


# Modeling household fleet choice as a function of fuel price using a multiple discrete-continuous choice model

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2 **continuous choice model**

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**ABSTRACT**

1 In this Paper, a new model of fleet choice for households is presented that uses the multiple  
2 discrete-continuous extreme value (MDCEV) model as a framework. The aim of the model is  
3 to establish a model to allocate car types to activity based microscopic agent based transport  
4 simulations. What is new in the presented model, is that in addition to socioeconomic attributes  
5 of households, the choice is also influenced by fuel price. To model a range of fuel prices up to  
6 20 USD/gallon a data base from a sophisticated stated adaption survey about mobility residential  
7 choice among approximately 400 Swiss households was used. The model had a choice set of 17  
8 alternatives distinguishing car type and drive train. In the MDCEV model, a household chooses  
9 multiple car types and distributes an overall budget of vehicle miles traveled among the chosen  
10 alternatives. The model shows that fuel price has a much greater influence on the selection of  
11 the car type than on the use (VMT) of the car. In a certain range of fuel prices, households tend  
12 to switch from gasoline to diesel cars. The paper also contains an assessment of the residuals of  
13 the simulation that shows a reasonable performance of the model.

## INTRODUCTION

### 1 Context

2 One of the mayor global ecological problems is the expected rise in average world temperature  
3 due to the greenhouse effect, known as global warming. According to the Intergovernmental  
4 Panel on Climate Change (1), the increasing concentration of green house gases (GHG) is the  
5 main anthropogenic cause for this phenomenon. Of all GHG, the biggest impact has Carbon  
6 Dioxide CO<sub>2</sub> which is emitted burning fossil fuel. In Switzerland, 34% of energy consumption  
7 is in the transportation sector (2), therefore various policies and taxes are discussed to reduce  
8 carbon emission in the private transport sector, which could incorporate an significant rise in  
9 fuel prices. Regulatory agencies therefore are interested how an increase in fuel prices change  
10 the fleet composition, vehicle miles traveled (VMT) and the resulting energy and CO<sub>2</sub> savings.

11 But also other factors can influence fuel prices, mainly the world oil-market. The increase  
12 in demand of the developing countries as well as stagnation and shortages on the supply side  
13 (crude oil as well as refineries) influence the oil price. The Reference scenario of the oil price  
14 projections of Energy Information Administration (EIA) (3) is substantially higher than the price  
15 spike in 2008.

### 16 Research Question

17 The main research question now is how these unprecedented changes in fuel costs affect fleet  
18 choice and usage, how this can be modeled and how the resulting models can be implemented in  
19 existing transportation models.

20 In sophisticated transport models like the SACSIM model of the Sacramento Area, California  
21 (4), the ILUTE model in Toronto (5) or the Albatross model from the Netherlands (6), choice  
22 modeling is used to capture a wide range of behaviors, such as mode choice, fleet choice or  
23 route choice. Discrete choice models in their standard formulations cannot integrate multivariate  
24 choices and associated continuous attributes of these choices. Still, there a number of questions  
25 where this capability would allow the modeler to improve the realism of the description. One  
26 prime example is the composition of the fleet of mobility tools (7, 8, 9, 10) and their associated  
27 mileage. The recent development of the MCDEV framework by Bhat (11) offers a new approach  
28 to address this gap.

29 The overall transport model currently developed at IVT in collaboration with TU-Berlin  
30 is MATSim (12, 13, 14), an agent based micro-simulation tool for travel demand and traffic  
31 flow modeling. The present paper is part of the ongoing work to implement multiple discrete-  
32 continuous extreme value (MDCEV) models into the model frameworks of different fields.

33 In MATSim travel demand is activity based and generated using activity chains from the  
34 Swiss national travel diary survey, the Mikrozensus (15). The Mikrozensus is conducted every  
35 five years. In the current version of MATSim, the agents can conduct activities (e.g. home,  
36 shopping, work, leisure, etc.) inside facilities (buildings). In the iterative solution process the  
37 agents optimize their given activity chain. The agents are not part of a household and they have  
38 no specific car type allocated to them yet. They only have an attribute that describes their car  
39 availability for the mode choice processes.

40 The aim of this work is part of the future improvement of MATSim, so that the agents shall  
41 be members of households and specific car fleets will be allocated to the households. This  
42 will not only enable analysis of energy consumption on a microscopic level, but also allow the

1 implementation of a behavioral model to forecast the development of the car fleet based on  
2 scenarios of different fuel prices and, as a result, of the energy consumption.

### 3 **Literature**

4 The model presented is estimated using the MDCEV approach by Bhat (11) on Stated Adaptation  
5 data collected in a survey conducted by Erath and Axhausen (16). To test the performance of  
6 such a model for an application like MATSim, we applied a MDCEV model and analyzed the  
7 residuals comparing the results to the actual choices in the experiment. Since 2004, when the  
8 MDCEV model was originally developed to analyze time use (11), various researchers have  
9 used it to estimate preferences: (17) presented a MDCEV Model in the context of examining  
10 vehicle type, model and usage decisions of households in his dissertation Bhat and Sen (18). The  
11 impact of demographics, built environment attributes, vehicle characteristics and gasoline prices  
12 on the same issue are analyzed in (19). Pinjari *et al.* (20) analyzed residential self-selection  
13 effects in time-use models and Spissu *et al.* (21) presented an analysis of weekly out-of-home  
14 activity participation. Copperman and Bhat (22) analyzed the determinants of childrens week  
15 end activity participation. In Pinjari and Bhat (23), the authors introduce the nested version of  
16 the MDCEV, the multiple discrete-continuous nested extreme value (MDCNEV) model and  
17 present an application on non-worker time-use behavior. A detailed description of the MDCEV  
18 and the role of its parameters can be found in (24).

19 Early studies of household fleet composition models were undertaken by Lave and Train  
20 (25) and Hensher and Le Plastrier (26). de Jong (27) found a negative relationship between fixed  
21 and variable car costs on ownership and use respectively. A good overview over all different  
22 types of car ownership and use models is given in de Jong *et al.* (28). All these models focus  
23 on the influence of income and costs generally. The work presented focuses only on the part  
24 of costs due to fuel. An increase in this area does not necessarily only mean a decrease in  
25 use, but could also lead to a change of car type (to a type with lower fuel consumption) or to  
26 a switch of drive-train technology. The spectrum of fuel price for revealed preference data is  
27 small compared to what is expected to become reality within the next decades. Stated Preference  
28 experiments with a fuel price variation in the expected range of up to +400% were not found in  
29 the literature, except for the study whose data is used in this paper (16).

30 Other studies focus explicitly on the purchase of low consumption cars. A study about  
31 acceptance of alternative-fuel vehicles by Ewing and Sarigöllü (29) found that given equal  
32 performance, alternative fuel vehicles are preferred over conventional, particularly for younger  
33 and high income participants. Achtnicht (30) found in his model that emissions have a negative  
34 influence on car choice in general and particularly for younger and female individuals. Using  
35 a sophisticated consumer choice model for car purchase, de Haan *et al.* (31) showed how  
36 incentives for environmentally friendlier cars could decrease CO<sub>2</sub> emissions of new cars.

**FIGURE 1** Screen shot of interactive computer software used in the survey

Kosten Treibstoff [CHF/l]	1.5	
Typ CO2-Bonus/Malus	Einmalzahlung für Energieeffizienzklasse A	
CO2-Bonus/Malus pro Monat	Bei Neukauf: -1500 CHF	
Preise ÖV relativ zu heute	-10%	
Wohnlage	Innenstadt	
	IV bisher	ÖV bisher
Reisezeit zur Arbeit [min]	-	-
Reisezeit nächstes Zentrum [min]	-	-
Total Wohnkosten	1183.00	
Veränderung Wohnkosten	-17.00	
	Fahrzeug 1	
Wahl PW	Mittelklasse	
Wahl Hubraum	1500-2000ccm	
Typ Motor	Benzin	
Neuwagen	<input type="checkbox"/>	
Jahresfahrleistung	10000.00	
Jahresfahrleistung bisher	12000.00	

## DATA

### 1 Survey

2 The primary data set used here was collected within a project funded by the Swiss Federal Office  
 3 of Energy and the Federal Office for the Environment on long term fuel price elasticity and  
 4 the effects on mobility tool ownership and residential location choice (16). In the survey, 409  
 5 households were questioned about their long term reactions to rising fuel costs. The survey  
 6 was divided in a part on socioeconomic and mobility tool related questions and a three stage  
 7 stated response survey. In the first part, the respondents are presented six scenarios of fuel prices  
 8 ranging from CHF 1.5/l to CHF 5.5/l for gasoline. The survey was conducted in face-to-face  
 9 interviews, in which the interviewer was equipped with a computer-software that simultaneously  
 10 calculated the personalized mobility costs (fixed cost separate from variable cost) based on  
 11 personal information collected previously. The respondents could choose their car fleet and  
 12 annual mileage for every chosen car at a high level of detail including car type, engine size,  
 13 drive-train, and if they would buy a new or a used car, while being supported by the real time  
 14 calculations of the computer. Public transport season tickets, a common alternative, was always  
 15 available as a choice. Figure 1 shows a screen shot of the survey.

16 They could also choose and/or change the mileage traveled by public transport. In the second  
 17 stage of the respondents were confronted with six different residential locations as well as  
 18 varying fuel prices and were again asked to choose the preferred mobility tool (and mileage) for  
 19 each situation. For the third stage of stated preference experiment another six choice situations  
 20 were created. The choice sets in this consisted of two alternatives, one from both previous stages  
 21 each. The data used in this paper comes from the first stage only.

**TABLE 1 Sample Characteristics**

<b>Variable</b>	<b>MZ</b>	<b>Sample</b>	<b>Variable</b>	<b>MZ</b>	<b>Sample</b>
	<b>[%]</b>	<b>[%]</b>		<b>[%]</b>	<b>[%]</b>
<i>Sex</i>					
Male	48.3	55.0	<i>Car Availability</i>		
Female	51.7	45.0	always	83.5	84.0
<i>Age in years</i>					
18 - 35	27.2	25.0	occasional	16.5	12.8
36 - 50	32.0	38.0	<i>Transit Season Ticket</i>		
51 - 65	24.5	25.5	none	63.2	73.8
> 65	16.4	11.5	Half-Fare	29.9	16.1
<i>Highest Ed.</i>					
Compulsory Education	18.4	20.6	GA	6.9	4.1
Professional School	55.6	57.6	<i>Cars in Household</i>		
Tertiary Ed.	26.0	21.8	1	62.4	
<i>Household Inc. [CHF/month]</i>					
< 2,000	1.8	2.4	2	32.0	
2,000 - 4,000	14.6	12.5	> 2	6.6	
4,000 - 6,000	28.6	25.7	<i>Car Type</i>		
6,000 - 8,000	23.6	17.6	Sports Car	2.6	8.1
8,000 - 10,000	14.3	15.4	Luxury / SUV	6.3	6.3
10,000 - 12,000	7.8	10.3	Upper middle Class	22.3	17.9
12,000	9.3	9.0	Middle Class	22.3	17.9
n.a.	-	6.8	Minivan/Van	14.1	13.3
<i>Persons per Household</i>					
1	20.5	34.5	Compact	23.1	20.3
2	38.9	39.1	Subcompact	19.0	18.1
3	14.7	11.0	Micro	3.7	8.1
4	18.0	12.0			
> 4	7.9	3.4			

## 1 Data Overview

2 The representativeness of the data in term of mobility tools, car ownership and socioeconomic  
3 variables is summarized in table 1. The column MZ describes the targeted share according to  
4 the Swiss national transport survey (15), the column sample the actual share in the survey. In  
5 our data, male participants are slightly over-represented, as well as the age group of 36-50 years  
6 old. We have also a significantly higher share of single person household and persons without a  
7 public transport season ticket. In terms existing fleet composition, the most frequent car types,  
8 such as upper middle class, middle class, minivan and compact, are under-represented while the  
9 more special ones like sports car and micro are over-represented. The income distribution is  
10 matched reasonably well, although there are more high income households than expected.

## MDCEV

### 1 Review of Methodology

2 The methodology used in this fleet choice model is the multiple discrete-continuous extreme  
 3 value (MDCEV) approach developed by Bhat (11). In his paper he gives a detailed description  
 4 and derivation of the model. The following section is a short summary of the third chapter of  
 5 the paper. The MDCEV was originally developed to estimate the influence of attributes on  
 6 the decisions of allocating time (continuous) to activities (discrete) within a 24-hour budget.  
 7 Because the various activities are equivalent and simultaneously chosen for each day the model  
 8 considers multiple chosen alternatives. In the presented model, the discrete choices are car types,  
 9 the continuous amount is annual mileage (VMT) and it is a multiple discrete model because  
 10 households can own and use more than one car simultaneously.

11 Kim *et al.* (32) defines the utility an individual obtains for his decisions as a sum over all  $j$   
 12 alternatives (in our case: car types):

$$U = \sum_{j=1}^K \psi(x_j, \varepsilon_j)(t_j + \gamma_j)^{\alpha_j} \quad (1)$$

13 In this utility structure,  $t_j$  is the continuous amount of annual mileage driven with car type  $j$   
 14 ( $j = 1, 2, \dots, K$ ),  $\gamma_j$  and  $\alpha_j$  are satiation parameter to estimated within the model. These Satiation  
 15 parameter are two different ways to account for the decreasing marginal utility of the continuous  
 16 amount (VMT). The function  $\psi(x_j, \varepsilon_j)$  gives the baseline utility function for the mileage driven  
 17 with car type  $j$ . In section 3.1 of his paper, Bhat (11) presents a random utility function for the  
 18 baseline utility:

$$\psi(x_j, \varepsilon_j) = \exp(\beta' x_j + \varepsilon_j) \quad (2)$$

19 In which  $\beta'$  is a vector of parameters that define the influence of the observed characteristics  
 20 of the alternative  $x_j$ .  $\varepsilon_j$  captures the unobserved random utility. By combining the formulas (1)  
 21 and (2) the overall random utility function for the MDCEV model can be defined as:

$$\bar{U} = \sum_{j=1}^K \exp(\beta' x_j + \varepsilon_j) \cdot (t_j + \gamma_j)^{\alpha_j} \quad (3)$$

22 By forming the Lagrangian and applying the Kuhn-Tucker conditions and assuming that  
 23 the optimal allocation of annual mileage satisfies the budget constraint  $\sum_{j=1}^K t_j^* = T$  (with  $T$   
 24 equals the total VMT of the household), the probability function can be derived. Bhat specifies  
 25 a standard extreme value distribution for  $\varepsilon_j$  and assumes that it is independent from  $x_j$  as well as



1 independently distributed across alternatives. The final result for the probability function is:

$$P(t_2, t_3, \dots; t_M, 0, 0, \dots, 0) = \left[ \prod_{i=1}^M c_i \right] \left[ \prod_{i=1}^M \frac{1}{c_j} \right] \left[ \frac{\prod_{i=1}^M e^{V_i}}{(\sum_{j=1}^K e^{V_j})^M} \right] (M-1)! \quad (4)$$

2 whereas:

$$c_i = \left( \frac{1 - \alpha_i}{t_i + \gamma_i} \right) \quad (5)$$

3 M is the number of alternatives chosen by the individual. If only one alternative is chosen,  
4 the model collapses to the form of a standard Multinomial Logit model. Therefore this model  
5 is an extension of the standard MNL model, allowing multiple choices of continuous amounts.  
6 The parameters of the model are estimated using the Log-Likelihood method that maximizes the  
7 sum of the log of P over all observations.

## 8 **Model Specification**

9 The model used for this paper has no outside good, meaning that there was no alternative that  
10 was chosen in every observation. It is obvious that there is no car type which has to be chosen by  
11 all households, as for example 'in home time' in time use models or 'housing costs' in household  
12 budget allocation models.

13 For the estimation process, the Gauss code provided at Bhat's Web-page (33) is used. The  
14 programm 'No Outside Good' is used and two configurations were tested. In the first the  
15 estimated satiation parameters of the model are  $\alpha$  parameters and the  $\gamma$  values are constraint to  
16 be equal to one for all goods. In this case, the specific utility function is:

$$U(t) = \sum_{j=1}^K \frac{1}{\alpha_j} \exp(\beta' x_j + \varepsilon_j) \cdot \{(t_j + 1)^{\alpha_j} - 1\} \quad (6)$$

17 In the other configuration tested  $\gamma$  parameters are estimated while  $\alpha$  values are fixed to be  
18 equal 0. In that case, the specific utility function is:

$$U(t) = \sum_{j=1}^K \gamma_j \cdot \exp(\beta' x_j + \varepsilon_j) \cdot \ln \left( \frac{x_j}{\gamma_j} + 1 \right) \quad (7)$$

19 The models estimated assumed satiation parameters that differ across individuals. The  $\gamma$   
20 parameters are estimated as a function of household income, fuel price and a constant. We did  
21 not reach convergence for models using  $\alpha$  parameters differing across individuals. Because of  
22 this, and because of the slightly better model fit, only results using  $\gamma$  satiation parameters are  
23 presented in this paper.

**TABLE 2 Alternatives for Fleet Choice Model B**

<b>Alternative</b>	<b>Drive-train</b>	<b>Car Types</b>	<b>Observations</b>
D0	Diesel	Micro	58
D1	Diesel	Subcompact	123
D2	Diesel	Compact	134
D3	Diesel	Mini MPV	103
D4	Diesel	Mid-Sized	127
D5	Diesel	MiniVan, Full-Sized	100
D6	Diesel	Luxurious, Sportscar	56
B0	Gasoline	Micro	135
B1	Gasoline	Subcompact	366
B2	Gasoline	Compact	289
B3	Gasoline	Mini MVP	149
B4	Gasoline	Mid-Sized	222
B5	Gasoline	MiniVan, Full-Sized	77
B6	Gasoline	Luxurious	69
B7	Gasoline	Sportscar	136
Other	Gas, Hybrid, Electric	All Types	268
OEV		Public Transport	

1 With the software application used in the interviews, the respondents could determine the  
 2 type of every car choosing among nine different car types, five classes of engine size, five  
 3 drive-trains(gasoline, diesel, natural gas, hybrid, electric) vehicle) and whether it would be a  
 4 newly bought car or a used car (used means either to keep the currently owned car or to buy a  
 5 second hand car). The options give  $9 \cdot 5 \cdot 5 \cdot 2 = 450$  alternatives, which requires a classification.  
 6 The choices were classified in 17 alternatives distinguishing between gasoline, diesel and  
 7 alternative drive-trains (ATD) and between the separate car types. 17 was an upper bound for  
 8 alternatives due to computational reasons. The list of alternatives is shown in table 2. The  
 9 variable observations is how often this alternative was chosen as first car to give a sense of the  
 10 distribution of the classification and explains why certain car types are put together.

## ESTIMATION RESULTS

1 The estimation results are shown in table 3. Please note that **boldly** written numbers are  
2 significant at a 95% level and numbers written in *italic* are significant at a 90% level. The  
3 Alternatives are labeled according to table 2. For an easier and quicker reading of the table, an  
4 indication is given in the column "Alternative", where the car type is indicated. Alternatives D0  
5 to D6 are diesel cars, B0 to B7 are gasoline cars and other means all car types with alternative  
6 drive-trains.

7 In the next three sections, first the  $\beta$  parameters for the discrete choice are discussed with  
8 the exception of fuel price, then fuel price is looked at separately and in the third section  $\theta$   
9 parameters that determine satiation of the allocated VMT are analyzed.

### 10 Choice Model Parameters

11 To evaluate the model in terms of model fit, the mean log likelihood values are compared with  
12 mean log likelihood value when all parameters are set zero which is -6.1. That gives a pseudo  
13  $\rho^2$  of 0.55, which seems to be very high. However, this value should not be compared with  
14 pseudo  $\rho^2$  of Multinomial Logit Models, but only with values of the same MDCEV modeling  
15 framework.

16 The variable Const is the alternative specific constant compared to the Diesel-Micro choice.  
17 In general (few exceptions) bigger cars have lower constant than smaller cars. The strongest  
18 negative constants have the two luxurious car types. But the constants are most likely also driven  
19 by the availability and market penetration of the car types in question. People are less used to  
20 and aware of diesel cars which reflects the lower constant. For Mid-Sized (= "normal") cars this  
21 difference is particularly evident (diesel: -4.38, gasoline: 0.7). Alternative drive-trains (ADT)  
22 are favored over most conventional car types.

23 Income is defined in the model as gross household income in CHF 1'000 per month. The  
24 significant effect indicates, that high income households are less likely to use small and family  
25 cars and are also less likely to use public transport. Interestingly, cars with ADT are negatively  
26 influenced by income, although they are more expensive. This indicates that early adopters are  
27 not necessarily high income people. In general the effect of income is not as strong as expected.  
28 However, it has a stronger influence on the satiation parameters as discussed below.

29 Dist. is the respondent's distance between home and workplace in 100 km. The longer this  
30 distance, the more mileage the respondents have to allocate to commuting. All alternatives have  
31 a high parameter for commuting distance. That means that people with longer distance to the  
32 workplace tend to own more cars, because the utility of making the discrete choice for every car  
33 type increases. The difference between the car types is very small. We can see no effect, that  
34 people with longer commuting distances, and therefore higher consumption, would favor more  
35 efficient cars.

36 Male is a dummy for the gender of the respondent. ADT, public transport and gasoline  
37 are preferred by women, while diesel is preferred by men. This is a quite interesting finding,  
38 because it rejects the general assumption, that men are more interested in, and therefore more  
39 open to new technologies. The most visible effect is between diesel SUVs which are preferred  
40 by men and gasoline Micro cars preferred by women.

41 The influence of age of the respondent is modeled linearly, because neither a quadratic  
42 function nor a division in age groups showed better results. But it is still hard to make clear

**TABLE 3** Estimated  $\beta$  and  $\theta$  Parameters of Fleet Choice Model, mean log likelihood: -2.70

Alternative	Const	Income	Fuel	Fuel2	DistW	Male	Age	Urban	Inertia	Ac.1	Ac.2	GA	HT	$\theta_C$	$\theta_I$	$\theta_F$
D0 (Micro)														<b>4.30</b>	<b>-0.39</b>	0.39
D1 (Subcompact)	0.95	<b>-0.07</b>	0.30	-0.05	<b>6.71</b>	0.12	-0.07	-0.54	<b>1.73</b>					<b>5.55</b>	<b>-0.30</b>	-0.34
D2 (Compact)	-0.96	0.00	0.24	-0.05	<b>7.14</b>	0.31	0.13	0.16	<b>2.73</b>					3.38	-0.22	0.53
D3 (MiniMVP)	-1.70	<b>-0.10</b>	0.69	-0.13	<b>7.12</b>	0.41	0.20	0.01	<b>2.69</b>					<b>0.89</b>	2.69	1.95
D4 (MidSized)	<b>-4.38</b>	<b>0.14</b>	<b>1.34</b>	<b>-0.23</b>	<b>7.01</b>	0.18	<b>0.27</b>	-0.32	<b>2.37</b>					<b>3.56</b>	<b>-0.09</b>	-0.29
D5 (FullSized)	-2.00	<b>0.12</b>	-0.06	-0.02	<b>7.30</b>	0.15	0.11	-0.19	<b>3.84</b>					4.24	-0.26	0.02
D6 (Luxus)	<b>-5.13</b>	0.00	0.98	-0.15	<b>6.62</b>	<b>1.45</b>	<b>0.40</b>	0.39	<b>3.59</b>					<b>0.50</b>	<b>0.08</b>	0.09
B0 (Micro)	-1.12	0.00	-0.01		<b>7.68</b>	<b>-1.40</b>	<b>0.25</b>	0.19	<b>3.00</b>					<b>1.00</b>	<b>-0.13</b>	0.06
B1 (Subcompact)	0.89	<b>-0.11</b>	-0.19		<b>6.71</b>	0.08	<b>0.22</b>	-0.13	<b>2.33</b>					<b>1.93</b>	<b>-0.10</b>	-0.12
B2 (Compact)	0.14	-0.06	<b>-0.32</b>		<b>7.38</b>	-0.15	0.12	0.30	<b>3.20</b>					<b>2.20</b>	<b>-0.13</b>	-0.01
B3 (MiniMVP)	<b>-2.00</b>	0.08	<b>-0.73</b>		<b>6.90</b>	-0.60	<b>0.21</b>	0.36	<b>5.65</b>					<b>1.37</b>	<b>-0.17</b>	0.15
B4 (MidSized)	0.68	0.00	<b>-0.40</b>		<b>7.38</b>	-0.02	-0.12	<b>0.70</b>	<b>3.38</b>					<b>1.77</b>	<b>-0.16</b>	0.31
B5 (FullSized)	-0.37	0.01	<b>-0.53</b>		<b>7.06</b>	0.57	-0.08	-0.59	<b>4.31</b>					<b>3.17</b>	<b>-0.22</b>	-0.02
B6 (Luxus)	-7.14	<b>-0.09</b>	<b>-0.59</b>		<b>6.48</b>	-0.56	-0.23	<b>0.29</b>	<b>14.57</b>					<b>0.00</b>	-0.05	<b>0.34</b>
B7 (Sport)	-1.43	<b>0.12</b>	-0.81		<b>7.75</b>	-0.38	-0.03	<b>-0.01</b>	<b>6.85</b>					-2.23	-0.04	0.45
Other	-0.51	-0.08	<b>0.17</b>		<b>6.95</b>	<b>-0.91</b>	0.33	<b>0.22</b>	<b>3.24</b>	<b>0.08</b>	<b>0.16</b>			<b>0.39</b>	<b>2.32</b>	<b>1.37</b>
Public Transport	<b>4.12</b>	<b>-0.12</b>	-0.24		7.11	<b>-0.28</b>	0.22	<b>0.22</b>		0.00	<b>-0.02</b>	<b>2.39</b>	<b>1.04</b>	<b>-4.25</b>	0.11	0.08

1 statements about the influence for the linear formulation.

2 Urban is a dummy which is equal one for people living in inner city or urban areas and  
3 zero for people in suburbs and rural areas. Resident location has not a big influence on fleet  
4 choice, except that public transport and ADT are preferred in urban areas, which is plausible.  
5 SUV, which are cars designed and advertised for the use in rural, mountainous regions have a  
6 positive sign for urban environment. This indicates that the possibility of driving off road is  
7 more appealing to people that need it less.

8 Inertia is a dummy to capture inertia effects. It is one if the chosen car type is one of the  
9 actual cars types the household already owns. This has the expected significant and substantial  
10 influence, because it can be considered as capturing a substantial part of unobserved influence  
11 that led to the decision for the specific car type. The higher this parameter, the more likely the  
12 car type is chosen because it is already known. To lower this parameter, the more this alternative  
13 is considered to be a car type to change to. The parameter is smaller for all diesel alternatives,  
14 indicating that households switch from gasoline to diesel. The smaller the car type, the more  
15 likely it is to be switched to. Inertia effects are especially high for three different car types:  
16 Luxurious, sports and family gasoline cars. Luxurious and sports cars in many cases fulfill  
17 the purpose of a status symbol and thus bring an increased utility from unobserved emotional  
18 attributes. Because they have an already high fuel consumption in general, these car types are  
19 chosen in the case of rising fuel prices predominantly because they are already owned. In the  
20 case of MiniMVP it is rather its function than status that limits the choice to household that  
21 already have one.

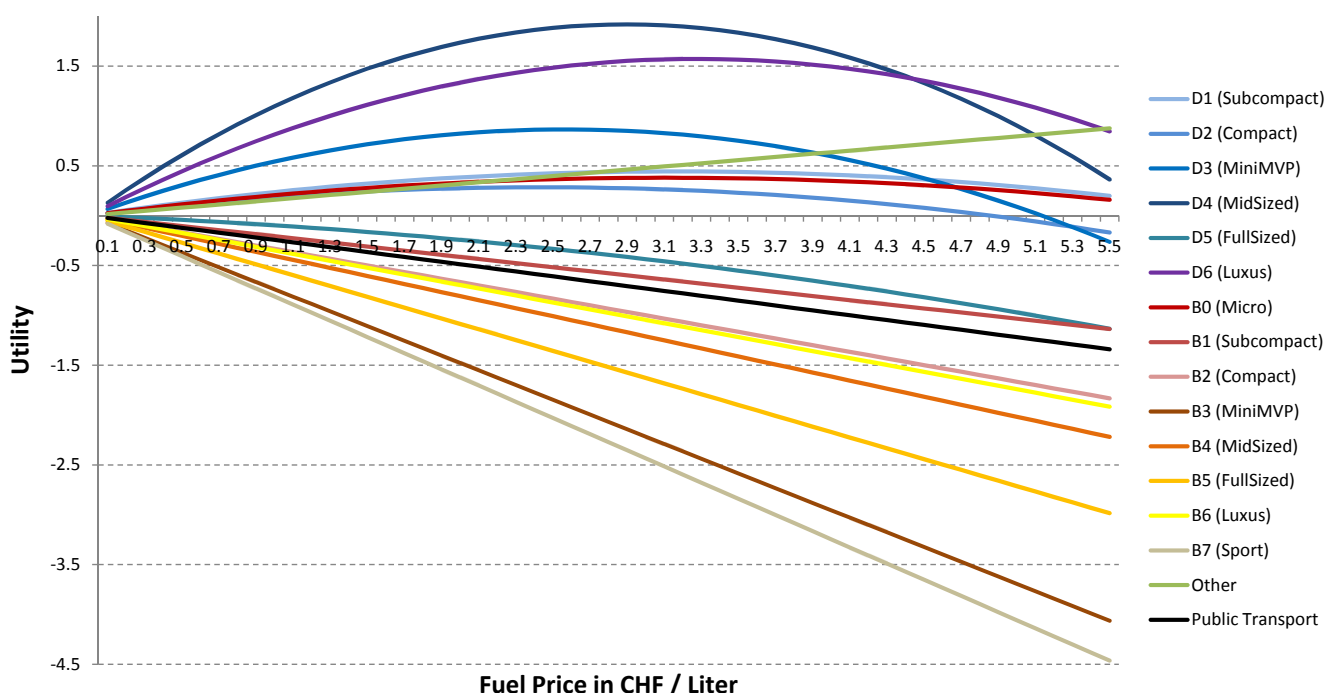
22 Acc.1 and Acc.2 are two variables for accessibility, coming from a factor analysis of private  
23 transport accessibility and public transport accessibility, based on a national aggregate transport  
24 model (34). Ac.1 stands for general accessibility of the respondent's home municipality (or  
25 quarter in the case of a city) and Ac.2 for any differences in public transport accessibility. The  
26 parameter is only estimated for alternative fuel alternatives and public transport, because differ-  
27 ences between conventional alternatives regarding accessibility impacts are neither expected nor  
28 found. ADT are more often chosen in areas with higher accessibility in comparison to gasoline  
29 and diesel cars, and the effect is even greater for the public transport accessibility. ADT cars  
30 have not yet the same capability level as gasoline or diesel cars. This can be less space (Toyota  
31 Prius), small network of fuel stations (natural gas cars) or less range (electric cars). Thus it  
32 cannot necessarily be used for every occasion and the more suitable the public transport option  
33 is, the less important is the described lack in its capability.

34 The parameters for GA, HT and SC describe the influence of existing mobility tools for the  
35 public transport use in the model which includes public transport. GA (Generalabonnement) is a  
36 dummy for a season card for the whole of Switzerland, HT (Halbtax) one for a half-fare card for  
37 the whole of Switzerland and SC for a regional season card. The presence of such a mobility  
38 tool has the expected strong positive effect on the choice to use public transportation.

### 39 **Influence of Fuel Price on Fleet Choice**

40 Fuel is the fuel price, varying in the experiment from 1.5 CHF/l to 5.5 CHF/l, Fuel<sup>2</sup> is the  
41 square of the fuel price. The impact of these parameters is summarized in figure 2 which shows  
42 the influence of fuel price on the utility and thus on the decision of the household for every  
43 alternative. Higher utility means that the alternative is more likely to be chosen. The graph  
44 assumes all other parameters equal to make the different curves of the alternatives comparable.

**FIGURE 2 Influence of Fuel Price on Utility of Model B**



1 The x-axis indicates the fuel price from 0 to the maximum of CHF 5.5 per liter (USD  
 2 27 per gallon as of July 2011); the value range in the survey. Three different shapes can be  
 3 distinguished: linearly negative for gasoline cars and Full-sized diesel cars, parabolic for other  
 4 diesel cars and Micro gasoline cars linearly positive for ADT. The best visible parabolic curves  
 5 are for these three diesel cars: MiniMVP, Mid-sized and Luxus. Households do not want do  
 6 down-grade initially when fuel gets expensive but rather switch to diesel cars that have a lower  
 7 consumption. Switching increases up to a price level of about CHF 3.0 per liter (USD 15 per  
 8 gallon), after that level utility declines also for diesel cars. Car types with higher consumption  
 9 tend to be more negatively influenced by fuel prices as expected.

10 Utility of ADT increases with fuel prices, although only weakly. The maximum differences  
 11 between the maximum and minimum is only about a fifth of the differences for gasoline sports  
 12 cars. But still the results indicate that households begin to switch also to ADT cars, but only  
 13 when fuel prices get very high, or in other words: Fuel needs to be extremely expensive to  
 14 overcome the lack of comfort and capability of ADT cars that still exists. We can assume that  
 15 results would look different in ten years if the comfort gap was shrunk by then.

16 **Individual Satiation of VMT**

17 Above we stated that the influence of income on choice is smaller than in the allocation of VMT.  
 18 This makes sense considering the following: Households with higher income may also have  
 19 more cars than ones with lower income and the second or third car is often a smaller than the first.  
 20 That means that car types are more equally distributed over income levels than VMT allocated  
 21 to them. The satiation parameter determines how much VMT is allocated to a car type once it is  
 22 chosen. Satiation for Sport-cars and Luxus-cars is low, that means that if a household owns such  
 23 a car, it is likely to be used often. This is also true for Public Transport and to MiniMVP-cars,  
 24 which are often used by families. Small diesel cars are used less frequently when chosen than

1 their gasoline counterparts, indicating that they usually function as secondary car.

2 As mentioned, the effect of Income on the satiation for allocating VMT is interesting. In  
3 general the effect is negative, meaning that higher income means more VMT which this particular  
4 car type. However, for MiniMVP (family-car) and ADT higher income means less use of this  
5 type. While lower income people depend more on these car types, richer household can afford  
6 own such a car for status reasons or because they are interested in the technology while relying  
7 on other (conventional) car types for traveling. A direct policy advise that would follow from  
8 this is if ADT are to be promoted for environmental reasons, it would be important to focus on  
9 lower income families because here usage is much higher.

10 The influence of fuel price on satiation is much weaker, but is strongest also for family-cars  
11 and ADT-cars. This is interesting insofar that high fuel prices gives additional satiation mainly  
12 to cars that have already a high efficiency. When households decide to switch to more efficient  
13 cars due to high fuel prices, they also reduce the allocated VMT, which is surprising in first view.  
14 The interpretation resulting is that the VMT of an existing (or well known) fleet is very inelastic  
15 to fuel prices and more determined by commuting distance and lifestyle choices. The first  
16 reaction would be to change the car to a more efficient diesel or smaller gasoline car that fits the  
17 accustomed lifestyle best. When fuel prices are so high that a more severe change is necessary, a  
18 switch to ADT is needed that comes with a change of lifestyle and results in adjusted VMT. The  
19 associated lifestyle change may come from the fact that the offer of ADT cars is much smaller  
20 than for conventional cars and they still differ in convenience and range. If ADT-technology  
21 manages to adapt further to the comfort and lifestyle level of conventional cars in the future, this  
22 behavior may be different, and the usage of ADT begins at lower fuel prices and for broader  
23 layers.

24 The satiation parameters  $\gamma = f(\text{Income, fuel price})$  describe the decreasing marginal utility  
25 with an increasing amount of traveled kilometer. The  $\theta$  constant is highly significant. The more  
26 luxurious the car type, the lower that constant. That means that people are more likely to  
27 allocate their annual mileage in the more luxurious of two or more cars. For example: the main  
28 car, with a higher mileage, is the bigger, more comfortable car and the second car is for the case  
29 the first is not available. Cars with alternative fuel are not likely to be affected by reduction,  
30 meaning that if one has for example a hybrid car, the person is not likely to have a second car  
31 with which it drives even more. Income has the expected influence on the satiation such that  
32 higher income gives less satiation throughout all car types except alternative fuels. Fuel price  
33 has almost no significant impact on satiation which is surprising.

## CONCLUSION

1 The model presented is not the first one using a multiple discrete-continuous framework to  
2 model car choice and use simultaneously. But it is the first that includes a wide range fuel prices  
3 as explanatory variable. The model gives insight in how car choice and car use is influenced  
4 by fuel price. The low effect of fuel price on satiation and strong impact on car type choice  
5 indicates that car use is inelastic regarding fuel price compared to car type selection. Household  
6 are willing to change the car type, especially switch to diesel car with less consumption but  
7 they will not reduce their VMT substantially. This indicates for further policy consideration  
8 that, given a choice set with sufficient low consumption alternatives, a rise in fuel price would  
9 lower the overall consumption and the environmental burden, but not diminish the mobility of  
10 the population. But it also shows that for this purpose very high fuel prices are necessary.

11 A study of Ewing and Sarigöllü (29) using discrete choice experiments showed a preference  
12 for cleaner vehicle in the case of equal comfort and capability. The gap between the current  
13 level of fuel prices and the level where households switch to ADT can be seen as a willingness  
14 to pay for the comfort differences between gasoline/diesel and ADT vehicles. A optimal policy  
15 approach would consider a mixture of closing that gap by both increase fuel prices and decrease  
16 the differences in comfort. Further research in this area would be to repeat a similar survey not  
17 only in other regions than Switzerland, but also after a few years when the choice set of car  
18 types with ADT has increased and the comfort gap has decreased. Further research should also  
19 include electric vehicles more explicitly than in this work. When the survey was conducted only  
20 few electric vehicles were available in the market and they were not broadly known. Given the  
21 technological development in the field the situation might be very different within the next five  
22 years.

23 The other conclusion we can draw from this work is that the multiple discrete-continuous  
24 framework used is appropriate and useful. Performance tests of disaggregate simulation of  
25 the model have confirmed this finding. The classification is reasonable although limited to 17  
26 alternatives. Future work includes further exploration of the existing data set with a greater  
27 (or different) choice set classification and a nested structure to capture similarities between  
28 drive-train technologies or other attributes.



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