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Economics Working Paper Series

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

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March 2010

Abstract

This paper empirically examines the determinants of the demand for alternative energy sources and propulsion technologies in vehicles. The data stem from a stated preference discrete choice experiment with 598 potential car buyers. In order to simulate a realistic automobile purchase situation, seven alternatives were incorporated in each of the six choice sets, i.e. hybrid, gas, biofuel, hydrogen, and electric as well as the common fuels gasoline and diesel. The vehicle types were additionally characterized by a set of attributes, such as purchase price or motor power. Besides these vehicle attributes, our study particularly considers a multitude of individual characteristics, such as socio-demographic and vehicle purchase variables. The econometric analysis with multinomial probit models identifies some population groups with a higher propensity for alternative energy sources or propulsion technologies in vehicles, which can be focused by policy and automobile firms. For example, younger people and people who usually purchase environment-friendly products have a higher stated preference to purchase biofuel, hydrogen, and electric automobiles than other population groups. Methodologically, our study highlights the importance of the inclusion of taste persistence across the choice sets. Furthermore, it suggests a high number of random draws in the Geweke-Hajivassiliou-Keane simulator, which is incorporated in the simulated maximum likelihood estimation and the simulated testing of statistical hypotheses.

JEL-Classification: R41, C25, C15, Q54, Q58

Keywords: Alternative energy sources and propulsion technologies in vehicles, stated preferences, discrete choice, multinomial probit models, unobserved heterogeneity, simulated maximum likelihood estimation

1. Introduction

Climate change is often considered one of the most important environmental and societal challenges due to its strong impacts on the natural environment and human lives (e.g. IPCC, 2007). In order to avoid further anthropogenic global warming, drastic reductions of greenhouse gases and particularly CO_2 emissions from energy conversion and use have been suggested. One important source for these emissions is transportation and particularly fuel consumption in road traffic, such as in the use of privately owned vehicles. In Europe, for example, the transport sector is responsible for more than one quarter of the CO_2 emissions and road transport alone accounts for more than four-fifth of the emissions attributable to transportation (e.g. European Commission, 2000, Commission of the European Communities, 2001). Furthermore, transportation is a major contributor of local air pollutants, such as nitrogen oxides (NO_x) or carbon monoxide (CO) (e.g. Potoglou and Kanaroglou, 2007). Against this background, national and international environmental and energy policy, such as in the European Union (EU), aims at a reduction of gasoline and diesel consumption in private road transport. The reduction can, as a side-effect, additionally lead to a higher independence from oil-exporting countries and from possible increases of the oil price.

This objective can, for example, be achieved by the decrease of vehicle miles traveled or the shifting of individual road traffic from automobiles to alternative means of transportation. Another direction for a reduction of gasoline and diesel consumption is an increasing use of alternative energy sources and propulsion technologies in vehicles, such as biofuel, electric, or hybrid. One advantage of an environmental and energy policy, which supports this direction, is that the individual driving behavior need not be influenced. However, it should also be mentioned that this policy approach is not without controversy: Biofuel, for example, is criticized due to the required agricultural areas for its cultivation. Concerning the use of electric automobiles, it is argued that they can currently be more polluting than specific gasoline vehicles when the electricity is mainly generated in coal-fired power plants. Indeed, this problem could be solved when the intended increase of the proportion of renewable energy sources in the generation of electricity is reached. In spite of these concerns, the support of alternative fuels has been formulated in several publications of the EU (e.g. Commission of the European Communities, 2006). In their white paper (Commission of the European Communities, 2001) the EU particularly suggests biofuel in the short and medium term, natural gas in the medium and long term and hydrogen in the very long term.

In order to develop effective and cost-efficient policy measures, an understanding of consumer preferences for energy sources and propulsion technologies in automobiles seems to be necessary. Against this background, several empirical studies have already examined the demand for different vehicle types. Since alternative energy sources and propulsion technologies in vehicles are still in limited supply or even do not exist in the current marketplace, most of these discrete choice analyses are based on data from stated preference (SP) experiments (e.g. Bunch et al., 1993, Ewing and Sarigöllü, 1998, Brownstone and Train, 1999, Dagsvik et al., 2002, Sándor and Train, 2004, Horne et al., 2005, Potoglou and Kanaroglou, 2007, Achtnicht et al., 2008, Ahn et al., 2008). Other studies (e.g. Brownstone et al., 2000, Axsen et al., 2009) combine SP and revealed preference (RP) data. Concerning the SP discrete choice experiments, the automobiles are characterized by different attributes, such as purchase price, fuel costs, and service station availability, besides the energy source or propulsion technology. The estimated parameters for these vehicle attributes can then be used for the simulation of possible policy measures, which are able to further alternative energy sources and propulsion technologies in automobiles, such as a carbon taxation, a taxation of the purchase price of conventional fuel (i.e. gasoline and diesel) vehicles, or a subsidization of the service station availability for alternative fuels. These policy simulations can be conducted by the additional use of energy-economy models (e.g. Horne et al., 2005, Axsen et al., 2009) or directly on the basis of the underlying discrete choice models (e.g. Dagsvik et al., 2002, Achtnicht et al., 2008).

We contribute to this strand of literature by focusing on the importance of individual characteristics for the preferences for alternative energy sources and propulsion technologies in automobiles. While few studies have examined some of these variables, they mostly refer to the interrelationship between selected individual characteristics and vehicle attributes. For example, it is analyzed whether price elasticities differ between several age and gender groups (e.g. Dagsvik et al., 2002). In contrast, a systematic and robust econometric analysis of the impact of, for example, socio-demographic and vehicle purchase variables on the choice between different automobile types, has surprisingly only been conducted rudimentary so far (e.g. Ewing and Sarigöllü, 1998, Potoglou and Kanaroglou, 2007). Our estimation results allow us to identify some population groups with a higher propensity to purchase alternative energy sources and propulsion technologies in vehicles. This information can be used by automobile firms for specific marketing and promotion strategies (e.g. Bunch et al., 1993) and particularly by environmental and energy policy for information campaigns, which are oriented towards these population groups. Such campaigns as a voluntary proactive approach can

be considered useful supplements to traditional mandatory command and control regulations, but also to economic incentives, since the efficient designing of taxes or subsidies is rather sophisticated and costly. Against this background, it is also argued that opposition from industry has often hindered the introduction of effective measures (e.g. Arimura et al., 2008).

In order to simulate a realistic future automobile purchase situation, we do not examine a rather restricted set of vehicle types in our SP experiment, but consider seven choice alternatives of different energy sources and propulsion technologies. The vehicle types in each of the six choice sets are additionally characterized by a set of common attributes. Due to the high number of choice alternatives and the inclusion of repeated choices for each interviewee, we methodologically apply multinomial probit models (e.g. Geweke et al., 1994) instead of restricted approaches, such as multinomial logit models (e.g. McFadden, 1973) or nested logit models (e.g. McFadden, 1978). These flexible discrete choice models are able to incorporate correlations between the choice alternatives as well as taste persistence and memory effects (e.g. Dagsvik et al., 2002) across the choice sets in order to circumvent possible biased parameter estimations. Due to the arising multiple integrals in the choice probabilities, we apply the simulated maximum likelihood method for the parameter estimation as well as the simulated counterpart of classical tests for the testing of statistical hypotheses. Against this background, this paper additionally analyzes the advantageousness of different specifications of multinomial probit models with a high number of choice alternatives as well as the relevance of the number of random draws in the used Geweke-Hajivassiliou-Keane (GHK) (Börsch-Supan and Hajivassiliou, 1993, Geweke et al., 1994, Keane, 1994) simulator, which is incorporated in the simulated maximum likelihood estimation and the simulated testing of statistical hypotheses.

The remainder of the paper is organized as follows: Section 2 explains the data from our SP discrete choice experiment as well as the variables used for our econometric analysis. Section 3 describes the specifications of our discrete choice models. Section 4 discusses the estimation results and section 5 concludes.

2. Data and variables

2.1 SP discrete choice experiment

For our empirical analysis we use data from Computer Assisted Personal Interviews (CAPI), which were conducted in selected car dealerships and technical inspection agencies (TÜV)

between August 2007 and March 2008 in 35 towns and municipalities across the German federal territory. The population of the survey refers to German residents with valid drivers' licenses who intend or at least could imagine purchasing an automobile in the near future. Overall, N = 598 potential car buyers participated in the survey. The survey comprised different parts: First, interviewees were asked for details (e.g. size, motor power) with respect to their currently used as well as to their future vehicle. Furthermore, the questionnaire comprised several socio-demographic variables, such as age, gender, or education. Indeed, the main part of the survey referred to a SP discrete choice experiment with respect to the hypothetical purchase of a vehicle.

This experiment was based on six choice sets, which comprised seven hypothetical vehicle types, respectively. While the presentation of the choice sets was designed as an unlabeled experiment, each of the respective seven vehicles refers to exactly one of the following energy sources and propulsion technologies:

- Gasoline
- Diesel
- Hybrid
- Gas (i.e. natural gas or liquid petroleum gas)
- Biofuel
- Hydrogen
- Electric

Therefore, the experiment can be considered quasi-labeled, i.e. the energy sources and propulsion technologies can be handled as a label for the vehicle types. As a consequence, the choice between these seven energy sources and propulsion technologies in automobiles can be incorporated as dependent variable in our multinomial probit models as discussed below.

The seven vehicle types were additionally characterized by the following five attributes:

- Purchase price (in Euro)
- Motor power (in horsepower)
- Fuel costs (in Euro per 100 kilometers)
- CO_2 emissions (in gram per kilometer)
- Service station availability (in % of stations with respective fuel)

In order to avoid unrealistic purchase situations for the interviewees, the attribute levels for the first two variables were customized as it is common in SP discrete choice experiments

(e.g. Bunch et al., 1993, Ewing and Sarigöllü, 1998, Horne et al., 2005, Potoglou and Kanaroglou, 2007, Axsen et al., 2009). For this reason, each potential car buyer was asked for the expected range of purchase prices and motor powers with respect to the new vehicle. On this basis, the possible values in the experiments were 75%, 100%, and 125% of the stated average of the respective individual minimums and maximums. Concerning the fuel costs, the random values varied between 5 Euro, 10 Euro, and 20 Euro across the seven automobile types. While the considered values for the purchase price, motor power, and fuel costs can be combined with each energy source or propulsion technology in vehicles, this scenario would not be realistic for CO_2 emissions and service station availability. Therefore, the CO_2 emission levels in the experiments were strictly positive for gasoline, diesel, hybrid, and gas automobiles with values between 90, 170, and 250 gram. For the (at least potentially non-fossil) energy sources biofuel, hydrogen, and electric, we included the option "no emissions". Since the interviewees, in line with the current situation, had to assume that the use of biofuel, hydrogen, and electric vehicles, can lead to positive CO_2 emissions in the future, the aforementioned values (90, 170, 250 gram) were considered besides this option. Finally, possible values for the service station availability were 20%, 60%, and 100% for hybrid, gas, biofuel, hydrogen, and electric vehicles. Since 20% service stations for gasoline and diesel are unrealistic, the values only varied between 60% and 100% for these two fuels. It should be noted that the interviewees were instructed to assume that all non-listed properties (e.g. safety, reliability) beyond these attributes are identical for all automobile types in the choice sets.

Table 1 reports the absolute and relative frequencies for the stated preferences to purchase the different energy sources and propulsion technologies in vehicles across all 3588 observations, i.e. for all 598 potential car buyers across the six choice sets. According to this, gasoline and diesel automobiles are most popular with relative frequencies of about 20%, while the frequencies for the stated choice for some alternative energy sources and propulsion technologies in vehicles are relatively high as well. For example, about 15% of all observations state a choice for hydrogen vehicles. In this respect, hypothetical biases are possible, i.e. the stated preferences for socially desirable or politically correct public good attributes could be unrealistically high in such experiments, although in reality potential car buyers would not purchase possibly more expensive alternative vehicle types (e.g. Brownstone et al., 2000, Horne et al., 2005, Axsen et al., 2009). This argumentation also applies to the estimated effect of CO_2 emissions on the stated choice for a vehicle type, so that the corresponding parameter estimations should be interpreted with caution (e.g. Bunch et al., 1993). Concerning the stated pref-

erences for different energy sources and propulsion technologies in vehicles, however, it should be noted that the respective frequencies are not of high relevance since our econometric analysis focuses on the determinants of the choice between the different automobile types.

2.2 Variables in the econometric analysis

As aforementioned, the dependent variable in the multinomial probit models refers to the choice between the seven energy sources and propulsion technologies in vehicles, i.e. gasoline, diesel, hybrid, gas, biofuel, hydrogen, and electric. The explanatory variables can be divided into two main groups, namely vehicle attributes and individual characteristics. Concerning the first group, "purchase price", "motor power", "fuel costs", "CO_2 emissions", and "service station availability" as discussed above are included. These variables vary across the potential car buyers and the choice sets in the SP experiment. Since the incorporation of heterogeneous values of different explanatory variables is problematic for the stability of parameter estimations in flexible multinomial probit models, these automobile attributes are scaled. While motor power (in horsepower) and CO_2 emissions (in gram per kilometer) are divided by 1000, fuel costs (in Euro per 100 kilometers) and service station availability (in % of stations with respective fuel) are divided by 100. The purchase price (in Euro) is divided by ten and additionally logarithmized in order to analyze non-linear effects. In line with the estimation results in former studies as discussed above, we expect positive effects of motor power and service station availability as well as negative effects of purchase price, fuel costs, and CO_2 emissions on the stated choice between the different vehicle types.

However, the main focus of this paper refers to the second main group of explanatory variables, namely individual characteristics. While most former discrete choice analyses of the demand for alternative energy sources and propulsion technologies in vehicles do not examine this type of explanatory variables at all, Potoglou and Kanaroglou (2007), as one of the few exceptions, also consider several individual characteristics in their nested multinomial logit analysis of gasoline, hybrid (electric), and alternative fuel vehicles. However, apart from some exceptions as discussed below, their study mainly examines interaction terms between these individual characteristics (also including household and dwelling location variables) and vehicle attributes. Our econometric analysis is somewhat more in line with Ewing and Sarigöllü (1998), who indeed consider several individual characteristics, even when they do not focus on this group of explanatory variables and furthermore only consider a limited set of three automobile types ("vehicle like present one", "more fuel-efficient gasoline or alterna-

tive-fuel vehicle", "electric vehicle") in their restricted multinomial logit analysis. Similar to their study, we distinguish between socio-demographic factors, a variable for environmental concern, a commuting variable, and a series of vehicle ownership and purchase variables for the potential car buyers.

Concerning the common first group of individual characteristics, we consider "age" and the dummy variable "male". As an indicator for environmental concern or environmental orientation, we examine the dummy variable "environment-friendly purchases", which takes the value one if the potential car buyer usually purchases environment-friendly products. It should be mentioned that, unfortunately, we cannot include (household) income as a possibly relevant socio-economic factor in our discrete choice analysis since the number of missing values for this explanatory variable would be too high for reliable estimation results. While our commuting factor refers to the dummy variable "driving of vehicle for journey to work", we consider the dummy variable "more than one vehicle in household" as a vehicle ownership factor. Finally, we analyze six additional vehicle purchase variables. Besides the three dummy variables "new vehicle is small" (that takes the value one if the intended purchase refers to a small or lower middle-sized class automobile), "new vehicle is company car", and "new vehicle is first-hand", our discrete choice analysis considers "horsepower of new vehicle", "range of new vehicle", and "mileage of new vehicle".

Table 2 reports some descriptive statistics for these individual characteristics. Besides the discussed eleven variables, this table comprises five further individual characteristics. First, it consists of three additional socio-demographic factors, namely "number of children in household" as well as the dummy variables "higher education" (that takes the value one if the highest educational achievement is at least "Fachhochschule", i.e. university of applied sciences) and "full-time employment". Moreover, the table comprises a dwelling location factor, namely the dummy variable "habitation in a rural area", which is in line with the study of Potoglou and Kanaroglou (2007), and "price of new vehicle" as a further vehicle purchase variable. While these variables have also been examined in our econometric analysis, none of them have a robust effect on any energy source or propulsion technology in vehicles. As a consequence, the estimation results in the multinomial probit models that comprise these additional individual characteristics are not reported for brevity, but are available upon request. With respect to the education variable, this estimation result is in contrast to Potoglou and Kanaroglou (2007), who report a significantly positive effect of higher education on the choice for hybrid automobiles and some significant impacts of their dwelling location factors.

It should be mentioned that some of the individual characteristics are also scaled in the econometric analysis, namely "age" (that is measured in years divided by 100), "horsepower of new vehicle" (that is divided by 1000), "range of new vehicle" (that is measured in kilometers per tank capacity divided by 1000), and "mileage of new vehicle" (that is measured by the logarithm of kilometers divided by ten). Furthermore, it should be noted that the multinomial probit models as discussed below comprise, for each individual characteristic, parameters for all vehicle types considering one energy source (namely gasoline) as omitted choice alternative. On this basis, the impact of an individual characteristic (e.g. age) on the choice for one specific energy source or propulsion technology in vehicles can be analyzed. In contrast, the multinomial probit models comprise one parameter for each vehicle attribute, so that the general effect of an attribute (e.g. fuel costs) on the stated choice between the different automobile types can be examined in this case.

3. Discrete choice models

The basis for our discrete choice analysis is that a potential car buyer chooses in each choice set among the seven mutually exclusive vehicle types as discussed above. The hypothetical utility of the potential car buyer i ($i = 1,...,N = 598$) for energy source or propulsion technology in vehicle j ($j = 1,...,J = 7$) in choice set k ($k = 1,...,K = 6$) is:

$$U_{ijk} = \beta'x_{ijk} + \gamma_j'z_i + \varepsilon_{ijk}$$

The latent variables U_{ijk} depend on the vectors $x_{ijk} = (x_{ijk1},...,x_{ijk5})'$ of five vehicle attributes as well as on the vectors $z_i = (z_{i1},...,z_{i,12})'$ of eleven individual characteristics and one alternative-specific constant. The unknown parameter vectors are $\beta = (\beta_1,...,\beta_5)'$ and $\gamma_j = (\gamma_{j1},...,\gamma_{j,12})'$. The values of the latent variables cannot be observed and depend on the stochastic components ε_{ijk}, which summarize all unobserved factors that influence the choice between the different energy sources and propulsion technologies in vehicles.

This approach is flexible enough to comprise a multitude of discrete choice models. For example, if we assume that the ε_{ijk} are independently and identically distributed with type I extreme value density functions, we obtain the popular multinomial logit model (e.g. McFadden, 1973). However, the common multinomial logit model has very limitative properties, such as the independence of irrelevant alternatives (IIA). Therefore, the reliability of the parameter estimations in this discrete choice model, but also in extensions, such as the nested logit

model (e.g. McFadden, 1978), is restricted. As a consequence, we consider a more flexible approach, namely the multinomial probit model. This discrete choice model is based on the assumption that the ε_{ijk} are jointly normally distributed:

$$\varepsilon_i = (\varepsilon_{i11},...,\varepsilon_{i71},......,\varepsilon_{i16},...,\varepsilon_{i76}) \sim N_{42}(0; \Sigma)$$

It is assumed that the random vectors ε_i are independent of each other and independent of all explanatory variables. Different versions of multinomial probit models result from different restrictions in the variance covariance matrix Σ. If Σ is the identity matrix, one obtains the independent multinomial probit model, which has similar properties as the restrictive multinomial logit model. However, the attractiveness of multinomial probit models is that they allow a flexible stochastic structure and thus are able to incorporate, for example, correlations between the choice alternatives (i.e. the energy sources and propulsion technologies in vehicles) or taste persistence and memory effects across the choice sets. Against this background, the stochastic components can be formulated as follows (e.g. Ziegler, 2007):

$$\varepsilon_{ijk} = \alpha_{ij} + \nu_{ijk}$$

with

$$\nu_{ijk} = \rho_j \nu_{i,j,k-1} + \sqrt{1-\rho_j^2}\ \eta_{ijk}$$

The normally distributed components η_{ijk} (which are uncorrelated across all choice sets) comprise possible correlations between the choice alternatives, while the ρ_j (with $|\rho_j| < 1$) denote the autocorrelation coefficients for the different vehicle types. The latter coefficients refer to possible memory effects (e.g. Dagsvik et al., 2002) since perception capacities can vary across the choice sets. In other words, the choices in the last and current choice sets could be stronger correlated than choices that are more remote. The normally distributed components α_{ij} (which are uncorrelated with ν_{ijk}) represent stochastic effects that are invariant across the choice sets and thus refer to taste persistence. With respect to formal model identification (e.g. Dansie, 1985, Bunch, 1991), 32 variance covariance parameters (i.e. 20 variance covariance parameters for the correlations between the choice alternatives, six variance parameters for the invariant stochastic effects, and six autocorrelation coefficients) can be determined in the most flexible multinomial probit model. All free parameters, i.e. the utility function coefficients and the unrestricted variance covariance parameters, are summarized in the vector $\theta = (\theta_1, \theta_2 ,...)$ in the following.

According to the stochastic utility maximization hypothesis, the potential car buyers choose in each of the six choice sets the vehicle type that offers the highest utility among all seven energy sources and propulsion technologies. Therefore, they choose between $7^6=117649$ possible alternative sequences across the six choice sets. The resulting probability P_{is} that a potential car buyer i chooses a certain alternative sequence s particularly depends on the unknown parameters in θ and is characterized by a 36-dimensional integral in the most flexible multinomial probit models. The computation of these multiple integrals is not feasible with deterministic numerical integration methods. But the choice probabilities can be quickly and accurately approximated with (unbiased) stochastic simulation methods, i.e. with R repeatedly transformed draws of pseudo-random numbers (e.g. Hajivassiliou et al., 1996, Vijverberg, 1997). By incorporating such a simulator, one obtains the simulated counterpart $sim(P_{is})$ of P_{is}. In comparative Monte Carlo experiments, it has been shown that the so-called GHK simulator (Börsch-Supan and Hajivassiliou, 1993, Geweke et al., 1994, Keane, 1994) outperforms other simulation methods with respect to the approximation of the true probability (e.g. Mühleisen, 1994). For this reason the GHK simulator is considered in this paper.

If any (unbiased) simulator and the maximum likelihood method are combined, one obtains the simulated maximum likelihood method. The 117649-dimensional vector $Y_i = (Y_{i1}, Y_{i2},...)$ comprises the observable dependent variables:

$$Y_{is} = \begin{cases} 1 & \text{if i chooses s} \\ 0 & \text{else} \end{cases}$$

By incorporating the simulated choice probabilities $sim(P_{is})$ into the maximum likelihood approach and by examining the N = 598 independent potential car buyers, one obtains the following simulated maximum likelihood estimator:

$$\hat{\theta} = (\hat{\theta}_1, \hat{\theta}_2,...) = \text{argmax} \left[\sum_{i=1}^{598} \sum_{s} Y_{is} \ln sim(P_{is}) \right]$$

It can be shown (e.g. Hajivassiliou and Ruud, 1994) that the simulated maximum likelihood estimator is consistent if

$$R, N \rightarrow \infty$$

and asymptotically efficient if

$$\lim_{N \rightarrow \infty} \frac{\sqrt{N}}{R} = 0$$

The small sample properties of the simulated maximum likelihood estimation, incorporating the GHK simulator, of multinomial probit models have already been investigated in the past (e.g. Geweke et al., 1994, 1997). However the necessary number R of random draws in the GHK simulator for reliable parameter estimations is not completely unambiguous. Therefore, we additionally consider the effect of an increasing R in our specific multinomial probit models with a quite high number of choice alternatives across a series of choice sets. This additionally allows the analysis of the effect of R on the simulated classical testing of statistical hypotheses (e.g. Lee, 1999, Ziegler, 2007), which includes the GHK simulator in classical tests, such as the z-test or the likelihood ratio test. The simulated z-test as specific case of the simulated Wald test is applied for the testing whether a parameter is equal to zero. In this respect, we consider a robust version that is derived from quasi-maximum likelihood theory according to White (1982) and thus comprises both the gradient and the Hessian matrix of the simulated loglikelihood function. The simulated likelihood ratio test is particularly considered for the testing of different multinomial probit models, such as the simple independent multinomial probit model or the multinomial probit model that includes invariant stochastic effects.

In this respect, it should be noted that the autoregressive processes as well as the invariant stochastic effects across the choice sets can be considered two related types of unobserved heterogeneity. Furthermore, it should be mentioned that the memory effects with respect to the autocorrelation processes seem to be more appropriate for the application of panel data over time instead of our cross-sectional analysis of several choice sets. Although some investigations have shown that the autocorrelation coefficients are often significantly different from zero when they are included as the only indicator for unobserved heterogeneity, it has also been shown that the effects of the invariant stochastic effects across the choice sets are stronger and indeed overlay the autoregressive processes. As a consequence, the estimation results in the multinomial probit models that comprise these autocorrelation coefficients are not reported for brevity, but are available upon request.

4. Estimation results

4.1 Vehicle attributes and alternative-specific constants

In spite of the focus on the effects of individual characteristics, we first analyze different multinomial probit models that, in line with former studies as discussed above, only include the five vehicle attributes as well as alternative-specific constants. Table 3a and Table 3b report

the corresponding simulated maximum likelihood estimation results. Table 3a refers to the independent multinomial probit model and to the multinomial probit model that exclusively includes correlations between the choice alternatives. In contrast, Table 3b refers to the multinomial probit model that exclusively includes invariant stochastic effects across the choice sets and to the flexible multinomial probit model, which includes both correlations between the choice alternatives and taste persistence. The three columns for each multinomial probit model differ with respect to the number R of random draws in the GHK simulator in both the simulated maximum likelihood estimations and the simulated classical testing. In this respect, we compare R = 10, R = 100, and R = 1000.

The main estimation results in both tables refer to the strong impacts of all vehicle attributes in a direction, which is in line with the findings in former studies as discussed above. In other words, motor power and service station availability have a positive effect, whereas purchase price, fuel costs, and CO_2 emissions have a negative effect. These impacts are statistically extremely robust with mostly very high absolute simulated z-test statistics, which indicate that the underlying null hypotheses that the appropriate parameters are zero can be rejected at all common significance levels. The only exceptions in this respect are the estimation results in the multinomial probit model that exclusively includes correlations between the choice alternatives on the basis of R = 10 random draws in the GHK simulator. In this case, not a single parameter (including the alternative-specific constants) is significantly different from zero. However, it should be noted that the very high underlying estimated standard deviations of the simulated parameter estimates only refer to the small number of R = 10. In contrast, the vehicle attributes have significant impacts if R = 100 or R = 1000, which is in line with the estimation results in the three other multinomial probit models. It should also be mentioned that further investigations have shown that the application of an alternative simulated z-test statistic that includes only the gradient of the simulated loglikelihood function (e.g. Lee, 1999, Ziegler, 2007) leads to more reliable test results, so that the null hypotheses that the appropriate parameters are zero can be rejected at all common significance levels as well in this case.

This finding suggests that the use of robust simulated z-test statistics that comprise both the gradient and the Hessian matrix of the simulated loglikelihood function according to White (1982) is obviously not generally superior. However, the instable estimation results in the multinomial probit model that exclusively includes correlations between the choice alternatives with R = 10 random draws in the GHK simulator particularly points to two further conclusions: First, the simulated maximum likelihood estimation in our multinomial probit mod-

els with a quite high number of choice alternatives across a series of choice sets obviously requires a high number R of random draws in the GHK simulator. Table 3a and Table 3b show that the maximal simulated loglikelihood values strongly increase in each multinomial probit model when R rises, particularly when the numbers increase from R = 10 to R = 100. Second, the estimation results suggest that the inclusion of correlations between the choice alternatives is less substantial than the inclusion of taste persistence across the choice sets. The simulated likelihood ratio test statistics reveal that the independent multinomial probit model can be rejected in favor of the multinomial probit model with invariant stochastic effects and that the multinomial probit model with correlations between the choice alternatives can be rejected in favor of the flexible multinomial probit model at all common significance levels, respectively. In contrast, the increase of the maximal simulated loglikelihood values is quite moderate when (on the basis of the same R) the multinomial probit model with correlations between the choice alternatives is compared with the independent multinomial probit model and when the flexible multinomial probit model is compared with the multinomial probit model with taste persistence.

4.2 Additional inclusion of individual characteristics

With respect to the inclusion of individual characteristics as explanatory variables, it should again be mentioned that in a first step 16 additional variables have been analyzed. However, none of the aforementioned five individual characteristics have a robust effect on any energy source or propulsion technology in vehicles, as discussed above. As a consequence, Table 4 only reports the simulated maximum likelihood estimation results for multinomial probit models that include five vehicle attributes, eleven individual characteristics, and the alternative-specific constants. The two columns for each of the four multinomial probit models differ with respect to the number R of random draws in the GHK simulator. On the basis of the previous analysis of only vehicle attributes and alternative-specific constants, which highlights the importance of a high R, we now particularly consider R = 100 and R = 1000. Therefore, the estimation results with R = 10 are not reported, but are available on request. In this respect, it should be mentioned that the calculation times are extremely high due to the high numbers of parameters that are estimated in multinomial probit models with many individual characteristics. For example, the simulated maximum likelihood estimation of the flexible multinomial probit model with R = 1000 required (on the basis of a self-developed GAUSS program) more than two weeks on a quite powerful computer, namely an Intel® Xeon® Proc-

essor E5405 (2 GHz, 8 GB of RAM). These calculation times make a more systematic analysis of an even higher number R of random draws in the GHK simulator for this multinomial probit model specification computationally infeasible.

According to Table 4 (as well as the unreported estimation results with R = 10), the main findings of the previous section hold true. First of all, the strong positive impact of motor power and service station availability as well as the strong negative effect of purchase price, fuel costs, and CO_2 emissions are confirmed. In addition, the maximal simulated loglikelihood values again increase in each multinomial probit model when R rises. Furthermore, the simulated likelihood ratio test statistics again reveal that the independent multinomial probit model can be rejected in favor of the multinomial probit model with taste persistence and that the multinomial probit model with correlations between the choice alternatives can be rejected in favor of the flexible multinomial probit model at all common significance levels, respectively, whereas the increase of the maximal simulated loglikelihood values is quite moderate when only correlations between the choice alternatives are added. Therefore, in line with the estimation results in Table 3a and Table 3b, the estimation results in Table 4 again emphasize the importance of the inclusion of invariant stochastic effects across the choice sets. Finally, further investigations have again shown that the null hypothesis that the appropriate parameter is zero is rejected at a lower significance level when the alternative simulated z-test statistic that exclusively includes the gradient of the simulated loglikelihood function is applied.

In spite of the obvious importance of the inclusion of invariant stochastic effects and a high number R of random draws in the GHK simulator, it should be mentioned that the application of the corresponding multinomial probit model that does not include correlations between the choice alternatives reveals on the basis of R = 1000 in some cases ambiguous estimation results. According to the antepenultimate column, the simulated maximum likelihood estimates and the respective simulated z-test statistics for some parameters significantly differ from the corresponding values on the basis of R = 100 (and also R = 10) as well as from the values in the last two columns. For example, while the (more stable) estimation results in the flexible multinomial probit models with R = 100 or R = 1000 suggest no significant effect of age on the stated choice for the energy source diesel and a significantly positive impact of the variable "new vehicle is small" on the stated preference to purchase hydrogen automobiles, the corresponding age parameter is significantly different from zero and the vehicle purchase parameter is not significantly different from zero in the multinomial probit model with only invariant stochastic effects on the basis of R = 1000. In particular, the corresponding parameters

for the variables "horsepower of new vehicle" and "mileage of new vehicle" as well as the alternative-specific constants differ in this respect.

These results imply that a high number R of random draws in the GHK simulator is not at all times sufficient to receive stable simulated maximum likelihood estimations, at least in our multinomial probit models with a quite high number of choice alternatives across a series of choice sets and a fairly high number of included parameters, particularly on the basis of many individual characteristics. The estimation results rather suggest that the stable estimation of such complex models requires an even higher number of observations compared with the already quite high number of 3588 observations in our study (e.g. Geweke at al., 2004). However, it should also be noted that this conclusion only refers to multinomial probit models that include a complex variance covariance structure since the estimation results in the simple (and thus unreliable) independent multinomial probit model are almost identical with $R = 100$ or $R = 1000$ (as well as already with $R = 10$). The stability of these estimation results is confirmed by the same number of 49 iterations until convergence in the iterative maximization process of the simulated loglikelihood function. In contrast, these numbers strongly vary between 61 (on the basis of $R = 1000$) and 84 (on the basis of $R = 100$) in the multinomial probit model that exclusively includes invariant stochastic effects across the choice sets.

In the following, we summarize the most robust estimation results for the individual characteristics that are reported in the last four columns in Table 4, i.e. on the basis of both multinomial probit models that include taste persistence: The age of the potential car buyers has a significantly negative impact on the choice for gas, biofuel, hydrogen, and particularly electric vehicles. This estimation result is in line with the study of Potoglou and Kanaroglou (2007), who report a significantly negative effect of age on the stated choice for alternative fuel vehicles, as well as the study of Ewing and Sarigöllü (1998), who report a significantly negative impact of age on the choice for fuel-efficient and electric vehicles. Furthermore, males have a significantly higher stated preference for hydrogen and (somewhat less robust) gas automobiles. The finding for hydrogen could be considered surprising since empirical environmental consciousness studies mostly find that women have a stronger preference towards the environment and a stronger willingness to contribute (e.g. Torgler et al., 2008). According to this literature, the higher concern of women for the maintenance of environment is due to their traditional socialisation towards caregivers and encouragements to be cooperative and feel compassion (e.g. Torgler and García-Valiñas, 2007). However, it should be noted that our estimation results need not contradict these findings when we bear in mind that the environ-

mental friendliness of alternative fuel vehicles including hydrogen vehicles is currently controversial, as discussed above. In spite of this controversy, our environmental concern indicator "environment-friendly purchases" indeed has no robust significant effect on the choice for hybrid and gas vehicles, but a significantly positive impact on the stated preference to purchase biofuel, hydrogen, and electric automobiles. This finding is in line with the study of Ewing and Sarigöllü (1998), who report a significantly positive effect of environmental concern on the choice for fuel-efficient and electric vehicles.

Our commuting variable, which refers to the use of a vehicle for the journey to work, has a significantly negative effect on the stated preference to purchase diesel vehicles and a significantly positive effect on the choice for gas vehicles. Moreover, our vehicle ownership variable, i.e. the existence of more than one vehicle in the household, has a significantly positive impact on the choice for biofuel automobiles. This is not completely in line with the results in Ewing and Sarigöllü (1998), who report a corresponding significantly negative effect. However, their finding refers to the stated choice for fuel-efficient vehicles, while not specifically analyzing the energy source biofuel, so that these estimation results cannot directly be compared. Concerning the vehicle purchase variables, the dummy variable "new vehicle is company car" also has a significantly positive effect on the stated choice for biofuel vehicles. Furthermore, the dummy variable "new vehicle is first-hand" has a strong significantly positive impact on the preference for the omitted choice alternative, namely the energy source gasoline, and particularly a significantly negative impact on the choice for diesel, hybrid, and biofuel vehicles. Finally, the range of the new vehicle has indeed a significantly positive effect on the choice for the energy source diesel, but an additional significantly positive impact on the stated preferences for electric vehicles and (less robust) hydrogen vehicles. These latter estimation results seem to be surprising since hydrogen and electric automobiles are currently not characterized by a high range due to technical constraints. However, we argue that this finding rather strengthens the reliability of our SP discrete choice experiment since the interviewees were instructed to consider hypothetical vehicle types and thus to assume that all non-listed attributes beyond purchase price, motor power, fuel costs, CO_2 emissions, and service station availability are identical for all vehicle types in the choice sets. In other words, they had to compare hypothetical automobiles with different energy sources and propulsion technologies, which are indeed identical in their range. Against this background, such estimation results are definitely possible.

4. Conclusions

Based on data from a SP discrete choice experiment with 598 potential car buyers in Germany, this paper analyzes the impact of individual characteristics on the preferences for different vehicles types. Our estimation results allow the identification of the following population groups with a higher propensity to purchase an alternative energy source or propulsion technology in automobiles:

- Younger male potential car buyers, who use their vehicle for the journey to work, have a higher preference for gas vehicles (compared with gasoline automobiles).

- Younger potential car buyers, who usually purchase environment-friendly products, who have more than one vehicle in the household, and who state that the new vehicle is a company car and not first-hand, have a higher preference for biofuel vehicles (compared with gasoline automobiles).

- Younger male potential car buyers, who usually purchase environment-friendly products and who state that the new vehicle has a high range, have a higher preference for hydrogen vehicles (compared with gasoline automobiles).

- Younger potential car buyers, who usually purchase environment-friendly products and who state that the new vehicle has a high range, have a higher preference for electric vehicles (compared with gasoline automobiles).

This information can be used by automobile firms, for example, for specific marketing strategies. In addition, it can particularly be used by environmental and energy policy for corresponding information campaigns. For example, campaigns to increase the demand for gas vehicles can specifically be oriented towards younger males who use their vehicle for the journey to work. Such specific public advertising efforts could supplement common policy approaches, such as carbon taxation, taxation of the purchase price of gasoline and diesel vehicles, or a subsidization of the service station availability for alternative fuels when alternative energy sources and propulsion technologies are to be supported as stated by the EU (Commission of the European Communities, 2001, 2006).

Due to the high number of choice alternatives and the inclusion of repeated choices for each interviewee, our econometric analysis applies multinomial probit models instead of restricted approaches, such as multinomial logit models or nested logit models. Our estimation results highlight the relevance of the use of such less restrictive discrete choice models since the sim-

ple independent multinomial probit model, which has similar limiting properties as the common multinomial logit models, is rejected in favor of more flexible multinomial probit models. In this respect, our econometric analysis suggests that the inclusion of invariant stochastic effects across the choice sets is even more important than the inclusion of only correlations between the choice alternatives. Besides the relevance of the inclusion of taste persistence across the choice sets, the estimation results in our fairly complex multinomial probit models also suggest the use of a quite high number R of random draws in the GHK simulator, which is incorporated in the simulated maximum likelihood estimation and the simulated testing of statistical hypotheses.

Indeed, our study also points to strong instabilities in the simulated maximum likelihood process of less restrictive multinomial probit models, even when R is very high. These instable simulated maximum likelihood estimates and simulated z-test statistics are obviously a result of the complexity in these approaches. This discussion so far refers to the estimation results for the utility function coefficients, i.e. the parameters for the vehicle attributes and particularly for the individual characteristics, which are focused in this paper. However, it should additionally be noted that the estimation of the variance covariance parameters in Σ, i.e. the parameters for the correlations between the choice alternatives and the invariant stochastic effects, is even more ambiguous (these estimation results are not reported for brevity, but are available upon request). These instabilities are in line with the estimation results of Geweke at al. (2004), who examine up to 5000 observations in their Monte Carlo experiments of flexible cross-sectional multinomial probit models, which also comprise seven choice alternatives and correlations between these alternatives, but only include a small number of explanatory variables. Against this background, we conclude that more reliable estimation results for both the utility function and variance covariance parameters in our flexible multinomial probit models, which additionally include taste persistence and a high number of individual characteristics as explanatory variables, require a distinctly higher number of observations than the 3588 observations in our econometric analysis.

However, an unlimited increase of the number of people (and also choice sets) in SP discrete choice experiments or other empirical analyses is not feasible. Therefore, the overall reliability of the estimation results on the basis of typical numbers of observations as in our study is ambiguous. As a consequence, a direction for further research are additional comparative analyses of small sample properties of simulated maximum likelihood estimates as well as simulated test statistics in flexible multinomial probit models. In contrast to former Monte

Carlo experiments, such new studies should not be based on simulated data (e.g. Geweke et al., 1997), but on real survey data. Furthermore, the experiments should be based on data from SP discrete choice experiments, which are common in empirical transportation research. Besides the comparison between different multinomial probit models (including different types of unobserved heterogeneity) and the relevance of the number R of random draws in the GHK simulator, these experiments could additionally examine the application of alternative simulated z-test statistics. This suggestion is based on our finding in further investigations that different versions of simulated z-tests (e.g. Lee, 1999, Ziegler, 2007) can lead to different test results. Finally, the analysis of alternative flexible discrete choice models besides multinomial probit models, such as the popular mixed logit models (e.g. Brownstone and Train, 1999, McFadden and Train, 2000, Brownstone et al., 2000, Bhat, 2001, Sándor and Train, 2004), would also be valuable in the future.

Acknowledgements

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Appendix: Tables

Table 1: Frequencies for the stated preferences to purchase an alternative energy source or propulsion technology in vehicles, N = 598, six choice sets, 3588 observations

Energy sources and propulsion technologies in vehicles	Absolute frequencies (relative frequencies)
Gasoline	700 (19.51%)
Diesel	749 (20.88%)
Hybrid	456 (12.71%)
Gas	438 (12.21%)
Biofuel	393 (10.95%)
Hydrogen	541 (15.08%)
Electric	311 (8.67%)

Table 2: Descriptive statistics for individual characteristics, N = 598, six choice sets, 3588 observations

	Mean	Standard deviation	Minimum	Maximum
Age (in years)	44.71	15.47	18	83
Male	0.75	0.44	0	1
Number of children in household	0.42	0.77	0	5
Higher education	0.52	0.50	0	1
Full-time employment	0.64	0.48	0	1
Habitation in rural area	0.41	0.49	0	1
Environment-friendly purchases	0.31	0.46	0	1
Driving of vehicle for journey to work	0.70	0.46	0	1
More than one vehicle in household	0.62	0.49	0	1
New vehicle is small	0.43	0.40	0	1
New vehicle is company car	0.14	0.35	0	1
New vehicle is first-hand	0.33	0.47	0	1
Horsepower of new vehicle	127.13	55.58	37.5	500
Range of new vehicle (in km per tank capacity)	632.70	170.22	100	1100
Mileage of new vehicle (in km per year)	19519.9	15037.87	2000	170000
Price of new vehicle (in Euro)	20725.12	15131.16	525	125000

Table 3a: Simulated maximum likelihood estimates (simulated z-test statistics) in multinomial probit models (independent multinomial probit model, correlations between choice alternatives), different numbers R of random draws in the GHK simulator, choice between seven alternative energy sources and propulsion technologies in vehicles, explanatory variables: vehicle attributes, alternative-specific constants, N = 598, six choice sets, 3588 observations

Explanatory variables	Independent multinomial probit model			Correlations between choice alternatives		
	R=10	R=100	R=1000	R=10	R=100	R=1000
Purchase price	-5.42*** (-8.57)	-5.50*** (-8.57)	-5.56*** (-8.65)	-4.47 (-0.11)	-4.77*** (-5.45)	-4.71*** (-6.39)
Motor power	3.63*** (7.04)	3.67*** (7.04)	3.71*** (7.08)	2.84 (0.14)	3.60*** (5.43)	3.76*** (5.96)
Fuel costs	-4.56*** (-17.43)	-4.66*** (-17.60)	-4.69*** (-17.62)	-3.65 (-0.13)	-4.38*** (-7.94)	-4.47*** (-9.94)
CO_2 emissions	-2.48*** (-12.41)	-2.51*** (-12.40)	-2.52*** (-12.41)	-1.99 (-0.13)	-2.24*** (-6.55)	-2.25*** (-8.17)
Service station availability	0.77*** (15.10)	0.77*** (14.88)	0.77*** (14.94)	0.65 (0.13)	0.72*** (7.51)	0.73*** (9.45)
Constant diesel	0.15*** (2.58)	0.07 (1.24)	0.06 (1.00)	0.40 (0.23)	0.06 (0.49)	-0.01 (-0.07)
Constant hybrid	-0.05 (-0.78)	-0.11* (-1.66)	-0.11* (-1.72)	-0.05 (-0.01)	-0.00 (-0.04)	-0.10 (-0.73)
Constant gas	-0.11 (-1.64)	-0.13** (-2.04)	-0.14** (-2.09)	-0.25 (-0.02)	-0.27 (-1.37)	-0.18 (-1.32)
Constant biofuel	-0.38*** (-6.05)	-0.40*** (-6.44)	-0.40*** (-6.44)	-0.23 (-0.05)	-0.32* (-1.76)	-0.27* (-1.88)
Constant hydrogen	-0.19*** (-2.93)	-0.20*** (-3.07)	-0.20*** (-3.10)	-0.05 (-0.01)	-0.05 (-0.42)	-0.08 (-0.61)
Constant electric	-0.57*** (-8.92)	-0.59 *** (-9.25)	-0.59*** (-9.19)	-0.26 (-0.04)	-0.32** (-2.15)	-0.35** (-2.57)
Correlations betw. choice alternatives	no	no	no	yes	yes	yes
Invariant stochastic effects	no	no	no	no	no	no
Simulated loglikelihood value	-6227.58	-6142.51	-6128.73	-6197.28	-6126.63	-6111.49

Note:
* (**, ***) means that the appropriate parameter is different from zero at the 10% (5%, 1%) significance level, respectively

Table 3b: Simulated maximum likelihood estimates (simulated z-test statistics) in multinomial probit models (invariant stochastic effects, flexible multinomial probit model), different numbers R of random draws in the GHK simulator, choice between seven alternative energy sources and propulsion technologies in vehicles, explanatory variables: vehicle attributes, alternative-specific constants, N = 598, six choice sets, 3588 observations

Explanatory variables	Invariant stochastic effects			Flexible multinomial probit model		
	R=10	R=100	R=1000	R=10	R=100	R =1000
Purchase price	-7.07*** (-9.23)	-7.55*** (-9.45)	-7.90*** (-9.58)	-7.94*** (-8.38)	-9.75*** (-7.61)	-10.69*** (-7.58)
Motor power	4.85*** (7.69)	5.33*** (7.79)	5.43*** (7.77)	5.78*** (6.84)	7.05*** (6.85)	7.38*** (6.54)
Fuel costs	-5.61*** (-18.01)	-6.04*** (-17.92)	-6.23*** (-18.17)	-6.20*** (-12.21)	-7.57*** (-11.51)	-8.21*** (-10.42)
CO_2 emissions	-3.06*** (-12.64)	-3.28*** (-12.95)	-3.35*** (-12.84)	-3.67*** (-9.48)	-4.35*** (-9.08)	-4.70*** (-8.56)
Service station availability	0.99*** (15.96)	1.04*** (16.09)	1.08*** (16.00)	1.19*** (11.16)	1.38*** (10.39)	1.52*** (8.94)
Constant: Diesel	0.04 (0.60)	-0.22*** (-2.75)	-0.28*** (-3.31)	0.18* (1.89)	-0.54*** (-2.74)	-0.62*** (-3.07)
Constant: Hybrid	-0.27*** (-3.24)	-0.33*** (-4.02)	0.37*** (-4.32)	-1.06*** (-3.10)	-1.03*** (-3.37)	-1.29*** (-3.03)
Constant: Gas	-0.34*** (-4.11)	-0.50*** (-5.26)	-0.49*** (-5.24)	-0.79*** (-2.97)	-1.29*** (-3.50)	-1.48*** (-3.42)
Constant: Biofuel	-0.54*** (-6.69)	-0.60*** (-7.29)	-0.60*** (-7.22)	-1.34*** (-2.99)	-1.32*** (-3.53)	-1.49*** (-4.39)
Constant: Hydrogen	-0.43*** (-5.08)	-0.50*** (-5.75)	-0.53*** (-5.92)	-0.76*** (-3.53)	-0.95*** (-4.13)	-1.34*** (-4.76)
Constant: Electric	-0.75*** (-8.76)	-0.81 *** (-9.34)	-0.88*** (-9.37)	-1.01*** (-4.80)	-1.35 *** (-5.37)	-1.42*** (-4.85)
Correlations betw. choice alternatives	no	no	no	yes	yes	yes
Invariant stochastic effects	yes	yes	yes	yes	yes	yes
Simulated loglikelihood value	-5785.77	-5605.64	-5572.86	-5737.78	-5574.87	-5533.59

Note:
* (**, ***) means that the appropriate parameter is different from zero at the 10% (5%, 1%) significance level, respectively

Table 4: Simulated maximum likelihood estimates (simulated z-test statistics) in multinomial probit models (independent multinomial probit model, correlations between choice alternatives, invariant stochastic effects, flexible multinomial probit model), different numbers R of random draws in the GHK simulator, choice between seven alternative energy sources and propulsion technologies in vehicles, explanatory variables: vehicle attributes, individual characteristics, alternative-specific constants, N = 598, six choice sets, 3588 observations

	Independent multinomial probit model		Correlations between choice alternatives		Invariant stochastic effects		Flexible multinomial probit model	
Explanatory variables	R=100	R=1000	R=100	R=1000	R=100	R=1000	R=100	R=1000
Purchase price	-5.92*** (-9.05)	-5.97*** (-9.13)	-5.49*** (-3.28)	-6.02*** (-5.18)	-7.80*** (-9.73)	-8.07*** (-9.88)	-9.39*** (-7.77)	-9.65*** (-8.00)
Motor power	4.00*** (7.42)	4.03*** (7.45)	3.73*** (3.81)	4.02*** (5.23)	5.19*** (7.60)	5.55*** (8.00)	6.17*** (7.29)	6.38*** (6.91)
Fuel costs	-4.85*** (-17.98)	-4.88*** (-18.02)	-4.57*** (-4.29)	-4.90*** (-6.87)	-6.11*** (-18.05)	-6.32*** (-18.54)	-7.29*** (-11.95)	-7.38*** (-11.42)
CO_2 emissions	-2.55*** (-12.30)	-2.56*** (-12.34)	-2.36*** (-4.04)	-2.56*** (-6.50)	-3.28*** (-12.99)	-3.29*** (-12.73)	-3.94*** (-9.45)	-4.21*** (-9.76)
Service station availability	0.79*** (15.29)	0.80*** (15.34)	0.76*** (4.29)	0.82*** (6.90)	1.05*** (16.29)	1.06*** (16.26)	1.29*** (10.74)	1.35*** (10.81)
Age: Diesel	-0.95** (-2.24)	-0.94** (-2.20)	-0.94 (-1.61)	-0.96* (-1.91)	-0.73 (-1.41)	-1.43*** (-2.65)	-0.56 (-0.87)	-0.72 (-1.19)
Age: Hybrid	-1.05** (-2.26)	-1.06** (-2.28)	-1.08 (-1.43)	-1.20** (-2.15)	-1.22** (-2.28)	-1.46*** (-2.68)	-0.87 (-1.37)	-1.01 (-1.59)
Age: Gas	-1.59*** (-3.63)	-1.60*** (-3.66)	-1.73 (-1.58)	-1.84*** (-2.77)	-1.77*** (-3.27)	-2.14*** (-3.90)	-1.74** (-2.44)	-2.04*** (-2.83)
Age: Biofuel	-1.40*** (-3.36)	-1.42*** (-3.42)	-1.30** (-2.35)	-1.43*** (-2.95)	-1.22** (-2.52)	-1.54*** (-3.18)	-1.04* (-1.88)	-1.19** (-2.08)
Age: Hydrogen	-1.62*** (-3.25)	-1.64*** (-3.29)	-1.67 (-1.64)	-1.73*** (-2.58)	-1.79*** (-3.08)	-2.18*** (-3.64)	-1.60** (-2.41)	-1.99*** (-2.77)
Age: Electric	-2.21*** (-4.86)	-2.19*** (-4.79)	-2.17*** (-3.35)	-2.24*** (-4.32)	-2.40*** (-4.55)	-2.44*** (-4.57)	-2.42*** (-4.03)	-2.25*** (-3.81)
Male: Diesel	0.21 (1.53)	0.20 (1.50)	0.17 (1.30)	0.21 (1.47)	0.20 (1.21)	0.21 (1.22)	0.19 (0.95)	0.11 (0.55)
Male: Hybrid	0.24* (1.73)	0.24* (1.70)	0.21 (1.39)	0.27* (1.76)	0.32* (1.93)	0.28* (1.66)	0.27 (1.39)	0.24 (1.25)
Male: Gas	0.35** (2.44)	0.35** (2.44)	0.35* (1.67)	0.40** (2.29)	0.35** (1.99)	0.38** (2.18)	0.38 (1.64)	0.46** (1.96)
Male: Biofuel	0.08 (0.62)	0.08 (0.63)	0.05 (0.37)	0.07 (0.57)	0.04 (0.28)	0.03 (0.23)	-0.05 (-0.29)	-0.08 (-0.47)
Male: Hydrogen	0.32** (2.23)	0.32** (2.23)	0.29 (1.59)	0.33** (2.08)	0.36** (2.05)	0.39** (2.18)	0.39** (1.99)	0.41* (1.94)
Male: Electric	0.17 (1.17)	0.15 (1.09)	0.16 (1.18)	0.15 (1.11)	0.20 (1.27)	0.12 (0.72)	0.17 (0.95)	0.11 (0.62)
Environment-friendly purchases: Diesel	-0.09 (-0.65)	-0.10 (-0.68)	-0.10 (-0.71)	-0.14 (-0.89)	-0.19 (-1.12)	-0.24 (-1.31)	-0.40* (-1.83)	-0.32 (-1.56)
Environment-friendly purchases: Hybrid	0.24 (1.64)	0.24 (1.61)	0.25 (1.41)	0.29* (1.80)	0.29* (1.73)	0.27 (1.57)	0.22 (1.09)	0.26 (1.28)
Environment-friendly purchases: Gas	0.19 (1.21)	0.20 (1.24)	0.18 (0.87)	0.19 (1.02)	0.17 (0.86)	0.15 (0.80)	0.06 (0.24)	0.10 (0.38)
Environment-friendly purchases: Biofuel	0.41*** (3.06)	0.42*** (3.10)	0.38** (2.36)	0.42*** (2.87)	0.48*** (3.15)	0.50*** (3.27)	0.47*** (2.63)	0.51*** (2.79)
Environment-friendly purchases: Hydrogen	0.39*** (2.66)	0.39*** (2.67)	0.39* (1.74)	0.39** (2.32)	0.51*** (2.89)	0.50*** (2.80)	0.44** (2.24)	0.48** (2.28)
Environment-friendly purchases: Electric	0.36** (2.50)	0.37** (2.52)	0.40** (2.52)	0.42*** (2.84)	0.45*** (2.73)	0.42** (2.52)	0.36* (1.94)	0.43** (2.36)

Table 4 (continued)

	Independent multi-nomial probit model		Correlations between choice alternatives		Invariant stochastic effects		Flexible multinomial probit model	
Explanatory variables	R=100	R=1000	R=100	R=1000	R=100	R=1000	R=100	R=1000
Driving of vehicle for journey to work: Diesel	-0.27** (-1.97)	-0.29** (-2.10)	-0.25* (-1.81)	-0.30** (-2.03)	-0.33** (-1.98)	-0.34** (-1.98)	-0.40* (-1.80)	-0.43** (-2.06)
Driving of vehicle for journey to work: Hybrid	-0.18 (-1.23)	-0.19 (-1.26)	-0.14 (-0.83)	-0.16 (-1.01)	-0.20 (-1.14)	-0.23 (-1.30)	-0.29 (-1.39)	-0.30 (-1.36)
Driving of vehicle for journey to work: Gas	0.41*** (2.76)	0.40*** (2.70)	0.44* (1.78)	0.43** (2.14)	0.45** (2.38)	0.39** (2.06)	0.59** (2.11)	0.63** (2.30)
Driving of vehicle for journey to work: Biofuel	-0.05 (-0.38)	-0.06 (-0.41)	-0.06 (-0.47)	-0.07 (-0.51)	-0.07 (-0.47)	-0.08 (-0.52)	-0.13 (-0.68)	-0.17 (-0.84)
Driving of vehicle for journey to work: Hydrogen	0.02 (0.17)	0.03 (0.20)	0.06 (0.35)	0.06 (0.43)	0.08 (0.48)	0.10 (0.57)	0.10 (0.52)	0.08 (0.39)
Driving of vehicle for journey to work: Electric	0.15 (1.02)	0.15 (1.05)	0.09 (0.54)	0.09 (0.60)	0.14 (0.86)	0.19 (1.13)	0.12 (0.65)	0.16 (0.82)
More than one vehicle in household: Diesel	0.16 (1.28)	0.16 (1.27)	0.13 (1.10)	0.14 (1.07)	0.11 (0.72)	0.13 (0.80)	0.07 (0.39)	0.12 (0.68)
More than one vehicle in household: Hybrid	0.28** (2.17)	0.28** (2.15)	0.28** (2.07)	0.28** (1.97)	0.23 (1.48)	0.30* (1.92)	0.25 (1.32)	0.30 (1.57)
More than one vehicle in household: Gas	0.01 (0.04)	0.00 (0.01)	-0.01 (-0.04)	-0.01 (-0.04)	-0.06 (-0.35)	-0.01 (-0.08)	-0.08 (-0.37)	-0.10 (-0.45)
More than one vehicle in household: Biofuel	0.42*** (3.31)	0.41*** (3.30)	0.43*** (3.04)	0.42*** (3.26)	0.46*** (3.21)	0.46*** (3.22)	0.59*** (3.35)	0.58*** (3.23)
More than one vehicle in household: Hydrogen	0.17 (1.33)	0.17 (1.28)	0.17 (1.24)	0.18 (1.32)	0.16 (1.01)	0.18 (1.12)	0.15 (0.83)	0.11 (0.55)
More than one vehicle in household: Electric	0.23* (1.73)	0.22 (1.63)	0.25** (1.97)	0.24* (1.82)	0.21 (1.38)	0.23 (1.50)	0.17 (1.00)	0.19 (1.14)
New vehicle is small: Diesel	-0.01 (-0.07)	-0.01 (-0.07)	0.00 (0.03)	0.02 (0.11)	0.12 (0.68)	-0.14 (-0.79)	0.10 (0.48)	0.08 (0.43)
New vehicle is small: Hybrid	-0.07 (-0.46)	-0.07 (-0.47)	-0.03 (-0.22)	-0.05 (-0.30)	0.08 (0.48)	-0.05 (-0.28)	0.07 (0.35)	0.05 (0.23)
New vehicle is small: Gas	-0.20 (-1.21)	-0.20 (-1.20)	-0.20 (-0.96)	-0.21 (-1.06)	-0.26 (-1.29)	-0.28 (-1.40)	-0.31 (-1.21)	-0.43 (-1.59)
New vehicle is small: Biofuel	0.07 (0.45)	0.08 (0.49)	0.07 (0.49)	0.07 (0.48)	0.16 (0.91)	0.14 (0.81)	0.16 (0.81)	0.22 (1.03)
New vehicle is small: Hydrogen	0.18 (1.12)	0.18 (1.10)	0.17 (1.04)	0.19 (1.14)	0.42** (2.16)	0.28 (1.45)	0.54** (2.42)	0.48** (2.15)
New vehicle is small: Electric	-0.08 (-0.51)	-0.07 (-0.46)	-0.06 (-0.37)	-0.05 (-0.31)	-0.08 (-0.44)	-0.05 (-0.30)	-0.08 (-0.44)	-0.08 (-0.43)
New vehicle is company car: Diesel	0.36* (1.93)	0.38** (1.99)	0.35* (1.82)	0.40* (1.90)	0.39* (1.73)	0.45* (1.88)	0.40 (1.42)	0.34 (1.26)
New vehicle is company car: Hybrid	0.35* (1.80)	0.35* (1.79)	0.35* (1.68)	0.37* (1.67)	0.48** (2.08)	0.43* (1.83)	0.58** (2.01)	0.46 (1.62)
New vehicle is company car: Gas	0.21 (1.01)	0.22 (1.07)	0.16 (0.69)	0.20 (0.83)	0.14 (0.53)	0.18 (0.70)	0.24 (0.74)	0.14 (0.42)
New vehicle is company car: Biofuel	0.57*** (2.87)	0.57*** (2.86)	0.51** (2.44)	0.51** (2.44)	0.63*** (2.76)	0.64*** (2.78)	0.70** (2.56)	0.65** (2.33)
New vehicle is company car: Hydrogen	0.33 (1.57)	0.33 (1.58)	0.32 (1.32)	0.31 (1.38)	0.37 (1.47)	0.42 (1.61)	0.43 (1.52)	0.46 (1.49)
New vehicle is company car: Electric	0.11 (0.58)	0.11 (0.58)	0.16 (0.87)	0.14 (0.75)	0.07 (0.32)	0.14 (0.64)	0.02 (0.08)	0.04 (0.15)
New vehicle is first-hand: Diesel	-0.32** (-2.29)	-0.33** (-2.32)	-0.32** (-2.39)	-0.34** (-2.36)	-0.47*** (-2.76)	-0.35** (-1.96)	-0.54** (-2.57)	-0.50** (-2.41)
New vehicle is first-hand: Hybrid	-0.34** (-2.31)	-0.34** (-2.33)	-0.33** (-2.29)	-0.36** (-2.31)	-0.42** (-2.43)	-0.38** (-2.22)	-0.47** (-2.31)	-0.46** (-2.20)
New vehicle is first-hand: Gas	-0.29** (-2.04)	-0.30** (-2.09)	-0.31* (-1.94)	-0.31** (-1.96)	-0.32* (-1.83)	-0.27 (-1.51)	-0.37 (-1.64)	-0.31 (-1.31)
New vehicle is first-hand: Biofuel	-0.34** (-2.51)	-0.33** (-2.45)	-0.30** (-2.36)	-0.30** (-2.28)	-0.44*** (-2.84)	-0.36** (-2.32)	-0.48*** (-2.66)	-0.43** (-2.29)
New vehicle is first-hand: Hydrogen	-0.21 (-1.36)	-0.21 (-1.38)	-0.23 (-1.49)	-0.24 (-1.54)	-0.39** (-2.08)	-0.27 (-1.42)	-0.42** (-1.96)	-0.34 (-1.50)
New vehicle is first-hand: Electric	-0.21 (-1.42)	-0.21 (-1.43)	-0.23 (-1.63)	-0.21 (-1.43)	-0.23 (-1.41)	-0.21 (-1.25)	-0.19 (-1.06)	-0.21 (-1.13)

Table 4 (continued)

Explanatory variables	Independent multi-nomial probit model		Correlations between choice alternatives		Invariant stochastic effects		Flexible multinomial probit model	
	R=100	R=1000	R=100	R=1000	R=100	R=1000	R=100	R=1000
Horsepower of new vehicle: Diesel	1.68 (1.43)	1.67 (1.41)	1.70 (1.44)	1.86 (1.56)	3.16** (2.09)	1.29 (0.85)	3.92** (2.02)	3.93** (2.15)
Horsepower of new vehicle: Hybrid	0.77 (0.60)	0.73 (0.56)	0.76 (0.63)	0.74 (0.55)	1.59 (1.03)	0.46 (0.30)	2.10 (1.10)	1.51 (0.78)
Horsepower of new vehicle: Gas	-0.49 (-0.36)	-0.46 (-0.34)	-0.47 (-0.32)	-0.49 (-0.32)	-1.14 (-0.68)	-0.47 (-0.28)	-0.95 (-0.44)	-1.48 (-0.66)
Horsepower of new vehicle: Biofuel	-0.43 (-0.33)	-0.42 (-0.32)	-0.41 (-0.33)	-0.46 (-0.35)	-0.86 (-0.55)	-0.34 (-0.22)	-1.22 (-0.65)	-1.09 (-0.55)
Horsepower of new vehicle: Hydrogen	1.00 (0.81)	0.98 (0.80)	1.00 (0.82)	1.12 (0.90)	2.97** (2.03)	1.00 (0.65)	3.54** (2.14)	3.06* (1.74)
Horsepower of new vehicle: Electric	-1.36 (-1.06)	-1.35 (-1.05)	-1.34 (-1.08)	-1.44 (-1.12)	-2.67* (-1.75)	-1.20 (-0.83)	-3.38* (-1.89)	-3.62* (-1.92)
Range of new vehicle: Diesel	1.92*** (4.95)	1.97*** (5.03)	1.87*** (3.71)	2.01*** (3.79)	2.42*** (5.06)	2.54*** (5.08)	2.66*** (4.20)	2.87*** (4.42)
Range of new vehicle: Hybrid	0.71* (1.75)	0.73* (1.79)	0.62 (1.57)	0.66 (1.45)	0.61 (1.31)	0.82* (1.73)	0.44 (0.80)	0.45 (0.78)
Range of new vehicle: Gas	0.06 (0.14)	0.05 (0.13)	0.15 (0.33)	-0.00 (-0.01)	-0.49 (-0.92)	-0.04 (-0.08)	-0.86 (-1.11)	-0.90 (-1.27)
Range of new vehicle: Biofuel	0.83** (2.13)	0.83** (2.14)	0.80** (2.17)	0.81** (2.02)	0.60 (1.32)	0.80* (1.79)	0.56 (1.05)	0.84 (1.56)
Range of new vehicle: Hydrogen	1.14*** (2.97)	1.16*** (3.02)	1.07** (2.28)	1.10** (2.34)	1.05** (2.18)	1.16** (2.38)	0.98* (1.78)	1.06* (1.77)
Range of new vehicle: Electric	1.43*** (3.71)	1.42*** (3.68)	1.29*** (3.39)	1.32*** (3.22)	1.46*** (3.33)	1.46*** (3.24)	1.63*** (3.45)	1.50*** (3.06)
Mileage of new vehicle: Diesel	1.56 (1.34)	1.59 (1.35)	1.56 (1.18)	1.76 (1.42)	3.36** (2.45)	0.97 (0.66)	4.36*** (2.71)	4.55*** (2.83)
Mileage of new vehicle: Hybrid	-0.32 (-0.26)	-0.33 (-0.27)	-0.32 (-0.18)	-0.39 (-0.27)	0.13 (0.09)	-0.12 (-0.08)	0.33 (0.19)	0.31 (0.18)
Mileage of new vehicle: Gas	0.45 (0.34)	0.45 (0.34)	0.36 (0.16)	0.41 (0.24)	1.76 (1.10)	0.75 (0.47)	1.94 (0.90)	2.32 (1.15)
Mileage of new vehicle: Biofuel	0.29 (0.25)	0.26 (0.22)	0.38 (0.28)	0.35 (0.28)	1.70 (1.29)	0.47 (0.35)	2.24 (1.53)	2.32 (1.54)
Mileage of new vehicle: Hydrogen	-0.01 (-0.01)	-0.04 (-0.03)	0.02 (0.01)	0.02 (0.01)	0.78 (0.52)	-0.01 (-0.00)	1.28 (0.75)	1.14 (0.65)
Mileage of new vehicle: Electric	0.62 (0.52)	0.61 (0.52)	0.81 (0.57)	0.90 (0.74)	2.56** (1.97)	0.66 (0.49)	3.45** (2.55)	3.46** (2.43)
Constant: Diesel	-2.39** (-2.11)	-2.45** (-2.14)	-2.36* (-1.83)	-2.74** (-2.38)	-4.90*** (-3.72)	-2.09 (-1.46)	-6.31*** (-3.97)	-6.51*** (-3.91)
Constant: Hybrid	-0.03 (-0.02)	-0.01 (-0.01)	0.09 (0.05)	0.04 (0.03)	-0.73 (-0.53)	-0.32 (-0.23)	-1.48 (-0.91)	-1.42 (-0.87)
Constant: Gas	-0.27 (-0.22)	-0.26 (-0.21)	-0.37 (-0.18)	-0.36 (-0.22)	-1.31 (-0.86)	-0.55 (-0.36)	-2.01 (-1.01)	-2.39 (-1.26)
Constant: Biofuel	-0.91 (-0.78)	-0.87 (-0.75)	-0.89 (-0.65)	-0.89 (-0.73)	-2.35* (-1.81)	-1.20 (-0.91)	-3.30** (-2.30)	-3.77** (-2.51)
Constant: Hydrogen	-0.80 (-0.66)	-0.78 (-0.64)	-0.69 (-0.37)	-0.79 (-0.57)	-2.15 (-1.49)	-1.08 (-0.74)	-3.07* (-1.89)	-3.09* (-1.84)
Constant: Electric	-1.30 (-1.13)	-1.28 (-1.12)	-1.12 (-0.71)	-1.29 (-1.05)	-3.16** (-2.50)	-1.52 (-1.17)	-4.29*** (-3.25)	-4.30*** (-3.05)
Correlations between choice alternatives	no	no	yes	yes	no	no	yes	yes
Invariant stochastic effects	no	no	no	no	yes	yes	yes	yes
Simulated loglikelihood value	-5920.59	-5904.60	-5902.29	-5888.62	-5459.57	-5437.21	-5433.67	-5397.14

Note:
* (**, ***) means that the appropriate parameter is different from zero at the 10% (5%, 1%) significance level, respectively

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