Impact of service station networks on purchase decisions of alternative-fuel vehicles

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Abstract

In this paper we analyze the impact of service station availability on the demand for alternative-fuel vehicles and the consumers' willingness to pay for an enlarged fueling infrastructure. We examine a stated preferences choice experiment conducted as a CAPI survey with about 600 interviews of potential car buyers in Germany and estimate the coefficients of a discrete choice model. We simulate different scenarios and analyze how individual choice probabilities for alternative fuel types are changing with a modified fueling infrastructure. In our scenarios hybrids, LPG/CNG and hydrogen will be real alternatives to the existing conventional technologies. However, biofuels and electric power trains are well behind even in a situation where their infrastructure is equally developed. Moreover, on the basis of our model we compute what increases in fixed or variable costs consumers of different income groups are willing to accept for an increasing station density.

JEL classification: C51, L62, R41.

Keywords: Fueling Infrastructure; Alternative Fuels; Automobile Market; Stated Preferences; Discrete Choice; Network Effects.

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This paper was written within the research project "ECO-CARS". We would like to thank our partners in this project for helpful discussions and suggestions and the German Federal Ministry of Education and Research (BMBF) for financial support.

1 Introduction

Motorized individual transport plays a major role in the current political debate on climate change and energy security. According to the European Commission, transport accounts for some 71% of oil consumption and for 26% of CO_2 emissions in the European Union. The automobile sector alone depends on oil at 98%. To reduce oil dependency and to make transport more sustainable, the Commission set out an objective to substitute 10% of traditional automotive fuels with alternatives by the year 2020 (EU (2000), EU (2006)). But a penetration of the market with alterative fuels requires an acceptable level of infrastructure.

In this paper we study the impact of service station availability on the demand for alternative-fuel vehicles. The lack of a widespread fueling station network for alternative fuels may constitute a barrier to the entry of alternative-fuel vehicles into the market. Additionally, network externalities arising from the existence of the installed fueling infrastructure for gasoline and diesel may deter consumers to switch to new incompatible technologies. In the literature this problem is referred to as "excess inertia" (Farell and Saloner (1986)).

However, the expansion of the fueling station networks for alternative fuels requires high investments. Reducing or replacing filling pumps for fossil fuels by others will be only profitable for service station owners if the demand, i.e. the number of vehicles using alternative fuels, considerably increases.

The complementary of vehicle demand and fueling infrastructure supply is often described as chicken-egg problem and raises the question of political intervention. But are public subsidies for the development of an alternative fueling station network really necessary? How much are the consumers willing to pay for a network expansion? Will the consumer really switch to vehicles running on alternative fuels if a fully developed station network exists?

Based on a stated preferences choice experiment we try to answer these questions for the German market. We analyze car purchase decisions for a broad set of existing fossil fuel based and future alternative fuel based propulsion technologies. Our analysis is based on a stated preference (SP) experiment conducted as a computer assisted personal interview (CAPI) with about 600 interviews of potential car buyers in Germany. Using a nested logit model, we estimate the impact of the fueling station network on the purchase decision of passenger cars running with alternative fuel types. We show that the impact of a larger service station network on the purchase decision is positive with a diminishing marginal utility. We identify the influence of different socio-demographic and socio-economic characteristics and the ecological attitude on individual choice probabilities. We can not confirm the hypothesis that consumers with intensive car use are more sensitive regarding fueling infrastructure. Likewise, we found no empirical evidence for a varying effect of the service station network on different fuel types. In this regard, new technologies have no systematical disadvantage compared to conventional technologies.

To illustrate the impact of service station availability on the purchase decision for passenger cars, we simulate different scenarios and analyze how the choice probabilities for alternative fuel types are changing with a modified fueling infrastructure. We show that an enlargement of infrastructure for alternative fuel types will raise the market shares of LPG/CNG and hydrogen considerably. Thus, these alternative technologies can be seen as real alternatives to existing conventional technologies. On the other hand, biofuels and electric power train are well behind even in a situation where their infrastructure is equally developed.

Moreover, on the basis of our model we compute the absolute and relative willingness to pay (WTP) for an enlarged fueling station network and show how it differs in relation to the income of the consumers. We find that the relative WTP for an enlargement of the infrastructure decreases with the size of the existing fueling network and with an increasing purchase prices of a vehicle. However, for very expensive cars the relative WTP increases again. The amount of additional variable costs the consumers are willing to pay for an enhanced network is just as well decreasing in the size of the already existing network.

The paper is organized as follows. In section 2 we describe the survey and the data set. Section 3 introduces our discrete choice model. Section 4 displays our estimation results with the presentation of the coefficients in subsection 4.1, the description of the simulations in subsection 4.2, and the computation of the willingness to pay in subsection 4.3. The last section discusses the results and concludes.

2 Description of the survey

The estimations in this paper are based on a German-wide consumer survey amongst potential car-buyers. This survey was designed to estimate their preferences for cars with alternative technologies and fuel types by creating choice situations with hypothetical vehicles.

Available datasets concerning car purchase decisions do not deliver sufficient information for our analysis due to their focus on already existing technologies. They are based upon historical data and do not cover new technologies like electric or hydrogen cars which are actually not available in the market. Moreover, technologies like hybrids, CNG and LPG or conventional cars using biofuels with a negligible market penetration are not sufficiently represented in the databases (Horne et al. 2005). In addition, details on the socio-demographic and socio-economic status of the interviewees are often missing. But these information are expected to be relevant for the choice decision of passenger cars (Dragay 2001).

The survey was conducted from August 2007 to March 2008 as a computer assisted personal interview (CAPI) in Germany. The interviewers were requested to ask consumers of all population groups. Restrictions were made only for the age of the respondents. They should be of age and have a valid driving license. We interviewed about 600 people living in different regions in Germany (Eastern vs. Western Germany, urban vs. rural areas). The interviews took place in showrooms of car dealers from different brands and in selected offices of the technical inspection authority.

The survey consisted of a multi-sectional questionnaire. The respondents were asked for socio-demographic and -economic details and for their actual car ownership. They were asked whether they intend to replace an existing car or to buy a new car. In these cases the respondents were asked for further details about the envisaged vehicle. An additional set of questions covered mobility patterns and car use with a special focus on environmental-friendly behavior.

The core of the questionnaire was a stated preference (SP) choice experiment concerning a car purchase decision. Each respondent had to answer six choice sets. Each choice set consisted of seven alternative vehicles, each characterized by the six following attributes:

- Selling price of a vehicle.

- Variable costs per 100 kilometers.
- Engine power.
- CO_2 emissions.
- Fuel availability (given by the size of the service station network).
- Fuel type.

Selling price, variable costs and engine power are standard explanatory variables in vehicle choice models (Horne et al. 2005, Ewing and Sarigollu 2000, Brownstone et al. 2000, McCarthy and Tay 1998, McCarthy 1996, Bunch et al. 1993 as well as Manski and Sherman 1980). CO_2 emissions and fuel availability are used in just a few surveys (Horne et al. 2005, Brownstone et al. 2000 and Bunch et al. 1993).

Table 1 illustrates the possible values of the attributes in our choice experiment. The SP-experiment is quasi-labeled. Each fuel type is covered once in each choice set and can therefore be handled as a label of the alternatives. But the presentation of the choice sets is designed as an unlabeled SP-experiment such that the fuel type looks like an attribute of a car and not as an alternative itself.

To create a realistic choice situation the respondents were asked beforehand to characterize the vehicle they could imagine to buy. This characterization referred to the car classification (full-size, compact, mid-size, Van, sports car, ...) as well as to the selling price and engine power. The possible values of the selling price and engine power in the SP-experiment were equal to 75%, 100% and 125% of the values given by the respondent. Although this determination causes some correlation between selling price and engine power it avoids unimaginable situations for the respondent.[1]

The set of possible CO_2 values differs with respect to the fuel types. There are always strictly positive emissions of vehicles running on fossil fuels like diesel, gasoline, CNG or LPG. But we include the alternative "no emissions" for electric, hydrogen or biofuel cars because their CO_2 emissions are zero. But because emissions emerge in the course of fuel-production, we allow positive CO_2 emissions.

[1] In reality, selling price and engine price are correlated. More expensive cars usually have a higher engine performance than inexpensive cars. Such correlations are typical for revealed purchase decisions (Fowkes and Wardman 1988).

3 The model specification

Choice decisions are characterized by a discrete outcome. To analyze them it requires the use of discrete choice models (DCM). Such models owe their theoretical grounding in microeconomics especially to McFadden and his *random utility* approach (McFadden 1974). A utility U_{nj} provided by an alternative j to a person n is assumed to be

$$U_{nj} = V_{nj}(x_j, z_n) + \varepsilon_{nj}, \tag{1}$$

where $V_{nj}(x_j, z_n)$ is a deterministic (observed) utility component, depending on attributes x_j of alternative j and sociodemographic variables z_n of person n, and ε_{nj} is a (unobserved) stochastic component.[2] According to the economic theory of the utility-maximizing individual, person n will choose that alternative from the set $\{1, \ldots, J\}$ of alternatives that provides him the greatest utility. Since utility is modeled as a random variable, however, only choice probabilities can be econometrically estimated. Depending on the assumptions made about the distribution of the random variables ε_{nj} $(n = 1, \ldots, N; j = 1, \ldots, J)$, different discrete choice models are defined (cf., for instance, Train 2003).

In this paper, we use a nested logit model to analyze the choice decisions for passenger cars running with alternative fuel types. Likewise in multinomal logit models (MNL), the marginal distributions of the ε_{nj}'s are univariate extreme value. But by portioning similar alternatives into subsets B_k $(k = 1, \ldots, K)$ (so called nests), we virtually allow the associated ε_{nj} to be correlated. Hence, we can relax the *independence from irrelevant alternatives* (IIA) assumption regarding alternatives in different nests. For example McFadden (1978) showed that this model specification results in the following choice probability that person n chooses alternative $i \in B_k$:

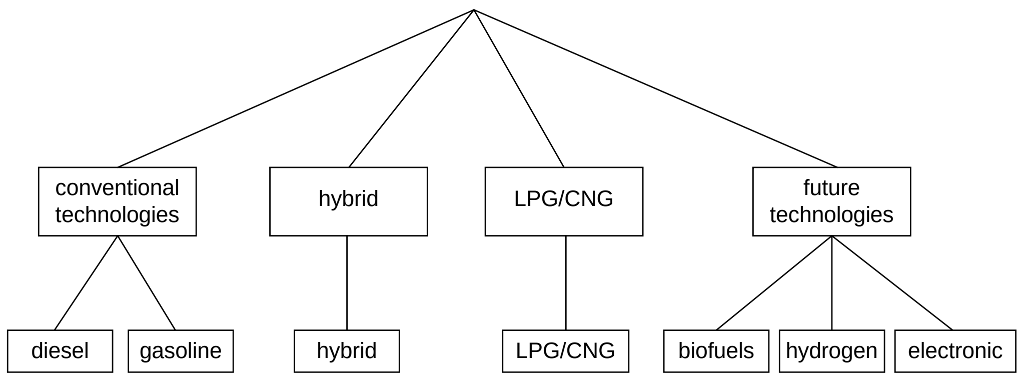
$$P_{ni} = \frac{e^{V_{ni}/\lambda_k} (\sum_{j \in B_k} e^{V_{nj}/\lambda_k})^{\lambda_k - 1}}{\sum_{l=1}^{K} (\sum_{j \in B_l} e^{V_{nj}/\lambda_l})^{\lambda_l}}, \tag{2}$$

where λ_k is called dissimilarity parameter of nest B_k and captures the degree of independence among the alternatives in B_k.[3] To be consistent with utility-

[2] For a discussion on the use of unobserved components see Ben-Akiva and Lerman (1985).

[3] Heiss (2002) compares different specifications of nested logit models and shows that this one

Figure 1: Structure of the nested logit model



maximizing behavior for all values of the independent variables the λ_k's need to be between zero and one.[4]

In our case, we partitioned the seven alternative fuel types into four nests. The first nest contains gasoline and diesel and can be described as the *conventional technology nest*. Within this nest the technologies are well established and have substantial market shares. Technologies that already entered the market in the past few years but currently have a small market share could be allocated into a second nest. However, we belief that hybrids and LPG/CNG differ fundamentally.[5] Consequently, we decide to model two separate degenerated nests[6] for the two alternatives hybrid and LPG/CNG. The fourth nest can be described as the *future technology nest*, containing all technologies which have not already entered the market. Some of these technologies are close to market penetration, others are not. Nevertheless we cannot identify a substantial reason to build more than one nest for these technologies. Figure 1 displays the structure of the nested logit model.

The independent variables that enter our model and the underlying hypotheses

(so called random utility maximization nested logit (RUMNL)) is preferable in most situations. He also introduces an implementation of RUMNL in Stata.

[4]Nested logit models might also be locally consistent with utility maximization if $\lambda_k > 1$. Herriges and Kling (1996) present a useful test of consistency in this regard.

[5]To a substantial share hybrid vehicles use the same fuel type like the alternatives in the first nest. In addition hybrids run on electricity which requires a different engine technology. On the other hand, LPG or CNG passenger cars use another kind of fuel but the same engine technology like gasoline cars.

[6]Since dissimilarity parameters of degenerate nests are not identified in the RUMNL model, they have to be restricted to a nonzero constant (Heiss 2002). We choose 1 for this restriction.

are briefly discussed in the following. The deterministic component of utility V is - as usual - specified linearly in parameters. As indicated in section 2 the attributes describing the seven alternatives are the purchase price, variable costs, engine power, CO_2 emissions and the density of the fueling station network. While the correlation between the purchase price, the variable costs and the CO_2 emissions with the choice probability is expected to be negative, it should be positive for the engine power and the density of the network.

Concerning the network density effect it might be assumed that the impact on the choice probability varies between the available alternatives. New technologies might have a disadvantage compared to conventional technologies because of the skepticism they are confronted with. To control for these differences we generate interaction variables. Furthermore it might be expected that persons with an intensive use of the passenger car wish to have a higher network density which guarantees more flexibility in the use of the passenger car. This relation is captured by the planned annual mileage and the requested maximum distance that can be covered by one refueling process, as indicated by the interviewees.

We moreover describe the impact of specific sociodemographic characteristics on respondents' stated choice decisions. Firstly, we focus on the eco-orientation of the consumers. We assume that consumers with a higher attitude for environmental friendly goods have a stronger focus on the CO_2 emissions performance of passenger cars, too. Therefore we asked the interviewees about their eco-orientation by a sequence of questions describing choice decisions in several situations of daily life. Depending on their answers they scored a certain level on a defined eco-scale. People who scored more on this eco-scale than the sample mean are defined as ecologically motivated, consumers who did not, consistently, as ecologically not motivated. Secondly, we assume that older consumers have some prejudices against innovative products (Carlsson-Kanyama et al. 2005). Estimating the effect of the consumers' age on the car purchase decision of new technologies is expected to be negative. Thirdly, the income of the household will have an impact on the car purchase decision. We assume that consumers with a low income are more price-sensitive.

4 Empirical results

4.1 Coefficients

Table 2 shows the estimation results.[7] The coefficient of the purchase price has, as expected, a negative sign and is highly statistically significant, whereas the square of the purchase price is positively signed. This indicates a diminishing marginal disutility. This means: the higher the price of a passenger car, the greater the disutility - but paying an additional Euro is hurting less if the price is already relatively high. Further analysis of the price-utility relation reveals a maximum disutility at a price of €145,000, approximately. One could assume that in such price categories consumers derive benefit simply from the fact that the car is that expensive. However, the average prices stated by the respondents range from €525 to €125,000.[8] Therefore, the estimated utility function is particularly valid for this range - where it behaves normally. Our estimation results moreover confirm the hypothesis that the lowest income group of respondents (i.e. individuals with a net monthly household income below €1000) is more price-sensitive. Their price coefficient (which is the sum of "Purchase Price" and "PriceXIncomeBelow1000") is clearly lower than the one for the reference group (i.e. individuals with a net monthly household income above €2000). This implies a lower WTP for improvements regarding passenger car attributes.[9]

As expected, the coefficient for variable costs is negative and the one for engine power is positive, the related quadratic terms are both not significant. In contrast to the purchase price, every Euro which increases the variable costs of car use burdens equally. So, consumers differentiate clearly between one-off costs and recurring costs.

The estimation furthermore shows that ecologically motivated consumers are more concerned about CO_2 emissions in their car purchase decision.[10] This is

[7] Interaction terms regarding different fuel types have to be interpreted with reference to the baseline alternative diesel.

[8] We asked the respondents to indicate a lower and an upper bound for the purchase price of their next car, and then used the average to design individual choice sets.

[9] We will consider this in our discussion about WTP for an enlarged fueling infrastructure below.

[10] In our sample the majority of people is ecologically motivated. So we used them as reference and checked for differences to not motivated people with the help of interaction terms.

remarkable, though not surprising. But the negative sign of the quadratic CO_2 term suggests that there is an increasing marginal disutility of CO_2 emissions for all people. It seems that the ongoing debates about CO_2 emissions as the driving factor for climate change have their impacts. People are aware of the problem, and they are not willing to accept arbitrary many CO_2 emissions due to their car driving.

Besides, we checked whether sociodemographic or other individual variables influence the utility of the alternatives. Our results show that ecologically motivated people prefer alternative fuel types - compared to diesel - more clearly than people do, who are not ecologically motivated. Older people, however, seem to have some prejudices against future technologies, particularly against electric and hydrogen cars. Hence, the probability to choose conventional cars increases with the age of the respondent. The estimation further shows that the larger the preferred range and the planned annual mileage, the more likely a diesel-driven car is to be chosen. Although respondents were asked to assume that all presented alternatives of a choice set equal in omitted attributes, it seems that experienced economic advantages of diesel-driven cars are causing this.

The impact that a larger service station network has on the purchase decision is positive with a diminishing marginal utility. This effect does not vary between people from rural and urban areas and does not depend on the preferred range or the planned annual mileage. So, we can not confirm our hypothesis that people with intensive car use are more sensitive regarding the fueling infrastructure. It rather seems that flexibility, guaranteed by a dense service station network, is equally important to all passenger car drivers. Likewise, there is no empirical evidence in our data for a varying effect of the service station network on different fuel types (compared to our reference alternative diesel). For consumers it is just important that there is a network, no matter for which specific technology. In this regard, new technologies have no systematical disadvantage compared to conventional technologies. An additional barrier in terms of market penetration does not exist for future technologies.

4.2 Simulations

To illustrate what impact the service station availability actually has on the purchase decision for passenger cars, we simulate different scenarios. Based on our estimated model we analyze how the average choice probabilities[11] for alternative fuel types are changing with a modified fueling infrastructure. Therefore we underlie a standard car defined by the average attribute levels occurring in our data set. More precisely, we set a purchase price of €20,740, variable costs of 11.67 €/100 km, engine power of 127 PS and CO_2 emissions of 130 g/km for the standard car. The only attribute that we let vary between the different propulsion technologies is the network density.

In scenario 1 we look at a simplified version of the status quo in Germany. For gasoline-driven, diesel-driven and hybrid cars almost every fueling station is convenient (100% network density). The network density of LPG/CNG and biofuels are set to 30% and 13%, respectively. Regarding the rather embryonic technologies hydrogen and electric power train we set a network density of 1% to simplify matters. The resulting average choice probabilities indicate that those propulsion technologies are demanded most for which the highest network density is provided. Gasoline-driven, diesel-driven and hybrid cars are all around 25% - with slight advantages for the conventional technologies. On average, LPG/CNG cars with their 30% network density definitely have a fair chance to be chosen (10.7%). However, biofuel, hydrogen and electric cars only have minor potentialities in such a situation. Interestingly, the choice probability for hydrogen cars (4.8%) is even higher than the one for biofuel cars (4.3%) - although the latter are equipped with a rather developed infrastructure. Due to the recently recognized coherences between subsidized biofuels and increasing food prices, the commonly image of biofuels is worsened. It might be that this development is reflected in our sample.

Throughout the scenarios 2 to 6 we continuously increase the network densities of LPG/CNG and future technologies up to 100%. Although this conforms the rather naive idea that all regarded technologies are advancing likewise, it nevertheless gives an insight on how the situation could look like if the network density would no longer differ between fuel types. The results of scenario 6 show

[11] At first, the choice probabilities are predicted separately for every respondent within our data set, and then these predicted probabilities are averaged. If the sample would be representative, the average probabilities could be interpreted as potential market shares.

that gasoline- (19%) and diesel-driven cars (18.7%) would keep ahead of others, but their lead would dwindle considerably. In addition to hybrids (16.1%) and LPG/CNG (14.2%), hydrogen (13%) would now also be a real alternative to the conventional propulsions. According to present preferences, biofuel cars (10.1%) and electric cars (9%) would be rated worst. We already mentioned above possible drawbacks of biofuels. Regarding electric cars it could well be that existing practical difficulties (e.g. long charging, short range) are known by the respondents and made it less attractive for them. The scenarios and the corresponding simulation results are shown in detail in Tables 3 and 4, respectively.

Based on the situation given by scenario 6 (i.e. all technologies are provided with a network density of 100%) we furthermore examine what impact the ecological attitude of people has on individual choice probabilities. Therefore, we underlie a standard individual defined by the average levels of sociodemographic and other individual variables occurring in our data set. This person is 45 years of age and lives in a household in a rather urban area with a net monthly income of more than €2000. He prefers a range of 630 km and plans an annual mileage of 19,500 km with his new car (both values are slightly below the sample average). But in the one case he is ecologically motivated (scenario 6c) and in the other he is not (scenario 6b). The differences in the resulting choice probabilities are striking. In scenario 6b gasoline (23.2%) and diesel (21.1%) are favored clearly. But these conventional technologies would lose their leading position immediately the ecological attitude turns. In scenario 6c hybrids (17.8%) are the most probable choice. The choice probabilities of hydrogen, LPG/CNG, biofuel and electric cars would increase likewise. This makes clear that the attitudes of individuals influence the choice probabilities for propulsion technologies - even if all available technologies are provided with the highest possible network density. Table 5 shows the simulation results in detail.

With the above discussion we provide empirical evidence regarding one aspect of the chicken-egg problem. The choice probabilities - and ultimately the demand - for passenger cars with alternative fuel types strongly depend on the provided infrastructure. That is, conventional technologies will still dominate the individual road transport in future, without an expansion of fueling networks of alternatives. Such an expansion would require high investments. It is difficult to imagine that car users would not have to partly pay for it, in one way or another.

4.3 Willingness to Pay

On the basis of our model we are able to identify the WTP for an increasing service station network. That is, the amount φ that a person is willing to pay in addition to the baseline price p for an increase η of the baseline network density d, without a change in utility. Since we let squared terms (of the purchase price as well as of the network density) enter our model the WTP do not fit in with the ratio of the corresponding coefficients of the linear terms. Due to the fixed utility level equation (3) has to hold:

$$\begin{aligned} V &= \beta_p p + \beta_{p^2} p^2 + \beta_d d + \beta_{d^2} d^2 + c \\ &\overset{!}{=} \beta_p (p+\varphi) + \beta_{p^2}(p+\varphi)^2 + \beta_d (d+\eta) + \beta_{d^2}(d+\eta)^2 + c \end{aligned} \tag{3}$$

where β_p, β_{p^2} and β_d, β_{d^2} denote the estimated cofficients of the price and the network density variables, respectively. c is the value that the remaining independent variables of the model contribute to the deterministic component of utility V. Simple algebraic transformations of equation (3) result in a quadratic equation in the variable φ, its meaningful solution is given by

$$\varphi = -\frac{\beta_p/\beta_{p^2} + 2p}{2} - \sqrt{\left(\frac{\beta_p/\beta_{p^2} + 2p}{2}\right)^2 - \frac{(\beta_d + \beta_{d^2} 2d)\eta + \beta_{d^2}\eta^2}{\beta_{p^2}}}. \tag{4}$$

For given purchase price p, network density d and its increase η, this formula provides the WTP φ.[12]

We computed the absolute WTP for $\eta = 10$ (i.e. a raise of the service station network by 10 percentage points) for different baseline scenarios. Concretely, we let p vary from €10,000 to €110,000 (at intervals of 10,000), and d from 20% to 90% (at intervals of 10). Table 6 shows the results in detail. By dividing these absolute terms by the corresponding baseline purchase price, we derived the relative WTP. Figure 2 illustrates their behavior. In this figure the horizontal plane, formed by

[12] Actually, it is the WTP for an increased service station network for diesel-fueled cars of individuals with a net monthly household income above €2000, who are living in urban areas and are average car users (with respect to preferred range and annual mileage). Since all network-interaction terms do not differ significantly from zero we interpret φ as (an approximation of) the WTP of individuals with an net monthly household income above €2000 for any enlarged service station network.

the network-density-axis (which range from 20% to 90%) and the car-price-axis (which range from €10,000 to €110,000), defines all regarded baseline scenarios, whereas the vertical axis defines the WTPs.

The first finding is that with an increasing fueling infrastructure the WTP for further raising network density decreases. This holds for every baseline purchase price. First improvements regarding a rather underdeveloped network are valued highest by potential car buyers. For example the relative WTP on a baseline price of €10,000 varies extremely from about 35% (on a baseline network of 20%) to less than 8% (on a baseline network of 90%). This result suggests that people want to be provided with an infrastructure as comfortable as possible for the respective propulsion technology - but not at any price. This is in line with the diminishing marginal utility of network density we identified above.

Secondly, we find that the relative WTP decreases with increasing purchase prices. For example the relative WTP for an enlargement of network density from 20% to 30% is falling from about 35% (on a baseline price of €10,000) down to about $9,5\%$ (on a baseline price of €70,000). The negative effect of a higher purchase price is dominating the positive impact of the squared price term. But this development stops at about a baseline price of €70,000. For more expensive cars the relative WTP is increasing again. This suggests that in this price category, money does not any more play that big role for purchase decisions. Here, the positive impact of the squared price term is dominating. However, it is important to note that the derived WTP measures are highly uncertain, as indicated by the standard errors (see Table 6). In particular, the WTPs regarding high baseline prices (i.e. prices greater than €80,000) and the highest baseline network density (i.e. 90%) do mostly not differ significantly from zero.

Note that this discussion refers to potential car buyers with a net monthly household income above €2000. For comparison, Table 7 and Figure 3 show the absolute and the relative WTPs, respectively, for individuals of the lowest income group.[13] Basically there are two differences. First, the discussion takes place on a different level. The WTPs are significantly lower. And second, within the observed range, the relative WTP decreases continuously with increasing baseline car prices. Despite one can assume that upper price categories are not relevant for

[13]To compute the WTP's in this case, we have to substitute β_p in equation (4) by the sum of the coefficients of the independent variables Purchase Price and PriceXIncomeBelow1000.

these individuals, it illustrates how strong the negative impact of the linear price term is.

Alternatively, it is imaginable that car drivers would be participated in costs for an expansion of infrastructure by an increase in variable costs of driving. We analyze what increase in variable costs people are willing to accept for a simultaneous increase of the network density. Therefore, we proceed analogously as above. We quantify the additional variable costs ϑ that do not change the utility - given an increase η of the baseline network density d. That ϑ is given by[14]

$$\vartheta = -\frac{(\beta_d + \beta_{d^2} 2d)\eta + \beta_{d^2}\eta^2}{\beta_v}, \tag{5}$$

where β_d, β_{d^2} and β_v denotes the estimated coefficients of the network density variables and the variable costs, respectively. As the baseline variable costs v do not enter equation (5), the willingness to pay additional variable costs is independent from their original level.[15] Table 8 shows our results.

Again, we find that with an increasing baseline network density the amount of additional variable costs that people are willing to pay for an even denser network is decreasing. Based on a network density of 20% people would be willing to pay over €2 more per 100 km car driving. As long as the network would be upgraded to 30% their utility would not change. In comparison, people would pay less than €0.50 to guarantee that they can refuel their car on all service stations - instead on nine out of ten anyway. However, likewise the WTP measures based on the purchase price, these values are highly uncertain (see standard errors in Table 8).

5 Conclusion

In our paper we have shown that the demand for passenger cars with alternative fuel types strongly depends on the provided infrastructure. Without further expansions of the service station network for alternative fuels, conventional technologies will still dominate the individual road transport in the next decades. But

[14]Note: Since only the linear term of variable costs differs significantly from zero, we do not consider the quadratic term for this purpose.

[15]Remind that variable costs take on the values 5, 10 and 20 €/100km in our experimental design.

the consumers are willing to pay for the development and many of them would switch to new technologies if the infrastructure improves.

In our simulations we have demonstrated that the consumers distinguish between different non-fossil fuel alternatives and that not all of them are equally favored. Even though the respondents of our survey were asked to imagine that the described cars in the SP-experiment were identical except for the given attributes, some technologies were more often rejected. Biofuels and electric power train were not very popular even in a situation where their infrastructure is equally developed. On the other hand, hybrids, LPG/CNG and hydrogen have the potential to be alternatives to conventional technologies.

In this regard, the question arises whether the preferences of the consumer will change over time and to what extend their attitudes towards different technologies are influenced by public opinion, political discussions and events. The unpopularity of biofuels in our data set, for instance, could be biased by the actual discussion about the rivalry between biofuel and food production. Therefore, an interesting experiment would be to repeat the survey and to compare the results.

It is also important to emphasize, that the estimations and results in our paper base upon our survey data. They are not representative for the German population even though we tried to choose the group of respondent as representative as possible. An extension of our analysis could be to weight the different consumer types in our survey with the corresponding raising factors to reproduce the composition of the German population in terms such as sex, age, income, family structure and ecological attitude.

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Figure 2: Relative WTP for an increase of network density (net monthly household income: more than €2 000).

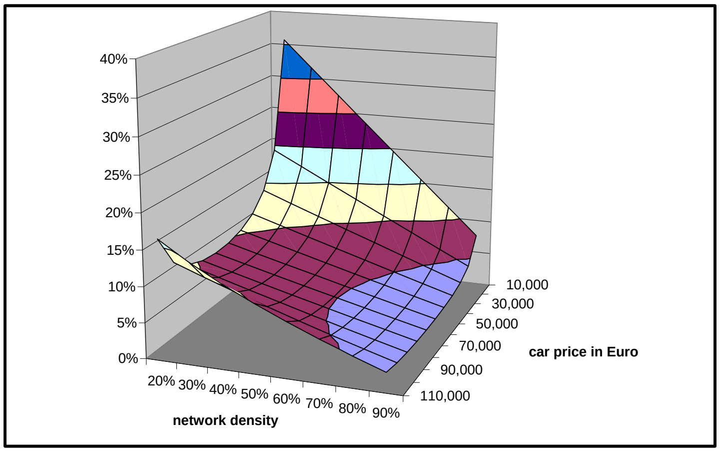

Figure 3: Relative WTP for an increase of network density (net monthly household income: less than €1 000).

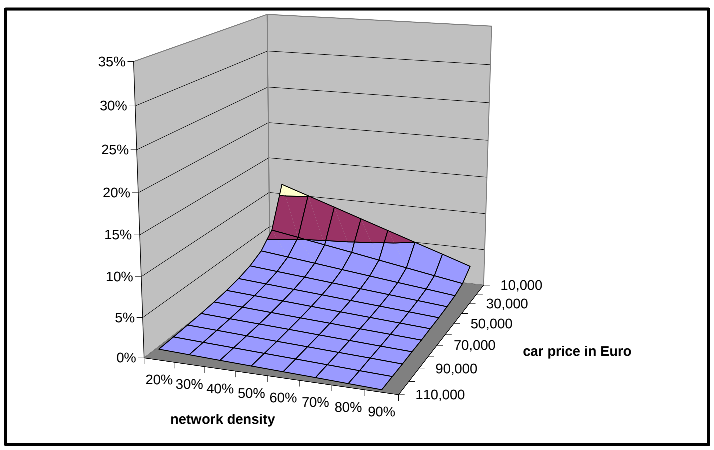

Table 1: Within the SP experiment used attribute levels (according to the fuel type).

Fuel Type	Diesel	Gasoline	LPG/CNG	Hybrid	Electric	Biofuel	Hydrogen
Purchase price	125	125	125	125	125	125	125
(% of given value)	100	100	100	100	100	100	100
	75	75	75	75	75	75	75
Variable costs	20	20	20	20	20	20	20
(€)	10	10	10	10	10	10	10
	5	5	5	5	5	5	5
Engine power	125	125	125	125	125	125	125
(% of given value)	100	100	100	100	100	100	100
	75	75	75	75	75	75	75
CO_2 emissions	-	-	-	-	no emissions	no emissions	no emissions
(gCO_2/km)	90	90	90	90	90	90	90
	170	170	170	170	170	170	170
	250	250	250	250	250	250	250
Service station network	100	100	100	100	100	100	100
(%)	60	60	60	60	60	60	60
	-	-	20	20	20	20	20

Table 2: Coefficients of the estimated nested logit model.

Explanatory Variable	Coefficient	StdErr	t-value
Gasoline	1.685591***	0.4256968	3.96
Hybrid	1.324387***	0.4635192	2.86
LPG/CNG	2.235748***	0.4592655	4.87
Biofuels	1.276084***	0.4584939	2.78
Hydrogen	1.441803***	0.439613	3.28
Electric	0.7485304	0.4742836	1.58
Purchase Price	−0.0000557***	7.94e − 6	−7.02
Purchase Price2	1.92e − 10***	7.18e − 11	2.67
PriceXIncomeBelow1000	−0.0001091*	0.0000555	−1.96
PriceXIncomeBetween1000and2000	0.0000219	0.0000142	1.54
Variable Costs	−0.0882831***	0.0200931	−4.39
Variable Costs2	0.000629	0.0007997	0.79
Engine Power	0.0079624***	0.0014932	5.33
Engine Power2	−5.44e − 6	3.50e − 6	−1.55
CO2 Emissions	−0.0032838***	0.0009438	−3.48
CO2 Emissions2	−6.85e − 6**	3.29e − 6	−2.08
CO2XNonEcologists	0.0020165***	0.0006079	3.32
Service Station Network	0.0233777***	0.0063087	3.71
Service Station Network2	−0.0001023***	0.0000347	−2.95
NetworkXRuralArea	0.0009867	0.0013007	0.76
NetworkXRange	−0.0009815	0.0013319	−0.74
NetworkXMileage	0.0003688	0.001328	0.28
GasolineXNetwork	0.0013404	0.003329	0.40
HybridXNetwork	0.0032981	0.0034072	0.97
LPG/CNGXNetwork	−0.0006386	0.0034033	−0.19
BiofuelXNetwork	0.0026075	0.0033839	0.77
HydrogenXNetwork	0.000948	0.0032649	0.29
ElectricXNetwork	0.0049467	0.003426	1.44
GasolineXNonEcologists	0.1029412	0.1168687	0.88
HybridXNonEcologists	−0.4444745***	0.1430908	−3.11
LPG/CNGXNonEcologists	−0.3563097**	0.1411524	−2.52
BiofuelXNonEcologists	−0.5178417***	0.1538032	−3.37
HydrogenXNonEcologists	−0.6262525***	0.1430078	−4.38
ElectricXNonEcologists	−0.4801181***	0.160911	−2.98
GasolineXRange	−0.0030094***	0.000429	−7.01
HybridXRange	−0.0019316***	0.0004425	−4.37
LPG/CNGXRange	−0.0027116***	0.0004447	−6.10
BiofuelXRange	−0.0022286***	0.0004435	−5.02
HydrogenXRange	−0.0011233***	0.0003971	−2.83
ElectricXRange	−0.0009531**	0.0004447	−2.14
GasolineXMileage	−0.0000221***	4.84e − 6	−4.57
HybridXMileage	−0.0000116**	4.85e − 6	−2.39
LPG/CNGXMileage	−0.00001**	4.85e − 6	−2.06
BiofuelXMileage	−3.44e − 6	4.34e − 6	−0.79
HydrogenXMileage	−6.54e − 6	4.06e − 6	−1.61
ElectricXMileage	−4.67e − 6	4.46e − 6	−1.05

(continued)

Explanatory Variable	Coefficient	StdErr	t-value
GasolineXAge	0.0109605***	0.0038356	2.86
HybridXAge	−0.0036411	0.0046592	−0.78
LPG/CNGXAge	−0.0089882*	0.0046419	−1.94
BiofuelXAge	−0.0064626	0.0047191	−1.37
HydrogenXAge	−0.0155903***	0.0043976	−3.55
ElectricXAge	−0.0209377***	0.0050959	−4.11
λ_{conv}	0.9181889***	0.0857245	10.71
λ_{hybrid}	1	.	.
$\lambda_{\text{lpg/cng}}$	1	.	.
λ_{future}	0.8461599***	0.0681653	12.41
Number of observations: 20251			
Log likelihood: −4734.79			
McFadden's R2: 0.1589			

Significance level: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Underlying network densities (%) of simulated scenarios.

Scenario	1	2	3	4	5	6
Gasoline	100	100	100	100	100	100
Diesel	100	100	100	100	100	100
Hybrid	100	100	100	100	100	100
LPG/CNG	30	50	70	90	100	100
Biofuels	13	30	50	70	90	100
Hydrogen	1	30	50	70	90	100
Electric	1	30	50	70	90	100

Table 4: Choice probabilities (%) in simulated scenarios (Standard Errors in parentheses).

Scenario	1	2	3	4	5	6
Gasoline	27.2 (0.19)	24.5 (0.17)	22.3 (0.17)	20.5 (0.16)	19.4 (0.15)	19.0 (0.15)
Diesel	27.1 (0.20)	24.2 (0.18)	22.0 (0.17)	20.2 (0.16)	19.0 (0.15)	18.7 (0.14)
Hybrid	23.7 (0.07)	21.2 (0.06)	19.1 (0.05)	17.5 (0.04)	16.5 (0.04)	16.1 (0.04)
LPG/CNG	10.7 (0.05)	12.7 (0.05)	14.2 (0.06)	14.9 (0.06)	14.5 (0.06)	14.2 (0.05)
Biofuels	4.3 (0.02)	5.4 (0.02)	7.0 (0.02)	8.5 (0.03)	9.7 (0.03)	10.1 (0.03)
Hydrogen	4.8 (0.03)	8.0 (0.04)	10.0 (0.05)	11.5 (0.06)	12.7 (0.06)	13.0 (0.06)
Electric	2.1 (0.01)	4.0 (0.03)	5.4 (0.03)	6.9 (0.04)	8.3 (0.05)	9.0 (0.05)

Table 5: Choice probabilities (%) depending on ecological attitude.

	Scenario 6b: negative ecological attitude of the standard individual	Scenario 6c: positive ecological attitude of the standard individual
Gasoline	23.2	15.8
Diesel	21.1	16.0
Hybrid	15.0	17.8
LPG/CNG	13.7	14.8
Biofuels	9.0	11.4
Hydrogen	10.3	14.8
Electric	7.7	9.4

Table 6: WTP (€) for an increase of network density by 10 percentage points (household income > 2 000€; Standard Errors in parentheses).

	Network density (%)							
Purchase price (€)	20	30	40	50	60	70	80	90
10,000	3566.78	3162.64	2759.74	2358.06	1957.59	1558.32	1160.23	763.33
	(1039.03)	(914.59)	(798.70)	(695.08)	(609.44)	(564.53)	(532.31)	(539.81)
20,000	3860.34	3422.04	2985.31	2550.14	2116.51	1684.40	1253.79	824.68
	(1107.54)	(974.12)	(850.25)	(740.04)	(649.69)	(587.60)	(580.78)	(585.64)
30,000	4207.55	3728.57	3251.63	2776.72	2303.80	1832.86	1363.87	896.80
	(1195.99)	(1050.85)	(916.50)	(797.46)	(700.50)	(634.69)	(609.06)	(640.25)
40,000	4624.97	4096.63	3571.03	3048.14	2527.91	2010.30	1495.28	982.80
	(1317.54)	(1156.13)	(1007.07)	(875.28)	(768.20)	(695.70)	(667.56)	(687.75)
50,000	5136.95	4547.34	3961.53	3379.45	2801.05	2226.24	1654.96	1087.15
	(1496.99)	(1311.26)	(1139.87)	(988.19)	(864.34)	(779.26)	(743.94)	(763.12)
60,000	5781.04	5113.03	4450.55	3793.46	3141.63	2494.93	1853.25	1216.48
	(1782.54)	(1557.28)	(1349.26)	(1164.16)	(1010.78)	(901.40)	(849.18)	(860.92)
70,000	6618.68	5846.23	5082.29	4326.58	3578.84	2838.83	2106.31	1381.04
	(2271.87)	(1976.50)	(1703.41)	(1458.27)	(1250.33)	(1093.42)	(1004.22)	(994.28)
80,000	7759.32	6839.27	5933.49	5041.35	4162.24	3295.62	2440.95	1597.77
	(3178.50)	(2745.47)	(2346.12)	(1985.16)	(1671.44)	(1419.94)	(1252.16)	(1188.84)
90,000	9423.56	8274.33	7152.57	6056.40	4984.14	3934.30	2905.53	1896.60
	(5045.97)	(4299.16)	(3621.21)	(3011.81)	(2475.94)	(2026.88)	(1689.97)	(1500.52)
100,000	12,161.16	10,586.58	9080.56	7634.84	6242.71	4898.62	3597.92	2336.66
	(9753.75)	(8044.75)	(6575.89)	(5308.22)	(4218.48)	(3299.91)	(2568.13)	(2070.03)
110,000	18,236.83	15,344.71	12,823.06	10,557.96	8484.11	6559.98	4757.13	3055.21
	(31,951.75)	(22,652)	(16,604.25)	(12,308.00)	(9092.10)	(6616.60)	(4711.92)	(3335.35)

Table 7: WTP (€) for an increase of network density by 10 percentage points (household income $< 1\,000$€; Standard Errors in parentheses).

	Network density (%)							
Purchase price (€)	20	30	40	50	60	70	80	90
10,000	1136.25	1008.88	881.55	754.25	627.00	499.78	372.60	245.46
	(486.34)	(430.53)	(376.44)	(324.89)	(277.28)	(235.96)	(204.75)	(188.67)
20,000	1164.08	1033.58	903.13	772.71	642.34	512.00	381.71	251.46
	(506.17)	(448.12)	(391.79)	(338.04)	(288.27)	(244.87)	(211.77)	(194.23)
30,000	1193.31	1059.53	925.79	792.09	658.44	524.84	391.28	257.76
	(527.72)	(467.23)	(408.48)	(352.33)	(300.20)	(254.53)	(219.34)	(200.17)
40,000	1224.05	1086.81	949.62	812.48	675.38	538.33	401.34	264.39
	(551.20)	(488.04)	(426.65)	(367.88)	(313.18)	(265.01)	(227.51)	(206.53)
50,000	1256.42	1115.54	974.71	833.94	693.21	552.54	411.93	271.36
	(576.81)	(510.75)	(446.48)	(384.85)	(327.33)	(276.42)	(236.38)	(213.34)
60,000	1290.55	1145.83	1001.17	856.56	712.01	567.52	423.09	278.71
	(604.83)	(535.60)	(468.17)	(403.41)	(342.79)	(288.86)	(246.00)	(220.67)
70,000	1326.59	1177.81	1029.10	880.45	731.86	583.34	434.87	286.47
	(635.56)	(562.83)	(491.94)	(423.75)	(359.72)	(302.47)	(256.49)	(228.58)
80,000	1364.70	1211.64	1058.64	905.71	752.85	600.06	447.34	294.68
	(669.33)	(592.78)	(518.08)	(446.09)	(378.32)	(317.40)	(267.94)	(237.13)
90,000	1405.07	1247.46	1089.93	932.47	775.08	617.77	460.53	303.37
	(706.54)	(625.77)	(546.87)	(470.71)	(398.80)	(333.81)	(280.48)	(246.40)
100,000	1447.91	1285.48	1123.13	960.86	798.67	636.56	474.53	312.58
	(747.65)	(662.22)	(578.67)	(497.89)	(421.40)	(351.90)	(294.26)	(256.49)
110,000	1493.45	1325.89	1158.42	991.03	823.74	656.53	489.41	322.38
	(793.20)	(702.59)	(613.90)	(528.00)	(446.42)	(371.90)	(309.45)	(267.51)

Table 8: WTP (€/100km) for an increase of network density (Standard Errors in parentheses).

Network density (%)							
20	30	40	50	60	70	80	90
2.07 (0.71)	1.84 (0.63)	1.61 (0.55)	1.37 (0.48)	1.14 (0.41)	0.91 (0.36)	0.68 (0.33)	0.45 (0.33)