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Who is afraid of electric vehicles? An analysis of stated EV preferences in Switzerland

Jeremy van Dijk and Mehdi Farsi

Who is afraid of electric vehicles? An analysis of stated EV preferences in Switzerland*

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Abstract

We provide novel evidence for the size of key electric vehicle (EV) adoption barriers, purchase price and battery range, and the driver, operating cost, in the broadening EV market. We further demonstrate the heterogeneity of these across consumer segments, plus determine groups most resistant to EV adoption and the relationship with transport habits and car ownership. To this end we analyse the results of a choice experiment of 882 respondents across Switzerland, a market that has favourable adoption criteria, however realises a low EV market share. We find low and inelastic elasticities of price, range and driving cost, and high variation across levels of urbanisation, income and car ownership. We additionally see high technological preference inertia among car owners, and a larger probability of non-owners and public transport users to choose EVs. We finally propose targeting EV adoption policies to relatively sensitive consumer groups to maximise efficiency, and support alternative policies to overcome low overall elasticities and achieve greater effectiveness.

Keywords: Transport; Electric vehicles; Adoption; Choice experiment; Stated preferences; Environmental policy; Behaviour

JEL Codes: D90, O33, Q40, Q48, Q50, Q58, R40

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1 Introduction

The global transition to a carbon-neutral economy requires large changes to existing transport systems, notably, electrification (Sims et al., 2014; Pietzcker et al., 2014).¹ Such a change has both technological and behavioural dimensions. The development and adoption of electric vehicles (EVs) is vital for the decarbonisation of transport, yet while the market share of EVs has increased over the past decade, in many countries it remains a minor fraction of new car sales. A number of policy measures have been implemented by jurisdictions worldwide to encourage EV purchases. Studies show that these have largely been effective in increasing EV market shares, however, there remains a large adoption gap and more attention needs to be paid to consumer heterogeneity to foster adoption across the broader population (Archsmith et al., 2022; Jenn et al., 2020; DeShazo et al., 2017).

This paper’s objective is twofold. Firstly, we identify the key barriers to EV adoption and analyse their relative heterogeneity across consumers. Secondly, we identify the consumer segments that are relatively resistant to adoption. We investigate the importance of consumer travel behaviours and habits, in addition to more traditional socio-demographic characteristics. We finally propose potential policies to address the adoption imbalance and encourage broader EV adoption. To do this, we conduct a choice experiment and exploit stated preferences to analyse those of the broad consumer base, rather than the primarily early adopters from the revealed preference literature. We analyse consumer preferences in a market with wide EV availability but low uptake – Switzerland. We particularly focus on the relationship between consumer heterogeneity (i.e. differences in consumer characteristics) and EV preferences. We provide novel evidence for variation in car price and battery range adoption barriers across consumer segments, as well as driving cost as an adoption driver. We elucidate the moderating and augmenting influences of transport mode habits and car ownership experiences, including technological preference stickiness. We further demonstrate the importance of environmental values for car preferences.

¹ This electrification must necessarily proceed hand-in-hand with a reduction in carbon intensity of electricity production. That process is underway and as it continues generates increasingly larger benefits to the electrification of other sectors (Holland et al., 2020).

Electric vehicles, especially battery electric vehicles (BEVs), are largely sold on their environmental credentials – namely, a reduction in negative pollution externalities – compared to traditional internal combustion engine vehicles (ICEs). BEVs emit no tailpipe emissions and therefore have the potential for large transport sector emissions reductions.² From the private consumer’s perspective, one of the key BEV adoption drivers is the relatively low use cost per kilometre driven. The low operating cost compared to ICEs stems from the often lower price of electricity than petroleum fuels, the greater efficiency of electric motors, and lower BEV maintenance costs (Rapson and Muehlegger, 2021). Lower use costs are offset, however, by often a significantly higher upfront purchase price than equivalent ICEs (Archsmith et al., 2022). The ‘payback period’ (time it takes for lower operating costs to fully offset the greater purchase price) depends on the car type and use intensity. Recent estimates find that this period could be between 5 and 8 years on average, however, for some scenarios (eg. low use and low gasoline prices) could be up to 10 (Weldon et al., 2018; IEA, 2020). Moreover, some estimates indicate that highly intensive drivers (eg. taxis, ride sharing or other driving services) could currently recoup the purchase price difference as early as 2 years (Baik et al., 2019), and recent gasoline prices of well over 90 USD/barrel could reduce the payback period to 4-5 years for average drivers (extrapolated from IEA, 2020). As technology continues to improve and battery costs continue to fall, purchase prices could further decrease and payback periods increasingly shrink.

Switzerland presents an opportune case study to investigate our research questions, as although it possesses many fitting characteristics for high EV adoption, the market share remains low. The country has a high average per capita income (5th in the world according to the World Bank (2021)), low average daily travelling distance (under 37km) (FSO, 2017), and some of the strongest environmental preferences (Franzen and Vogl, 2013). At a national level, BEVs are exempt from the 4 percent car tax (value added tax-equivalent) (BAZG, 2021),

² However, energy generation for recharging BEV batteries is shifted upstream, meaning that the true emissions produced through BEV use and whole lifecycle emissions depend on the marginal electricity generation at point-of-use, plus location of production and end-of-life. Overall, BEVs tend to currently produce fewer global and local air pollutants than their ICE counterparts, and the emissions continue to decline as electricity generation becomes cleaner (Rapson and Muehlegger, 2021; Ambrose et al., 2020; Holland et al., 2020; Ellingsen et al., 2016). However, it must be noted that in some places, currently, BEVs can produce higher air pollutant emissions.

and 20 out of 26 cantons give partial reductions or complete exemptions from registration fees (Electrosuisse, 2022). Despite all this, the market share of BEVs in 2018, the year of our experiment, was only 1.8 percent (BFE, 2021). EV market share as a whole (including plug-in hybrid vehicles – PHEVs) was 3.2 percent, compared to 49 percent in Norway, 4.5 in China, 2.2 in Western Europe, and 2.0 in the USA (IEA, 2021).³ Furthermore, approximately 22 percent of Swiss households do not own a car (FSO, 2017), enabling the analysis of a variety of individual transport habit typologies.⁴ Car ownership per person, however, rose slightly over the 21st century – by 9.1 percent from 2001 to a peak in 2016, before falling by 0.5 percent to 2021 (BFS, 2022).

We run a choice experiment with 995 respondents across Switzerland that provides insights into new and emerging car preferences. We set the available car technologies and attributes to match the newest market standards, and include a range of BEVs and PHEVs, in addition to conventional hybrids (CHs) and ICEs. Asking respondents to purchase a new car from these alternatives (or no car), simulates car market developments over the coming 5 years or more as consumers decide to replace existing vehicles or buy new ones (van Dijk et al., 2021; Comparis, 2013). We employ a mixed logit model to analyse responses, which allows us to account for heterogeneity in respondent sensitivity to car attributes and correlations between alternatives. We focus on the 882 respondents who choose to adopt a car of any sort in the experiment. Through a series of model specifications, we estimate the relative importance of car attributes, demographics and socio-economic factors for car choices.

Our experimental approach allows us to avoid endogeneity issues faced in revealed data lacking information about the alternatives not selected. Moreover, the EV market in most countries is still relatively new and small. In this setting, most EV purchases are not across a representative sample of the population, but concentrated in distinct segments of early adopters – for example, high-income households, highly educated, young-middle aged (eg. Archsmith et al., 2022). We are thus able to analyse the choices of a broad spectrum of the

³ Since 2018 EV market shares have risen in most of the world. The 2020 shares for the same countries are: Switzerland, 14.3 percent; Norway, 75; China, 5.7; Western Europe, 10; and the USA remains at 2 (IEA, 2021).

⁴ This figure has been fairly stable since the 1990s.

population, and car preferences over the coming years as more people choose to purchase new or replacement vehicles. Our stated preference (SP) approach further allows analysis of the trade-offs consumers make, as we observe their full choice set, rather than solely the revealed final decision. Our results, therefore, should be more representative of the EV market going forward, progressing towards a larger and broader consumer base.

Our results show that all specified adoption barriers and drivers are relatively small, however there is significant heterogeneity across consumer segments. On average, driving cost is the largest driver of adoption (of the three car attributes we analyse), with an elasticity that's slightly larger than that of upfront purchase price, -0.84 versus -0.67 , respectively. While the BEV price barrier is relatively large, BEV battery range is a minor barrier, with an estimated average elasticity of -0.12 . Nonetheless, all BEV demand with regard to all these attributes is inelastic. These aggregate findings vary somewhat from the existing literature. Studies based on real EV purchases estimate elastic demand (eg. -1.3 to -2.8 : Springel, 2021; Xing et al., 2021; Li et al., 2017). Driving costs, more similarly to our study, are found to have a small effect on car demand, though our estimate is somewhat larger. One study of Norwegian vehicle purchases finds highly inelastic BEV demand with regards to electricity (i.e. fuel) price of -0.18 (Fridstrøm and Østli, 2021); and an earlier Danish stated preference study estimates an 'EV fuel cost' elasticity of demand of -0.36 (Jensen et al., 2013). A previous study of conventional hybrid car demand in the USA estimates an elasticity of 0.52 with regards to gasoline prices (Beresteanu and Li, 2011). Finally, in contrast to our average result, Jensen et al. (2013) also estimate a mean elasticity of BEV demand with regard to battery range of about 0.55 , a larger effect than that for driving cost, above. These differences in car price and driving cost demand elasticities are to a large extent due to the research designs used. As previously explained, most previous studies analyse data of real car purchases and therefore encounter endogeneity between consumer choices and car prices and other attributes. They also cannot observe the full individual consumer choice sets and the specific trade-offs made. This focus on aggregate purchases and resulting endogeneity can bias the estimated elasticities. Our SP approach overcomes these issues and a large, representative sample allows us to explore EV preferences over the broad population, moving past early adopters.

We find significant heterogeneity in relative adoption barriers across various consumer groups. Specifically, we estimate different car attribute elasticities by residential location, income and existing car ownership. We would not expect BEV price and driving cost elasticities to vary significantly by region, after controlling for other respondent characteristics and conditional upon purchasing some car. While we find this result for driving cost, upfront BEV purchase price elasticity varies. Rural respondents are the most price sensitive, with city dwellers only a little more inelastic. Agglomeration residents, however, are significantly more price inelastic than both other groups. On the other hand, we would expect BEV battery range sensitivity to progressively increase the more rural one lives, due to a lower density of public charging stations and greater driving needs (longer distances and fewer public transport alternatives) (Li et al., 2017; Davis, 2019; Xing et al., 2021). Our results indicate, however, an inverted-U shape, where city dwellers have a positive but relatively low BEV elasticity with regards to battery range, those in agglomerations the highest sensitivity, and rural respondents essentially zero.

EV barrier and driver sensitivities also vary by household income. We would expect relatively low-income households to have greater price and driving cost elasticities due to diminishing marginal utility of income, and as previously found from real car purchase data (Muehlegger and Rapson, 2018; Xing et al., 2021). Driving range sensitivity should theoretically not vary significantly by income once controlling for factors such as home ownership. Our results match our hypothesis for BEV purchase price, however, we find the opposite for driving costs – i.e. above median-income households are significantly more sensitive to driving costs. Furthermore, driving range elasticity is similar for both low- and high-income groups, though slightly greater for the latter.

Finally, car ownership also affects the barriers to adoption. One could expect car owners to have a lower purchase price and driving cost elasticity due to a demonstrated past willingness to pay the upfront price of a car and continuous regular payments of car driving costs. On the other hand, battery range elasticity could be higher among car owners due to the existing experience of (mostly) higher ICE ranges and associated habit formation. Our results indicate that there is no real difference in car price sensitivity for car owners, though a large variation in driving cost elasticities. Non-car owners have a relatively large sensitivity

to marginal driving costs, while car owners have little. Battery range reactions match the hypothesised directions. We find relatively large range elasticity for car owners, but little sensitivity to range for non-owners.

In addition to car attributes and consumer socio-demographics, as in previous studies (Rezvani et al., 2015; Fevang et al., 2021), we also focus on consumer behaviours, including car ownership and transport mode use, and find these to be significantly larger determinants of car type choices. We identify the most EV-resistant groups as those who own an ICE, those who use their car for all regular commuting and leisure trips, and those with low environmental values. These groups show the highest probabilities of choosing an ICE over all other options and greatest marginal effects relative to their comparison groups. ICE owners have a 46 percent probability of continuing to choose the same technology, those who always use their car for trips have 44 percent probability of ICE choice, and respondents with low environmental values have 60 percent. In sum here, we find strong preference stickiness through past choices and habits, where ICE owners and regular drivers are most hesitant to shift to the new technology.

On the other hand, those most likely to choose an EV are essentially consumers with green values and travel habits (among those choosing some car). Specifically, respondents who are car free, who always use public or soft transport modes for their usual work and leisure trips, and who specify high environmental values. Car-less respondents have about a 30 percentage point lower probability of choosing an ICE and 25 higher for BEV compared to car owners. Respondents who only use public transport (PT) for all trips have a 56 percent likelihood of choosing a BEV, compared to 18 percent for an ICE. Exclusive users of soft transport (ST: walking, cycling, scootering) show a significant, but slightly smaller difference – 41 percent BEV choice probability and 32 for ICE. In addition to these demonstrated environmentally-friendly transport habits, we construct an indicator variable of respondents' environmental values based on a series of questions. We find that those with the strongest environmental values are relatively more likely to choose a BEV and less likely an ICE compared to those with low environmental values. We find a marginal effect of 14 percentage points more for BEVs and 16 less for ICEs.

We further find a strong preference inertia among green car owners. Owners of EVs

and CHs are overwhelmingly likely to continue to choose green cars. This group only has a 10 percent probability of choosing an ICE in the experiment. This lack of green car owner return to ICEs indicates potential for preference shifts to stick once EV adoption barriers are overcome.

Finally, we find smaller effects for other respondent and household characteristics that largely match the existing literature on early technology adopters. BEV choice is relatively higher (and ICE lower) for high-income households, males and those under 55 years old. Respondents living in a city are most likely to choose a BEV, while in agglomerations and rural areas, there remains stronger hesitancy. Those living in a house and home owners are more likely to choose a BEV than residents of a flat and tenants. Home location and type effects somewhat indicates the importance of EV charger availability. In more urban areas, there is a denser network of public charging stations, while home owners and residents of houses can relatively easily install home charging systems.

Our findings highlight some challenges for EV policies. Firstly, the inelastic responses to the key EV attributes, namely price, driving range and driving cost, indicate that it is difficult and relatively ineffective for any policy focusing on one of these to significantly increase adoption rates. At an aggregate level, we find focusing on reducing the operating costs of EVs would have the largest effect – for example, subsidising EV annual registration fees, insurance, or electricity for charging. A package of various policies that are targeted at different consumer groups, though, could be relatively effective. Providing purchase subsidies for low-income households and/or those in rural areas would be more cost effective than universal subsidies, for example.⁵ Additionally, increasing public charger availability in agglomerations and localities with high car ownership could reduce the range anxiety of these relatively range-sensitive groups. Furthermore, supporting home-charger installation particularly in or around multi-family dwellings could increase EV adoption in this segment. Overall, however, it seems like stronger policies such as technology mandates could be required to generate significant shifts in EV adoption in a short to medium time frame.⁶

⁵ This could be somewhat similar to the proposals of DeShazo et al. (2017) or the existing California Clean Vehicle Rebate Project (CVRP).

⁶ Such as, for example, those planned in France, UK, Canada, some US states, some Chinese cities (IEA, 2021).

Given the preference stickiness of existing ICE owners and regular car users, information campaigns and EV driving experiences could be implemented to potentially shift their preferences. To overcome the influences of habit and familiarity, information provision about the use and benefits of EVs could reduce resistance. Promoting experiences of driving, borrowing or hiring EVs (eg. through car dealerships or car-share/hire companies) could further provide learning experiences and reduce the ‘unknown’ factor of technology change and any required learning curve.

Finally, in light of the observation of car-less respondents adopting a BEV rather than staying without a car, a multi-model transport pass could reduce any increase in overall car use and other externalities such as congestion. This consumer segment could be incentivised to maintain public and soft transport habits rather than using the BEV for all trips. This could take the form of a free public transport subscription upon BEV purchase, or alternatively a package with PT access and discounted car sharing.⁷

The remainder of this paper is structured as follows. Section 2 further contextualises the paper in the existing literature. Section 3 outlines our methodology, including the experimental design and econometric framework. Section 4 then summarises our data and section 5 presents our results. Results are presented in three parts: first the overall choice statistics in 5.1; second, the mixed logit estimation results in 5.2; and third, the choice probabilities and marginal effects in 5.3. Finally, section 6 concludes.

2 Literature

This paper addresses each of the following aspects of the EV adoption literature, and additionally provides novel evidence about consumer-barrier heterogeneity, the importance of travel habits, preference inertia, environmental values, and new car owners. The policy space for promoting EV diffusion is large. Most commonly, governments provide financial incentives for EVs in order to reduce the larger upfront costs in comparison to conventional ICEs (Hardman et al., 2017). Monetary incentives such as rebates and exemptions from registra-

⁷ This could be similar to the “Green Class” offered by the Swiss Federal Railways (SBB), that, for a fixed fee, offers an EV lease plus unlimited public transport access (Martin et al., 2019).

tion tax and VAT have been shown to be effective in increasing EV purchases in a variety of regions, including the USA and Europe (Jenn et al., 2020; Clinton and Steinberg, 2019; Münzel et al., 2019; Figenbaum, 2017; Bjerkan et al., 2016; Tal and Nicholas, 2016; Helveston et al., 2015; Jenn et al., 2013). This is largely a continuation of early fuel efficiency policies, such as the financial incentives for CH adoption (Chandra et al., 2010; Gallagher and Muehlegger, 2011).

Additionally, many jurisdictions have implemented other EV incentives, such as use of bus lanes, or high-occupancy vehicle (HOV) lanes, free parking, and free toll road use (Jenn et al., 2018; Tal and Nicholas, 2016; Fevang et al., 2021). Charging options are an important consideration for potential EV adopters, and home charging opportunity especially is a facilitator of EV ownership (Hardman et al., 2018). The existence and extent of a local public charging network is a further consideration, which is especially relevant for those who cannot charge at home, and has been shown to be an important driver of EV adoption (Li et al., 2017; Delacrétaç et al., 2021). Some governments do also support public charging station infrastructure through subsidies (Springel, 2021).

Consumer heterogeneity, however, leads to variation in responses to incentives and therefore in adoption rates. This has not yet directly had much policy attention. One aspect of heterogeneity that relates to financial incentives is household incomes. Much evidence has shown that this is an important factor determining EV purchases and particularly, early adopters have relatively high incomes (Archsmith et al., 2022; Chen et al., 2020; Hardman and Tal, 2016; Lane et al., 2014; Tal and Nicholas, 2016). Xing et al. (2021) describe how EV rebates and subsidies are therefore greatly mistargeted and lead to inefficiencies in financial support policies. They show that EV adoption in North America is concentrated among high-income earners, and particularly those who would have bought a low-polluting car or EV anyway, even without a subsidy. Therefore, broader EV adoption among middle and lower income households requires different or larger, targeted incentives.

Lifestyle and behavioural factors, habits, education and environmental preferences are all further determinants of transport choices and EV adoption. Choo and Mokhtarian (2004), for example, show that travel attitudes, mobility behaviours, and lifestyle factors strongly determine the type of car one buys. They find that consumers in urban centres are more likely

to prefer small and luxury cars over other types, which matches well with early EV models. Small car owners have, on average, stronger pro-environmental attitudes, and also use their car less often for short trips. Those who use their car most often are more likely to have larger cars. Others have since demonstrated that many various environmental preferences are significant predictors of CH adoption (Kahn and Vaughn, 2009; Kahn, 2007) and that of EVs (Chen et al., 2020; Egbue and Long, 2012).

Individuals' regular driving distances and related range anxiety have been found to be key hindrances to EV adoption (Rezvani et al., 2015; Dimitropoulos et al., 2016). EV driving range and charging station networks are intimately linked, with a dense charger network (especially fast chargers) enabling greater driving distances even with relatively low battery ranges. These factors both demonstrate significant spatial variation, though. Urban centres often have higher numbers of charging stations, and urban residents also drive less on average. The less urban one lives, however, the larger the average driving distances and concurrently the less dense the network of EV chargers (Li et al., 2017). Davis (2019) shows that EVs are driven significantly less on average in the USA compared to ICEs and CHs. Rather than being solely related to the limited battery range of early models, EVs have on average been bought by consumers who drive less – particularly, more highly urban residents and those with greener lifestyles – and those with additional, ICE vehicles. However, longer regular driving distances do not necessarily always end in reduced EV adoption likelihood. Mukherjee and Ryan (2020), for example, find that BEV adoption in Ireland has been greater among those with the longest daily commutes.

Finally, Chen et al. (2020) and Jensen et al. (2013) demonstrate that experience with owning or using an EV significantly increases preferences for adopting or continuing to own future EVs. This personal experience and learning-by-doing aspect is a potentially important factor for adoption, indicating that once the initial hurdles and potential anxieties are overcome, consumers preferences can persistently shift. Hoerler et al. (2021) further shows that other alternative car-use experiences are also positively associated with EV adoption – specifically in this case, use of car sharing.

3 Methodology

3.1 Experimental design

We embed a choice experiment as part of the annual Swiss Household Energy Demand Survey (SHEDS).⁸ For a detailed description of our experimental design, see van Dijk et al. (2021).⁹ This paper focuses on the first part of the experiment, the car choice task. Respondents are asked to initially choose a car size, or no car at all, and then to choose a specific car alternative.

We follow standard discrete choice experiment (DCE) practice for accurate preference elicitation. We provide a priming script to encourage truthful and accurate responses, asking for their own personal preferences and explaining potential impacts on Swiss public policy (in line with Carson and Groves, 2007; Vossler et al., 2012). We further remind respondents about their household budget constraints and the trade-offs involved in purchasing and travel decisions (as per, for example, Johnston et al., 2017).

Our hypothetical car purchasing scenario states that respondents have to make a choice about purchasing a primary household car “within the next year”. The full questionnaire can be seen in van Dijk et al. (2021). The range of cars available and their attribute values (eg. price) are set to match the current market, with a weighting towards providing green alternatives, and are based on data from the TCS (2018). The values further depend on the car size initially chosen. If a respondent chooses to buy some car, we offer them the choice between 6 car alternatives (2 BEVs, 2 PHEVs, 1 CH, and 1 ICE). We specifically provide details for 5 car attributes in addition to the engine type. These are the car purchase price, the driving cost, the range of the battery (for EVs) the maximum speed, and the CO₂ emissions from using each car alternative. Descriptions of each attribute are available as pop-ups when respondents hover over the attribute title.

⁸ For more details on SHEDS see Weber et al. (2017)

⁹ Briefly, from 5515 total respondents, 995 are randomly assigned to take our experiment. This assignment targets a representative sample along gender, age, region, and housing status.

3.2 Econometric framework

We estimate the impact of car attributes on car selection, and of respondent characteristics and behaviours on the choice of car engine type. We also examine preference heterogeneity across a range of social segments and socio-demographic characteristics. To do this we propose a choice model that allows for potential correlations between car alternatives and heterogeneity in the sensitivity of individuals to alternative attributes. We then estimate the probabilities of car-type choice, and marginal effects (including elasticities).

Based in the standard random utility model (RUM) framework (McFadden, 1974), we estimate respondents' utility for each car alternative based on the levels of the car attributes and their choices. We assume respondents choose the alternative that provides them with the greatest level of utility.

To allow for flexible correlations between alternatives, particularly within fuel types or greener versus conventional vehicles, we relax the independence from irrelevant alternatives (IIA) condition. This further accounts for heterogeneity in respondents' attribute sensitivity. We thus employ a mixed logit (ML) model and estimate a utility function with random coefficients (McFadden and Train, 2000; Brownstone et al., 2000):

$$V_{ni} = \alpha A_{ni} + \beta_n X_{ni} + \gamma_i Z_{ni}, \quad (1)$$

where V_{ni} is the observed component of the utility function, of respondent n for car alternative i .¹⁰ We use unlabelled choice sets, meaning that we do not estimate alternative specific constants (ASCs) and instead focus on the outcome of primary interest, the choice of car type, between BEV, PHEV, CH, and ICE. A_{ni} is a vector of car attributes that are assigned a fixed coefficient, elements of the vector α . Z_{ni} is a vector of respondent characteristics, however, each characteristic is interacted with the car engine type in order to generate by-alternative variation and estimate its effect on selection probability of each engine type. Finally, X_{ni} is the vector of car attributes allowed a random coefficient. Thus the coefficients β_n vary across respondents according to the density function $f(\beta)$. In our case we specify the density to be

¹⁰ The utility function is: $U_{ni} = V_{ni} + \varepsilon_{ni}$, where ε_{ni} is the unobserved stochastic component.

normal: $\beta_n \sim N(\mu, \sigma)$. Where μ is the mean vector and σ the variance-covariance matrix.

The mixed logit choice probability is then the integral of the base logit probabilities over all possible values of β_n weighted by the density $f(\beta)$:

$$P_{ni} = \int \left(\frac{\exp(V_{ni})}{\sum_{j \in E} \exp(V_{nj})} \right) f(\beta) d\beta, \quad (2)$$

where E is the set of possible car alternatives. We simulate the probability estimates using $R = 1000$ Halton draws, and estimate simulated maximum likelihood (Train, 2009; Bhat, 2001). The averaged simulated probabilities are used to calculate the simulated log likelihood function:

$$SLL = \sum_{n=1}^N \sum_{j=1}^J d_{nj} \ln \left[\frac{1}{R} \sum_{r=1}^R \left(\frac{\exp(V_{ni}(\beta^r))}{\sum_{j=1}^J \exp(V_{nj}(\beta^r))} \right) \right], \quad (3)$$

where $d_{nj} = 1$ if respondent n chooses alternative j and 0 otherwise, and (β^r) refers to the r -th draw from the distribution.

We exploit this ML framework to estimate a set of models that focus on different aspects of respondent choice determinants. We include each car's fuel type, price, maximum speed, and driving cost in A_{ni} , and assign random coefficients to battery range (for BEVs) and CO₂ emissions (for non-EVs) through X_{ni} . Then in Z_{ni} we include respondent characteristics. Specifically, these are household income (above or below median), residential location (city, agglomeration, rural), age category (younger or older than 55), reported gender, whether the respondent lives in a house or apartment (multi-family building), if they are tenants or owners of the dwelling, and if they own a car. We additionally include an indicator variable of the respondent's level of environmental preferences.

The environmental values variable measures the importance respondents attribute to environmental protection and pollution prevention, and is constructed as follows. Respondents rated four values (respecting the earth, unity with nature, protecting the environment, and preserving nature) as "guiding principles in their lives" on a 5-point scale ranging from 1 "not important" to 5 "extremely important" (as per Steg et al., 2014). Aggregating the four answers gives the respondent's average biospheric value. We create a binary variable,

environment-important, with a value of 1 if respondents have an average biospheric value of 4 or more.

We further include respondents' travel behaviours through Z_{ni} , including whether they commute to work and a set of constructed travel mode typologies. We indicate if a respondent states in real life they always travel by public transport (PT), by soft transport (ST) (meaning walking, cycling or scootering), a mixture of PT and ST, or always uses their private car. The base category for comparison is using a mixture of car and other transport modes. These indicators are based upon responses to earlier survey questions about respondents' normal travel mode for work commutes, for local leisure or shopping trips, and relatively long-distance weekend trips. We also add the intensity of respondents' regular car use, specifically defined as low use if they drive their car less than 10,000 kilometres per year (km/yr), medium use from 10,000 to 20,000 km/yr, and high use of 20,000 km/yr or more. Finally, we include the type of car owned in real life between ICE or alternative car, and if the car is small, medium or large sized. Due to the low number of EV owners in the sample, we aggregate BEV, PHEV and CH owners to compare against those with an ICE.

We finally predict the choice probabilities for each car engine type at the median of observed variable values, and calculate the elasticities and marginal effects for each independent variable. Elasticities are calculated as the percentage change in choice probability for a one percent change in a continuous variable (car attributes). The marginal effects are the difference in probability of choosing a particular car type between variable category levels. For example, the probability difference for a car owner versus a non-car owner. To calculate the elasticity and marginal effect standard errors we bootstrapped the model and predicted probabilities with 100 repetitions.

We additionally estimate supplementary models separately interacting car price, BEV battery range and driving cost with the respondent characteristics location, income group and car ownership. From this, we calculate separate choice probability elasticities within these different groups. In this way we partially identify and explain the heterogeneity in EV adoption barriers and drivers across consumer segments.

4 Descriptive statistics

Our data stem entirely from our choice experiment, as described in Section 3.1. The SHEDS sampling ensures representativeness at the Swiss-level (excluding Ticino) (Weber et al., 2017), and our choice experiment largely matches this (for further details see van Dijk et al., 2021). For this study we analyse respondents who choose to ‘purchase’ a car in the experiment, giving 882 respondents.

Respondent characteristics that we use in our analysis are summarised in Table 1, including our constructed travel behaviour typologies as described in Section 3.2. We implement a binary variable for whether a household’s income is above the median, based on the original 6 SHEDS income categories. Here *above the median* means having a monthly income of 9000 CHF or more, and contains 37 percent of respondents. The distribution across residential regions is almost half living in cities, 30 percent in agglomerations, and 22 percent in rural areas. For age, we again use a constructed indicator of those 55 years old or more (34 percent). Slightly over half are male. Typically for Switzerland, over two thirds (68 percent) of respondents live in apartments, and we have nearly 60 percent tenants, matching the national 61 percent figure (BFS, 2019). Based on an aggregation of the four ecological value questions, as described in Section 3.2, over 62 percent of respondents place a high importance on the environment. Such a high fraction fits with the national-level findings of Franzen and Vogl (2013).

About 20 percent of respondents do not have a car in real life, close to the national 22 percent proportion (FSO, 2017). Only 3 percent of respondents have a CH or EV in their household, meaning ICEs are almost ubiquitous in terms of real-life car experiences. It must be noted that 5 respondents have a car but did not report an engine type, thus we include these in the base category of ‘no car’. There is an increasing trend from small car owners to large cars. Here 36 respondents have a car to which we could not attribute a size and they are included in the base category.

As for travel behaviours, nearly 78 percent of respondents commute to work (at the time of the survey). About 13 percent usually only use PT as their transport mode for all trip types. A further 11 percent usually only used ST for commuting and local leisure trips, while

Table 1: Descriptive statistics – respondent characteristics and travel behaviours

Characteristics			Car and travel		
	Frequency	Percent		Frequency	Percent
<i>Income level¹</i>			<i>Car ownership</i>		
Below or at median	559	63.4	None	177	20.1
Above median	323	36.6	At least one	705	79.9
<i>Location</i>			<i>Owned car type⁴</i>		
City	428	48.5	ICE	674	76.4
Agglomeration	261	29.6	EV or CH	26	2.9
Countryside	193	21.9	<i>Owned car size⁵</i>		
<i>Age group</i>			Small	170	19.3
< 55	584	66.2	Medium	225	25.5
≥ 55	298	33.8	Large	274	31.1
<i>Gender</i>			<i>Commuter</i>		
Male	459	52.0		684	77.6
Female	423	48.0	<i>Always use Public Transport⁶</i>		
<i>Dwelling type</i>			<i>Always use Soft Transport⁶</i>		
Flat ²	602	68.3		96	10.9
House	280	31.7	<i>Use Public and Soft Transport⁶</i>		
<i>Dwelling ownership</i>			<i>Always use car⁶</i>		
Owner	357	40.5		264	29.9
Tenant	525	59.5	<i>Environmental values³</i>		
<i>Environmental values³</i>			Unimportant	333	37.8
Unimportant	333	37.8	Important	549	62.2
Important	549	62.2			

Note: Based on the total of 882 respondents. Percentages may not sum to 100 due to rounding. CH: Conventional Hybrid. EV: Electric Vehicle. ICE: Internal Combustion Engine vehicle. (1) Median category is 6000-8999 CHF/month. (2) A dwelling in a multi-family building. (3) Based on the environmental values questions described in section 3.2. (4) The omitted base category of *no car* includes 5 respondents who have a car but we cannot attribute a fuel type. (5) The omitted base category of *no car* includes 36 respondents who have a car but we cannot attribute a size. (6) Respondents' usual travel mode, as described in section 3.2.

11 percent used PT and ST exclusively for all trip types. On the other hand 30 percent of respondents usually always used their personal car for all trip types.

Table 2 provides a summary of the range of car attribute values offered to respondents. Prices vary considerably across the range of car sizes and engine types. There is significant overlap across these categories, though a trend for comparable BEVs being more expensive than hybrids (though not always) and ICEs. ICEs are always the cheapest alternative. For example, the cheapest car at 13,000 CHF is a small ICE, while the most expensive at 95,000 CHF is a large BEV. Driving cost is also related to engine type, with BEVs the cheapest to

Table 2: Descriptive statistics – offered car attribute values

	Mean	Median	Min.	Max.
Price (CHF)	45,091	42,000	13,000	95,000
BEV	49,902	47,000	21,000	95,000
ICE	30,222	24,000	13,000	61,000
Driving cost (CHF/100km)	4.9	4.3	2.0	11.0
BEV	2.7	2.6	2.0	4.1
ICE	8.5	8.3	6.2	11.0
BEV battery range (km)	271	220	90	450
PHEV battery range (km)	42	45	20	55
Max. speed (km/hr)	182	175	130	250
Non-EV CO ₂ emissions (g/km)	110	110	65	165

Note: BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. EV: Electric Vehicle. ICE: Internal Combustion Engine vehicle.

run and ICEs most inefficient – up to 11 CHF/100km. BEV battery range spans the range available in the market at the time of the experiment, up to 450 km, with a mean around 271 km. PHEVs have significantly smaller batteries than BEVs. Maximum car speeds are correlated with size and have an overall mean of 182 km/hr. The CO₂ emissions of BEVs are 0, and PHEVs small, while those from CHs and ICEs have an average of around 110 g/km.

5 Results

We initially present choice statistics in section 5.1, summarising respondent decisions at a high level. We subsequently present the results from our mixed logit regressions in section 5.2, which provide estimates of our utility function. We briefly discuss the estimates, as they create the basis for our primary focus, the estimated probabilities and marginal effects. We present the probabilities of car choice, attribute elasticities and marginal effects of the variables included in the ML models in section 5.3.

5.1 Respondent choice statistics

In total 882 respondents choose to ‘buy’ a car in the experiment, of whom over a third (34 percent) choose a BEV and a similar proportion choose an ICE (Table 3: Panel A). In total

Table 3: Choice statistics – experimental car choices by actual car types

Panel A						
<i>Car engine type</i>	Frequency	Percent	Percent if own no car	Percent if own a car		
BEV	303	34.4	57.1	28.7		
PHEV	149	16.9	19.2	16.3		
CH	133	15.1	13.0	15.6		
ICE	297	33.7	10.7	39.4		

Panel B						
<i>Car size</i>	Frequency	Percent	Percent if own no car	Percent if own small car	Percent if own medium car	Percent if own large car
Small	307	34.8	54.0	60.0	18.7	17.5
Medium	386	43.8	38.5	27.7	63.1	42.0
Large	189	21.4	7.5	12.4	18.2	40.5

Note: Based on the total of 882 respondents. Percentages may not sum to 100 due to rounding. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. Choices vary within car engine categories – BEV 1: 17%; BEV 2: 17.4%; PHEV 1: 13.8%; PHEV 2: 3.1%. Car sizes are denoted by the aggregate levels employed in our analysis.

17 percent choose a PHEV and 15 percent a CH. There is a correlation of car choice with the ownership of a car in real life. Those who actually own a car tend to opt more for an ICE and relatively less for a BEV. Respondents who do not own a car mostly choose a BEV.

For our analysis we aggregate the raw car sizes selected by respondents into 3 categories: small, medium, large. Table 3: Panel B shows that the largest proportion of respondents chooses a medium-sized car, followed by small cars and large cars. There is also a correlation between the size of car a respondent owns in real life and their selection of car size in the experiment. Of those who own a small car, 60 percent choose the same size, with 28 percent moving one size larger, and a minority choosing a large car. We see a similar pattern for medium car owners. Over 63 percent of them select the same car size, while the remainder almost equally opted for one size smaller or larger. Finally, only around 41 percent of large car owners kept the same size in the experiment. A slightly larger proportion preferred a medium-size car, and a minority a small. At the margin, however, there could be an effect on large versus medium car choices or small versus medium due to differences in respondent perception of their car size and the official classification we use from the TCS (TCS, 2018).

5.2 Regression estimates

The results of model (1) in Table A.1 show that all car attributes are significant and therefore important in differing ways to respondents' car purchase decisions. Respondents do gain some utility from BEVs compared to all other fuel types on average beyond the other attributes controlled for. Higher car prices reduce respondent utility and likelihood of selection. A higher driving cost decreases respondent utility, however the marginal (negative) effect of driving cost decreases, fitting a quadratic functional form.

Maximum car speed was not valued by respondents, however the exact effect varied. At lower maximum speeds, below 160 kilometres per hour (km/hr), respondents are largely indifferent to variation in speed. Above that, up to 200 and then even more beyond 200 km/hr maximum, respondents preferred reduced maximum speeds. We postulate this stems from the lack of practical usefulness of high maximum car speeds. In Switzerland, like many other countries, the legal maximum speed is 120 km/hr, thus the benefit of having a car capable of much more is small or zero, *ceteris paribus*.

Controlling for the absolute positive utility gained from choosing a BEV, we then find, however, significantly heterogeneous responses to battery range. Respondents are more likely to prefer vehicles with a lower battery range on average, however, the distribution of this coefficient was very large. We further explore this respondent heterogeneity throughout the following models.

Finally, from model (1), the CO₂ emissions from the non-EV alternatives also entailed significant response heterogeneity, however the utility distribution remains close to zero. On average, and across most of the distribution, respondents prefer cars with combustion engines that are more polluting. However, the size of the coefficient indicates this was a very minor concern relative to other attributes. We hypothesise that those who are more concerned about emissions would be more likely to opt for a technology change, to BEV, rather than minimise emissions from the more polluting car category.

In model (2), accounting for all car fuel types and a large range of respondent characteristics does not change the coefficients from the base model by much. The one notable change is the random variable BEV battery range, whose mean becomes insignificant (0), and whose

distribution spread also reduces.

In terms of respondent characteristics, we find that high-income households have significantly greater preferences for both types of EVs, which matches the existing literature from Archsmith et al. (2022) and others. Both agglomeration and rural households gain negative utility from conventional hybrid vehicles, while regionality has little impact on the utility from other non-ICEs at this stage. Overall this is a surprising finding, however, residential location also correlates with many other variables through which the effect on car choice could be most pronounced, and further varyingly influences responses to other car attributes, as we will show.

Older respondents have a preference against PHEVs, specifically, however seem relatively indifferent between other car types, *ceteris paribus*. Female respondents also gain a significant disutility from PHEVs, however, we find no significant gender difference in BEV or CH utilities. Our measure of respondents' overall environmental preferences and interest, *environment-important*, shows a large and significant effect on EV preferences. Those who have greater stated eco-preferences are significantly more likely to choose an EV of either type, with highest utility gained from BEVs. We further find in this model that living in a house, compared to an apartment, and being a tenant, rather than home owner, did not have any significant effect on car choice estimates, when also controlling for other characteristics.

Finally, model (2) also accounts for households' real car ownership. Controlling for all the household characteristics above, the simple fact of owning a car means a respondent is much more likely to choose to buy an ICE than any other car. This group gains significantly less utility from BEVs, followed by a smaller coefficient for PHEVs and smaller again for CHs. This indicates a possible inertia in technological preferences, given the vast majority of cars owned are ICEs. It also demonstrates significantly greener preferences among non-car owners.

Delving into the impact of existing travel behaviours and habits, model (3) further indicates a significantly greater willingness among non-car users to purchase greener cars, especially EVs. We find that respondents who usually always take PT, ST, or both, for all commuting and leisure trips are much more likely to purchase a BEV than an ICE, and to some extent also gain positive utility from other green vehicles. Compared to the base category of mixed mode usage, respondents who say they always use their own car show little

difference in car type selection, having only a significant disutility from PHEVs. These travel mode choices accounted for, being a commuter or not engenders no difference in car utilities.

Model (4) adds to the previous mode use categorisation more nuanced variation in the extent of own car use, based on annual kilometres driven. The previous behavioural findings largely hold, and we find slight variation in utility by car use. All car users gain significant disutility from EVs, being most likely to select an ICE. Though the differences in coefficients are relatively small, the findings indicate among car users, medium users would have the least disutility from EVs. Low and medium car users are less likely to choose a CH over an ICE, however high car users gain no significant disutility, perhaps being the most likely group to want to benefit from fuel savings despite remaining technologically relatively static.

Finally, model (5) accounts for variation in the types of cars owned in real life. Most car use and car type utility coefficients are insignificant. We do see, however, that large car owners gain utility from a BEV or PHEV compared to others. Overall, we conclude that there seems to be a greater impact from regular car use on purchasing decisions compared to the type of car owned. That said, we next present the predicted probabilities of car type choice and calculate the marginal effects (on choice probability) by respondent characteristics, which demonstrates some nuances to the utility findings.

5.3 Choice probabilities and marginal effects

We further explore here the barriers to adoption addressed through the experiment, and the most- and least-resistant consumer segments. We present our estimates of the probability of car choice by engine type and marginal effects of the estimated variables on these probabilities. We sequentially focus on the barriers of car price, BEV battery range and driving cost, followed by the characteristics of car ownership, travel behaviours, and then basic respondent characteristics.

Adoption barrier elasticities

As previously discussed, one of the great barriers to EV adoption is the upfront purchase price. In our experiment, the median BEV price offered is 96 percent more than the median

Table 4: Car attribute elasticities

Panel A		Car type	
Attribute		BEV-own	ICE-cross
Price		-0.67 (0.48)	0.21 (0.23)
Range		-0.12 (0.28)	-0.06 (0.08)
Driving cost		-0.84 (0.82)	0.23 (0.33)

Panel B		Car type	
Attribute	Group	BEV-own	ICE-cross
Price	City	-0.79	0.31
	Agglomeration	-0.34	0.14
	Rural	-0.91	0.47
	Income \leq median	-0.39	0.11
	Income $>$ median	-0.14	0.06
	No car	-0.41	0.45
	Own car	-0.39	0.12
Range	City	0.19	-0.08
	Agglomeration	0.36	-0.23
	Rural	-0.04	0.02
	Income \leq median	0.44	-0.16
	Income $>$ median	0.53	-0.37
	No car	0.01	-0.01
	Own car	0.43	-0.19
Driving cost	City	-0.03	0.01
	Agglomeration	-0.04	0.01
	Rural	0.01	0.00
	Income \leq median	-0.05	0.01
	Income $>$ median	-0.26	0.07
	No car	-0.40	0.65
	Own car	-0.05	0.01

Note: Presenting BEV own-elasticities of choice probability, and ICE cross-elasticities from changes in BEV attributes. Panel A elasticities calculated from model (2), and Panel B from the supplementary estimations (Table A.2). Standard errors in parentheses, from 100 bootstrap model repetitions. BEV: Battery Electric Vehicle; ICE: Internal Combustion Engine Vehicle.

ICE price. On average, we find a price elasticity of -0.67 (Table 4: Panel A), meaning a 64 percent lower probability of choosing a BEV, at the median, on this basis alone. Comparing this to battery range shows price to be a significantly larger adoption barrier on average. The elasticity estimate of battery range based on model (2) is small and negative. The moderating factor for high purchase price is lower BEV driving costs. We find that these operating costs are a relatively large driver of BEV adoption, having a higher elasticity than the upfront price at -0.84 . The cross-elasticities on ICE choice probability show that there isn't a direct substitute between ICEs and BEVs. A significant proportion of respondents would switch to/from PHEVs or CHs, which has implications for estimates of pollution emissions changes, for example (as per Xing et al., 2021). Overall, however, all of these barriers and drivers of BEV adoption are inelastic. While there are relative differences in attribute importance, we find that varying any one will not have a significantly large effect on actual car type choices in itself.

Nonetheless, there are great differences in relative adoption barriers between consumer segments. Table 4: Panel B presents attribute elasticity estimates across residential location, income group and car ownership. These estimates are based on the supplementary regressions found in Table A.2 which expand model (2) to separately and sequentially interact car price, BEV range, and driving cost with the above consumer groups.

We find that respondents from rural areas are much more price sensitive than their city and agglomeration counterparts, having almost unitary elasticity. In comparison, city dwellers have slightly lower but still relatively high price elasticity, but those from agglomerations are comparatively price insensitive. For the highly price-concerned rural respondents, BEV driving range is comparatively a negligible barrier. City dwellers also display a relatively low BEV range elasticity, though it is still greater than that of the rural segment. Respondents in agglomerations, however, have a relatively large elasticity for battery range. While we hypothesised a somewhat linear increase in range sensitivity from city to increasingly less-urban areas, we find an inverted-U shape. Finally, driving cost elasticity does not appear to vary by location.

Attribute elasticities further vary by income group. We estimate that the upfront purchase cost is a larger barrier for those with a median-or-below household income, compared to

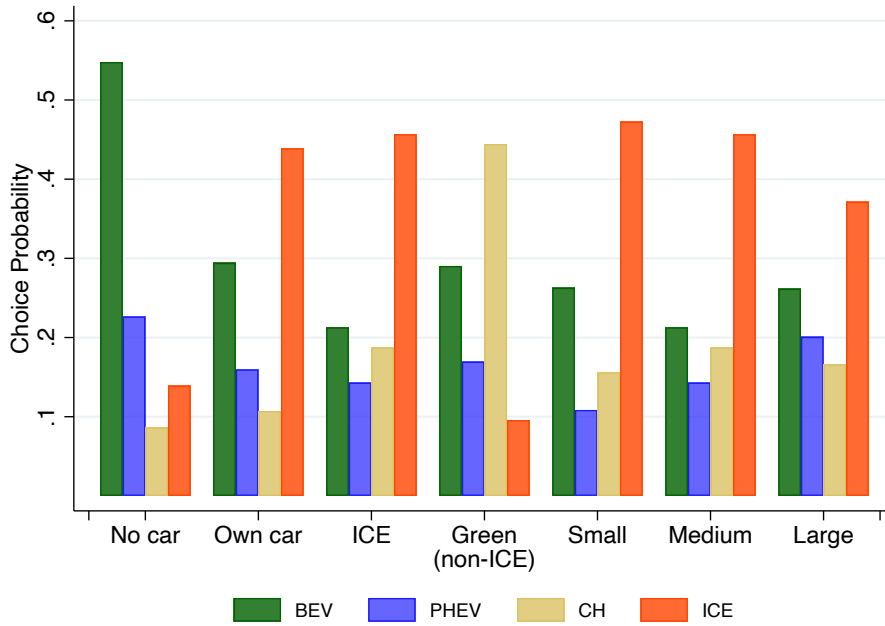
those above the median. Driving cost displays the opposite result to purchase price, whereby high-income households are more sensitive to this attribute than low-income. The purchase price elasticity difference matches the previous literature, as lower income households have a greater marginal utility of money, however, driving cost is the opposite. Nonetheless, this can be explained as those with a lower income being less concerned about small ongoing payments compared to large once-off expenditures that can be harder to save for. Both income groups display more similar and relatively large elasticities for battery range, however, this is a slightly more important barrier for higher income households.

Car ownership does not seem to impact sensitivity to purchase prices. On the other hand, existing car owners find BEV battery range to be a relatively significant adoption barrier. Their range elasticity is similar to that of purchase price, however respondents who do not already own a car do not see BEV range as an issue. This is perhaps due to existing car owners being used to their regular car's driving distance and fuelling frequency, and therefore being hesitant to change these habits. Conversely, driving cost is not a concern for current car owners, while it is a large adoption driver for non-car owners. We speculate that this could be due to existing drivers' experience with regular car expenditures, whereas new car purchasers would have fewer pre-conceived ideas or habits.

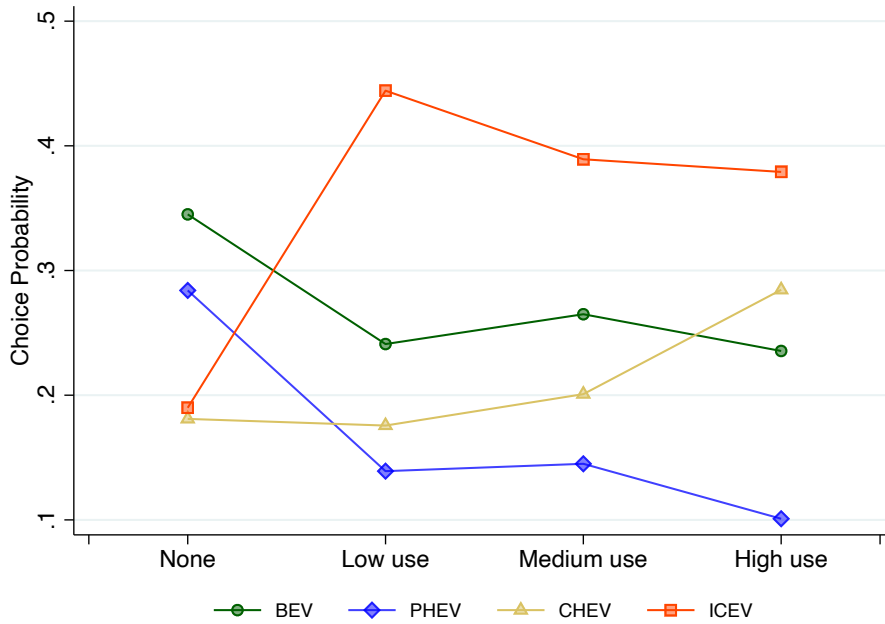
Marginal effects of characteristics

We next discuss the influence of respondent characteristics and behaviours on car choice probabilities, and identify key consumer segments. Figure 1 shows the probabilities of choice across the various categories of car ownership and use. Panel 1a demonstrates the relationship between car ownership and car choice, from model (2), and we see the experience of existing car ownership has one of the greatest impacts on new car choice. Coinciding with the findings in Table A.1, we see that car owners are most likely to opt for a new ICE, about 44 percent probability. All other car types are significantly lower – BEVs around 29 percent, PHEVs 16 and CHs 11. On the other hand, respondents who are car free have the greatest probability of choosing a BEV, 55 percent. While PHEVs are have a 23 percent probability, ICEs and CHs are 14 and 9 percent, respectively. In terms of marginal effect, car owners

Figure 1: Probabilities of car-type choice by car ownership and use



(a) Car ownership type



(b) Car use¹

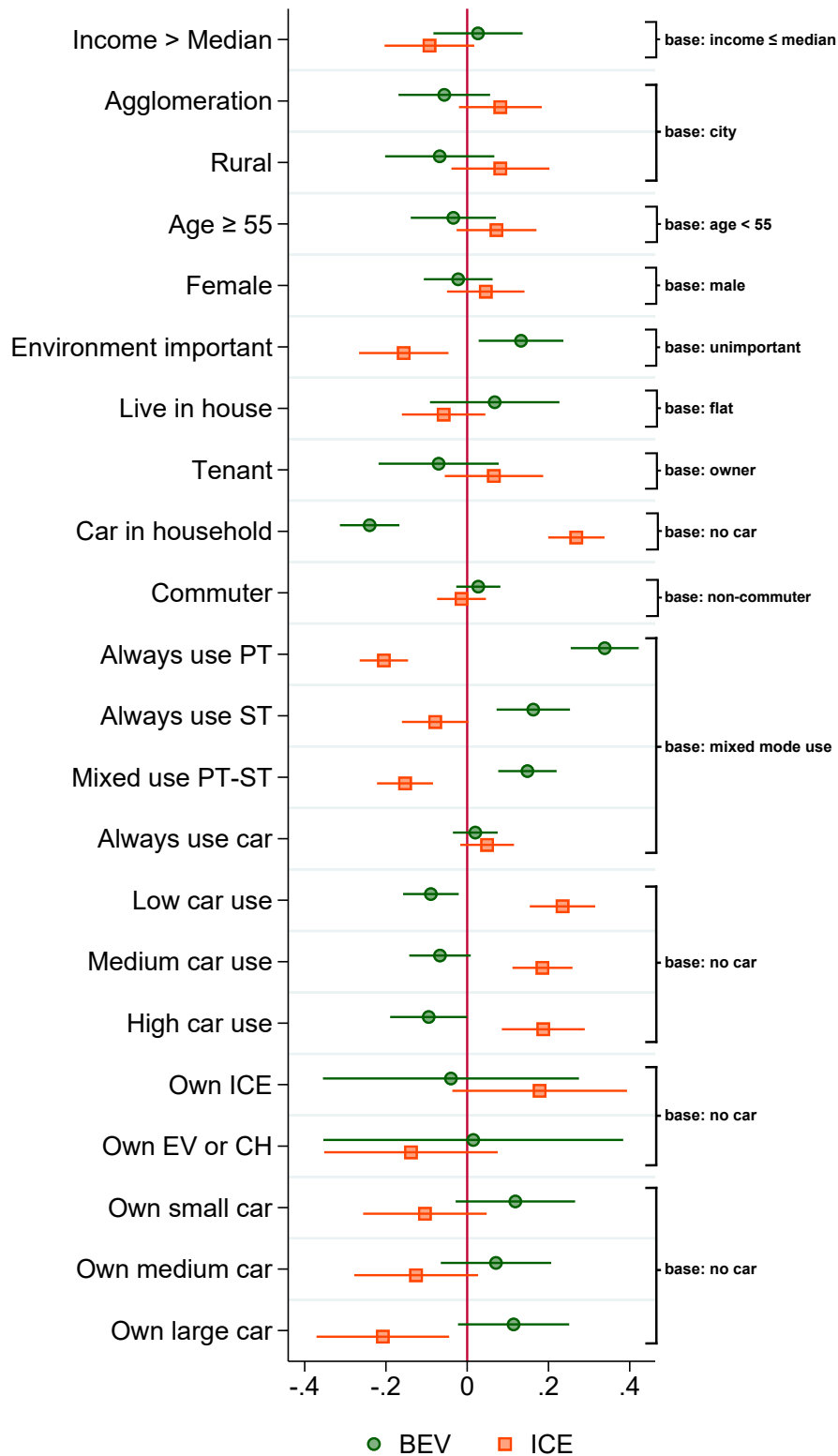
Notes: Car ownership is calculated from model (2), car use is from model (4), and car type from model (5). (1) Low car use is defined as under 10,000km/yr, medium is up to 20,000km/yr, and high use is 20,000km/yr and above.

are 30 percentage points more likely to choose an ICE than a non-car owner, on average (marginal effects on BEV and ICE choice are displayed in Figure 2). This is one of the largest effects of our study. They are also slightly more likely to opt for a CH, which essentially is a more efficient ICE. EV selection shows the opposite marginal effect. BEV selection is over 25 percentage points more likely for those who do not own a car, and PHEV is 7 points. We find, therefore, that BEVs could be greatly adopted over coming years by new car owners, and could potentially induce some car-less households to opt for purchasing one instead of remaining without a car at all.

Within car owners, however, there is significant heterogeneity by the car type owned. Respondents who currently own an EV or a conventional hybrid car (3.7 percent of car owners) have a significantly smaller likelihood of purchasing an ICE, on average, than other car types (Figure 1a). These respondents have about a 10 percent probability of choosing an ICE, and a 17 percent for PHEVs. This is significantly overshadowed by a 29 and 44 percent probability of opting for a BEV or CH, respectively. Conversely, the majority of car owners, who have an ICE, prefer to stick with that technology. On average we calculate a 46 percent probability of ICE choice by ICE owners, compared to 19 and 21 percent for CHs and BEVs, respectively, and only 14 percent for PHEVs. In sum this gives a marginal effect of green car ownership of 26 percentage points higher probability of CH choice and 8 points for BEVs. This indicates a strong inertia in technological preferences. Those customers that have decided to own a green vehicle are mostly satisfied and want to continue with that same type or different green car in the future. While ICE owners show similar unwillingness to change technologies towards a green car. Potentially this adoption-resistant group believes EVs don't fulfil their needs or find a change in technology too much of an 'unknown', requiring too-steep a learning curve.

In terms of existing car size, the clearest trends are decreasing ICE choice probability and increasing PHEV probability the larger the owned car. Large car owners are 10 percentage points less likely to opt for an ICE than small car owners, down from 47 percent probability. Conversely, they are 5 percentage points more likely to select a PHEV, up from 11 percent probability. Otherwise, the choice probabilities of BEVs and CHs remains fairly similar at the extremes, with medium sized car owners slightly less likely to opt for BEVs and more for

Figure 2: Marginal effects on BEV and ICE choice probability at sample median



Notes: Central points show mean marginal effect and lines show 95 percent confidence intervals. Standard errors calculated through 100 bootstrap repetitions.

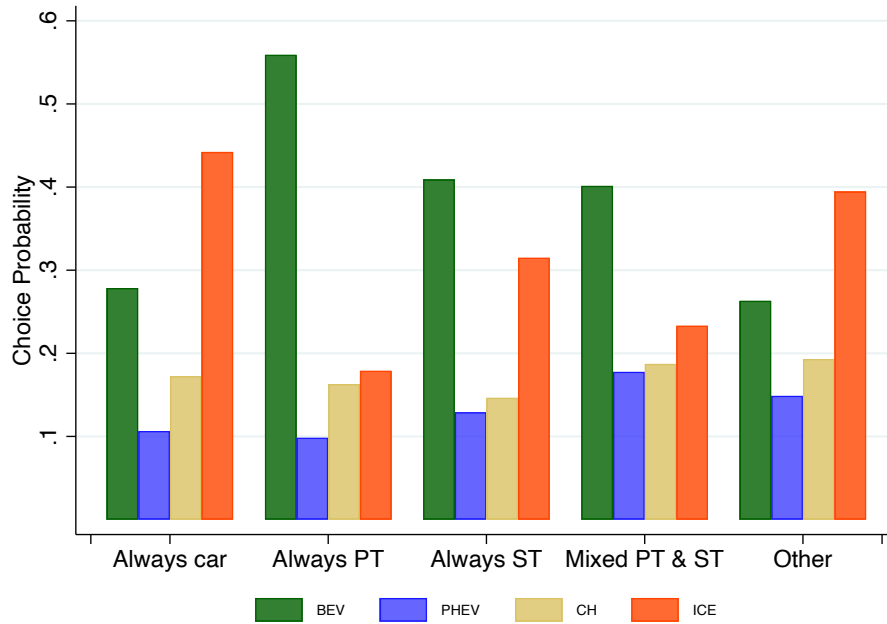
CHs (about 5 and 3 percentage points, respectively). We speculate that owners of large cars have a higher preference for overall driving comfort, and are thus somewhat more willing to adopt a PHEV, which also continues to allow for traditional driving distance and fuelling behaviours.

Intensiveness of car use is a further important factor for car choice, demonstrated in Figure 1b. The more a respondent uses their car in a given year, the less they are likely to select an ICE. Overall, respondents who drive over 10,000 km per year have about a 38 percent probability of choosing an ICE, compared to 44 percent for low users. Despite this reduction, all drivers are greatly more likely to choose an ICE over other car types. BEVs, for example, are only 24-26 percent likely to be selected, and PHEVs even less, around 10-14 percent, lowest for the biggest drivers. Conversely, conventional hybrids are more likely to be chosen the more a respondent drives. Low users have a lower CH choice probability than BEVs, at 18 percent, however this consistently rises by 11 percentage points to 28 percent for intensive car users.¹¹ These results indicate that respondents who use their cars the most are likely to look for fuel savings through selection of a hybrid car. Despite this, they are not especially interested in switching technologies to an EV.

In addition to respondents' existing car ownership patterns, transport habits greatly influence stated car choices. Figure 3 shows firstly that respondents who consistently use their own car for commuting and leisure trips are more likely to choose an ICE on average than those who take other modes or a mixture. The marginal effect compared to its base 'other', however, is only 5 percentage points (Figure 2). The effect on the choice probability of other engine types is even smaller. Much larger differences are seen between those who always use PT or ST (or both) and others who don't. These groups all display somewhat similar preferences and marginal effects, with some variance. Exclusive PT users are about 30 percentage points more likely to select a BEV than others. Along with car ownership, this is one of the largest differences in the study. The marginal effect on BEVs for ST-only and mixed PT-ST travellers is around 14 percentage points. A similar but inverse effect is found for ICE choice probabilities. PT-only users have a 22 percentage point lesser probability of choosing that

¹¹ Note that this doesn't add up correctly here due to rounding.

Figure 3: Probabilities of car-type choice by respondent travel behaviour



Notes: Calculated from model (4).

car type, and mixed PT-ST users about 16 points. We find ST-only travellers have about a 8 percentage point lower likelihood of choosing an ICE. As for PHEVs and CHs, these non-car travellers have on average a slightly lower probability of selecting them, or show no difference. Again, as previously with car owners versus non-owners, we find that those with the experience and habit of owning and using a car are more likely to stick with buying the same technology (mostly ICE), while those who have historically been car free or do not use a car regularly are more inclined to adopt the new car technology. Therefore, in the absence of incentive policies, EV adoption could develop initially amongst new car owners and users, and potentially also be associated with increased overall car purchases and car usage.

We further estimate the choice probabilities and average marginal effects of respondent characteristics from model (2). Overall, these characteristics have a much smaller effect on car choice than the above car ownership and travel behaviours and habits, as also seen in Figure 2. Firstly, household income has a reasonable effect on car preferences (Figure A.1a). Though still more likely to choose an ICE over other cars, high-income earners have a 9 percentage lower probability of choosing an ICE relative to lower and median-income

earners. The marginal effect of high-income is slightly positive for all other car types – 3 percentage points for BEVs, 6 for PHEVs and under 1 for CHs.

The less urban a respondent lives, the greater their preference for ICEs and less for BEVs and CHs, as shown in Figure A.1b. The average city dweller has a similar probability for choosing an ICE and BEV on average, 35 percent. Those in an agglomeration and rural areas are both about 9 percentage points more likely to choose an ICE than respondents in a city. Agglomeration and rural respondents are 5 and 6 percentage points less likely to choose a BEV, respectively, compared to those in a city, on average. The marginal effect of residential location on CH selection is half that size. PHEV preferences barely vary from their 17 percent probability. The overall preference trend towards ICEs and away from BEVs in more rural areas is consistent with greater technological hesitancy, lower peer and network effects, lower public charging availability, and differing transport needs (eg. larger distances), as discussed, for example, in Delacrétaz et al. (2021). As shown previously, we find further location variations in terms of price, BEV range and driving cost elasticities.

Older respondents, over 55 years old, show a preference for older technology. Figure A.1c shows that over-55s are 7 percentage points more likely to choose an ICE compared to younger respondents. They also demonstrate a lower BEV and PHEV probability (4 and 3 percentage points less, respectively), however no real difference in conventional hybrid selection. The respondent's reported gender also plays a role in their car choice (Figure A.1d). We find that on average female respondents are more likely to opt for a CH than males, and also show a slightly greater preference for ICEs (6 and 3 percentage points greater probability, respectively). This demonstrates a relative aversion to new EV technologies, being offset by a 3 and 7 percentage point reduced likelihood of selecting a BEV or PHEV, respectively. This fits with the previous literature on early technology adopters being more likely to be younger, male, and have higher incomes (Chen et al., 2020; Hardman and Tal, 2016; Xing et al., 2021).

Figures A.1e and A.1f then demonstrate the impact of housing status on car choices. Respondents who live in a house (single-family home), compared to an apartment (multi-residential building), have a lower probability of choosing an ICE and relatively greater one for BEV or CH. The average marginal effects are -6, 7 and 1 percentage points, respectively.

Additionally, home owners are significantly less likely to select an ICE, by 7 percentage points, and more likely to take a BEV (7 percentage points) or CH (2 percentage points) on average, compared to tenants. These results are consistent with the groups' relative access to garages, charging points, and their ability to make modifications and potentially install a faster EV charger at home, which itself has been shown to be an important factor for EV adoption (Hardman et al., 2018).

Finally, the environmental and ecological attitude and preferences a respondent has greatly influence their car choice (Figure A.1g). Those with strong environmental preferences are 16 percentage points less likely to choose an ICE than those with weaker preferences on average. They concurrently have a 14 percentage point greater probability of opting for a BEV. Preferences for hybrids also vary, with respondents holding high environmental importance 2 percentage points less likely to adopt a CH and 4 percentage points more likely to select a PHEV, on average. This fits with our behavioural findings above. We see that those who hold strong environmental values and who enact these day-to-day through transport habits are on average much more likely to adopt a BEV and less likely to opt for an ICE compared to less eco-friendly groups.

6 Conclusion

In this paper we exploit a stated preference study of a market with relatively strong EV-adoption resistance despite seemingly favourable early adoption characteristics. We provide evidence for the relative barriers to and drivers of EV adoption as the potential market broadens past early adopters over the coming decade. We further determine the key consumer groups who are most hesitant to adopt EVs. Building beyond the previous literature, we explore the variation in key barriers by consumer segments, and analyse the effect of current travel behaviours, car ownership and car use patterns on EV adoption. Our choice-experimental approach allows us to analyse the potential for changes in car-purchasing preferences over the medium term as increasing numbers of consumers decide to buy (or replace) a car and EV adoption starts to expand.

We find that at an aggregate level, BEV driving cost has a greater influence on BEV se-

lection than the barriers of purchase price and driving range. Price elasticity is not greatly smaller, however, and these two cost factors are significantly more important for respondents than driving range, on average. Nonetheless, all three car attributes are inelastic and thus do not engender large sensitivity to variation in their levels. Our inelastic BEV price elasticity estimate is significantly lower than elastic findings of the previous literature based on real car purchases (Xing et al., 2021; Li et al., 2017). Our experimental study is more representative of future market changes, rather than relatively early EV adopters, and is conditional on the selection of some car.

Regardless, there exists significant heterogeneity in relative barrier importance across consumer segments. Contrary to our hypothesis, price sensitivity varies greatly across residential locations. Rural residents, followed by city dwellers, have the greatest BEV price elasticities, with this a relatively smaller barrier for those from agglomerations. Driving cost sensitivity, however, is small and equal across these groups. Further contrary to our hypothesis, sensitivity to BEV driving range did not increase inversely to level of urbanisation, but rather displayed an inverted-U shape. City residents had a relatively small but positive range elasticity, and rural respondents almost zero. Those from agglomerations, however, had a relatively large sensitivity to battery range.

Furthermore, household income has opposing relationships with upfront purchase price and marginal driving cost. Respondents from lower income households demonstrate a greater sensitivity to BEV purchase price than higher income households, as theorised based on the literature. However, it is higher income respondents with a greater BEV driving cost elasticity. Both groups have relatively similar sensitivity to BEV battery range.

Existing car ownership significantly varies sensitivities to battery range and driving cost. Car owners have a greater BEV range elasticity than non-owners, as expected based on past habit formation and expectations of existing driving distances. Car-free respondents, though, are significantly more sensitive to BEV operating costs, perhaps partially due to a lack of existing knowledge and experience with ongoing car costs.

The strongest consumer group preferences that we find in our study are based on travel habits, car ownership, and environmental values. We find that those who are most resistant to choosing an EV are car owners, but especially ICE owners and car owners who use their car

for all trips, as well as consumers with relatively low environmental and ecological values. Our results show that car owners are significantly more likely to choose an ICE than those without a car, who prefer BEVs. We also observe strongly sticky technology preferences, whereby ICE owners are particularly resistant to choosing alternative technologies, while current owners of EVs or CHs overwhelmingly choose greener car options. Those with green car use experience, therefore, remain happy with their choice and find it suits their needs, however there is a large hurdle in getting ICE owners to shift demand to EVs.

On the other hand, we find that respondents holding strong environmental values are much less likely to opt for an ICE and shift towards BEVs, on average. People who regularly enact greener travel behaviours then show an even stronger preference difference. Respondents who choose to exclusively travel to work and for leisure purposes by PT or ST, rather than ever take a car, have a significantly greater probability of choosing a BEV than an ICE and a large marginal effect compared to the base mixed-mode category. Furthermore, the inverse of the car ownership above is that car-less respondents are much more likely to choose a BEV.

Though with relatively small marginal effects, we broadly confirm the findings from the literature that the usual EV adopters, particularly at an early stage, are more likely to have high incomes, be younger, and male. We further show that residential location and style matters for car choices. Respondents living outside of a city are more likely to stick with ICEs. This is consistent with non-urban residents having different transport needs, for example, comparatively greater distances, as well as fewer public EV charging stations, and lower peer and network effects due to lower urban density. Those living in a house have a higher probability of moving away from ICEs, compared to apartment dwellers, and conversely, tenants, rather than home owners, are more likely to buy ICEs and not shift towards EVs. We postulate that this is related to the availability of home EV charging and the possibility for installation of such chargers in the respective living situations.

A large constraint to effective policy is the result of inelastic demand with regard to the key EV adoption barriers and drivers – upfront purchase price, driving range, and driving cost. This means that policies that target these, such as price subsidies or rebates, will be inefficient and ineffective in driving adoption over the longer term. Nonetheless, as far as

such policies go, accounting for consumer heterogeneity and targeting them to appropriate segments could maximise efficiency. For example, offering price subsidies to relatively low-income households has a greater effect on BEV choices than those with above-median incomes. Such an income test for subsidy eligibility has already been proposed (for example, by DeShazo et al., 2017) and implemented in the California Clean Vehicle Rebate Project (CVRP). Additionally, we find price subsidies to rural regions could also be relatively more effective.

Driving cost reductions for those without an existing car (eg. first car buyers) and higher income households could also be relatively effective for increasing BEV adoption. While the latter could be controversial, the former seems feasible. This could take the form of subsidies for charging electricity, BEV insurance premiums, annual BEV registration fees, or periodic maintenance. At an aggregate level, though, this was also the most elastic attribute, so applying such policies to the entire population would still be relatively effective.

Furthermore, overcoming driving-range sensitivity among agglomeration residents and existing car owners would be relatively effective and could be feasibly achieved through a targeted approach. Increasing public charging stations installations in agglomerations, and areas with relatively high car ownership in general could reduce range anxiety and the perceived need for higher battery range. Additionally, support for destination chargers at work and leisure sites (eg. offices and shopping centres or tourist destinations), and home chargers (especially for multi-family dwellings) could be a relatively effective approach.

Given the strong technology preference stickiness we observe, we suggest there is opportunity for providing BEV information and experiences to nudge this group. Targeted information campaigns and providing the experience of using a BEV could decrease the unknown factors of EV ownership and use, and reduce the learning curve associated with the technological switch. For example, learning about local EV charging options and experiencing that EVs meet drivers' day-to-day needs could significantly reduce adoption hesitancy (as also somewhat indicated by Jensen et al. (2013)). This could potentially be implemented through car dealerships, charging station operators, and car-hire or -share companies.

Overall, however, our findings indicate that governments wishing to significantly increase a shift from ICEs to BEVs may have to opt for stronger policies. Technology mandates or ICE

sale and use restrictions or complete bans would be more effective at increasing BEV adoption in a shorter time frame. Such policies are already being discussed at various governmental levels across the globe. While some cities such as Oslo are introducing ICE driving bans, other state and national governments are planning bans on the sale of ICEs at future time points (commonly 2030 to 2040) (IEA, 2021).

Finally, future transport strategies cover the whole system, including all transport modes and infrastructure – such as road and PT use, and electricity demand. We find the potential to influence the combination of mode use and car type choice. Given currently car-free respondents and PT users show a significant preference for EVs, there is a potential to incentivise the maintenance of existing PT-use habits to some extent and minimise additional negative externalities of car use, such as congestion. For example, the offer of PT subscriptions or passes to buyers of an EV could encourage multi-modal travel and the (continued) use of PT when feasible.

Appendix

Table A.1: Regression results

	(1) Base	(2) Characteristics	(3) Behaviours	(4) Car usage	(5) Own car type
BEV	3.108 [*] (1.598)	3.144 ^{**} (1.545)	-0.601 (1.471)	1.913 (1.530)	1.499 (1.519)
PHEV	-	2.077 [*] (1.171)	-0.273 (1.018)	1.600 (1.117)	1.622 (1.182)
CH	-	1.581 ^{**} (0.727)	0.087 (0.516)	1.013 (0.655)	1.262 [*] (0.734)
ICE	-	<i>base</i>	<i>base</i>	<i>base</i>	<i>base</i>
Car price (10,000 CHF)	-0.618 ^{***} (0.102)	-0.579 ^{***} (0.135)	-0.574 ^{***} (0.137)	-0.587 ^{***} (0.137)	-0.545 ^{***} (0.139)
Driving cost (CHF/100km)	-0.886 ^{**} (0.362)	-1.272 ^{***} (0.311)	-1.075 ^{***} (0.340)	-1.049 ^{***} (0.331)	-1.135 ^{***} (0.334)
Driving cost ²	0.034 ^{**} (0.014)	0.054 ^{**} (0.015)	0.043 ^{***} (0.015)	0.041 ^{***} (0.015)	0.053 ^{***} (0.017)
Max speed 160 - 200km/hr	-1.156 ^{**} (0.490)	-0.528 [*] (0.273)	-0.680 ^{**} (0.332)	-0.638 ^{**} (0.309)	-0.610 ^{**} (0.292)
Max speed \geq 200km/hr	-1.338 ^{**} (0.531)	-0.667 ^{**} (0.323)	-0.863 ^{**} (0.381)	-0.803 ^{**} (0.360)	-0.780 ^{**} (0.353)
BEV \times Range (100km)	-3.237 [*] (1.790)	-0.575 (0.407)	-1.171 (0.757)	-1.105 [*] (0.656)	-0.872 (0.620)
sd(Non-BEV \times Range)	4.654 ^{**} (2.353)	1.362 ^{**} (0.556)	2.133 ^{**} (1.012)	2.059 ^{**} (0.858)	1.769 ^{**} (0.789)
Non-EV \times CO ₂ emissions (g/km)	0.023 ^{**} (0.010)	0.028 ^{**} (0.013)	0.024 [*] (0.013)	0.023 [*] (0.012)	0.018 (0.013)
sd(Non-EV \times CO ₂ emissions)	0.012 ^{***} (0.005)	0.022 ^{**} (0.009)	0.019 ^{**} (0.007)	0.019 ^{**} (0.008)	0.022 ^{**} (0.011)
Income $>$ median \times BEV	-	0.763 [*] (0.457)	-	-	-
Income $>$ median \times PHEV	-	0.840 ^{**} (0.376)	-	-	-
Income $>$ median \times CH	-	0.432 (0.273)	-	-	-
Agglomeration \times BEV	-	-0.873 (0.555)	-	-	-
Rural \times BEV	-	-0.937 (0.589)	-	-	-
Agglomeration \times PHEV	-	-0.500 (0.401)	-	-	-
Rural \times PHEV	-	-0.422 (0.430)	-	-	-
Agglomeration \times CH	-	-0.522 [*] (0.298)	-	-	-
Rural \times CH	-	-0.569 [*] (0.325)	-	-	-
Age \geq 55 \times BEV	-	-0.725 (0.447)	-	-	-
Age \geq 55 \times PHEV	-	-0.594 [*]	-	-	-

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Table A.1 – Continued from previous page

	Base	Characteristics	Behaviours	Own car use	Own car type
Age \geq 55 \times CH	–	(0.349) -0.279 (0.259)	–	–	–
Female \times BEV	–	(0.429) -0.529 (0.429)	–	–	–
Female \times PHEV	–	-0.822 ^{**} (0.350)	–	–	–
Female \times CH	–	0.305 (0.252)	–	–	–
Environment-important \times BEV	–	2.243 ^{***} (0.701)	–	–	–
Environment-important \times PHEV	–	1.036 ^{**} (0.426)	–	–	–
Environment-important \times CH	–	0.362 (0.261)	–	–	–
House \times BEV	–	0.858 (0.636)	–	–	–
House \times PHEV	–	0.240 (0.443)	–	–	–
House \times CH	–	0.334 (0.326)	–	–	–
Tenant \times BEV	–	-0.921 (0.592)	–	–	–
Tenant \times PHEV	–	-0.270 (0.425)	–	–	–
Tenant \times CH	–	-0.433 (0.319)	–	–	–
Car in household \times BEV	–	-3.921 ^{***} (1.031)	–	–	–
Car in household \times PHEV	–	-2.469 ^{***} (0.725)	–	–	–
Car in household \times CH	–	-1.422 ^{***} (0.440)	–	–	–
Commuter \times BEV	–	–	0.451 (0.578)	–	–
Commuter \times PHEV	–	–	0.023 (0.360)	–	–
Commuter \times CH	–	–	0.032 (0.289)	–	–
Always PT \times BEV	–	–	4.433 ^{***} (1.242)	3.050 ^{***} (1.079)	2.739 ^{***} (1.022)
Always PT \times PHEV	–	–	0.754 (0.591)	-0.280 (0.601)	-0.392 (0.653)
Always PT \times CH	–	–	0.799 [*] (0.435)	0.383 (0.471)	0.214 (0.495)
Always ST \times BEV	–	–	2.168 ^{**} (0.868)	1.947 ^{**} (0.829)	1.854 ^{**} (0.833)
Always ST \times PHEV	–	–	0.237 (0.547)	0.188 (0.534)	0.128 (0.595)
Always ST \times CH	–	–	0.018 (0.451)	0.059 (0.440)	0.030 (0.459)

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Table A.1 – Continued from previous page

	Base	Characteristics	Behaviours	Own car use	Own car type
Mixed PT-ST × BEV	–	–	2.507 ^{***} (0.884)	1.206 (0.855)	1.105 (0.853)
Mixed PT-ST × PHEV	–	–	1.052 [*] (0.555)	-0.051 (0.579)	-0.172 (0.631)
Mixed PT-ST × CH	–	–	0.664 (0.440)	0.189 (0.487)	0.010 (0.512)
Always Car × BEV	–	–	0.023 (0.595)	0.081 (0.583)	-0.086 (0.575)
Always Car × PHEV	–	–	-0.572 [*] (0.347)	-0.419 (0.344)	-0.538 (0.381)
Always Car × CH	–	–	-0.287 (0.268)	-0.330 (0.268)	-0.434 (0.281)
Low car-use (<10,000km/yr) × BEV	–	–	–	-2.686 ^{***} (0.865)	-3.144 (2.375)
Medium car-use (<20,000km/yr) × BEV	–	–	–	-2.145 ^{**} (0.885)	-2.760 (2.357)
High car-use (≥ 20,000km/yr) × BEV	–	–	–	-2.585 ^{**} (1.167)	-2.976 (2.518)
Low car-use (<10,000km/yr) × PHEV	–	–	–	-2.208 ^{***} (0.662)	-2.666 (1.689)
Medium car-use (<20,000km/yr) × PHEV	–	–	–	-1.936 ^{***} (0.666)	-2.564 (1.697)
High car-use (≥ 20,000km/yr) × PHEV	–	–	–	-2.345 ^{***} (0.816)	-2.870 (1.754)
Low car-use (<10,000km/yr) × CH	–	–	–	-1.199 ^{**} (0.467)	-0.465 (1.184)
Medium car-use (<20,000km/yr) × CH	–	–	–	-0.882 [*] (0.485)	-0.181 (1.182)
High car-use (≥ 20,000km/yr) × CH	–	–	–	-0.533 (0.543)	0.244 (1.206)
ICE in household × BEV	–	–	–	–	-1.839 (2.439)
EV CH in household × BEV	–	–	–	–	1.321 (2.773)
ICE in household × PHEV	–	–	–	–	-1.665 (1.798)
EV CH in household × PHEV	–	–	–	–	0.836 (2.102)
ICE in household × CH	–	–	–	–	-1.097 (1.231)
EV CH in household × CH	–	–	–	–	1.759 (1.520)
Small car in household × BEV	–	–	–	–	2.189 (1.494)
Medium car in household × BEV	–	–	–	–	1.612 (1.436)
Large car in household × BEV	–	–	–	–	2.668 [*] (1.555)
Small car in household × PHEV	–	–	–	–	1.363 (1.157)
Medium car in household × PHEV	–	–	–	–	1.725

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Table A.1 – Continued from previous page

	Base	Characteristics	Behaviours	Own car use	Own car type
Large car in household × PHEV	–	–	–	–	(1.135) 2.563 ^{**}
Small car in household × CH	–	–	–	–	(1.258) -0.135
Medium car in household × CH	–	–	–	–	(0.604) 0.109
Large car in household × CH	–	–	–	–	(0.589) 0.334
					(0.622)
N respondents	882	882	882	882	882
N observations	5,292	5,292	5,292	5,292	5,292
Log simulated-likelihood	-1422.83	-1357.16	-1388.42	-1374.44	-1359.83
AIC	2865.66	2792.32	2830.84	2814.87	2815.67
BIC	2931.40	3048.71	3008.33	3031.81	3131.22

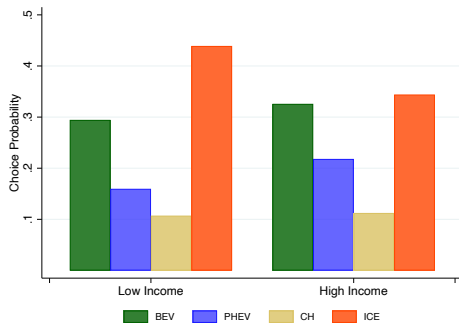
Notes: *, ** and *** respectively denote significance at 10%, 5% and 1% levels. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. EV: Electric Vehicle.

Table A.2: Supplementary estimation results – attribute interactions

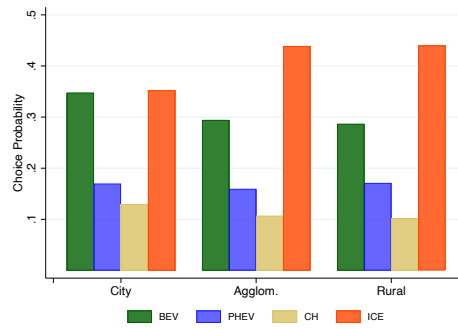
	Price	Range	Driving cost
BEV	3.439 ^{**} (1.649)	2.575 ^{**} (1.154)	0.294 (2.783)
PHEV	2.210 [*] (1.285)	2.279 ^{**} (1.035)	-0.979 (2.194)
CH	1.773 ^{**} (0.772)	1.434 ^{**} (0.655)	1.104 (1.154)
ICE	<i>base</i>	<i>base</i>	<i>base</i>
Car price (10,000 CHF)	-	-0.601 ^{***} (0.123)	-0.581 ^{***} (0.154)
Driving cost (CHF/100km)	-1.237 ^{***} (0.326)	-1.439 ^{***} (0.248)	-
Driving cost ²	0.056 ^{***} (0.016)	0.052 ^{***} (0.012)	-
Max speed 160 - 200km/hr	-0.575 [*] (0.295)	-0.267 (0.192)	-0.960 ^{**} (0.390)
Max speed ≥ 200km/hr	-0.725 ^{**} (0.342)	-0.386 [*] (0.215)	-1.032 ^{**} (0.433)
BEV × Range (100km)	-0.707 (0.449)	-	-1.429 ^{**} (0.717)
sd(BEV × Range)	1.579 ^{***} (0.596)	-	2.833 ^{**} (1.135)
Non-EV × CO ₂ emissions (g/km)	0.024 [*] (0.013)	0.040 ^{***} (0.010)	0.006 (0.020)
sd(Non-EV × CO ₂ emissions)	0.024 ^{***} (0.009)	0.013 ^{**} (0.006)	0.043 ^{**} (0.019)
City × Car price (10,000 CHF)	-0.564 ^{***} (0.205)	-	-
Agglom. × Car price (10,000 CHF)	-0.114 (0.212)	-	-
Rural × Car price (10,000 CHF)	-0.844 ^{***} (0.246)	-	-
Income ≤ median × Car price (10,000 CHF)	-0.250 (0.186)	-	-
No car × Car price (10,000 CHF)	0.180 (0.248)	-	-
City × BEV × Range (100km)	-	0.277 [*] (0.161)	-
Agglom. × BEV × Range (100km)	-	0.449 ^{**} (0.180)	-
Rural × BEV × Range (100km)	-	0.115 (0.190)	-
Income ≤ median × BEV × Range (100km)	-	-0.146 (0.141)	-
No car × BEV × Range (100km)	-	-0.120 (0.163)	-
City × Driving cost (CHF/100km)	-	-	-1.229 [*] (0.628)
City × Driving cost ²	-	-	0.111 ^{**} (0.045)
Agglomeration × Driving cost (CHF/100km)	-	-	-0.873 (0.844)
Agglomeration × Driving cost ²	-	-	0.042 (0.045)
Rural × Driving cost (CHF/100km)	-	-	-0.928 (0.723)
Rural × Driving cost ²	-	-	0.072 [*] (0.043)
Income ≤ median × Driving cost (CHF/100km)	-	-	0.942 (0.620)
Income ≤ median × Driving cost ²	-	-	-0.072 (0.044)
No car × Driving cost (CHF/100km)	-	-	-2.032 ^{**} (0.955)
No car × Driving cost ²	-	-	0.060 (0.063)
Characteristics	Yes	Yes	Yes
N respondents	882	882	882
N observations	5,292	5,292	5,292
Log simulated-likelihood	-1350.98	-1359.81	-1348.09

Note: *, ** and *** respectively denote significance at 10%, 5% and 1% levels. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. EV: Electric Vehicle.

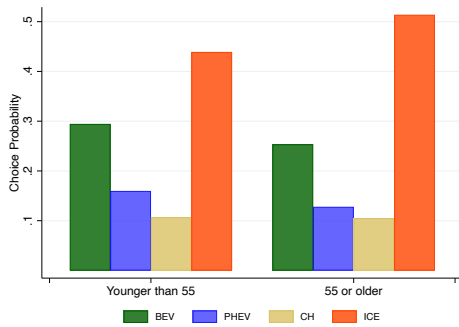
Figure A.1: Probabilities of car-type choice by respondent characteristics



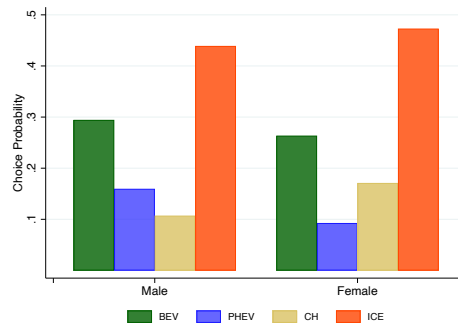
(a) Income group (\leq or $>$ median)



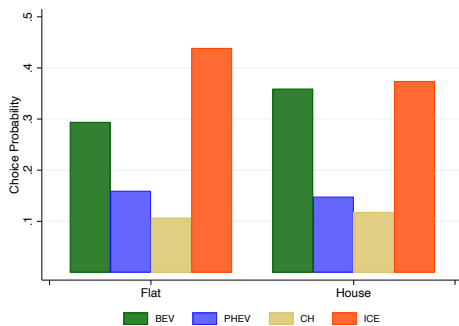
(b) Residential location



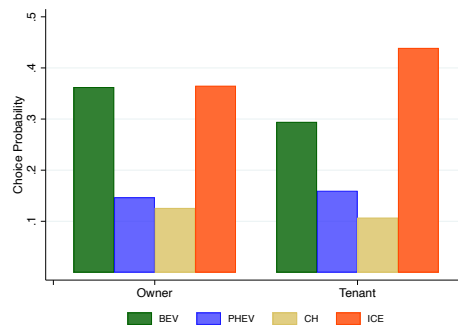
(c) Age group



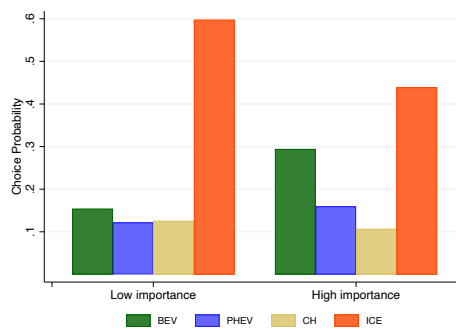
(d) Gender



(e) Dwelling type



(f) Dwelling tenancy



(g) Environmental values

Notes: Calculated from model (2).

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