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A choice-based conjoint analysis on the market potential of PHEVs and BEVs in Flanders

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Abstract

In this paper, the market potential for electric vehicles (EVs) in Flanders (Belgium) is forecasted with the use of a choice-based conjoint (CBC) analysis. In May 2011, a large-scale survey was conducted (n = 1.197). The goal of the survey was twofold: estimate the market potential for (plug-in hybrid) electric vehicles in Flanders (Belgium) and formulate recommendations for the further deployment of electric vehicles within the region of Flanders. When looking at the forecasts based on the CBC experiment, in 2020, battery electric vehicles (BEVs) could reach a market share of around 5% of the newly sold vehicles in Flanders. Plug-in hybrid electric vehicles (PHEVs) could have a market share of around 7%. In 2030, these figures could increase to respectively 15% and 29%. A sensitivity analysis reveals that, in order to increase the potential for (PH)EVs, the main focus should be on decreasing the purchase costs.

Keywords: Battery electric vehicle (BEV), Market, Plug-in hybrid electric vehicle (PHEV)

1 Introduction

The interest in electric vehicles has peaked three times during the last decades: in the mid-1960s (early concern about air quality), between 1974-1981 (concern about imported petroleum), and from 1985-present (renewed interest in reducing petroleum import and abatement of pollutants from automobiles) [1]. However, due to rising environmental concerns and the current development of battery systems with a focus on lithium-ion based batteries, the market development of EVs for passenger car applications has never been more promising [2].

EVs have certain characteristics that differ from conventional petrol or diesel vehicles. Their ecological impact is lower (especially when renewable energy such as wind or solar energy is used), the battery can be charged at home, the running costs (electricity) are low and the acceleration up to 50 km/h is very swift. Nevertheless, EVs still have some disadvantages: the purchase price is on average €10.000 to €15.000 higher compared to conventionally fuelled vehicles, charging a fully drained battery can take up to 8 hours, there is a lack of public charging infrastructure and the driving range is limited to around 100-200 kilometers.

In 2011, some of the world’s leading automobile manufacturers have inaugurated their first electric model since the beginning of the 21st century. This illustrates that manufacturers are interested in this technology that still needs to convince the public market. There still exists a lot of uncertainty.

Therefore, it is important to assess the demand for electric vehicles in the B2C market.

2 Methodology

2.1 Choice-based conjoint theory

There exist numerous methodologies within the stated preference approach. Conjoint analysis [3] is a multivariate technique that evaluates respondent trade-offs among multi-attribute alternatives in order to estimate consumers' utility functions [4,5,6]. Assuming that consumers choose the alternative that maximizes their utility, the conjoint methods map the preference structure of consumers based on their evaluation of the product's attributes. From the pool of conjoint techniques, the choice-based conjoint (CBC) methodology uses discrete choice models to collect consumer preferences [7, 8, 9, 10]. The respondents must select the product that fits them best among competing alternatives. This makes the choice experiment more realistic. It gives a better predicted accuracy, especially in market simulations [11, 12]. Hence, CBC is the conjoint technique applied in this experiment.

In the CBC experiment, the respondent is confronted with a choice of different alternatives. Each alternative is called a *profile* and their combination into a competing environment is called a *choice-set*. Table 1 illustrates a simple choice-set.

Table 1: Choice-set

	Vehicle A	Vehicle B	Vehicle C
Price	€12.500	€17.500	€15.000
Maximum speed	160 km/h	180 km/h	150 km/h
Driving range	400 km	600 km	500 km

First, the respondent has to investigate the three vehicle attributes (price, maximum speed and driving range) before evaluating which of the attributes is the most important. Next, the respondent looks at the different attributes and their values (the levels). Finally, he or she must choose the vehicle for which the combination of attributes gives the highest utility. This process is called *a task*. The respondent has to make trade-offs between the different vehicle attributes and levels. Finally, a non-option is added to the task. This way, the respondent chooses the vehicle that gives him the highest utility, and afterwards he or she has to indicate whether or not to purchase the vehicle.

Choice-based conjoint analysis is widely used particularly by market researchers in the field of new product development [12]. Within the field of environmentally friendly vehicles, including electric vehicles, we identified multiple studies in which the CBC methodology has been used [13-21].

2.2 CBC design

2.2.1 Literature review of vehicle attributes

In a CBC experiment, the respondent evaluates the profiles based on the considered attributes and chooses the option that gives them the highest utility. It is assumed that the respondent processes its total utility by summing up the utility brought by each attribute. As a result, our experiment needs to include every attribute that can influence the total utility of the respondent in order to simulate as close as possible the real decision making process. However, the survey needs to limit the number of attributes if the choice task is to be processed effectively by the respondent [9]. Identifying the determinant attributes is therefore an important task in the design of the experiment. Based on a scientific literature review of similar experiments, eight important vehicle attributes were identified (see Table 2): travel cost per 100 km, purchase costs, environmental performance, refuel or charging infrastructure, driving range, refuel or charging time, annual costs and maximum speed.

Table 2: Literature review for vehicle attributes

Literature review	Attributes							
	Travel cost per 100km	Purchase costs	Environmental performance	Refuel or charging infrastructure	Driving range	Refuel or charging time	Annual costs	Maximum speed
Hidrue et al. (2011)	✓	✓	✓		✓	✓		
Achtnicht et al. (2008)	✓	✓	✓	✓				
Potoglou & Kanaroglou (2007b)	✓	✓	✓	✓			✓	
Horne et al. (2005)	✓	✓	✓	✓				
Brownstone et al. (2000)	✓	✓	✓	✓	✓	✓		✓
Ewing & Sarigollu (1998)	✓	✓	✓		✓	✓	✓	
Bunch et al. (1993)	✓	✓	✓	✓	✓			
This study	✓	✓	✓	✓	✓	✓	✓	✓

2.2.2 Identification of the vehicle attributes

Since the selection of the attributes is an essential decision in the design of a CBC experiment, a test survey was conducted at the yearly Brussels Motorshow (January 2011). This was done through face-to-face interviews. The main outcome of the test survey was that a factor reflecting the prestige and quality of the car was missing to model the car purchase decision. A 9th attribute was therefore added and called "brand-image-design-quality".

Another outcome of the test survey was that it is very important to clearly define all vehicle attributes. It is essential that all survey respondents interpret the vehicle attributes the same way. Hence, in the final survey, right before starting the CBC experiment, the respondents received an overview of all vehicle attributes describing their measurement and definition (see Table 3).

Table 3: Definition of vehicle attributes

Vehicle attribute	Definition
Purchase costs	Purchase price, VAT, registration tax and possible governmental fiscal incentives
Annual costs	Insurance, maintenance and yearly driving tax
Travel cost for 100km	Fuel or electricity cost for 100km
Environmental performance	Based on Ecoscore (the higher the Ecoscore, the better the environmental performance of the vehicle)
Refuel or charging infrastructure alongside the road	Expressed in percentage of current fuel station coverage
Driving range	Number of kilometers that can be driven without refueling or recharging the battery
Refuel or charging time	Time to refuel or charge the battery
Maximum speed	Maximum speed of the vehicle
Brand / image / design / quality	How does the vehicle fulfill the consumers demand on brand, image, design and quality?

2.2.3 Selection of attribute levels

The attribute levels have to be communicable [9, 22, 23]. The selected levels, as illustrated in Table 4, were therefore indicated by quantitative measures that can easily be understood by respondents.

Within refuel or charging time, the first level (never) refers to inductive charging systems, where the battery of the electric vehicle is charged when driving (or standing still) on an installed coil, in which a magnetic field is created.

Also, the vehicle attribute "brand / image / design / quality" is expressed on a one to five star scale. This is done to make the vehicle attribute actionable. The respondent has to make a trade-off between different levels and thus has to be able to compare different attribute levels.

After identifying the attribute levels, prohibited pairs are eliminated. This approach involves the elimination of any unbelievable profiles resulting from inter-attribute correlation. For example: when the randomized CBC design chooses the "never" level from the refuel or charging time vehicle attribute, two other attributes become obsolete: driving range and refuel or charging infrastructure alongside the road. At that moment, both attributes are set to "not applicable".

Table 4: Measurement, number and magnitudes of attribute levels

Purchase costs	Annual costs	Travel costs per 100km	Environmental performance (Ecoscore)	Refuel or charging infrastructure	Driving range	Refuel or charging time	Maximum speed	Brand/ image/ design/ quality
10.000€	500€/year	0€/100km	60	5%	100km	Never	80km/h	1 star
12.500€	1.000€/year	2€/100km	65	10%	150km	5min (station)	100 km/h	2 stars
15.000€	1.500€/year	4€/100km	70	20%	200km	10min (station)	120 km/h	3 stars
17.500€	2.000€/year	6€/100km	75	40%	300km	2h (home) & 10min (station)	140 km/h	4 stars
20.000€	2.500€/year	8€/100km	80	60%	500km	8h (home) & 5min (station)	160 km/h	5 stars
22.500€	3.000€/year	10€/100km	85	80%	750km	8h (home) & 30min (station)	180 km/h	
25.000€	3.500€/year	12€/100km	90	100%	1.000km	8h (home)	200 km/h	
30.000€	4.000€/year	15€/100km	95	120%	1.250km			
35.000€	4.500€/year			150%				
> 35.000€	> 4.500€/year							

2.2.4 Choice task generation

The respondents do not rate the alternatives, they choose the best option. Adding many profiles in the choice-set does not entails a rich added statistical value. However, studies have shown that respondents are efficient with processing choice-sets with up to four profiles [23]. In this experiment, three profiles were given in each choice-set. Literature reveals this is a good number of profiles, whilst not burdening the respondents [24].
To generate partial fractional designs, we used the shortcut method [25, 26] because it satisfies the most the additive rule assumption [23]. This ensures that only main effects are considered in the model. Three hundred questionnaires were generated, each with ten different choice tasks. In practice, one questionnaire version is sufficient to design. However, multiple versions provide the shortcut method with more flexibility in respecting the orthogonality of the questionnaires as it can produce a wider range of unique choice tasks. Hence, the respondents answer a larger set of trade-offs, reducing potential biases of a unique questionnaire.
Finally, the entire survey was conducted on a user friendly internet based system in order to minimize the respondents' effort. Figure 1 illustrates a task for the CBC experiment. Respondents had to choose the vehicle that maximizes their utility and then indicate whether or not they would purchase the vehicle.

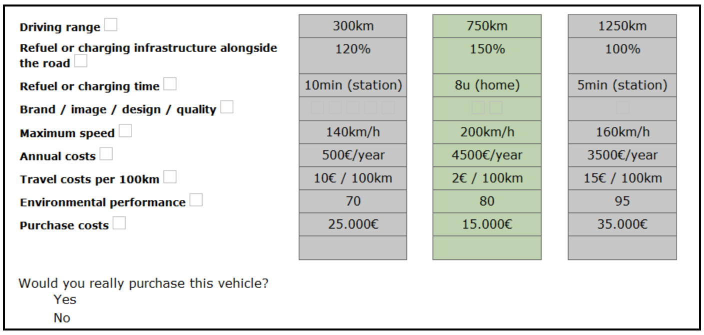

Figure 1: Screenshot of CBC task [26]

2.3 Estimation of results

After the results of the conjoint analysis have been gathered, the information has to be processed using a utility estimation method. Multiple regression and multinomial logit models have been a standard during many years for estimating the conjoint model. However, the development of the Bayesian estimation method (Hierarchical Bayes, HB) has recently changed the landscape [9]. It provides an accurate method to estimate individual level utilities, keeping the heterogeneity of the population intact [12, 25, 27-30]. In particular, HB was proofed to be efficient and accurate with CBC experiments [30]. It is therefore the selected method to estimate the utilities for this experiment.

3 Results

3.1 Survey scope

The target group for this survey was citizens of Flanders, older than 18 years. The data collection was in collaboration with a recognized market research company (iVOX). The survey was set up in May 2011 and was sent out to 2.037 people, from which 1.197 fully responded (response rate of 59%).

3.2 Part-worth utilities

The resulting individual utilities of all vehicle attribute levels are called part-worths (utilities). The raw part-worth utilities are rescaled according to the zero-centered diffs method so that their sum within an attribute equals to zero. Next, the adjusted part-worths are again rescaled so that the sum of the differences between the maximum and the minimum levels across all attributes for each respondent equals the number of attributes times a hundred. This way, the part-worths use a common interval scale across the different attributes. Hence, they must be interpreted in a relative way and their magnitude is meaningful. Moreover, every level can be compared with one another. Table 5 lists the average values of the rescaled individual part-worths.

Since the analysis uses the additive rule, the total utility of a car is calculated by summing up the part-worths associated to the attributes' value. The vehicle that will be preferred and hence chosen is the one with the highest utility. A clear example can be found in Table 5 when looking at the annual costs attribute. As expected, higher costs have lower part-worths and vice versa. However, some inconsistencies appear within other attributes. Some part-worths do not meet our expectations. For example, the level 60% of the attribute "refueling or charging infrastructure" is less desired than the level 40% and even 20%. These part-worths reveal an irrational evaluation of the respondent. These effects are called reversals. It can be interpreted as a psychological threshold. Also, the part-worth utility for the level 10.000€ in the "purchase costs" attribute is lower compared to the level 12.500€. This reversal can be explained by the impression of quality consumers may assign to cheaper products. In general, these reversals should be used with caution in the analyses. As a result, this research attends to not use these levels in order to ensure consistent results.

Table 5: Average part-worths for every level attribute

Purchase Costs	Part- worths	Annual costs	Part- worths	Travel costs / 100km	Part- worths
10.000 €	40,64	500 €/year	52,69	0€/100km	37,99
12.500 €	49,53	1.000 €/ year	36,33	2€/100km	29,51
15.000 €	36,34	1.500 €/ year	34,91	4€/100km	26,37
17.500 €	32,60	2.000 €/ year	18,73	6€/100km	6,24
20.000 €	15,91	2.500 €/ year	13,35	8€/100km	-8,83
22.500 €	4,36	3.000 €/ year	-10,68	10€/100km	-22,78
25.000 €	-1,78	3.500 €/ year	-16,32	12€/100km	-30,28
30.000 €	-33,58	4.000 €/ year	-34,47	15€/100km	-38,22
35.000 €	-50,62	4.500 €/ year	-41,59		
> 40000€	-93,39	> 5.000 €/ year	-52,96		

Environmental performance	Part- worths	Refuel or charging infrastructure	Part- worths	Driving range	Part- worths
60	-9,86	5%	-12,30	100 km	-33,98
65	-6,78	10%	-10,11	150 km	-27,33
70	0,14	20%	-3,50	200 km	-17,40
75	-5,88	40%	-2,93	300 km	4,05
80	1,34	60%	-7,22	500 km	11,74
85	-0,16	80%	9,48	750 km	19,61
90	9,21	100%	9,14	1.000 km	23,42
95	11,99	120%	8,64	1.250 km	19,87
		150%	8,79		

Refuel or charging time	Part- worths	Maximum speed	Part- worths	Quality / Design / Brand / Image	Part- worths
Never	54,48	80 km/h	-50,96	1 star	-25,74
5min (station)	3,47	100 km/h	-26,03	2 stars	-14,39
10min (station)	-5,13	120 km/h	12,71	3 stars	6,44
2h (home) / 10min (station)	3,15	140 km/h	14,45	4 stars	18,25
8u (home) / 5min (station)	-6,23	160 km/h	23,54	5 stars	15,44
8u (home) / 30min (station)	-19,42	180 km/h	15,34		
8u (home)	-30,32	200 km/h	10,95		

3.3 Market simulations

The individual part-worth utilities capture the preference structure of the population. By using a choice simulator, the reaction of the demand can be estimated for a specified market scenario in which different vehicles are identified. These vehicles are simulated through a combination of different attribute levels. The simulator uses the associated part-worths to calculate the preferred vehicle for each individual. Finally, the market shares are deduced from the simulated individual choices. Since the aim of this research is to predict the potential sales of (plug-in hybrid) electric vehicles in Flanders, different market scenarios are built for the years 2012, 2020 and 2030. In all three scenarios, eight types of vehicles are identified in order to simulate the market: city petroleum car (City P), medium class petroleum car (Medium P), premium class petroleum car (Premium P), city diesel car (City D), medium class diesel car (Medium D), premium class diesel car (Premium D), battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV). We included three sub-types of petroleum and diesel vehicles as their market supply is more diversified. The levels for each type of vehicle were selected taken into account the expected technological evolution as well as the expected evolution of the energy prices. Also, no level identified as a reversal was used in the scenario simulation. The outcomes are percentages of the number of newly sold vehicles in Flanders, not of the entire Flemish car fleet.

Conjoint simulation is based on an essential assumption that consumers choose their new car based on its attributes. It does not take into account other sales factors such as marketing tools (advertising and promotion) which also influence the effective market share. Therefore, the market shares depicted below illustrate the potential market shares. New technologies need some time before reaching their potential market share because their diffusion is slow.

The results for the scenario for 2012 are regarded as a validation for our model. We compare the results from this study with the 2010 Belgian market shares for newly sold vehicles. In the year 2010, diesel vehicles had the highest market share (76%), followed by petroleum cars (23,3%) and BEVs (0,01%) [31]. No PHEVs were available on the Belgian market in 2010. Our results indicate the following 2012 market shares: diesel (77%), petroleum (18%), BEVs (1%) and PHEVs (4%). Hence we conclude that our calculations approximate the current market situation.

Next to the market simulations, the model is able to explain the underlying reasons of the market shares based on the influences of the part-worths. Plug-in hybrid electric vehicles have a low market share because of the high purchase price of a PHEV (around €5.000 to €10.000 higher than that of a conventional car) but it benefits from a higher environmental score and cheaper driving costs (when running on the electric motor). However, even though PHEVs are more expensive than BEVs, its market share is higher. This is due to the flexibility the PHEVs can deliver: they have a similar range to conventional cars, they can use the existing fueling infrastructure and they can refuel in five minutes. Still, the market shares of PHEVs and EVs remain marginal compared to conventional petrol and diesel vehicles.

In 2020, the BEV and PHEV markets will increase. Still, the market share of PHEVs will be higher than that of BEVs (7% versus 5%). Both electric vehicle technologies will have an increased market potential because of different technical and economic enhancements: battery costs will drop, BEV range will improve and charging times will be shorter. Moreover, the charging infrastructure will be more developed and the maximum speed of BEVs will increase.

But it is in 2030 that BEVs and PHEVs will become a valid alternative for conventional cars.

Our simulations show that demand will create a potential market share of 15% for BEVs and 29% for PHEVs. Next to continuous technical improvements (higher driving range, a more developed charging infrastructure, shorter charging times, the diversification of the EV supply among brands), the main driver is the rising energy price. Even when taking into account increased electricity prices, the market potential for conventional cars still decreases.

3.4 Sensitivity analysis

In order to better understand consumer acceptance for BEVs and PHEVs, we investigate the influence on the market share for different actions, both from a policy and manufacturer's point of view. Our base scenario is the year 2012. This sensitivity analysis enables to indicate interesting recommendations to stimulate the introduction of electric vehicles in Flanders. Table 6 indicates the results for the sensitivity analyses.

Reducing the purchase costs and increasing the battery capacity to 300 km entails the largest increase in market potential in 2012 for BEVs. The high purchase costs and the limited driving range are indeed two often named bottlenecks for the successful market introduction of BEVs. For PHEVs, a reduction of the purchase costs and a rise of the fuel prices increase the 2012 market potential the most.

In general, government support can act on the purchase cost driver by offering incentives for the purchase of electrified vehicles. Moreover, technological improvements and economies of scale can also contribute in reducing the cost of the battery, which is still the most expensive component of BEVs [32].

The adoption of BEVs and PHEVs is driven by the market prices of conventional fuels. Even though governments have little direct influence on the energy market, they can still impact the final consumption price. By internalising the external costs of conventional vehicles [33], diesel and petroleum fuels can be more heavily taxed which in turn could encourage consumers to switch to electrified vehicles. In our model, a 2€ increase for petrol and diesel prices increases the market potential for both BEVs 1,23% to 1,68%) and PHEVs (3,61% to 6,08%).

Increasing the driving range for BEVs from 100km to 200km and improving the charging time to 30 minutes in the street have a similar effect on BEV and PHEV market potential. The total market share for electric vehicles rises to 5,09% and 5,14%. However, given the findings of the consumer sensitivity for purchase costs, we can conclude that research should be rather oriented on decreasing the costs of the battery rather than increasing the driving range or lowering charging time.

The development of the charging infrastructure (coverage of 10% of the actual filling stations) increases only the market potential for BEVs (1,23% to 1,99%). The PHEV market potential is not affected much. This can be explained by the fact that PHEVs are meant to be charged only at home.

Table 6: Sensitivity analyses: the effect on the market shares

Action	Effect on attribute levels	Market share BEVs	Market share PHEVs	Total market share
Base scenario 2012		1,23%	3,61%	4,84%
Higher reduction in purchasing costs	Purchase price of BEVs and PHEVs decrease with 5.000€	2,74%	6,57%	9,31%
More charging infrastructure	Infrastructure coverage develops from 5% to 10%	1,99%	3,52%	5,51%
Rise of fuel prices	Travel costs for diesel and petroleum cars rise with 2€ per 100km	1,68%	6,08%	7,76%
Battery leasing	Purchase price of BEVs decrease with 10.000€ and annual costs increase with 1.000€	1,64%	3,73%	5,37%
More battery capacity	Driving range for BEVs increases from 100km to 200km	1,63%	3,51%	5,14%
More battery capacity	Driving range for BEVs increases from 100km to 300km	2,82%	3,33%	6,15%
Faster charging time	Fast chargers are available in public areas and take 30minutes to recharge the battery	1,36%	3,73%	5,09%

4 Conclusion and recommendations

In this paper, the market potential for (plug-in hybrid) electric vehicles in Flanders (Belgium) was forecasted. We first identified the most important vehicle attributes within the decision-making process for a new car: purchase costs, travel cost for 100 km, annual costs, environmental performance of the vehicle, refuel or charging infrastructure, driving range, refuel or charging time, maximum speed and quality/design/brand/image. We conducted a choice-based conjoint experiment with nearly 1.200 respondents. We found all part-worth utilities for the vehicle attributes levels, enabling us to set up different scenarios for the years 2012, 2020 and 2030. This way, we were able to forecast the future market potential for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). In 2012, sales figures will still be low (1,23% for BEVs and 3,61% for PHEVs). In 2020, these figures could increase to respectively 5% and 7%, due to technological improvements and a decrease in purchase costs. Finally, in 2030, electrified transport could really set off with market shares of 15% (BEVs) and 29% (PHEVs).
Based on the scenario for 2012, we analyzed different actions to improve BEV and PHEV adoption in Flanders in order to draw the prior deployment needs. The results show that the most sensitive factors for both technologies are the reduction of the high purchase costs and the increase of the fuel prices for conventional cars. When improving one of these two attribute levels, the market shares for electrified transport (BEV + PHEV) rise from 4,84% to 9,31% (lower purchase costs) and 7,76% (higher conventional fuel prices). Increasing the driving range for BEVs to 300km would entail an increase to 6,15%.
We conclude by stressing the need for further research in battery development. More specific, the focus should be on decreasing the battery costs in order to leverage our findings for both BEV and PHEVs. Also, governments should regulate more efficiently travel costs by internalizing the external costs of conventional cars. This could be an efficient incentive for consumers to switch to electric vehicles.

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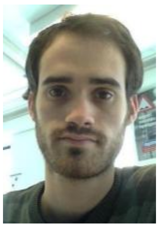

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