n* is observed sequence of choices of the *s* = 1, …, 8 choice tasks is given as

$$P_{n|c}^{*} = \prod_{s=1}^{S} \prod_{j=1}^{J} P_{nsj|c}^{y_{nsj}}. \quad (6)$$

The assumption that preferences vary between and not within respondents' accounts for the pseudo panel nature of DCE data (Revelt and Train 1998 and Train 2009). The final log-likelihood of the model is given as

$$LogL = \sum_{n=1}^{N} \ln \left(\int_{\eta_{n1|1}=-\infty}^{\infty} \int_{\eta_{n2|1}=-\infty}^{\infty} \dots \int_{\eta_{ng|C}=-\infty}^{\infty} \sum_{c=1}^{C} P_{nc} P_{n|c}^{*} \left(V_{nsj|c} \mid \eta_{n|c} \right) d\Phi\left(\eta_{n1|1}\right) d\Phi\left(\eta_{n2|1}\right) \dots d\Phi\left(\eta_{ng|C}\right) \right), \quad (7)$$

where $\Phi(.)$ is the cumulative distribution function for the normally distributed random terms associated with the g =1, …, 3 conditional class error components of the model. The Riemann-Stieltjes integral in Equation (7) is approximated using Monte Carlo simulation. To do so, we use 2,000 MLHS quasi random draws to simulate the integral for the model estimated in this paper. The final model is estimated using Biogeme version 3.3.2 (Bierlaire, 2023).

5.0 EMPIRICAL RESULTS

Various model specifications were tested on the data, with the final model with two latent classes reported in Table 4 being the best model found to fit the data. Selecting the number of classes in an LCM setting is a balance between statistical and behavioural considerations. From a statistical perspective, it is common practice to estimate models with an increasing number of classes and subsequently compare different goodness of fit measures that penalize models that produce a larger number of parameters, such as the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) or the consistent AIC (CAIC) criteria, choosing the model that performs best on whatever measure has been selected (see Louviere et al., 2000). However, estimating models with too many classes often leads to estimation instability with parameters tending toward ±∞ and/or classes with extremely large standard errors. Such errors are typically indicative of model identification issues and often arise when the class membership size of one or more of the classes gets too small (see Swait, 2007). In addition to parameter instability issues, as the number of classes increases, it is common for the parameter estimates of one or more of the classes to become behaviourally implausible in terms of their signs relative to *a priori* expectations, or for the parameter estimates to become statistically insignificant. In the current context, models with three or more classes resulted in such nonsensical classes despite producing better statistical fit, leading to more weight being placed on non-statistical criteria when choosing how many classes to report.

The final model shown in Table 4 produces decent goodness of fit outputs, with a ρ^2 of 0.166, adjusted ρ^2 of 0.155 based on 71 parameter estimates and an AIC of 11,878.176. Also reported in the table is a Negentropy (negative entropy or syntropy) measure (Ramaswamy et al., 1993). Computed as $E_c = 1 - \sum_{n=1}^{N} \sum_{c=1}^{C} -P_{nc} \ln\left(P_{nc}\right) \Big/ N \ln\left(C\right)$, Negentropy varies between zero and one and is used to express how well-differentiated the class membership component of the model is compared to a model involving a purely random assignment of individuals to each of the assumed classes. Negentropy values closer to zero suggest that the model's class assignment mechanism is indistinguishable from random assignment, whilst values closer to one represent near perfect classification of class membership. It is important to note, however, that the relationship between class membership and negentropy is highly non-linear. For the estimated model, the negentropy measure is computed to 0.248, suggesting that, whilst low, at the individual respondent level, the two classes formed by the model are quite well defined and able to be distinguished from one another. In order to determine if the negentropy measure is statistically different to zero, we calculate the measure for each respondent and using these, compute the bootstrap-*t* statistic based on 50,000 bootstrap resamples. The resulting bootstrap-*t* statistic is 48.60 indicating that the negentropy statistic is indeed statistically different from zero. Using a 4th order Taylor series expansion for the two class binary entropy measure and noting that $P_B = (1 - P_A)$, we are able to compute, assuming a single representative respondent, that $P_{\max(A,B)} \approx 0.5 + \sqrt{\frac{3}{8}\left(\sqrt{4 + \frac{16}{3}E_c \ln(2)} - 2\right)}$, which for $E_c = 0.248$ gives a value of $P_{\max(A,B)} \approx 0.7855$. This suggests that the model assigns an average respondent to one of the two classes up to a probability of 0.7855, irrespective of which class they are assigned to.

The class membership function associated with class A includes the decision maker's age, gender, the number of children residing in the person's household, and the weekly income level before tax for their household, divided by 100. Other covariates were tested, however these were found to be statistically insignificant and hence removed from the final analysis. Given the negentropy result, the model assigns on average each respondent to either class A or class B up to a probability of 0.7855, however when the estimated individual specific class assignment probabilities are averaged over the sample, the estimated class sizes are 0.585 and 0.415 for classes A and B respectively, with the membership function suggesting that older decision makers, females and respondents from households with less children or lower weekly incomes have a higher probability of belonging to the class A.

For both classes, ASCs associated with the three hypothetical vehicles are estimated relative to the no-choice alternative. In both instances, positive and statistically significant ASC parameters are found to exist, suggesting that *all else being equal*, individuals within the sample are more likely to select one of the vehicles shown within the DCE than not, irrespective of which class they belong to. With respect to the magnitudes of the estimated ASCs, individuals displaying preferences consistent with Class B appear to be much more likely to select one of the three vehicles shown in the DCE relative to the no choice alternative, compared to those whose preferences align more with Class A, *ceteris paribus*. Assuming scale parity across the two classes, computing the cross-class log-odds for the three ASCs (i.e., for alternative *j*, $OR_{2/1}(j \text{ vs } None) = \exp\left(ASC_{j|2} - ASC_{j|1}\right)$) we get 2.6234, 3.4569 and 3.3933 for alternatives one, two and three respectively, suggesting that respondents belonging to class B are 2.62 to 3.45 times more likely to select one of the vehicles on offer relative to respondents belonging to Class A, *all else being equal*. Computing the log-odds of the difference-in differences of the ASCs to determine relative preferences across the classes (i.e., $\Delta\Delta(j \text{ vs } i) = \exp\left(\left(ASC_{j|1} - ASC_{j|1}\right) - \left(ASC_{j|2} - ASC_{j|2}\right)\right)$), we observe odds ratios of $OR\left(\Delta\Delta(1 \text{ vs } 2)\right) = 1.3177$, $OR\left(\Delta\Delta(2 \text{ vs } 3)\right) = 0.9816$, and $\left(\Delta\Delta(1 \text{ vs } 3)\right) = 1.2935$, indicating a larger structural difference exists between the two classes in terms of choosing the various non-no choice alternatives, with those belonging to Class B shifting preference mass towards alternative 2 (and to a lesser extent 3) relative to alternative 1 when compared to Class A, whereas the relationship between alternatives 2 and 3 are effectively the same across the two classes.

Table 4: Model results

	Class A				Class B			
	Conditional class estimates							
	Par.		(t-rat.)		Par.		(t-rat.)	
ASC Option A	1.4310		(2.63)		2.3955		(18.68)	
ASC Option B	1.4843		(2.80)		2.7247		(23.11)	
ASC Option C	1.1361		(2.12)		2.3579		(17.92)	
	New		**2nd Hand**		**New**		**2nd Hand**	
	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)
Engine Type: Diesel	-0.8272	(-5.11)	-0.5880	(-3.63)	-0.0919	(-0.60)	0.1542	(0.82)
Engine Type: PHEV	-0.0527	(-0.30)	-0.2622	(-1.67)	0.3059	(1.97)	0.3938	(2.04)
Engine Type: HEV	0.0479	(0.19)	-0.5689	(-3.05)	0.1010	(0.47)	-0.0471	(-0.23)
Engine Type: BEV	-0.3773	(-1.36)	-0.9362	(-4.33)	0.2646	(1.08)	-0.0182	(-0.08)
Engine Type: Petrol								
Body Type: Liftback Sedan	0.2134	(1.08)	0.1846	(1.00)	0.6124	(3.31)	-0.0463	(-0.22)
Body Type: Sedan	0.4929	(2.28)	0.1055	(0.50)	0.2213	(1.09)	0.2524	(1.05)
Body Type: Station Wagon	-0.4340	(-1.05)	-0.0407	(-0.13)	-0.7723	(-2.38)	-0.6043	(-2.00)
Body Type: SUV	0.3845	(1.10)	-0.2334	(-0.99)	1.2585	(4.23)	0.5206	(2.00)
Body Type: Hatchback								
Vehicle Size: Large	-0.2229	(-1.09)	-0.3528	(-1.99)	0.3754	(2.38)	0.0086	(0.04)
Vehicle Size: Medium	0.2632	(1.81)	-0.0397	(-0.34)	0.4903	(3.13)	0.1456	(1.01)
Vehicle Size: Small								
Odometer			-0.0756	(-2.76)			-0.0442	(-1.57)
Range	0.2965	(3.75)	0.0651	(1.04)	0.0183	(0.28)	0.0708	(1.14)
Availability	-0.0704	(-2.42)			-0.0426	(-1.59)		
Condition			0.1185	(1.71)			0.0342	(0.48)
Price	-0.4119	(-6.30)	-0.2071	(-3.36)	-0.1245	(-2.48)	-0.0842	(-1.13)
	Error components							
	Par.		(t-rat.)		Par.		(t-rat.)	
Class error component	2.1617		(10.45)		0.0805		(0.23)	
	New		2nd Hand		New		2nd Hand	
	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)
Market error component	0.7289	(3.68)	0.6122	(2.93)	0.1502	(0.28)	0.8237	(7.04)
	Class membership function							
	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)	Par.	(t-rat.)
Class constant	-1.4335		(-3.06)					
Age	0.0490		(5.50)					
Female	1.1771		(4.51)					
Number of children	-0.2966		(-2.56)					
Income	-0.0250		(-3.53)					
	Model fit							
LL(0)	-7,031.285							
LL(β)	-5,868.088							
ρ^2	0.165							
Adj. ρ^2	0.155							
AIC	11,878.176							
Negentropy (E_c)	0.248 (48.60)*							

* t-ratio for the negentropy measure has been bootstrapped using 50,000 resamples

Irrespective of whether a vehicle is new or second hand, respondents belonging to Class A are less likely to select vehicles with diesel, hybrid electric or battery electric powertrains compared to vehicles with other powertrains, *all else being equal*. For respondents whose preferences more align with Class B however, new and second-hand PHEVs are preferred to all other vehicle types. In order to better understand the relative sensitivities, Table 5 reports odds ratios that translate the latent class model estimates into directly interpretable comparisons across both vehicle market segments (new *vs* second-hand) and latent classes. Cells shown in light grey are indicative of cases where both parameters in the odds ratio cross calculations are not statistically significant at the five percent level. Columns two and three of the table compare the effect of each attribute in the new-vehicle market relative to the second-hand market within each class (Class A and Class B). Under this construction, an odds ratio greater than one indicates that, within a given class, the attribute is more strongly associated with choosing a new vehicle than a second-hand vehicle (i.e., a "new-market tilt"), whereas an odds ratio less than one indicates the attribute is relatively more influential for second-hand vehicle choices. The final two columns compare classes within each market segment, reported separately for new vehicles and second-hand vehicles, with odds ratios greater than one indicating the attribute effect is stronger in Class A than Class B within that segment, whilst odds ratios less than one indicating a stronger effect in Class B.

Table 5: Cross new versus 2nd hand vehicle and cross class odds ratios

	Class A (new *vs* 2nd hand)	**Class B (new *vs* 2nd hand)**	**New (Class A *vs* Class B)**	**2nd hand (Class A *vs* Class B)**
Engine Type: Diesel	0.7873	0.7818	0.4794	0.4761
Engine Type: PHEV	1.2330	0.9158	0.6986	0.5189
Engine Type: HEV	1.8529	1.1596	0.9483	0.5935
Engine Type: BEV	1.7488	1.3268	0.5263	0.3993
Body Type: Liftback Sedan	1.0292	1.9323	0.6710	1.2598
Body Type: Sedan	1.4731	0.9694	1.3120	0.8634
Body Type: Station Wagon	0.6748	0.8454	1.4025	1.7571
Body Type: SUV	1.8549	2.0916	0.4173	0.4705
Vehicle Size: Large	1.1387	1.4431	0.5497	0.6967
Vehicle Size: Medium	1.3539	1.4116	0.7969	0.8308
Odomoter				0.9691
Range	1.4507	1.0645	1.3207	0.9944
Availability			0.9726	
Condition			1.0880	
Price	0.8148	0.9605	0.7502	0.8843

Across the powertrain attributes, interpretation of the reported odds ratios requires attention be placed to the reference category used in the dummy coding, which in this instance is defined as petrol vehicles. Table 5 reveals a clear segmentation between conventional and electrified technologies in terms of their association with new versus second-hand choices. Diesel vehicles exhibit odds ratios below unity in both Class A (0.7873) and Class B (0.7818), implying that relative to petrol vehicles, for both classes, diesel is relatively more associated with second-hand vehicle choice than with new vehicle choice. In contrast, the electrified engine types, PHEV, HEV, and BEV, generally exhibit odds ratios above one, indicating that, relative to petrol vehicles, electrification is more strongly linked to choosing a new vehicle than a second-hand vehicle, although the magnitude varies by class. In Class A, a predilection towards purchasing newer vehicles is particularly pronounced for HEVs (1.8529) and BEVs (1.7488) and is present but smaller for PHEVs (1.2330). In Class B, BEV and HEV also exhibits a stronger effect in the new-vehicle segment (1.3268 and 1.1596, respectively), whereas PHEV is close to parity (0.9158), suggesting that for this segment, plug-in hybrids do not differentiate the new market as strongly as they do for Class A. These within-class patterns are complemented by the cross-class comparisons in the final two columns of the table, which indicate that engine-type effects are systematically stronger in Class B than Class A in both market segments (all odds ratios for Diesel, PHEV, HEV and BEV are below one in both the "New" and "2nd hand" columns). The magnitude of these odds ratios is especially small for BEVs (0.5263 in new, 0.3993 in second-hand) and for diesel (0.4794 in new compared to 0.4761 in second-hand), implying that technology-driven differentiation is a more salient source of choice behaviour for Class B, and that this is particularly true in the second-hand market where perceived risk and uncertainty about technology condition may be more consequential.

Body type effects, interpreted relative to hatchbacks, display some of the strongest market-segment tilts. SUVs stand out as consistently "new-oriented" in both classes (Class A: 1.8549; Class B: 2.0916), indicating that, relative to hatchbacks, SUVs are disproportionately associated with choosing a new vehicle rather than a second-hand vehicle. This pattern is consistent with SUVs acting as a high-salience category where newer model features and higher willingness-to-pay are particularly relevant. The cross-class odds ratios for SUVs are below one in both segments (0.4173 for new; 0.4705 for second-hand), indicating that the SUV-related effect, relative to hatchbacks, is materially stronger in Class B regardless of market segment, reinforcing the interpretation that Class B reflects a segment with sharper preferences tied to salient vehicle-category cues. Sedans and liftback sedans show more nuanced segmentation. Liftback sedans are essentially neutral relative to hatchbacks in Class A (1.0292) but are more strongly preferred in the new-vehicle segment for Class B (1.9323). The corresponding cross-class odds ratios indicate that liftback sedan versus hatchback contrast is stronger in Class B for new vehicles (0.6710), but stronger in Class A for second-hand vehicles (1.2598). This "sign reversal" across segments suggests that the two classes differ not only in strength of preference but also in how those preferences map into the new versus second-hand vehicle markets, consistent with segmentation in perceived availability, search costs, or the distribution of liftback models across vintages. Preferences for conventional sedans exhibit the opposite within-class contrast relative to hatchback vehicles, being more highly preferred for new-vehicles relative to second hand vehicles in Class A (1.4731) but near parity in Class B (0.9694), with cross-class odds ratios indicating a stronger sedan versus hatchback effect for members of Class A for new vehicles (1.3120), but stronger for those with preferences more aligned to Class B for second-hand vehicles (0.8634). Station wagons are the only body type with odds ratios below one in both classes (Class A 0.6748 versus Class B 0.8454), implying a relatively stronger association with second-hand vehicles across the population relative to hatchbacks. Nevertheless, cross-class odds ratios above one in both segments (1.4025 for new versus 1.7571 for second-hand vehicles) show that this station wagon versus hatchback contrast is stronger in Class A, particularly in the second-hand market, consistent with a niche segment that engages with station wagons primarily through used-vehicle pathways.

Vehicle size effects, interpreted relative to small vehicles, are more modest in magnitude but remain directionally consistent, with medium and large vehicles exhibiting odds ratios above one within both classes, implying that relative to small vehicles, such vehicles are more associated with new-vehicle choice than second-hand choice (Class A: 1.3539 medium, 1.1387 large; Class B: 1.4116 medium, 1.4431 large). The cross-class odds ratios for medium to large vehicle sizes relative to small vehicles are below one for both segments (new vehicles: 0.7969 medium, 0.5497 large; second-hand vehicles: 0.8308 medium, 0.6967 large), indicating that size-related effects are stronger in Class B, especially so for large vehicles in the new vehicle market. This pattern is consistent with Class B being more sharply differentiated by major product-category attributes (such as SUV and large size), whereas Class A exhibits comparatively flatter responses on these broad vehicle-category dimensions.

Among the continuous attributes, range shows a clear segmentation between classes and between market segments. For respondents belonging to Class A, range has a larger impact for new vehicles (1.4507), whereas in Class B the within-class odds ratio is close to one (1.0645), implying that range is not a strong differentiator between new and second-hand vehicle choices for that class. The cross-class odds ratio for range in the new market is above one (1.3207), indicating that range is more influential in Class A than Class B when considering new vehicles, while the corresponding second-hand vehicle cross-class odds ratio is essentially neutral (0.9944). This combination implies that the heterogeneity in range valuation is expressed primarily through new-vehicle choice, consistent with the role of range as a salient attribute of newer electrified models and a potential proxy for technology frontier preferences. Price shows the opposite pattern. Within both classes the odds ratio for price are below one (Class A: 0.8148; Class B: 0.9605), indicating that price is relatively more influential for second-hand vehicle choice than new vehicle choice, whilst the cross-class odds ratios are below one for both segments (0.7502 for new vehicles and 0.8843 for second-hand vehicles) indicating that the price effect is stronger for respondents assigned to Class B than for those belonging to Class A. In other words, Class B appears more price-sensitive in both markets, particularly in the new vehicle market, which coheres with the broader theme that Class B exhibits sharper trade-offs on major determinants of choice. Finally, several attributes in the DCE that are relevant to only one market segment behave close to neutrality in cross-class comparisons. Odometer, present only for second-hand vehicles being always zero for new vehicles, has an odds ratio slightly below one in the "2nd hand (Class A vs Class B)" column of the table (0.9691), implying a marginally stronger odometer effect for individuals belonging to Class B. Availability and vehicle condition, related only to new vehicles, are near one in the "New (Class A vs Class B)" column (0.9726 and 1.0880 respectively), suggesting comparatively limited class differentiation on these dimensions relative to the more pronounced heterogeneity observed for powertrain, SUVs, and price.

Overall, the results of the model reported in Table 4, and the corresponding odds ratios shown in Table 5 suggest that individual's assigned to Class B display systematically stronger differentiation by salient vehicle-category and technology cues (engine type, SUV body style, size), and greater price sensitivity, whilst those belonging to Class A demonstrate comparatively stronger emphasis on vehicle range, particularly for the newer vehicle market and stronger anti station wagon sentiment, particularly in the second-hand market. The fact that several cross-class odds ratios are markedly below one for powertrains and SUVs in both market segments suggests that the latent segmentation is not merely a shift in baseline propensity to purchase new vehicles but reflects materially different valuation structures that persist within the new and second-hand vehicle market channels.

The final estimates of the model presented in Table 4 relate to the various error components described in Equation (5). Error components relax the assumption that the error terms of the standard multinomial logit are independently and identically distributed (IID) by allowing for correlation in the unobserved utility across subsets of alternatives, thereby allowing substitution patterns that are more consistent with the structure of the new and used vehicle markets. Within each class specific conditional utility specification, three error components are estimated. The first two relate to the presence of multiple new or used cars within the choice scenario presented to respondents and a third component that is common to the three vehicle alternatives (relative to the opt-out alternative), capturing additional covariance amongst the non-no choice vehicle options. As substitution between new and second-hand vehicle options can be influenced by more than one component, interpretation is most transparent when framed in terms of the implied variance–covariance structure of the composite error term. Accordingly, for respondents in class c, the variance and covariance of the unobserved components for any two new-vehicle alternatives are obtained from Equations (8a) and (8b),

$$Var\left(\xi_{nj,new|c}\right)=\sigma_{new|c}+\sigma_{vehicle|c}+\frac{\pi^2}{6}, \tag{8a}$$

$$Cov\left(\xi_{ni,new|c},\xi_{nj,new|c}\right)=E\left(\varepsilon_{nsi|c}+\sigma_{new|c}+\sigma_{vehicle|c}\right)\left(\varepsilon_{nsj}+\sigma_{new|c}+\sigma_{vehicle|c}\right), \tag{8b}$$

with corresponding correlation which follows directly by normalising the covariance by the square root of the product of the two variances terms, such that $\rho\left(new_{i|c},new_{j|c}\right)=\left(\sigma_{new|c}+\sigma_{vehicle|c}\right)\Big/\left(\sigma_{new|c}+\sigma_{vehicle|c}+\frac{\pi^2}{6}\right).$

An analogous set of expressions can be derived for second-hand vehicle alternatives

$$Var\left(\xi_{nj,2ndhand|c}\right) = \sigma_{2ndhand|c} + \sigma_{vehicle|c} + \frac{\pi^2}{6} \tag{9a}$$

$$Cov\left(\xi_{ni,2ndhand|c}, \xi_{nj,2ndhand|c}\right) = E\left(\varepsilon_{nsi|c} + \sigma_{2ndhand|c} + \sigma_{vehicle|c}\right)\left(\varepsilon_{nsj} + \sigma_{2ndhand|c} + \sigma_{vehicle|c}\right), \tag{9b}$$

with correlation equal to $\rho\left(2ndhand_{i|c}, 2ndhand_{j|c}\right) = \left(\sigma_{2ndhand|c} + \sigma_{vehicle|c}\right) \Big/ \left(\sigma_{2ndhand|c} + \sigma_{vehicle|c} + \frac{\pi^2}{6}\right)$.

Table 6 reports these implied within-segment correlation terms for new and for second-hand vehicle markets conditional on class membership, together with a “Weighted” correlation that aggregates across classes using the estimated class assignment model for the sample. Two clear results emerge. First, Class A exhibits strong positive within-segment correlation for both new vehicles ($\rho = 0.6351$) and second-hand vehicles ($\rho = 0.6127$). In substantive terms, this indicates that, within Class A, there are sizeable unobserved factors that are shared across alternatives within each market segment (new or second-hand), so that vehicles of the same segment behave as relatively close substitutes once observed attributes are controlled for. For example, for new vehicles in a choice set, the unobserved utility is positively correlated, suggesting that a change to the attractiveness of one new vehicle will tend to shift the probability mass disproportionately toward other new vehicles rather than uniformly across all alternatives. Second, the correlation structure in Class B is markedly weaker for new vehicles ($\rho = 0.0952$) and moderate for second-hand vehicles ($\rho = 0.3438$). The near-zero within-new correlation suggests that, for respondents belonging to Class B, unobserved utility components associated with new-vehicle alternatives are much less shared across new options, implying substitution patterns that are closer to those of a standard MNL within the new segment, whereas second-hand vehicle alternatives exhibit meaningful common unobserved influences, and hence a more segmented substitution pattern.

Table 6: Error component correlations

	Class A	Class B	Weighted
New Vehicles (*i,j*)	0.6351	0.0952	0.4618
2nd hand vehicle (*i,j*)	0.6127	0.3438	0.5264

When correlations are aggregated across classes, the weighted values imply moderate-to-strong within-segment correlation overall, with the implied substitution being stronger among second-hand vehicles (0.5264) than amongst new vehicles (0.4618). This weighting result is useful because it clarifies that even though Class B contributes relatively weak within-new correlation, the sample-level implication remains that unobserved similarity amongst second-hand vehicles is substantial, and that substitution away from a given second-hand alternative is, on average, more likely to be absorbed by other second-hand alternatives in the market than by new vehicle options or the opt-out alternative. Taken together, these patterns support the behavioural interpretation that the latent segmentation is not only about differences in taste weights for observed attributes, but also about differences in the error-correlation structure governing how respondents substitute among options within and across the new and second-hand vehicle markets.

Building on the odds-ratio and substitution results, Table 7 reports population-conditional preference parameters and implied willingness to pay (WTP) measures obtained by applying the estimated class-membership functions to population microdata rather than the estimation sample. Specifically, class-membership probabilities are computed for a large synthetic population drawn from the Australian Bureau of Statistics (ABS) 2021 census five percent sample microdata sample. In total, person level records are obtained drawn from 149,019 households located throughout the state of NSW. Given that the data is at the household level whereas the model is estimated at the individual person level, one adult is randomly selected per household and then mapped through the class-assignment model to obtain individual-level class probabilities. These are used to form individual conditional parameter and WTP estimates, the distributions of which are then summarised by their mean, median, and standard deviation in Table 7. The adopted approach is useful in that it converts latent-class heterogeneity into empirically grounded population distributions which can be interpreted as the implied spread of attribute valuations in the broader population rather than only amongst the surveyed respondents.

Table 7: Conditional parameter and WTP estimates

		Conditional parameter estimates			Conditional WTP estimates		
		Mean	**Median**	**Std**	**Mean**	**Median**	**Std**
New vehicles	Engine Type: Diesel	-0.5912	-0.6163	0.1596	-$11,267.75	-$12,205.36	$5,960.54
	Engine Type: PHEV	0.0623	0.0501	0.0778	-$8,755.95	-$7,960.82	$5,054.79
	Engine Type: HEV	0.0649	0.0631	0.0115	-$1,813.75	-$1,497.15	$2,012.67
	Engine Type: BEV	-0.1713	-0.1932	0.1393	-$13,040.58	-$12,627.71	$2,624.66
	Body Type: Liftback Sedan	0.3414	0.3278	0.0866	-$12,269.93	-$10,413.69	$11,800.41
	Body Type: Sedan	0.4057	0.4150	0.0589	$2,420.10	$3,435.51	$6,455.12
	Body Type: Station Wagon	-0.5425	-0.5310	0.0734	$12,755.35	$10,277.88	$15,749.66
	Body Type: SUV	0.6649	0.6351	0.1897	-$26,107.85	-$22,337.99	$23,965.58
	Vehicle Size: Large	-0.0309	-0.0513	0.1298	-$13,353.24	-$12,508.56	$5,369.80
	Vehicle Size: Medium	0.3361	0.3284	0.0493	-$8,301.56	-$6,738.76	$9,934.91
	Range	0.2072	0.2167	0.0604	$44.16	$47.12	$18.81
	Availability	-0.0615	-0.0624	0.0060	-$62.64	-$237.78	$1,113.36
	Price	-0.3197	-0.3295	0.0624			
Second hand vehicles	Engine Type: Diesel	-0.3498	-0.3752	0.1611	-$25,160.28	-$25,504.08	$2,185.56
	Engine Type: PHEV	-0.0517	-0.0741	0.1424	-$23,616.18	-$22,450.87	$7,408.05
	Engine Type: HEV	-0.4014	-0.4192	0.1132	-$16,855.77	-$17,984.49	$7,175.44
	Engine Type: BEV	-0.6416	-0.6729	0.1992	-$30,001.94	-$31,618.90	$10,279.23
	Body Type: Liftback Sedan	0.1105	0.1184	0.0501	$7,819.65	$7,935.95	$739.34
	Body Type: Sedan	0.1527	0.1477	0.0319	-$6,165.86	-$4,967.98	$7,615.11
	Body Type: Station Wagon	-0.2216	-0.2023	0.1223	$21,713.68	$19,195.21	$16,010.31
	Body Type: SUV	0.0086	-0.0172	0.1636	-$27,505.15	-$25,778.17	$10,978.71
	Vehicle Size: Large	-0.2368	-0.2492	0.0784	-$11,894.58	-$12,441.40	$3,476.27
	Vehicle Size: Medium	0.0197	0.0134	0.0402	-$6.86	-$6.33	$3.34
	Odomoter	-0.0655	-0.0666	0.0068	-$7.93	-$10.96	$19.31
	Range	0.0669	0.0667	0.0012	-$563.98	-$169.61	$2,507.07
	Condition	0.0915	0.0944	0.0183	$2,582.48	$2,916.63	$2,124.23
	Price	-0.1676	-0.1718	0.0267			

In interpreting the dummy-coded effects, engine types should be read relative to petrol, body types relative to hatchback, and vehicle size relative to small vehicles. The reported WTP measures follow from a linear in the parameters linear in the attributes price-attribute trade-off calculation assuming negative values represent a lower willingness to pay (i.e., the discount required) relative to the relevant reference level and positive values representing a price premium. For new vehicles, the conditional parameter estimates indicate particularly strong valuation gradients across body style and to a lesser extent powertrain type. Relative to a hatchback, SUVs have the largest positive mean effect (0.6649) and exhibit substantial dispersion (standard deviation 0.1897), consistent with SUVs being a highly salient differentiator with marked heterogeneity across the population. The implied WTP distribution mirrors this. The median valuation for an SUV relative to hatchback is large in magnitude (approximately AUD$22,000) with a standard deviation ≈ AUD$24,000, indicating that while many individuals place a sizeable premium (or require a sizeable discount, depending on their sign) on SUVs, there is also considerable dispersion in that valuation. Sedans and liftback sedans, once again relative to hatchbacks, are also positively valued in utility (means 0.4057 and 0.3414), but with smaller dispersions than SUVs, suggesting more stable average preferences for these body types. Station wagons stand out as negatively valued in the new market (mean −0.5425), with the corresponding WTP distribution indicating a large monetary equivalent and high dispersion, consistent with a niche pattern in which wagons are attractive to some but require substantial compensation for others relative to the hatchback baseline. For vehicle size, relative to small, the medium category is positively valued (a mean of 0.3361) while the large category is close to neutral on average (a mean of −0.0309) but with non-trivial dispersion, indicating that the "larger is better" gradient is not uniform and appears to be mediated by heterogeneity rather than a uniformly monotonic size preference.

With respect to powertrain effects, relative to petrol, diesel and BEVs are negative on average within the new vehicle market (−0.5912 and −0.1713), whereas PHEV and HEV are close to zero but slightly positive (0.0623 and 0.0649), suggesting that, once population composition is accounted for, preferences for hybrid and plug-in hybrid powertrains are comparatively weakly differentiated from petrol in the new-vehicle market, while diesel and BEV exhibit clearer average disutility. Consistent with this, the WTP magnitudes for diesel and BEV are sizable (median values around AUD$12,000 and AUD$13,000 in absolute terms), whilst the implied WTP for HEV is much smaller (median around AUD$1,500), reinforcing the interpretation that the main "money-moving" powertrain penalties/premia in the new vehicle market are associated with diesel and BEV rather than HEV. Among the continuous attributes explored within the DCE, range is valued positively in the new market (mean 0.2072) with a comparatively tight WTP distribution (with a mean of AUD$44 per km and standard deviation AUD$18.80), indicating a relatively stable marginal valuation of range compared with the much wider dispersion observed for discrete body-type shifts. Availability (months waiting time) enters utility only for new vehicles and is negative (mean −0.0615), with the implied WTP distribution suggesting that willingness to pay to avoid waiting varies materially across the population (i.e., large standard deviation), consistent with substantial heterogeneity in delay sensitivity.

For vehicles sold in the second-hand market, the conditional parameters show sharper and more uniformly negative powertrain effects (again relative to petrol) than for vehicles sold within the new vehicle market. Diesel, PHEV, HEV, and BEV are all negative on average (−0.3498, −0.0517, −0.4014, and −0.6416 respectively), with BEV exhibiting the largest mean disutility and substantial dispersion. The corresponding WTP distributions imply very large monetary equivalents for alternative powertrains in the used market, with BEV having the largest magnitude (with a median approximately equal to AUD$31,600 in absolute terms and a standard deviation of approximately AUD$10,300), diesel and PHEVs also exhibiting large magnitudes (medians ≈ AUD$25,500 and AUD$22,500), and HEVs somewhat smaller but still substantial values (with a median of approximately Au$18,000). This pattern is consistent with the idea that powertrain-related uncertainty and perceived risk (e.g., battery health, maintenance history, technology familiarity) may be more consequential in the second-hand market, yielding stronger differentiation from the petrol vehicle baseline. Relative to hatchbacks, preferences within the population are such that for liftback sedans and sedans preferences are positive on average (0.1105 and 0.1527) but negative for station wagons (−0.2216). The estimates for SUVs on the other hand are close to neutral on average (0.0086) but with a large dispersion (standard deviation of 0.1636), signalling substantial heterogeneity in the SUV–hatchback comparison within the used market, even if the mean effect is near zero. With respect to preferences for vehicle size (relative to small), the estimates are such that for large vehicles the population conditional estimates are negative (−0.2368) whilst for medium sized vehicles they are close to zero (0.0197), again suggesting a less uniformly monotone size gradient in the used market.

Examining the outcomes for attributes associated solely with second-hand vehicles, the outputs behave as expected. The conditional estimate for the odometer variable is negative (−0.0655), with a modest monetary effect per kilometre unit (a median around AUD$11.00 in absolute terms), whilst the condition rating is positive (0.0915) with an economically meaningful WTP magnitude (a median value of AUD$2,900 per star rating), indicating that the model recovers clear WTP signals for salient used-market quality indicators. Utility for vehicle range remains positive in utility with an average estimate of 0.0669, however the WTP distribution appears to be comparatively unstable as evidenced by a large standard deviation, suggesting that translating range into monetary values is more heterogeneous in the second-hand vehicle context, potentially due to "range" being interpreted through different lenses (e.g., battery condition versus advertised specification, or relevance varying with trip patterns and charging access) across households.

Figure 2 complements Table 7 by plotting the full conditional WTP distributions for the various powertrain types (i.e., diesel, HEV, PHEV, BEV), estimated relative to petrol. Each plot is plotted on a common scale to facilitate direct comparison across new and second-hand markets. Examination of the distributions suggest that valuations do not simply differ extensively by powertrain, but that both the location (central tendency) and dispersion change markedly between the new and used vehicle market contexts. Consistent with the results from Table 7, the WTPs for second-hand vehicle distributions for alternative powertrains appear to be shifted substantially further away from zero in absolute terms than their new-vehicle counterparts, with BEV in particular exhibiting the most extreme central tendency and the widest spread, indicating both stronger average aversion/premium effects relative to petrol and greater heterogeneity in valuation. Diesel and PHEV similarly appear much more strongly differentiated from petrol vehicles in the used car market than in the new car market, whilst HEVs are the least comparatively differentiated vehicle type in the new market (i.e., small magnitude and relatively tight dispersion), suggesting that conventional hybrids may face fewer valuation penalties (or command smaller premia) among new-vehicle considerations than BEVs or diesel, with such distinctions intensifying in the second-hand vehicle market. Given that the plots have been placed on a common scale, it is also possible to identify visually where overlap exists between the WTP for various powertrain and vehicle markets. For example, to the extent that new-HEV valuations cluster closer to zero whilst used-BEV WTP valuations are strongly shifted and diffuse, the policy and market implication is that the principal behavioural barriers (or premia) for electrification appears concentrated in the second-hand market but are distributed unevenly across the population rather than being a uniform average response.

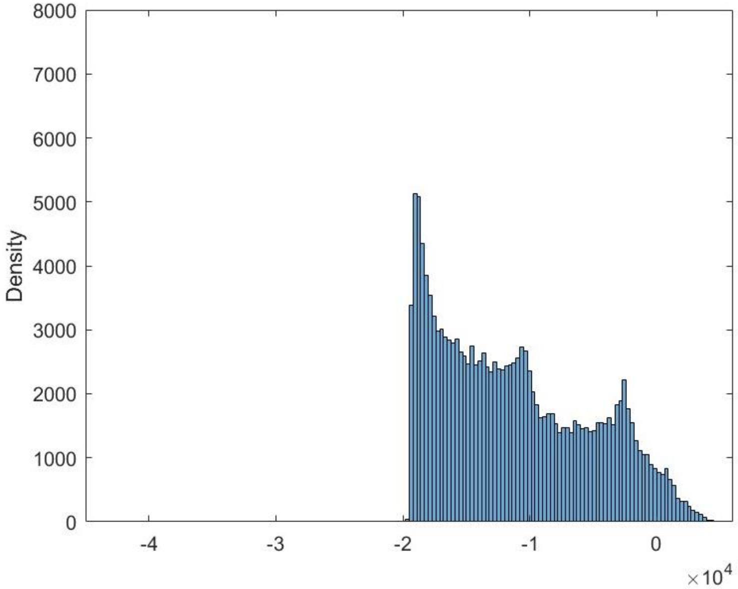
The final piece of analysis used to understand the role preferences play for vehicles sold in both the new and second-hand vehicle markets, we estimate demand, both in terms of absolute numbers and market shares, for 110 simulated vehicle types, consisting of 55 new and 55 second-hand vehicles. Given that the model includes a no-choice alternative, the ability to opt out and not purchase a vehicle is included as the 111th alternative in the simulation exercise. To generate the vehicles, for each market (new and used) and powertrain type (petrol, diesel, HEV, PHEV and BEV), we simulate the levels of average vehicles based on liftback sedans (small, medium and large), sedans (medium and large), station wagons (large), SUVs (small, medium and large) and hatchbacks (small and medium) combinations. The vehicle characteristics for each simulated vehicle profile is then formed by setting continuous attributes to their design means (or market segment-specific means) and categorical attributes to the relevant body-size-powertrain combination, where the levels for each vehicle type are averaged over the levels used in the DCE experimental design.

Table 8 reports predicted market shares for the set of 110 simulated vehicle profiles (55 new and 55 second-hand) plus the opt-out alternative, aggregated over 149,019 individuals drawn from the ABS five percent census microdata. To operationalise the simulation, the class membership probabilities based on the estimated model membership functions, followed by class-conditional choice probabilities, and finally the probability-weighted average across classes for each of the 111 possible choice outcomes assumed are computed for each of the 149,019 person records.

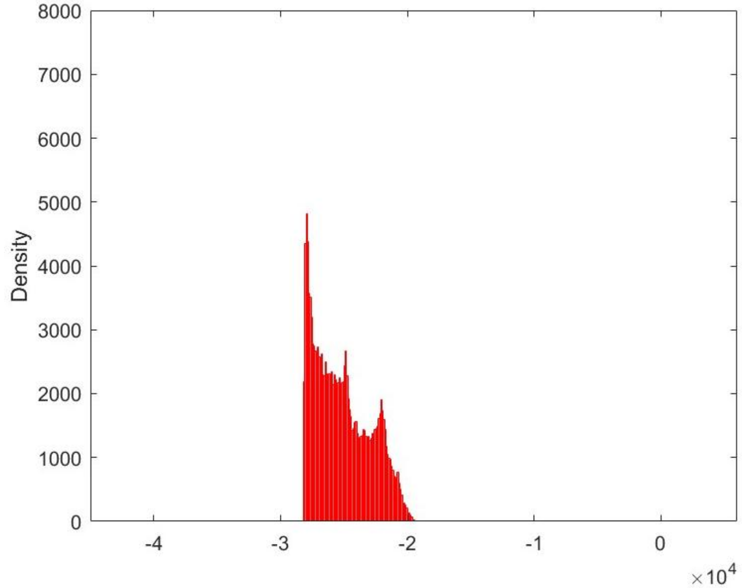
The table distinguishes between an uncalibrated application of the estimated model and a calibrated version that aligns the simulated new versus used vehicle split with observed 2024 sales totals (34.43 percent new against 65.57second-hand cars) and normalising for the presence of the opt out share which was estimated to be 4.20 percent of the observed choices. The calibration process involved simply multiplying the new and used vehicle choice probabilities by scaling factors and renormalising whilst leaving the within-segment (post constant adjustment) share composition unchanged. A first-order finding is that the uncalibrated model allocates almost equal shares to new (51.58 percent) and second-hand (48.42 percent) vehicle purchases, which materially overstates new-vehicle demand relative to the observed market split. The calibration process however shifts this balance to the known 34.43 percent new and 65.57 percent second-hand share split by construction. The discrepancy between calibrated and uncalibrated results is informative, implying that when the model is confronted with the average product mix used in the simulation, the latent class structure and estimated preference parameters alone imply a stronger propensity toward new vehicles than is realised in observed registrations/sales, suggesting that factors not fully represented in the simulation design, possible including supply constraints, search and transaction frictions, credit and liquidity constraints, and/or differences between the simulated profiles and the realised market offering, play a material role in determining the aggregate new-versus-used split.

The technology composition of demand for both the calibrated and uncalibrated forecasts shows a market dominated by petrol vehicles, but with substantial shares allocated to hybrid technologies and only a minority share to BEVs. Petrol vehicles account for 40.89 percent of total simulated purchases, followed by HEVs (21.95 percent), diesel (16.14 percent), PHEVs (13.29 percent), and BEVs (7.73 percent). Further, segmentation between the new and second-hand markets is pronounced, given that for every powertrain type, the second-hand market share exceeds the new vehicle market share, reflecting the calibrated dominance of the second-hand vehicle market overall. Nevertheless, it is worth commenting that the degree of skew differs by technology. Petrol vehicle demand is particularly concentrated on second-hand vehicle purchases (29.21 percent second-hand versus 11.68 percent new), whereas BEVs are the most evenly split across markets (3.82 percent second-hand versus 3.92 percent new). When considered alongside the earlier reported conditional WTP evidence, the relatively modest BEV market share in the calibrated results is consistent with the model recovering sizeable (and heterogeneous) monetary equivalents for alternative powertrains, especially in the second-hand market segment, so that expanding BEV penetration is not merely a question of shifting an average preference, but of overcoming a distribution of valuation (and likely risk-perception) barriers that appear to be more salient in the used car market.

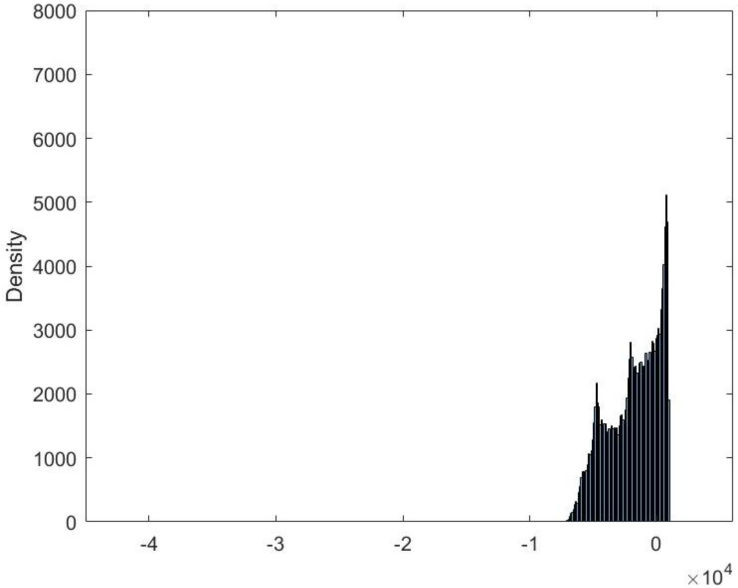
Body type and size predictions are comparatively stable across the uncalibrated and calibrated runs, implying that calibration mainly reallocates volume between new and second-hand without materially changing the within-market composition by vehicle type. In the calibrated outcomes, SUVs comprise the largest share of total demand (33.75 percent), followed by sedans (26.29 percent), liftbacks (20.43 percent), hatchbacks (16.18 percent), and station wagons (3.35 percent). By vehicle size, medium vehicles are predicted to dominate the market (44.93 percent), followed by small (31.53 percent) and large vehicles (23.54 percent).



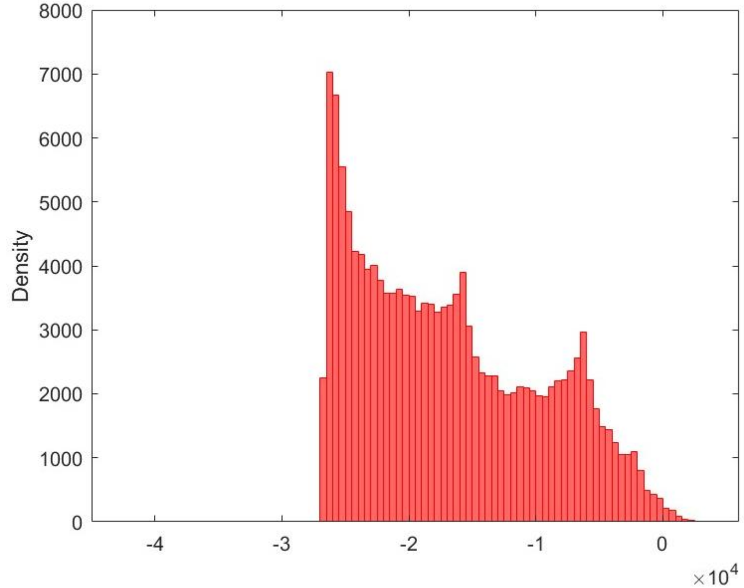
(a) New Diesel



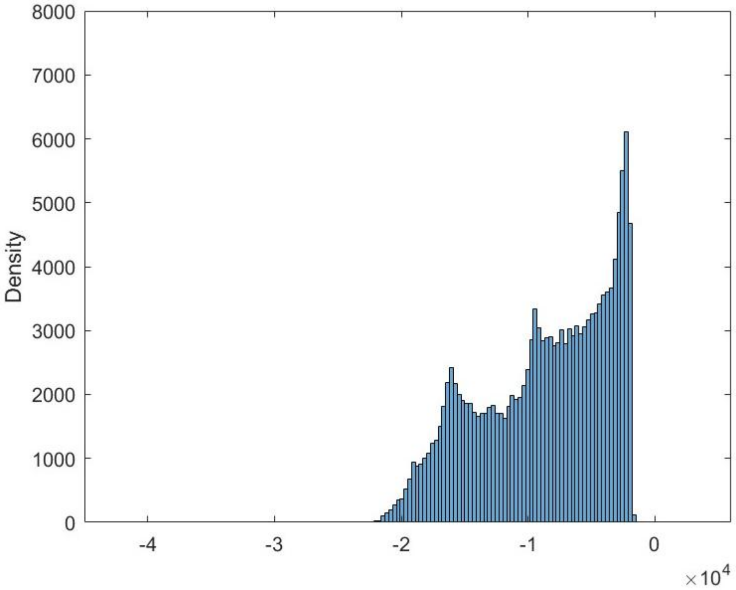
(b) 2nd Hand Diesel



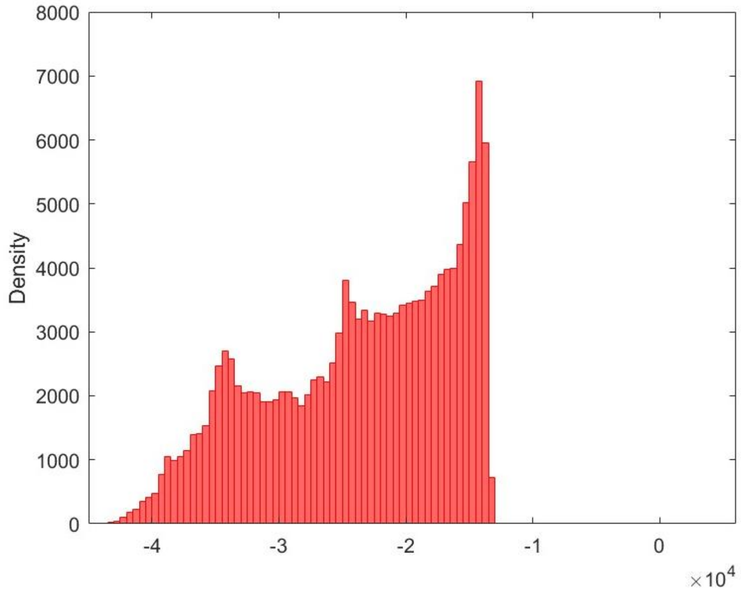
(c) New HEV



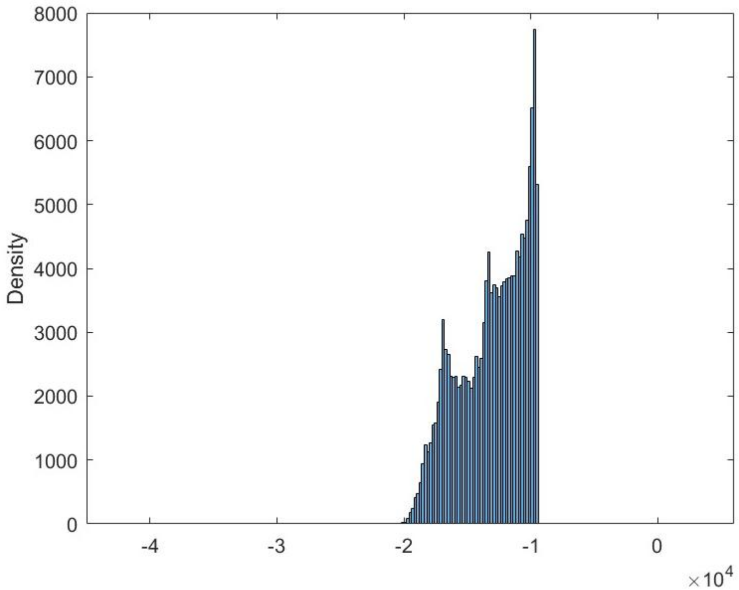
(d) 2nd Hand HEV



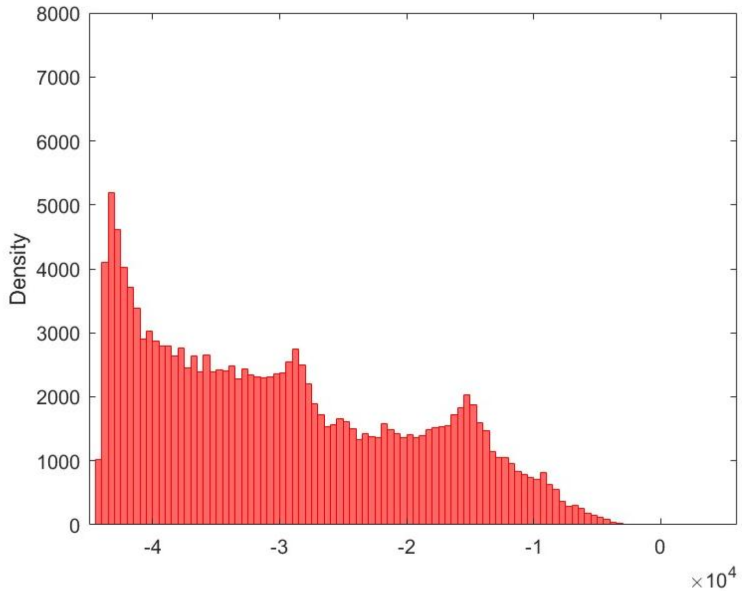
(f) New PHEV



(g) 2nd Hand PHEV



(h) New BEV



(i) 2nd Hand BEV

Figure 2: Conditional WTP distributions for Powertrain type (versus petrol)

Table 8: Predicted market shares and sales estimates

	Uncalibrated						Calibrated					
	New		2nd Hand		Total		New		2nd Hand		Total	
Market	**51.58%**	**1,839,298**	**48.42%**	**1,726,544**	**100.00%**	**3,565,842**	**34.80%**	**1,241,037**	**65.20%**	**2,324,805**	**100.00%**	**3,565,842**
Petrol	17.31%	617,176	21.69%	773,492	39.00%	1,390,667	11.68%	416,429	29.21%	1,041,513	40.89%	1,457,942
Diesel	8.12%	289,444	7.92%	282,395	16.04%	571,839	5.48%	195,298	10.66%	380,247	16.14%	575,545
HEV	10.79%	384,688	10.90%	388,581	21.69%	773,269	7.28%	259,562	14.67%	523,227	21.95%	782,789
PHEV	9.71%	346,363	5.00%	178,348	14.71%	524,711	6.55%	233,703	6.73%	240,147	13.29%	473,850
BEV	5.65%	201,627	2.91%	103,728	8.56%	305,355	3.82%	136,044	3.92%	139,671	7.73%	275,716
Liftback	9.94%	354,492	10.19%	363,436	20.13%	717,928	6.71%	239,188	13.72%	489,370	20.43%	728,558
Sedan	15.68%	559,231	11.67%	415,966	27.35%	975,198	10.58%	377,332	15.71%	560,102	26.29%	937,434
Station Wagon	0.64%	22,707	2.17%	77,285	2.80%	99,992	0.43%	15,321	2.92%	104,065	3.35%	119,386
SUV	19.73%	703,507	15.18%	541,221	34.91%	1,244,728	13.31%	474,680	20.44%	728,758	33.75%	1,203,439
Hatchback	5.59%	199,360	9.22%	328,635	14.81%	527,995	3.77%	134,515	12.41%	442,510	16.18%	577,025
Small	15.88%	566,263	15.46%	551,216	31.34%	1,117,479	10.71%	382,077	20.81%	742,217	31.53%	1,124,294
Medium	25.87%	922,478	20.41%	727,625	46.28%	1,650,103	17.46%	622,428	27.48%	979,753	44.93%	1,602,180
Large	9.83%	350,557	12.56%	447,703	22.39%	798,260	6.63%	236,532	16.91%	602,836	23.54%	839,368

The implications of these findings are twofold. First, irrespective of powertrain, the simulated market appears to be centred on SUVs and medium-sized vehicles, meaning that policy or product strategies aimed at shifting fleet composition (including decarbonisation) will have greatest leverage if they successfully address preferences and constraints in those high-share segments rather than focusing on niche body types. Second, the persistence of strong second-hand vehicle dominance after calibration reinforces the importance of the used market as the primary channel through which most households realise vehicle demand. As a consequence, interventions that reduce uncertainty and transaction risk in second-hand purchases (e.g., credible battery-health certification and warranty structures for electrified vehicles, transparent condition reporting, and market-making mechanisms that improve information quality) are likely to be pivotal for technology diffusion, even when new-vehicle incentives exist.

Conclusions and recommendations

This paper seeks to make a contribution by treating new and second-hand vehicle markets as jointly determined components of household vehicle demand rather than as separate domains, doing so by estimating a consumer demand model that accounts for both preference heterogeneity and substitution patterns within a unified modelling structure. The empirical results indicate most households do not face a simple “new BEV versus new ICE” but rather choose among new and second-hand vehicles across multiple powertrains under budget constraints and uncertainty about vehicle quality. Further, we find that consumer decision-making differs in systematic ways across the new and second-hand market segments, with preferences differing materially across both markets. In the second-hand vehicle market, attributes that proxy latent quality and future risk, most notably odometer and the condition rating, play a clear and economically meaningful role, which is consistent with a setting where buyers must infer reliability and future costs from imperfect signals. In the new-vehicle market, availability measured through delivery delay enters as a non-monetary cost that can materially affect utility, which is consistent with supply-side frictions shaping the attractiveness of new options beyond their sticker price and attributes. The two-class structure of the estimated LCM indicates that heterogeneity is not limited to taste parameters for observed attributes, but also extends to how respondents substitute among options within each market segment, supporting the interpretation that segmentation is partly behavioural and partly institutional, and reflecting different pathways that individual decision makers process uncertainty and choice constraints in new versus second-hand settings.

Conditional parameter and WTP distributions derived by integrating population microdata through the class-membership model provides a population-facing interpretation of the estimated heterogeneity. These results reinforce that the second-hand car market is not simply a scaled-down version of the new vehicle market, as shown by the dispersion of WTP valuations obtained as well as the way the relative importance of attributes that provide vehicle quality signals differ, suggesting that the same product characteristic can have different behavioural meaning when acquired used rather than new. While electrified powertrains are an important part of the attribute set and remain policy relevant, the central implication of the estimates is broader, namely that many policy levers that are evaluated using new-vehicle purchase responses will miss key behavioural margins if they do not account for the second-hand car market, where search, information quality, and perceived risk are likely to shape adoption and persistence of preferences over time. The simulated share predictions derived from the ABS-based synthetic population further strengthen this point, as the predicted composition of demand is governed not only by average attribute effects but also by the dominance of second-hand purchasing in the market and substitution operates within each segment. In practical terms, this suggests that interventions that only affect the flow of new vehicles can have limited and delayed influence on the stock purchased by most households unless complementary mechanisms improve the functioning of the second-hand channel.

Several recommendations follow from these findings. Policy design aimed at influencing fleet composition should explicitly incorporate the second-hand market as a primary site of behavioural response rather than treating it as a residual outcome of new-market policy. This implies prioritising interventions that improve information and reduce uncertainty for second-hand buyers, since the model results indicate that quality signals and perceived risk have meaningful welfare and demand implications. Standardised reporting and verification of condition, along with market institutions that reduce transaction uncertainty, are likely to increase the effectiveness of policies that seek to shift demand toward particular technologies or vehicle characteristics, because they act directly on the decision margins that are most salient in second-hand choice. Consumer assurance mechanisms also matter, including warranty and risk-transfer products that are credible and accessible in second-hand transactions, because they can reduce the perceived downside associated with latent defects that are not fully captured by observable signals. In parallel, supply-side frictions in the new market, reflected in the estimated effects of availability, suggest that policies and industry actions that reduce delivery delays can change the relative attractiveness of new purchases and, by extension, the characteristics of vehicles that enter the second-hand market in subsequent years. Finally, the results support focusing both policy and product strategies on dominant market segments, since predicted demand is concentrated on a small set of body types and sizes, and changes in those high-share segments will generate larger aggregate impacts than changes in niche categories.

A number of limitations of the current study should provide clear directions for, and motivate future work. The key limitation of the current study is that vehicle operating costs were not included in the experiment. Operating costs may be particularly important when comparing new and second-hand vehicles, and when interpreting technology-related attributes, because expected fuel or electricity costs, maintenance costs, and their uncertainty can differ substantially by vehicle age and drivetrain and can interact with quality perceptions. Future research should incorporate operating costs within the design, ideally in a way that allows respondents to process total cost of ownership and uncertainty, and should examine how operating-cost information interacts with second-hand quality signals such as condition and odometer. Second, while the design captures second-hand market quality via age, odometer, and an overall condition rating, future research could incorporate more granular and policy-actionable quality signals for electrified vehicles (e.g., explicit battery health metrics or warranty remainder) and test how alternative disclosure/certification regimes shift willingness-to-pay and predicted uptake. Finally, further work would benefit from linking stated preferences to market data on listings, transactions, and financing to better characterise the role of search frictions, credit constraints, and supply availability, which the calibration exercise suggests remain important in reconciling model-based predictions with observed new versus second-hand vehicle purchase shares.

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