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

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

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Abstract

We analyse the relative effect of potential barriers for the adoption of electric vehicles (EVs). While focusing on key factors such as purchase price, battery range, and driving costs, we investigate the heterogeneity of their effects across various groups of consumers and determine those most resistant to the new technology. To this end we develop a choice experiment conducted among 882 respondents across Switzerland. The stated-preference approach allows us to go beyond early adopters to the broader population of car owners, but also individuals potentially interested in buying a car in the near future. Our findings indicate relatively low demand elasticity with respect to purchase price, and statistically insignificant elasticity with respect to battery range and driving cost. Car ownership and habitual transport choices, as well as environmental preferences, are significant determinants of the selected technology. While respondents who do not own a car are more likely to choose an EV, regular car users present a strong resistance to the new technology. Overall, the results suggest that marginal promotion policies are unlikely to have a large impact on EV adoption.

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

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1 Introduction

The global transition to a carbon-neutral economy requires large changes in existing transport systems, notably, electrification (Sims et al., 2014; Pietzcker et al., 2014). The development and adoption of electric vehicles (EVs) has thus become an important factor, bringing many jurisdictions worldwide to implement policy measures to encourage EV purchases. Though increasing over the past decade, the market share of electric vehicles (EVs) remains low, limited in many countries to a minor fraction of new car sales (IPCC, 2022; IEA, 2021). While pointing to relative effectiveness of such policy measures, a number of studies suggest that fostering adoption requires targeted policies, hence a better understanding of key barriers and their heterogeneity across various population groups (Archsmith et al., 2022; Jenn et al., 2020; DeShazo et al., 2017).

This paper's objective is twofold. Firstly, we aim to quantify the key barriers to EV adoption and analyse their heterogeneity across consumers. Secondly, we seek to identify the consumer groups that are relatively resistant to the new technology. We specifically investigate the importance of different travel habits, in addition to socio-demographic characteristics. Adopting an experimental approach based on stated preferences, we endeavour to go beyond the relatively small group of early adopters to a broader population of potential buyers in a near future. This allows us to propose potential policies to address adoption barriers and encourage broader EV adoption.

To undertake this analysis, we conduct a choice experiment to elicit consumer preferences across Switzerland. We particularly focus on three key factors namely, upfront cost, battery range and driving cost. We identify the interactions between a number of consumer characteristics and EV choice preferences. In particular, we elucidate the moderating and augmenting influences of transport mode habits and car ownership. We further demonstrate the importance of environmental values, as well as the stability of the respondents' preferences in line with their current experience.

We conduct a choice experiment with a representative sample across Switzerland, pooling car owners together with those potentially considering a car purchase in the near future. The experiment design aims at simulating car market developments as consumers decide to replace existing vehicles or buy new ones (van Dijk et al., 2021). We ask respondents to imagine a car purchase scenario within the next year. They initially select a particular car size, or no car. Potential buyers follow the experiment by selecting a car among a realistic range of car technologies within the selected size category. Alternatives include Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV), in addition to conventional hybrids (CH) and Internal Combustion Engine Vehicles (ICE). We specify the available car attributes to match the actual market standards at the time of experiment (2018).

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 estimate probabilities of choice of each car type and the elasticities of EV adoption probability with respect to car attributes. We focus on 882 respondents who choose to adopt a car in the experiment. Through a series of model specifications, we estimate the effect of demographics and socio-economic factors, as well as the relative importance of car attributes, namely, upfront cost, operating costs and battery range. While relatively high purchase price and limited battery range can be considered barriers to EV adoption, the currently low operating costs could be a market driver.

While relying on hypothetical choices, the experimental approach provides important advantages in our study. As opposed to revealed-preference data where the individual choice sets are not observed, the experimental setup allows us to define a specific choice set for each respondent and identify the effects of various attributes. Lack of control for individual-specific choice sets could cause endogeneity bias typical in revealed data analysis. A choice experiment avoids such biases through a random design of choice attributes. Moreover, using an experiment, we are able to analyse the future preferences and trade-offs of a broad spectrum of the population, as opposed to a relatively small number of EV purchasers, which are likely to be concentrated in distinct segments of early adopters – for example, high-income households, highly educated, young-middle aged (e.g. Archsmith et al., 2022).

Our results show that all specified attributes represent relatively small or insignificant effects, in that a relative change in an attribute brings a small or negligible change in adoption probability. For instance, we do not find any evidence of statistically significant elasticity of BEV demand with respect to driving cost and battery range. The purchase price presents, however, a significant elasticity but greater than -1, suggesting an inelastic demand response. In particular, our estimations suggest that the average elasticity of adoption probability of a BEV with respect to purchase price is -0.21. This estimate is lower (in absolute value) than previous studies reporting an elastic EV demand based on revealed data. Nonetheless, it suggests that upfront costs could be a relatively important barrier compared to battery range and charging concerns.

Our estimation of elasticities by residential location, income and car ownership, does not point to much significant variation across various consumer groups. There emerges, however, a clear pattern of heterogeneity with respect to price elasticity across residential locations, suggesting a greater importance of BEV prices among respondents residing in urban centers and also rural areas, as opposed to those in agglomerations.

Analysing the marginal choice probability differences (marginal effects) between consumer groups, we focus on transport behaviours, including car ownership and transport mode use, in addition to the standard socio-demographics used in previous studies (Rezvani et al., 2015; Fevang et al., 2021). We find these behaviours to be significant determinants of car type choices. The most EV-resistant groups are regular car users; that is, respondents who use their car for all regular commuting and leisure trips. In addition, car owners and respondents with low environmental values are most likely to select an ICE. Finally, our mixed logit regression results indicate some smaller effects across socio-economic variables. There is, for instance, suggestive evidence for a general tendency for EVs among high income earners, male respondents and home owners.

Our findings highlight some challenges for EV promotion policies. Firstly, the inelastic adoption responses suggest that it is overoptimistic to expect a significant increase in EV adoption rates via any marginal change in the key attributes, namely price, battery range and driving cost. Our analysis focuses on marginal variation in car attributes within a realistic range. Therefore, we cannot extend our findings to radical measures such as large subsidies or disruptive regulation standards. Similarly, substantial incentive packages addressing multiple aspects of purchase and use could have detectable impacts beyond our analysis. However, our results suggest that much caution is warranted in assessing the effectiveness of relatively small EV policies. Ultimately, we can conclude that more radical incentive policies and/or technology mandates, such as those planned in France, UK and Canada (IEA, 2021), could be required to generate significant shifts in EV adoption in a short to medium time frame.

The remainder of this paper is structured as follows. Section 2 provides the paper's policy context and its relation to the existing literature. Section 3 outlines our methodology, including the experimental design and econometric framework. Section 4 summarises the data, and section 5 presents the results. Finally, section 6 concludes.

2 Policy context

Electric vehicles, especially battery electric vehicles (BEVs), are largely sold on their environmental credentials – namely, a reduction in pollution externalities – compared to traditional internal combustion engine vehicles (ICEs). BEVs emit no tailpipe emissions and therefore have a large potential for emissions reductions in the transport sector.[1] From the consumer's perspective, the relatively low cost per kilometre driven could be considered a key adoption driver. 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 can offset, within a "payback time", the significantly higher upfront purchase price compared to an equivalent ICE (Archsmith et al., 2022). According to recent estimates, the payback time is on average, between 5 and 8 years, but for some scenarios (e.g. low use and low gasoline prices) could go up to 10 years (Weldon et al., 2018; IEA, 2020). On the other hand, some estimates indicate that highly intensive drivers (e.g. taxis, ride sharing or other driving services) could currently recoup the purchase price difference as early as 2 years (Baik et al., 2019), and high gasoline prices could

[1] The emissions through BEV use depend on the marginal electricity generation at point-of-use, plus emissions embodied in production. Overall, BEVs tend to 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).

reduce the payback period to 4-5 years for average drivers (extrapolated from IEA, 2020).[2] As technology continues to improve and battery costs continue to fall, purchase prices could further decrease.

Switzerland presents an interesting context for our research questions, as although it possesses a number of characteristics for high EV adoption, the market share has remained 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 average environmental preferences (Franzen and Vogl, 2013). As opposed to many developed countries, Switzerland does not offer any considerable subsidies for EV purchases. There are fairly visible tax advantages, but they are unimportant relative to high purchase prices.[3] Therefore, one can expect that the EV adoption trends should be limited by serious market barriers without much assistance from any significant policy interventions. Nonetheless, EVs represent a relatively significant market share compared to similar economies. In 2020, EVs (including PHEVs) represented 14.3 percent share of new car registrations in Switzerland, higher than the average 10 percent share in Western Europe and a small 2 percent in the US (IEA, 2021).[4] Furthermore, EVs could potentially meet the needs and preferences of a portion of the approximately 22 percent of Swiss households that do not own a car (FSO, 2017) but could consider purchasing a car in the future.

The policy space provides a variety of financial incentives for promoting EV diffusion. Most commonly, governments focus on EVs' relatively large upfront costs in comparison to conventional ICEs, offering rebates and exemptions from registration tax and VAT for new EV purchases (Hardman et al., 2017). These are largely an extension of early policies, such as those adopted for the promotion of fuel efficiency, and in particular of CH vehicles (Chandra

[2] Payback period estimates vary depending on various assumptions, especially on gasoline and electricity prices, the adopted discount rate for future costs, annual mileage and battery replacement period. For instance, Weldon et al. (2018) does not discount, citing a lack of consensus over an appropriate rate, but considers several price scenarios and usages with battery replacement for the high-mileage users. Similarly, IEA (2020) does not discount future costs and considers a range of prices and usage, but assumes no battery replacement within the payback period.

[3] At a national level, BEVs are exempt from the 4 percent car tax (BAZG, 2021), and 20 out of 26 cantons give partial reductions or complete exemptions from registration fees/taxes (Electrosuisse, 2022).

[4] This is a quite reasonable share barring exceptional cases with substantial subsidies such as Norway with 75 percent share in 2020 (IEA, 2021). Note that at the time of conducting this paper's experiment in 2018, the corresponding EV share was only 3.2 percent in Switzerland, but a remarkable 49 percent in Norway.

et al., 2010; Gallagher and Muehlegger, 2011). Monetary incentives have been shown to be effective in increasing EV purchases in a variety of regions, including Europe and the US (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).

Additionally, many jurisdictions have implemented other incentive measures such as the use of exclusive lanes for buses or high-occupancy vehicles, free parking, and free usage of toll roads (Jenn et al., 2018; Tal and Nicholas, 2016; Fevang et al., 2021). Some governments do also support public charging station infrastructure through subsidies (Springel, 2021). Charging is in fact an important consideration for potential EV adopters. While home charging opportunity is a facilitator of EV ownership (Hardman et al., 2018), access to a local public charging network is also an important driver of adoption (Li et al., 2017; van Dijk et al., 2022).

Focusing on upfront costs in most policy measures is in line with previous findings that suggest a price-elastic demand for EVs (e.g. price elasticity of -1.3 to -2.8: Springel, 2021; Xing et al., 2021; Li et al., 2017). It is therefore expected that a given percentage rebate in purchase prices can lead to a more than proportional boost in adoption rates. These findings are however, generally based on a relatively limited pool of early adopters. Moreover, they do not fully observe each individual's full choice set and the trade-offs they make. While recognizing potential sources of endogeneity biases in these studies, we cannot identify a general direction in such biases.

As opposed to purchase prices, driving costs and battery range, are found to have a smaller effect on EV demand. However, these estimates can be similarly affected by various endogeneity issues. One study of Norwegian vehicle purchases finds an inelastic BEV demand with regards to electricity prices of -0.18 (Fridstrøm and Østli, 2021). As a comparison, an earlier Danish stated preference study estimates an 'EV fuel cost' elasticity of demand of -0.36 (Jensen et al., 2013), and a previous study of CH car demand in the US estimates an elasticity of 0.52 with regards to gasoline prices (Beresteanu and Li, 2011). As regards to the battery range, the few available studies point to an inelastic response, albeit with a somewhat larger effect than driving cost. For instance, Jensen et al. (2013) estimate a mean range-elasticity of 0.55 for BEV demand.

Many household and individual characteristics could potentially affect EV purchase decisions. Income in particular has been shown to be an important factor, with most early adopters concentrated in high-income groups (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 lead to inefficiencies by effectively targeting high-income earners, and particularly those who would have bought a low-polluting car or an EV even without a subsidy. Therefore, broader EV adoption among middle and lower income households requires targeted incentive measures.

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, which matches well with early EV models. They also find that people with stronger pro-environmental attitudes are relatively more likely to own small cars used for shorter trips, and that frequent car users are more likely to have large cars. Others have since demonstrated that many various environmental preferences are significant predictors of purchasing a green car, such as CH vehicles (Kahn and Vaughn, 2009; Kahn, 2007) and 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). A dense charging network (especially fast chargers) enables adoption even with relatively low battery ranges. The existing distribution of charging stations shows, however, an opposite pattern – urban centres often have a higher charger density but lower driving distances (Li et al., 2017). Davis (2019) shows that, on average, EVs are driven significantly less compared to ICEs and CHs. Adoption rates are generally higher among consumers who drive less – particularly, urban residents and those with greener lifestyles – but also those with additional, ICE vehicles. However, longer regular driving distances do not necessarily result in reduced EV adoption. 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 is a potentially important factor for adoption, indicating that once the initial hurdles and potential anxieties are overcome, consumers preferences can shift.

3 Methodology

3.1 Experimental design

We embed a choice experiment as part of the annual Swiss Household Energy Demand Survey (SHEDS).[5] The experiment simulates a realistic decision about purchasing a car. We start with a hypothetical scenario in which the respondent has to make a choice about purchasing a primary car "within the next year". The respondent is then asked to choose a car size among 6 categories plus a "no car" option. This is followed by a vehicle selection from among 6 alternative cars.[6]

We follow standard discrete choice experiment (DCE) practice for accurate preference elicitation. Namely, we provide a priming script to encourage truthful 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 of their household budget constraints and the trade-offs involved in a purchasing decision (as per, for example, Johnston et al., 2017).

The range of cars available and their attribute values (e.g. price) are set according to the current car market in Switzerland, in each size category, based on data from the TCS (2018). Table 1 provides a summary of the range of car attribute values offered to respondents. Those choosing to buy a car, are offered a choice between 6 car alternative engine types (2 BEVs, 2 PHEVs, 1 CH, and 1 ICE) within the size category of their initial choice. The alternatives are generic in that they do not belong to a specific brand, but include a number of attributes in addition to the engine type. These attributes consist of five variables: purchase price,

[5] For more details on SHEDS see Weber et al. (2017).

[6] For a detailed description of our experimental design, see van Dijk et al. (2021). 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.

Table 1: Experiment design – offered car attribute values

	Mean	Median	Min.	Max.
Price (CHF)				
BEV	49,902	47,000	21,000	95,000
PHEV	50,257	48,000	24,000	92,000
CH	40,006	33,000	20,000	84,000
ICE	30,222	24,000	13,000	61,000
Driving cost (CHF/100km)				
BEV	2.7	2.6	2.0	4.1
PHEV	4.5	4.3	3.2	7.7
CH	6.6	6.0	5.0	9.5
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. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid vehicle. ICE: Internal Combustion Engine vehicle.

driving cost, battery range (for EVs), maximum speed, and the CO_2 tailpipe emissions (zero for BEVs).[7] Descriptions of each attribute are available as pop-ups when respondents hover over the attribute title.

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 socio-demographic characteristics. To do this we adopt a discrete 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 and elasticities.

Based on the standard random utility model (RUM) framework (McFadden, 1974), we estimate respondents' utility for each car alternative based on car attributes and their choices.

[7] Tailpipe emissions are based on TCS (2018), and do not account for manufacturing or electricity generation. EVs are commonly marketed and classified as "zero-emissions". Actual emissions from electricity generation and EV manufacturing (particularly of batteries) remain important issues but beyond the scope of this study.

To allow for flexible correlations between alternatives, particularly within fuel types, we relax the independence from irrelevant alternatives (IIA) condition. We thus employ a mixed logit (ML) model and estimate a utility function with random coefficients (McFadden and Train, 2000; Brownstone et al., 2000):

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

where V_{ni} is the observed component of the utility function, of respondent n for car alternative i.[8] We use unlabelled choice sets and 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, corresponding to elements of the vector α. X_{ni} is the vector of car attributes allowed a random coefficient. Thus the coefficients β_n vary across respondents according to a normal density function $f(\beta)$, with: $\beta_n \sim N(\mu, \Sigma)$, where μ is the mean vector and Σ a diagonal variance-covariance matrix. Finally, Z_{ni} is a vector of respondent characteristics, interacted with the car engine type in order to generate by-alternative variation.

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

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

where E is the set of possible car alternatives. We simulate the probability estimates using $R = 500$ Halton draws, and estimate simulated maximum likelihood (Train, 2009; Bhat, 2001). The averaged simulated probabilities are used to calculate the simulated log likelihood function:

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

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

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

r-th draw from the distribution.

We exploit this framework to estimate a set of models that focus on different aspects of respondent choice determinants. We finally predict the choice probabilities for each car engine type at the median of observed variable values, and estimate 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 200 repetitions.[9]

4 Data

The data stem from our choice experiment, as described in Section 3.1. The SHEDS sampling ensures representativeness at the Swiss-level (excluding the Italian-speaking canton 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 select a car in the experiment, giving 882 respondents. We conduct a comparison of this group with those preferring 'no car' in Appendix A.

We include each car's fuel type, price, maximum speed, and driving cost,[10] and assign random coefficients to battery range (for BEVs) and CO_2 emissions (for non-EVs).[11] The respondent characteristics include household income (above or below median),[12] residential location (city, agglomeration, rural), age category (younger or older than 55), reported gender, whether the respondent lives in a house or apartment, if they are tenants or owners of

[9] Our exploratory analyses with various number of iterations going up to 500 show little variation after about 100 iterations.

[10] Driving cost is given a quadratic form as this significantly improves the model fit.

[11] The choice of variables with a random coefficient was achieved through testing various model specifications. Inclusion of other choice set attributes with a random coefficient, such as price, driving cost and fuel type, leads to serious convergence problems.

[12] Here *above the median* means having a monthly income of 9000 CHF or more, based on the 6 SHEDS income categories.

the dwelling, and if they own a car. We additionally include a binary indicator of the respondent's level of environmental preferences. All continuous variables are mean centred by subtracting their sample means.

The environmental-values indicator measures the importance respondents attribute to environmental protection and pollution prevention, and is constructed from the respondent's average biospheric value (as per Steg et al., 2014).[13] 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, including whether they commute to work and a set of constructed travel mode typologies. We indicate if a respondent states 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.

Respondent characteristics used in our analysis are summarised in Table 2. These include our constructed travel behaviour typologies. In particular, we observe that about 30 percent of respondents are intensive car users. ICEs are almost ubiquitous amongst these. On the other hand, about a third of respondents are mainly users of public or soft transport. 20 percent of respondents belong to households that do not own a car, close to the national 22 percent proportion (FSO, 2017). Over two thirds of respondents live in apartments and we have nearly 60 percent tenants, respectively compared to 72 percent and 61 percent nationally (BFS, 2019). In keeping with the relatively high national-level findings of Franzen and Vogl (2013), our environmental-value indicator shows 62 percent of respondents place a high importance on the environment.

[13] 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".

Table 2: Descriptive statistics – respondent characteristics and travel behaviours

Characteristics			Car and travel		
	Frequency	Percent		Frequency	Percent
Income level			*Car ownership*		
Below or at median category[1]	559	63.4	None	177	20.1
Above median category	323	36.6	At least one	705	79.9
Location			*Commuter*	684	77.6
City	428	48.5			
Agglomeration	261	29.6	*Always use Public Transport*[4]	111	12.6
Countryside	193	21.9			
			Always use Soft Transport[4,5]	96	10.9
Age group					
< 55	584	66.2	*Use Public and Soft Transport*[4,5]	100	11.3
≥ 55	298	33.8			
			Always use car[4]	264	29.9
Gender					
Male	459	52.0			
Female	423	48.0			
Dwelling type					
Flat[2]	602	68.3			
House	280	31.7			
Dwelling ownership					
Owner	357	40.5			
Tenant	525	59.5			
Environmental values[3]					
Unimportant	333	37.8			
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) Based on responses to respondents' usual travel modes across three different trip types. (5) Soft Transport generally includes moving by foot, bicycle or scooter.

5 Results

Table 3 provides a summary distribution of car choices with respect to engine type and car size. We aggregate the selected car sizes into 3 categories: small, medium, large. There is a correlation of experimental car choices with the household's actual ownership. The respondents who own a car tend to opt more for an ICE and relatively less for a BEV. There is also a correlation between the size of the actual car and car size selected in the experiment. This correlation is not however perfect, perhaps partly due to differences in respondent perception of their car size and the TCS official classification according to (TCS, 2018).

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

Panel A						
Car engine type	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		
Total	882		177	705		
Panel B						
Car size	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	57.1	60.0	18.7	17.5
Medium	386	43.8	35.6	27.7	63.1	42.0
Large	189	21.4	7.3	12.4	18.2	40.5
Total	882		177	170	225	274

Note: BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle. Adoption rates for BEV and PHEV are calculated based on the sum of the two corresponding offers. While being slightly different for 1st and 2nd BEV offers (BEV 1: 17.0%; BEV 2: 17.4%), the PHEV choices show a remarkable asymmetry toward the 1st offer (PHEV 1: 13.8%; PHEV 2: 3.1%).

5.1 Regression estimates

The regression results with four different specifications are summarised in Table 4 (with full results in Appendix Table B.1). These results show that most car attributes have statistically significant effects in respondents' experimental purchase decisions. In particular, car prices and driving cost reduce respondent utility and likelihood of selection.

Maximum car speed was not valued by respondents, however the exact effect varies. 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 higher speeds is small or zero, *ceteris paribus*.

Table 4: Regression results

	Base (1)	Characteristics (2)	Behaviours (3)	Car usage (4)
BEV	-0.301	1.359	-1.547	0.479
	(0.652)	(1.198)	(1.063)	(1.173)
PHEV	–	1.998*	-0.325	1.608
		(1.112)	(1.022)	(1.079)
CH	–	1.596**	0.177	1.082*
		(0.710)	(0.512)	(0.649)
ICE	–	*base*	*base*	*base*
Car price (10,000 CHF)	-0.592***	-0.577***	-0.552***	-0.574***
	(0.098)	(0.130)	(0.134)	(0.135)
Driving cost (CHF/100km)	-0.512**	-0.697***	-0.587**	-0.577**
	(0.234)	(0.223)	(0.238)	(0.238)
Driving cost-squared	0.036***	0.051***	0.044***	0.041***
	(0.013)	(0.014)	(0.015)	(0.015)
Max speed 160 - 200km/hr	-1.045*	-0.277	-0.441	-0.457
	(0.556)	(0.249)	(0.328)	(0.342)
Max speed $\geq$ 200km/hr	-1.295**	-0.447	-0.658*	-0.670*
	(0.579)	(0.307)	(0.391)	(0.40)
BEV $\times$ Range (100km)	-2.342***	-0.522	-1.047*	-1.132*
	(0.853)	(0.402)	(0.584)	(0.609)
sd(BEV $\times$ Range)	3.930***	1.353**	2.112**	2.251***
	(1.324)	(0.546)	(0.828)	(0.866)
Non-BEV $\times$ CO_2 emissions (g/km)	0.022**	0.029**	0.023*	0.022*
	(0.010)	(0.012)	(0.012)	(0.012)
sd(Non-BEV $\times$ CO_2 emissions)	0.012***	0.022**	0.023**	0.021**
	(0.004)	(0.009)	(0.009)	(0.009)
Socio-demographic	No	Yes	Yes	Yes
Travel behaviours	No	No	Yes	Yes
Car usage	No	No	No	Yes
N respondents	882	882	882	882
N observations	5,292	5,292	5,292	5,292
Log simulated-likelihood	−1422.82	−1357.78	−1388.26	−1374.58
AIC	2865.64	2793.56	2830.52	2815.17
BIC	2931.38	3049.94	3008.02	3032.11

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. The full regression results table is provided in Appendix B, Table B.1.

The results also point to two unexpected tendencies, suggesting that respondents value smaller battery range and higher tailpipe CO_2 emissions. However, the relatively high standard deviation of both coefficients indicate a strong heterogeneity of preferences among respondents. Moreover, as we will see later the average elasticity for both variables is negligible in magnitude and statistically insignificant. The main results mentioned above are more or less robust to various specifications (models 1 to 4).

In terms of respondent characteristics (model 2), 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 show a preference for ICEs over BEVs and CH vehicles. Older respondents have a preference against EVs, and seem relatively indifferent between CHs and ICEs, *ceteris paribus*. Female respondents also show a significant disutility for PHEVs, however, we find no significant gender difference in relative preferences for BEV or CH vehicles. Our measure of respondents' overall environmental value, *environment-important*, shows a large and significant effect on EV preferences. We further find that living in a house, compared to an apartment does not have any significant effect on car choice probabilities. As opposed to tenants, home owners do show a slightly significant preference for BEVs, which matches our assumptions about restrictions on home charging options for tenants.

Controlling for all the household characteristics above, the simple fact of owning a car means a respondent is much more likely to select an ICE over any other car. This indicates a possible stability in technological preferences, given the vast majority of cars owned are ICEs. It also demonstrates significantly greener preferences among those who do not own a car.

Delving into the impact of 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. 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 resistance to EVs.

5.2 Choice probabilities and marginal effects

We further explore here the adoption barriers addressed through the experiment, and the most- and least-resistant consumer groups. We present our estimates of the choice elasticities with respect to car attributes, focusing on the main factors namely, car price, BEV battery range and driving cost. We then follow on the effects of various characteristics on adoption rates, focusing on car ownership, travel behaviours, and basic socio-demographic variables.

Adoption barrier elasticities

As previously discussed, one of the main barriers to EV adoption is the upfront purchase price. On average, we find a price elasticity of -0.21 (Table 5: Panel A). Comparing this to battery range shows price to be a significantly larger adoption barrier on average. However, EV demand sensitivity in regard to purchase price is inelastic. This indicates that any marginal variations in EV prices through subsidies or other government policy will not have a significantly large effect on actual car type choices in itself, on average across the broad population. Furthermore, the cross-elasticities on ICE choice probability show that there isn't a direct substitute between ICEs and BEVs. Some 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).

Estimated elasticities are statistically insignificant and negligible in magnitude for both battery range and tailpipe emissions for all car types (not reported in the table). The elasticity with respect to driving cost, while being statistically insignificant, represent a fairly large magnitude. In particular, the point estimate of elasticity of BEV adoption with respect to driving cost is about -1 (Table 5: Panel A). This suggests that low driving costs of BEVs could be a reasonable driver of adoption.

There are some differences in relative adoption barriers between consumer segments found. Table 5: Panel B presents attribute elasticity estimates across residential location, income group and car ownership. These estimates are based on the supplementary regres-

Table 5: Car attribute elasticities

Panel A

Attribute	Car type: BEV-own	Car type: ICE-cross
Price	-0.21**	0.07
	(0.09)	(0.04)
Range	0.00	-0.05
	(0.21)	(0.09)
Driving cost	-0.96	0.36
	(0.75)	(0.30)

Panel B

Attribute	Group	Car type: BEV-own	Car type: ICE-cross
Price	City	-0.26**	0.09*
		(0.11)	(0.06)
	Agglomeration	-0.12	0.05
		(0.13)	(0.06)
	Rural	-0.32**	0.14
		(0.14)	(0.10)
	Income $\leq$ median	-0.12	0.05
		(0.13)	(0.05)
	Income $>$ median	-0.04	0.03
		(0.14)	(0.08)
	No car	-0.07	0.12
		(0.15)	(0.26)
	Own car	-0.12	0.05
		(0.13)	(0.05)
Range	City	0.13	-0.06
		(0.18)	(0.09)
	Agglomeration	0.24	-0.18
		(0.19)	(0.15)
	Rural	-0.01	0.00
		(0.36)	(0.12)
	Income $\leq$ median	0.24	-0.18
		(0.19)	(0.15)
	Income $>$ median	0.35	-0.30*
		(0.26)	(0.17)
	No car	0.07	-0.09
		(0.11)	(0.13)
	Own car	0.24	-0.18
		(0.19)	(0.15)
Driving cost	City	-0.13	0.04
		(0.70)	(0.29)
	Agglomeration	-0.14	0.07
		(1.16)	(0.38)
	Rural	-0.07	0.02
		(0.88)	(0.30)
	Income $\leq$ median	-0.14	0.07
		(1.16)	(0.38)
	Income $>$ median	-0.34	0.16
		(0.85)	(0.37)
	No car	-1.16	1.23
		(1.01)	(1.14)
	Own car	-0.14	0.07
		(1.16)	(0.38)

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 B.2). Standard errors in parentheses, from 200 bootstrap model repetitions. * and ** respectively denote 10% and 5% significance levels. BEV: Battery Electric Vehicle; ICE: Internal Combustion Engine Vehicle.

sions found in Table B.2 which expand model (2) to separately and sequentially interact car price, BEV range, and driving cost with the above consumer groups.

We specifically find that respondents from rural areas and cities are significantly more price sensitive than their agglomeration counterparts. Within those two, rural residents have a slightly greater elasticity point estimate. Across all other consumer groups and car characteristics, however, we find almost no significant elasticities. One exception is the cross-elasticity of demand for ICEs with regards to BEV battery range, which is significantly greater for high-income respondents. Otherwise, despite widely varying point estimates, they are only imprecisely estimated at the average.[14]

We conduct an additional test by estimating the mixed logit models and attribute elasticities for the sub-sample of respondents who own a car in real life. The resulting coefficients and elasticities are not significantly different from those of the main models above, indicating that the non-car owners are not significantly driving the elasticities.

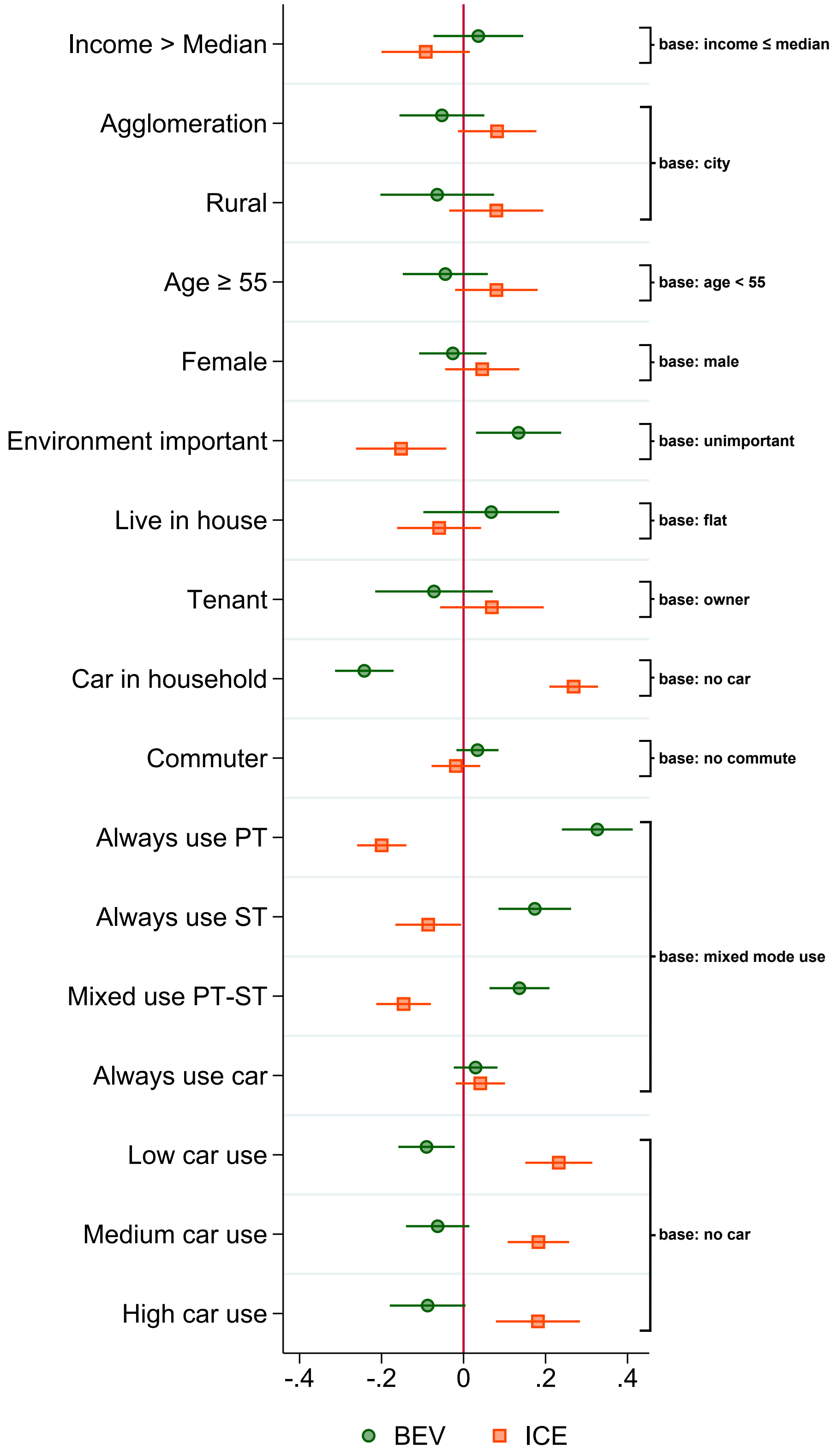
Marginal effects of characteristics

Figure 1 presents the estimated effects of respondent characteristics and travel behaviours on car choice probabilities, meaning the increase in BEV and ICE choice probabilities in each group compared to the corresponding base group. Existing car ownership has one of the largest marginal effects, where car owners are 30 percentage points more likely to choose an ICE than a non-car owner, on average. This group is significantly less likely to choose a BEV, by 25 percentage points. This indicates a significant stability of preferences of existing car owners to keep using their familiar technology. In absolute terms, car owners have a 44 percent probability of choosing an ICE, followed by 29 percent for BEV, 16 for PHEV and 11 for CH. On the other hand, respondents who are car free have the greatest probability of choosing a BEV, 55 percent. PHEVs have a 23 percent probability for this group, and ICEs and CHs are 14 and 9 percent, respectively.

Intensity of car usage is a further factor for car choice, as seen in Figure 1. In absolute

[14] Note that we estimate a range of incremental bootstrap repetitions from 50 to 500 and find no significant difference in the results, nor any convergence towards particular standard error values.

Figure 1: 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 200 bootstrap repetitions. Estimates stem from models (2) to (4).

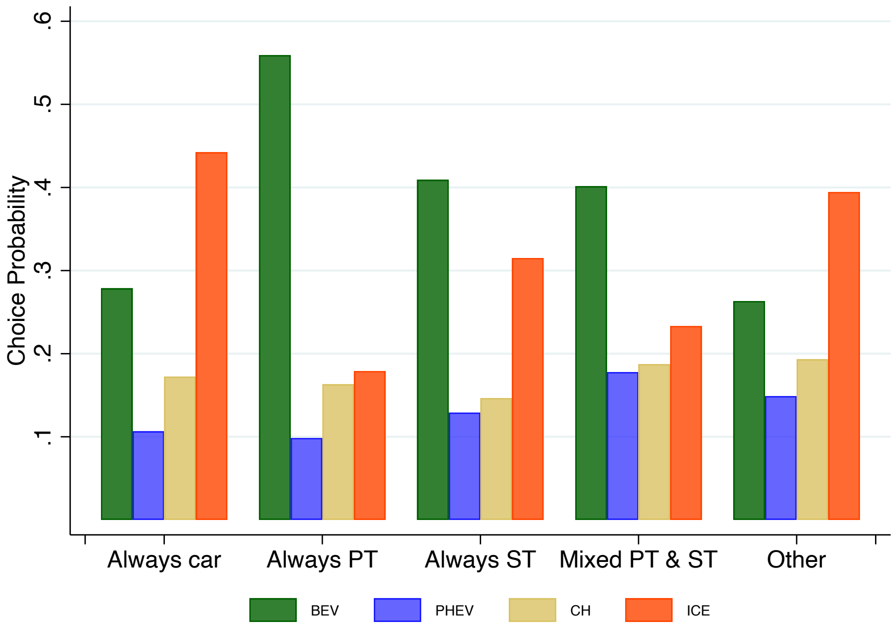
terms, the more a respondent uses their car in a given year, the less they are likely to select an ICE. However, the differences in marginal effects between use-levels are insignificant. Compared to those without a car, car drivers of all extents are statistically equally more likely to choose an ICE and less likely to choose a BEV. Overall, in point terms, 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. BEVs are only 24-26 percent likely to be selected.

In addition to respondents' existing car ownership, transport habits greatly influence stated car choices. Figure 1 also shows that compared to the base of mixed-mode-using respondents, those who use only their car for commuting and leisure trips are insignificantly different. However, those who always use PT or ST, or both, all have a significantly greater likelihood of choosing an EV if they buy a car, and a correspondingly lower probability of choosing an ICE. Exclusive PT users are about 33 percentage points more likely to select a BEV than mixed-mode users. 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 15 percentage points. Figure 2 shows the absolute probabilities for these travel type groups, additionally including PHEVs and CHs, where the trends are more mixed. 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 ICEs, while those who have historically been car free or do not use a car regularly are more inclined to adopt the new car technology.

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. As seen in Figure 1, high income earners and residents of agglomerations are significantly (at the 10% level) respectively less and more likely to choose an ICE, each by about 9 percentage points. Though not large, these effects do match with our theories and the literature. The overall preference trend towards ICEs agglomerations is consistent with lower public charging availability than in cities and differing transport needs (e.g. larger distances). The absolute choice probabilities for all characteristics and fuel types are shown in an appendix (Figure B.1).

Finally, the respondent's environmental preferences have a great influence on their car

Figure 2: Probabilities of car-type choice by respondent travel behaviour



Notes: Calculated from model (4).

choice. Those with strong environmental preferences are 15 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. The BEV and ICE differences fit 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 hypothetical car market with multiple green vehicle and EV options. 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 upon 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.

Our results indicate the importance of EVs' upfront costs relative to other car attributes such as battery range. We find, however, that the BEV adoption rates are inelastic with respect to purchase price (point estimate of -0.2), suggesting that marginal incentive measures such as price rebates might have limited effect on EV diffusion. Our elasticity estimate is significantly lower than the findings of the previous literature based on real car purchases (Xing et al., 2021; Li et al., 2017). Our experimental study is however more representative of future market changes, rather than relatively early EV adopters concentrated in specific consumer segments such as high-income groups.

Regardless, there exists significant heterogeneity in price elasticity across consumer groups. Price sensitivity varies across residential locations. Rural residents, followed by city dwellers, have the greatest BEV price elasticities, with this an insignificant barrier for those from agglomerations.

The strongest absolute 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 and those who use their car regularly for all trips, as well as consumers with relatively low environmental and ecological values. These groups are significantly more likely to choose an ICE than those without a car. This indicates a strong stability of car preferences and provides a large hurdle in getting existing car 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.

A large constraint to effective policy is the result of inelastic demand with regard to EV adoption barriers and drivers – particularly the upfront purchase price. This implies that marginal policy measures such as subsidies and price rebates will be of little effect over the longer term.

Given the strongly stable ICE preference among existing car owners, we suggest there is opportunity for alternative policies such as providing BEV information and experiences to nudge this group. Targeted information campaigns and providing opportunities for experiencing a BEV could decrease the unknown factors, 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 hinted by Jensen et al. (2013)). This could potentially be implemented through car-hire and car-sharing services, car dealerships, and charging station operators.

Overall, our findings indicate that governments wishing to significantly increase a shift from ICEs to BEVs may have to opt for more radical 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).

Appendix A Comparison of non-respondent statistics

Of the total 995 respondents taking part in the choice experiment, 882 chose to purchase a car in the experiment and continued through all car choice sets. The remaining 113 respondents chose the "no car" option at the first experiment question. This group was therefore not offered any car choice set and is excluded from this analysis.

Table A.1 provides a brief comparison of the key variables analysed between the two groups, similar to the descriptive statistics of Table 2. The respondents who chose not to purchase any car differ in many ways from those who did. We particularly see that those opting out of car ownership have somewhat lower incomes on average, tend to be more urban (city-resident), slightly older on average, and more likely to live in a unit and be renting. They also have higher environmental values and differ in terms of transport habits. The opt-out group are significantly less likely to own and use a car in real life, and more likely to use public transport (PT).

Table A.1: Summary statistics by respondent group – means and t-test for differences

	Group		
	Analysis	No car chosen	p-value
Income > median	0.37	0.24	0.004
Residential location	1.73	1.43	0.000
Aged $\geq$ 55	0.34	0.46	0.015
Female	0.48	0.53	0.307
Dwell in house	0.32	0.17	0.000
Tenant	0.60	0.72	0.009
Environmental values important	0.62	0.80	0.000
Car owner	0.80	0.24	0.000
Always uses PT	0.09	0.24	0.000
Always uses ST	0.06	0.11	0.095
Always uses car	0.30	0.04	0.000

Note: The 'analysis' group includes the 882 respondents used for analysis in the article. The 'no car chosen' group is the 113 respondents who chose "no car" and are excluded from the analysis. p-values from t-test of the two groups' means.

These differences seem to indicate that this study's analysis is not necessarily conducted across the entire (representative) population, but maybe rather the potential car-buying population. One potential limitation could stem from the way that the 'no car' choice was offered and the way in which the original question was framed. The question setup gets respondents to “please imagine that you decide to purchase a car or replace your current car within the next year”. This is followed by the choice of car size, and includes the option for “no car”. Overall, this could potentially induce some respondents who would not normally have selected any car to do so. Nonetheless, 13 percent of respondents still opted out and the group comparisons indicate substantial differences that backup the realistic and consistent choices made, all giving us confidence in the analysis.

Appendix B Supplementary tables and figures

Table B.1: Full regression results

	Base (1)	Characteristics (2)	Behaviours (3)	Car usage (4)
BEV	-0.301	1.359	-1.547	0.479
	(0.652)	(1.198)	(1.063)	(1.173)
PHEV	–	1.998*	-0.325	1.608
		(1.112)	(1.022)	(1.079)
CH	–	1.596**	0.177	1.082*
		(0.710)	(0.512)	(0.649)
ICE	–	*base*	*base*	*base*
Car price (10,000 CHF)	-0.592***	-0.577***	-0.552***	-0.574***
	(0.098)	(0.130)	(0.134)	(0.135)
Driving cost (CHF/100km)	-0.512**	-0.697***	-0.587**	-0.577**
	(0.234)	(0.223)	(0.238)	(0.238)
Driving cost-squared	0.036***	0.051***	0.044***	0.041***
	(0.013)	(0.014)	(0.015)	(0.015)
Max speed 160 - 200km/hr	-1.045*	-0.277	-0.441	-0.457
	(0.556)	(0.249)	(0.328)	(0.342)
Max speed $\geq$ 200km/hr	-1.295**	-0.447	-0.658*	-0.670*
	(0.579)	(0.307)	(0.391)	(0.400)
BEV $\times$ Range (100km)	-2.342***	-0.522	-1.047*	-1.132*
	(0.853)	(0.402)	(0.584)	(0.609)
sd(BEV $\times$ Range)	3.930***	1.353**	2.112**	2.251***
	(1.324)	(0.546)	(0.828)	(0.866)
Non-BEV $\times$ CO_2 emissions (g/km)	0.022**	0.029**	0.023*	0.022*
	(0.010)	(0.012)	(0.012)	(0.012)
sd(Non-BEV $\times$ CO_2 emissions)	0.012***	0.022**	0.023**	0.021**
	(0.004)	(0.009)	(0.009)	(0.009)
Income > median $\times$ BEV	–	0.671**	–	–
		(0.329)		
Income > median $\times$ PHEV	–	0.801**	–	–
		(0.363)		
Income > median $\times$ CH	–	0.413	–	–
		(0.270)		
Agglomeration $\times$ BEV	–	-0.658*	–	–
		(0.369)		
Rural $\times$ BEV	–	-0.697*	–	–
		(0.402)		
Agglomeration $\times$ PHEV	–	-0.512	–	–
		(0.389)		
Rural $\times$ PHEV	–	-0.398	–	–
		(0.419)		
Agglomeration $\times$ CH	–	-0.520*	–	–
		(0.295)		
Rural $\times$ CH	–	-0.558*	–	–
		(0.323)		
Age $\geq$ 55 $\times$ BEV	–	-0.608*	–	–
		(0.313)		

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Table B.1 – *Continued from previous page*				
	Base	Characteristics	Behaviours	Own car use
Age $\geq$ 55 $\times$ PHEV	–	-0.601*	–	–
		(0.344)		
Age $\geq$ 55 $\times$ CH	–	-0.304	–	–
		(0.259)		
Female $\times$ BEV	–	-0.420	–	–
		(0.301)		
Female $\times$ PHEV	–	-0.796**	–	–
		(0.339)		
Female $\times$ CH	–	0.315	–	–
		(0.250)		
Environment-important $\times$ BEV	–	1.551***	–	–
		(0.371)		
Environment-important $\times$ PHEV	–	0.924**	–	–
		(0.376)		
Environment-important $\times$ CH	–	0.334	–	–
		(0.256)		
House $\times$ BEV	–	0.595	–	–
		(0.418)		
House $\times$ PHEV	–	0.216	–	–
		(0.437)		
House $\times$ CH	–	0.335	–	–
		(0.327)		
Tenant $\times$ BEV	–	-0.658*	–	–
		(0.398)		
Tenant $\times$ PHEV	–	-0.260	–	–
		(0.420)		
Tenant $\times$ CH	–	-0.437	–	–
		(0.319)		
Car in household $\times$ BEV	–	-2.809***	–	–
		(0.546)		
Car in household $\times$ PHEV	–	-2.229***	–	–
		(0.595)		
Car in household $\times$ CH	–	-1.366***	–	–
		(0.421)		
Commuter $\times$ BEV	–	–	0.361	–
			(0.379)	
Commuter $\times$ PHEV	–	–	0.042	–
			(0.386)	
Commuter $\times$ CH	–	–	0.041	–
			(0.296)	
Always PT $\times$ BEV	–	–	2.804***	1.802***
			(0.561)	(0.572)
Always PT $\times$ PHEV	–	–	0.768	-0.351
			(0.603)	(0.601)
Always PT $\times$ CH	–	–	0.830*	0.377
			(0.450)	(0.476)
Always ST $\times$ BEV	–	–	1.446***	1.284**
			(0.541)	(0.521)
Always ST $\times$ PHEV	–	–	0.275	0.173
			(0.579)	(0.539)
Always ST $\times$ CH	–	–	0.048	0.066

Continued on next page

Table B.1 – *Continued from previous page*	Base	Characteristics	Behaviours	Own car use
			(0.462)	(0.444)
Mixed PT-ST × BEV	–	–	1.686***	0.710
			(0.539)	(0.567)
Mixed PT-ST × PHEV	–	–	1.081*	-0.047
			(0.581)	(0.587)
Mixed PT-ST × CH	–	–	0.697	0.208
			(0.454)	(0.487)
Always Car × BEV	–	–	-0.014	0.029
			(0.391)	(0.390)
Always Car × PHEV	–	–	-0.609	-0.429
			(0.378)	(0.360)
Always Car × CH	–	–	-0.288	-0.329
			(0.274)	(0.271)
Low car-use (<10,000km/yr) × BEV	–	–	–	-2.066***
				(0.571)
Medium car-use (<20,000km/yr) × BEV	–	–	–	-1.635***
				(0.612)
High car-use (≥ 20,000km/yr) × BEV	–	–	–	-1.901**
				(0.769)
Low car-use (<10,000km/yr) × PHEV	–	–	–	-2.203***
				(0.645)
Medium car-use (<20,000km/yr) × PHEV	–	–	–	-1.942***
				(0.662)
High car-use (≥ 20,000km/yr) × PHEV	–	–	–	-2.358***
				(0.817)
Low car-use (<10,000km/yr) × CH	–	–	–	-1.203***
				(0.466)
Medium car-use (<20,000km/yr) × CH	–	–	–	-0.885*
				(0.487)
High car-use (≥ 20,000km/yr) × CH	–	–	–	-0.531
				(0.546)
N respondents	882	882	882	882
N observations	5,292	5,292	5,292	5,292
Log simulated-likelihood	−1422.82	−1357.78	−1388.26	−1374.58
AIC	2865.64	2793.56	2830.52	2815.17
BIC	2931.38	3049.94	3008.02	3032.11

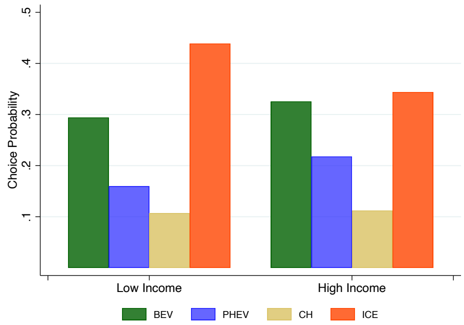
Notes: *, ** and *** respectively denote significance at 10%, 5% and 1% levels. BEV: Battery Electric Vehicle. PHEV: Plug-in Hybrid Electric Vehicle. CH: Conventional Hybrid. ICE: Internal Combustion Engine Vehicle.

Table B.2: Supplementary estimation results – attribute interactions

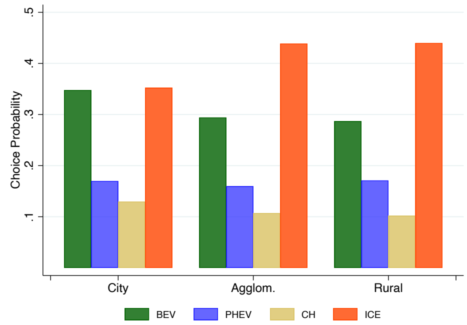
	Price	Range	Driving cost
BEV	3.439**	2.575**	0.294
	(1.649)	(1.154)	(2.783)
PHEV	2.210*	2.279**	-0.979
	(1.285)	(1.035)	(2.194)
CH	1.773**	1.434**	1.104
	(0.772)	(0.655)	(1.154)
ICE	*base*	*base*	*base*
Car price (10,000 CHF)	–	-0.601***	-0.581***
		(0.123)	(0.154)
Driving cost (CHF/100km)	-1.237***	-1.439***	–
	(0.326)	(0.248)	
Driving cost^2	0.056***	0.052***	–
	(0.016)	(0.012)	
Max speed 160 - 200km/hr	-0.575*	-0.267	-0.960**
	(0.295)	(0.192)	(0.390)
Max speed $\geq$ 200km/hr	-0.725**	-0.386*	-1.032**
	(0.342)	(0.215)	(0.433)
BEV $\times$ Range (100km)	-0.707	–	-1.429**
	(0.449)		(0.717)
sd(BEV $\times$ Range)	1.579***	–	2.833**
	(0.596)		(1.135)
Non-EV $\times$ CO_2 emissions (g/km)	0.024*	0.040***	0.006
	(0.013)	(0.010)	(0.020)
sd(Non-EV $\times$ CO_2 emissions)	0.024***	0.013**	0.043**
	(0.009)	(0.006)	(0.019)
City $\times$ Car price (10,000 CHF)	-0.564***	–	–
	(0.205)		
Agglom. $\times$ Car price (10,000 CHF)	-0.114	–	–
	(0.212)		
Rural $\times$ Car price (10,000 CHF)	-0.844***	–	–
	(0.246)		
Income $\leq$ median $\times$ Car price (10,000 CHF)	-0.250	–	–
	(0.186)		
No car $\times$ Car price (10,000 CHF)	0.180	–	–
	(0.248)		
City $\times$ BEV $\times$ Range (100km)	–	0.277*	–
		(0.161)	
Agglom. $\times$ BEV $\times$ Range (100km)	–	0.449**	–
		(0.180)	
Rural $\times$ BEV $\times$ Range (100km)	–	0.115	–
		(0.190)	
Income $\leq$ median $\times$ BEV $\times$ Range (100km)	–	-0.146	–
		(0.141)	
No car $\times$ BEV $\times$ Range (100km)	–	-0.120	–
		(0.163)	
City $\times$ Driving cost (CHF/100km)	–	–	-1.229*
			(0.628)
City $\times$ Driving cost^2	–	–	0.111**
			(0.045)
Agglomeration $\times$ Driving cost (CHF/100km)	–	–	-0.873
			(0.844)
Agglomeration $\times$ Driving cost^2	–	–	0.042
			(0.045)
Rural $\times$ Driving cost (CHF/100km)	–	–	-0.928
			(0.723)
Rural $\times$ Driving cost^2	–	–	0.072*
			(0.043)
Income $\leq$ median $\times$ Driving cost (CHF/100km)	–	–	0.942
			(0.620)
Income $\leq$ median $\times$ Driving cost^2	–	–	-0.072
			(0.044)
No car $\times$ Driving cost (CHF/100km)	–	–	-2.032**
			(0.955)
No car $\times$ 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.

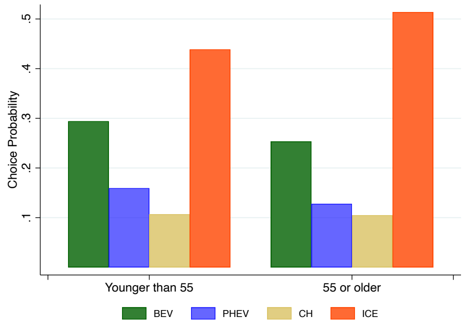
Figure B.1: Probabilities of car-type choice by respondent characteristics



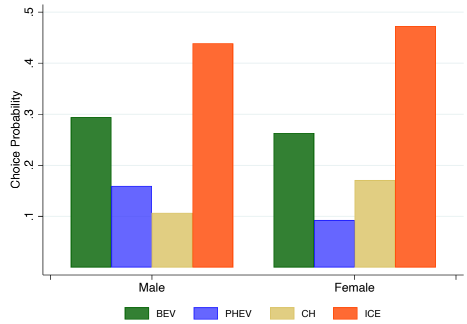
(a) Income group (≤ or > median)



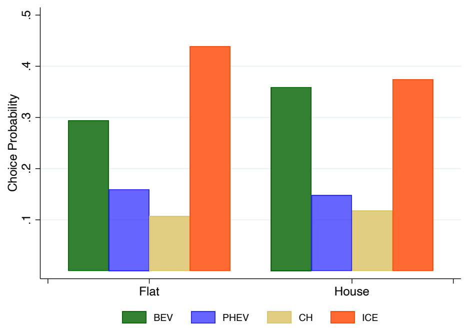
(b) Residential location



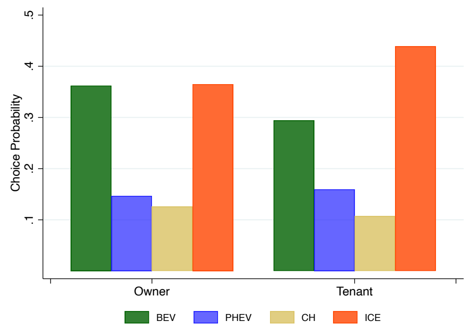
(c) Age group



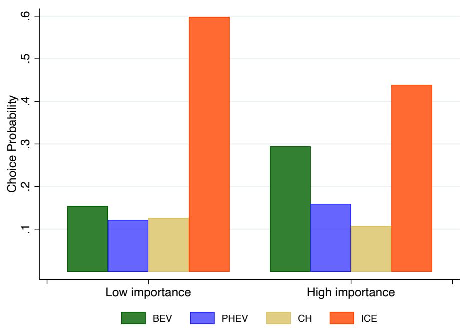
(d) Gender



(e) Dwelling type



(f) Dwelling tenancy



(g) Environmental values

Notes: Calculated from model (2).

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