Investigating preferences for powertrains when buying a car in Germany

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Short summary

Germany's Federal Climate Change Act requires the transport sector to reduce its greenhouse gas emissions by almost half until 2030. The government has set an ambitious goal of increasing the number of fully electric vehicles to 15 million within the same period. Data on the factors influencing the purchase of low- or zero-emission vehicles is still scarce. Based on stated preference data collected in spring 2022, we found that battery electric vehicles are the preferred choice of respondents in the hypothetical situation of buying a new car, but not in the used car market. Our results support the high demand for battery electric vehicles, suggesting that stagnating shares in new registrations could be due to supply shortages. Purchase price and energy costs are the most important factors leading to the choice of an electric powertrain, indicating that purchase premiums currently put into place in Germany are highly effective.
Keywords: transformation of transport, electrification and decarbonization of transport, powertrain purchase decision, low- or zero-emission vehicles, market share, discrete choice modelling, stated preference survey

1 Introduction

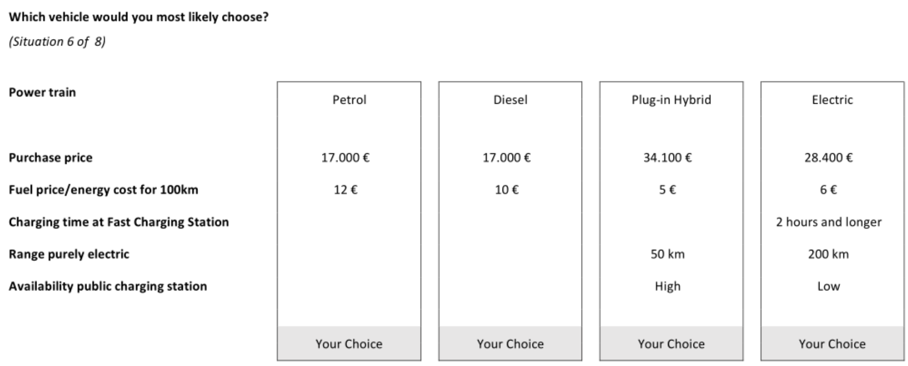
Despite long-lasting political negotiations on global level for reducing greenhouse gas emissions (GHG emissions) the transportation sector in most countries is still not showing a downward trend (Lamb et al., 2021; Intergovernmental Panel on Climate Change, 2022). This is especially true for road transport, which is still highly dependent on fossil oil. Hence, cutting down greenhouse gas emissions in transportation is still a challenging task (Creutzig et al., 2015) even though policy instruments, such as energy or carbon tax, exist (e.g., Kok et al. (2011); Stepp et al. (2009); Haasz et al. (2018); Whitehead et al. (2021); Dahl & Sterner (1991)).
Until 2030, Germany's Federal Climate Change Act (KSG) (Federal Ministry for the Environment, Nature Conservation and Nuclear Safety, 2021) requires the transport sector to reduce its GHG emissions by around 48% compared to 1990. The sector's emissions must then not exceed 85 Mt CO_2 equivalents. A halving of those emissions in less than ten years represents a challenge based on the stagnant development of GHG emissions over the past 30 years as described above. Additionally, the sector missed its KSG sector target in 2021, which puts pressure on the government to set up an immediate climate action program.
To achieve the climate protection targets for transport, the German government is taking measures aimed in particular at a transition of powertrains, i.e., increasing the number of vehicle kilometres travelled electrically via the gradual electrification of the passenger car fleet. These measures include, for example, purchase premiums, the suspension of the motor vehicle tax or the lower taxation of company cars for zero- or low-emission vehicles. The German government has set itself the goal of increasing the number of fully electric passenger cars to 15 million by 2030 (Sozialdemokratischen Partei Deutschlands,BÜNDNIS 90 / DIE GRÜNEN, Freie Demokraten, 2021).
Vehicle purchase decisions by households determine not only the short-term mode choice decision, but also the size and composition of the national vehicle fleet for longer periods. Modelling this behaviour accurately is therefore a key factor to secure sustainable transport planning and policy setting (Kickhöfer et al., 2019).
Car-specific variables such as fuel efficiency (e.g. Alberini et al. (2022)) and a suite of sociodemographic variables, such as age, gender, presence of young children or employment status have been

identified for significantly influencing travel behaviour (e.g. Bhat et al. (2009); Frondel & Vance (2018); Alberini et al. (2022)).
At this point, it is not clear under which circumstances companies and households choose low- or zero-emission vehicles and which factors play a role in their decision. Data on powertrain selections when purchasing a vehicle is still scarce.
To help gather data and gain a more profound understanding of the influencing factors on the decision process when purchasing a car with a specific powertrain, we conducted an online survey among the German population in spring 2022. Based on the reviewed literature, we aim to fill the gaps linking consumer purchase decisions of new and used vehicles with different powertrains. The main objective of the survey is to determine trade-offs and influencing factors on the decision of buying a car with a classic or alternative powertrain technology. To address these objectives and derive parameters for car stock models, we estimated an error component logit mixture model and derived demand elasticities and cross- elasticities respective to changes in the most important continuous variables.

2 Methodology

Survey

To examine car powertrain preferences, we conducted a survey in which respondents were asked to make trade-offs between different car powertrain alternatives in hypothetical car purchase situations. The survey consists of five blocks of questions: screening questions, car-specific questions, a stated preference part, attitudinal questions, and socio-demographic questions.
In eight labelled discrete choice games, respondents had to choose between the four powertrain options, petrol, diesel, full plug-in hybrid (PHEV) and battery electric power (BEV) for their car purchase. In addition, control attributes that can have an effect on powertrain choice were added, such as fuel price and specific attributes for alternative powertrains such as charging time, range driving with full electrical power and the availability of charging stations.
Figure 1 shows an example of a choice situation presented to the respondents.


Which vehicle would you most likely choose?
(Situation 6 of 8)

Power train	Petrol	Diesel	Plug-in Hybrid	Electric
Purchase price	17.000 €	17.000 €	34.100 €	28.400 €
Fuel price/energy cost for 100km	12 €	10 €	5 €	6 €
Charging time at Fast Charging Station				2 hours and longer
Range purely electric			50 km	200 km
Availability public charging station			High	Low
	Your Choice	Your Choice	Your Choice	Your Choice

Figure 1: Example of a Choice Situation Presented to a Respondent (Purchase of a New Car)

The survey contained a maximum of 62 questions. Recruited respondents were participants of a German automotive panel by an external panel provider. After a soft launch with 209 respondents, data was collected in March 2022 via a web-link to the survey. After data cleaning, the final sample contains 16,032 choices of 2,004 respondents. The average response time to answer all questions was 14.47 minutes.

Method

The choice of the powertrain technology is modelled using an error component model, which allows analysing the relative importance of the factors listed above by exploiting the Mixed MNL structure to allow for inter-alternative correlation and heteroscedasticity (Train, 2009). The error components are added in a "pseudo panel" setting: for each alternative, a different random variable, normally distributed with variance σ_{EC}, is added to the utility. The value of this variable is considered fixed across the choices of each individual, representing personal a priori preferences.

Different nested logit specifications, e.g. nests for alternative and classic powertrain, were tested as well, but were not found to lead to statistically significant improvements in model fit.
The model only represents the choice of powertrain technology in a new or used car scenario. In particular, the decision to purchase a new vehicle or to replace an old one, as well as the decision to search on the used or on the new vehicle market are taken as fixed, and are the responsibility of previous steps in car fleet models for which the estimated parameters shall be used in the future.
Selection of the variables to include in the model was supported through the methodology described by Hillel et al. (2019). In particular, this method showed that the answers to the attitudinal questions were a strong predictor of the powertrain technology choice.
Test of various model specifications suggested that the model works better with most continuous variables transformed by a logarithm, showing a decreasing sensitivity to changes of the variable with increasing values of the variable.

3 Selected results and discussion

The model results are presented in Tables 1 and 2. Estimation statistics are as follows: the final Likelihood of our mode is -13301.96, AIC 26681.92 and BIC 26981.53. The adjusted Rho-square is 0.58. Most parameters are significantly different from 0 at the 95% level (two stars) or 90% level (one star).
Age was found to be an important determinant of the choice. Indeed, respondents between 35 and 45 years old are much more prone to choose an electric or hybrid vehicle than the other age classes. Surprisingly, while the availability of charging stations is important to the respondents, they do not seem to react differently to “medium” and “high” availability. Whether it is because the “medium” level is sufficient for most decision makers, or because the respondents found it difficult to differentiate the two levels from their descriptions, unfortunately cannot be determined without additional data.
The availability of a private garage or parking spot does not have a significant effect, even though including this parameter leads to a significant increase in model fit. A difference is visible, including the interaction: depending on whether the decision maker is homeowner (who likely can decide to install a charging station, parameter $\beta_{garage,owner}$) or renter (who needs to accept the decisions of their landlord, parameter $\beta_{garage,renter}$).
The variance parameter for the error components σ_{EC} is much higher than the scale parameter for the logit error terms (fixed to 1). This indicates a strong influence of personal a priori preference in the choice of a powertrain, with little variations between the situations for a person that cannot be explained by the parameters that are part of the model.
In our survey, respondents with a positive environmental attitude (affect and cognition) and environmental behaviour prefer an alternative powertrain over a classical one. Respondents with a high score on environmental affect are less likely to purchase a diesel car. The effect of environmental cognition on alternative powertrain preferences is the strongest.
The main purpose of this model is to study the determinants of demand for electric vehicles. To this end, Table 3 shows the elasticities and cross-elasticities of demand respective to changes in the most important continuous variables, that is, the percentage change in the demand for each of the alternatives, given a 1% change in the continuous variable.
Elasticities are computed by predicting the demand for the exact situations in the sample, for a small change in each of the variables, and comparing to the predicted demands without the change in the variables.
In general, the demand is relatively inelastic, in the sense that a given percentage change in the studied variables always leads to a smaller change in the demand.
BEV Price is the variable that leads to the largest relative changes in BEV demand, followed by BEV energy costs, BEV range and then PHEV price. PHEV range only has a small effect on demand, which is consistent with the selling argument of PHEV that limitations in electric range can be compensated using an internal combustion engine.
While smaller than purchase price, the elasticities relative to energy costs are still in a similar range, meaning that an alternative to policies having an effect on purchase price would be policies that make energy costs for BEVs lower compared to other alternatives, either through subsidies or taxation.
Interestingly, charging time has a very limited effect on demand: decision makers very likely want to be able to perform their full trips in one drive, and charge the vehicle while they are performing their activities, making range a much more important factor than charging time.

Table 1: Model Estimates (dummies)

Parameter	Estimate	Std. Dev.	T-Test (0)	
$\alpha_{petrol,new}$	0			
$\alpha_{diesel,new}$	-3.1	0.37	-8.4	**
$\alpha_{phev,new}$	-1.7	0.5	-3.4	**
$\alpha_{bev,new}$	-1.2	0.45	-2.5	**
$\alpha_{petrol,used}$	0			
$\alpha_{diesel,used}$	-1.7	0.19	-9.1	**
$\alpha_{phev,used}$	-1.3	0.37	-3.6	**
$\alpha_{bev,used}$	-1.2	0.3	-4.1	**
$\beta_{classic,[18,25)}$	0			
$\beta_{classic,[25,35)}$	0			
$\beta_{classic,[35,45)}$	0			
$\beta_{classic,[45,55)}$	0			
$\beta_{classic,55+}$	0			
$\beta_{alternative,[18,25)}$	0			
$\beta_{alternative,[25,35)}$	0.26	0.3	0.85	
$\beta_{alternative,[35,45)}$	0.65	0.31	2.1	**
$\beta_{alternative,[45,55)}$	0.3	0.29	1	
$\beta_{alternative,55+}$	0.3	0.28	1.1	
$\beta_{petrol,children}$	0			
$\beta_{diesel,children}$	1	0.27	3.7	**
$\beta_{phev,children}$	0.35	0.29	1.2	
$\beta_{bev,children}$	0.4	0.28	1.5	
$\beta_{garage,owner}$	0.18	0.2	0.91	
$\beta_{garage,renter}$	-0.2	0.21	-0.98	
$\beta_{av,low}$	0			
$\beta_{av,medium}$	0.51	0.049	10	**
$\beta_{av,high}$	0.52	0.047	11	**

To test the effect of variables taking only discrete values, market shares under alternative "scenarios" were computed. Figure 2 presents the results for the "base" scenario (running predictions on the sample without changes), "high availability" scenario (availability of charging stations for BEV set to "high" in all choice situations) and "all garage" scenario (all respondents are assumed to have access to a private garage or parking spot). Two price variations are also included: -15% for all BEV alternatives, and a simulation of the "Umweltbonus" currently in effect in Germany (-9000 Euros for new BEVs with a price under 40000 Euros, -7500 Euros for new BEVs with a price over 40000 Euros). Predictions are simulated for random values of the parameters sampled from the asymptotic distribution of the parameters, to get a feeling for results variance.
Availability of charging stations does have a noticeable effect on BEV market shares, both in the new and used market, but the difference remains small. Access to a private garage does not have any noticeable effect. In comparison, the effect of the two price policies is much larger.
Overall, the results seem to point to the fact that the technology is mature enough, such that the most important factor leading to a purchase decision for a BEV is the price.

Table 2: Model Estimates (Continuous Variables)

Parameter	Estimate	Std. Dev.	T-Test (0)	
σ_{EC}	2.7	0.056	49	**
λ_{inc}	-0.051	0.042	-1.2	
$\lambda_{inc,fuel}$	0.049	0.062	0.79	
β_{price}	-2	0.055	-36	**
$\beta_{fuel\ price}$	-1.2	0.09	-13	**
$\beta_{fuel\ price,educated}$	-1.5	0.064	-23	**
$\beta_{loadtime}$	-0.12	0.037	-3.2	**
β_{km}	-0.82	0.092	-8.9	**
$\beta_{phev,range}$	0.15	0.073	2.1	**
$\beta_{bev,range}$	0.72	0.071	10	**
$\beta_{petrol,dist}$	0			
$\beta_{diesel,dist}$	0.72	0.12	5.9	**
$\beta_{phev,dist}$	0.26	0.094	2.7	**
$\beta_{bev,dist}$	0.27	0.12	2.4	**
$\beta_{petrol,COG}$	0			
$\beta_{diesel,COG}$	-0.096	0.12	-0.83	
$\beta_{phev,COG}$	0.39	0.11	3.4	**
$\beta_{bev,COG}$	0.64	0.12	5.3	**
$\beta_{petrol,AFF}$	0			
$\beta_{diesel,AFF}$	-0.23	0.11	-2.1	**
$\beta_{phev,AFF}$	0.24	0.11	2.2	**
$\beta_{bev,AFF}$	0.58	0.11	5.4	**
$\beta_{petrol,BEH}$	0			
$\beta_{diesel,BEH}$	0.24	0.13	1.8	*
$\beta_{phev,BEH}$	0.36	0.12	2.9	**
$\beta_{bev,BEH}$	0.4	0.12	3.3	**

4 Conclusions

This paper presents the findings of a stated preference survey on powertrain preference when purchasing a new or used vehicle. We report on the survey design, experiences made during data collection, preparation for model estimations and the results of an error component logit mixture model. It was shown that the collected data set holds rich information with a promising number of cases suitable for modelling the preferences.

Overall, the results seem to point to the fact that the technology is mature enough, such that the most important factor leading to a purchase decision for a BEV is the price. These results may help policymakers for continued or future measures aimed in particular at the transition of powertrains. In particular, the results show that while the current incentive put into place in Germany ("Umweltbonus", a reduction in purchase price) is very effective, a modification of the difference in price of energy per kilometre between technologies would also have a potentially important impact on the preference for electric powertrains. Under the hypothesis that the consumers see these changes as a long-term trend that will impact them for the whole lifetime of their vehicle, rather than a potentially short-lived policy.

Our survey also reflects a snapshot of how high the registration numbers of electric vehicles could be if supply shortages implying long delivery times and high purchase prices were overcome quickly.

Table 3: Demand Elasticities

	Elasticities							
	Petrol		Diesel		PHEV		BEV	
Parameter	Used	New	Used	New	Used	New	Used	New
BEV Price	0.2	0.27	0.2	0.29	0.21	0.28	-0.6	-0.47
PHEV Price	0.2	0.24	0.22	0.26	-0.66	-0.6	0.2	0.21
Petrol Price	-0.57	-0.66	0.28	0.24	0.26	0.19	0.25	0.16
Diesel Price	0.18	0.15	-0.7	-0.8	0.18	0.12	0.15	0.1
BEV Charge Time	0.012	0.016	0.012	0.017	0.013	0.017	-0.036	-0.029
BEV Range	-0.071	-0.099	-0.071	-0.1	-0.076	-0.1	0.21	0.17
PHEV Range	-0.015	-0.019	-0.017	-0.021	0.051	0.047	-0.015	-0.017
BEV Energy Costs	0.14	0.2	0.14	0.21	0.15	0.21	-0.42	-0.35
PHEV Energy Costs	0.14	0.18	0.15	0.19	-0.47	-0.44	0.14	0.15
Petrol Energy Costs	-0.4	-0.39	0.2	0.14	0.19	0.11	0.17	0.093
Diesel Energy Costs	0.12	0.11	-0.49	-0.58	0.13	0.092	0.11	0.075

Against the background of halving emissions in less than ten years, it is crucial how quickly battery electric vehicle's new registrations (and thus indirectly its stock) increase.
Finally, in our survey only the demand is modelled, but not the supply. In the current (pandemic and the Russia-Ukraine war) situation, manufacturers cannot produce as many electric vehicles as they are in demand. This is still foreseeable in the coming years and could therefore be a major problem for the ramp-up in passenger car traffic.

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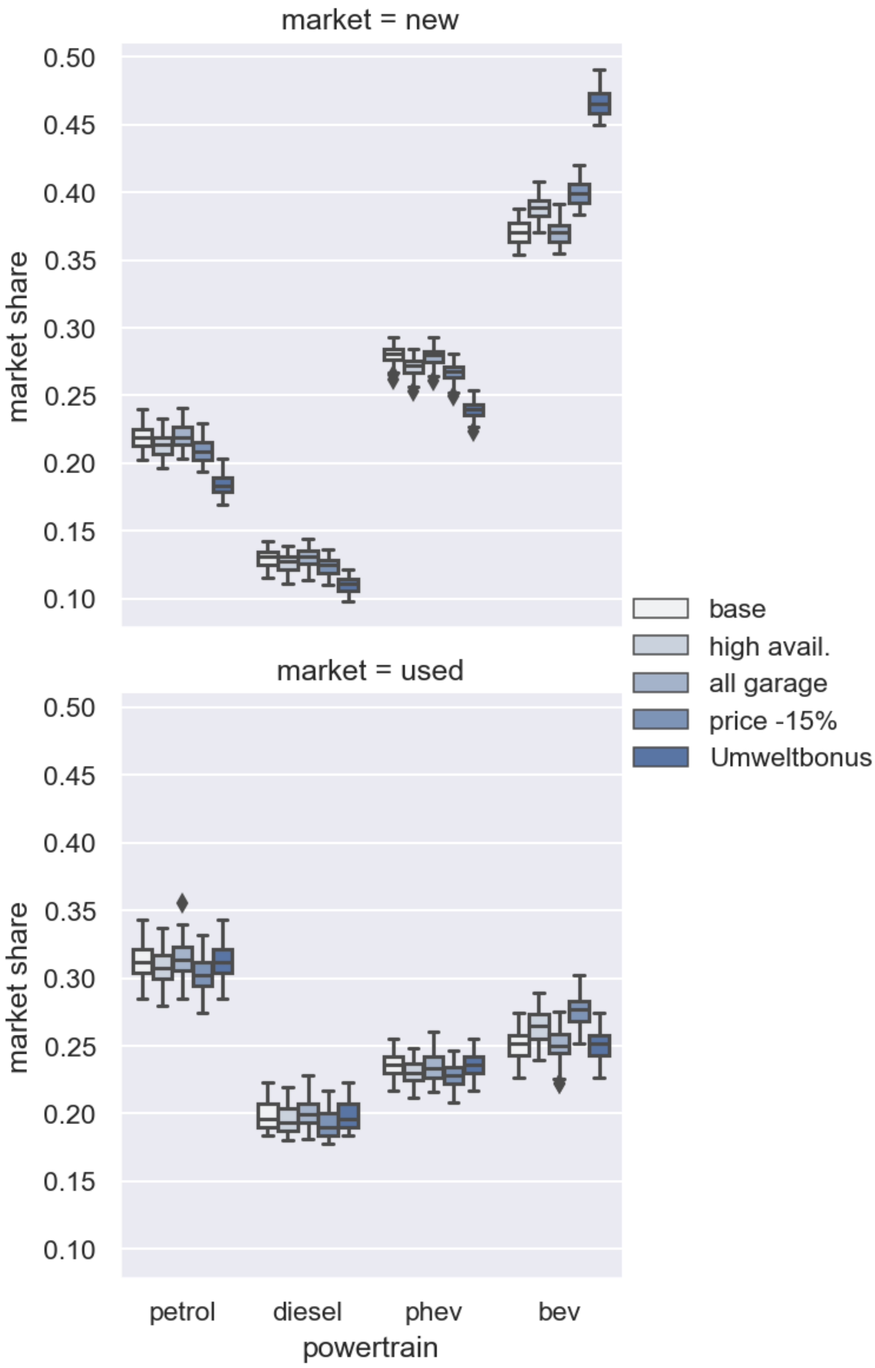

Figure 2: Market Shares Under Different Scenarios

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