Stated Response and Multiple Discrete-Continuous Choice Models: Analyses of Residuals

Boris Jäggi

Claude Weis

Kay W. Axhausen

Transport Planning and Systems **July 2011**

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Transport Planning and Systems

Stated Response and Multiple Discrete-Continuous Choice Models: Analyses of Residuals

Boris Jäggi	Claude Weis	Kay W. Axhausen
IVT	IVT	IVT
ETH Zurich	ETH Zurich	ETH Zurich
CH-8093 Zurich	CH-8093 Zurich	CH-8093 Zurich
phone: +41-44-633 67 37	phone: +41-44-633 39 52	phone: +41-44-633 39 43
fax: +41-44-633 10 57	fax: +41-44-633 10 57	fax: +41-44-633 10 57
boris.jaeggi@ivt.baug.ethz.ch	weis@ivt.baug.ethz.ch	axhausen@ivt.baug.ethz.ch

July 2011

Abstract

In sophisticated transport models choice modeling is used to capture a wide range of behaviors, such as mode choice, fleet choice or route choice. A newly developed approach to improve realism is the multiple discrete-continuous extreme value (MDCEV) model, which allows to model the allocation of continuous amounts of a consumption good. Before using this models in overall frameworks, knowledge about the accuracy of the forecasting procedure is important. In this paper a MDCEV model of fleet choice based on data collected in a Stated Adaptation survey is presented. A forecast of the model predicting annual mileage of households to 17 different car types was made and the results were compared to the actual data calculating the residuals. The residual analysis shows that the model performs significantly better than a totally random model, but the share of wrongly allocated mileage, 70% of total, remains high. However an assessment of the result is difficult with only one model. The differences between two sub-models, one without public transport, another including it, regarding the distribution of the residuals indicate that the model specification has a big influence on its performance. Therefore, following work forecasting additional MDCEV models will be necessary to have a base for comparison. We compare two further MDCEV models to obtain a fuller understanding of their performance.

Keywords

Stated Preference, Stated Adaption, Fleet Choice, MDCEV, Forecast, Simulation, Residual, Validation

1 Introduction

In sophisticated transport models like the SACSIM model of the Sacramento Area, California (Bradley *et al.*, 2010), the ILUTE model in Toronto (Salvini and Miller, 2005) or the Albatross model from the Netherlands (Beckx *et al.*, 2009), choice modeling is used to capture a wide range of behaviors, such as mode choice, fleet choice or route choice. Discrete choice models in their standard formulations cannot integrate multivariate choices and associated continuous attributes of these choices. Still, there a number of questions where this capability would allow the modeler to improve the realism of the description. One prime example is the composition of the fleet of mobility tools (Simma *et al.*, 2002; Simma and Axhausen, 2003, 2001b,a) and their associated mileage. The recent development of the MCDEV framework by Bhat (2005) offers a new approach to address this gap.

The overall transport model currently developed at IVT in collaboration with TU-Berlin is MATSim (Balmer, 2007; Meister *et al.*, 2009; Balmer *et al.*, 2008) , an agent based micro-simulation tool for travel demand and traffic flow modeling. The present paper is part of the ongoing work to implement multiple discrete-continuous extreme value (MDCEV) models into the model frameworks of different fields. As our and the literature's experience in the use of this approach is, given its recent development, small, an evaluation of actual forecasting results and their residuals is necessary.

In MATSim travel demand is activity based and generated using activity chains from the Swiss national travel diary survey, the Mikrozensus (Swiss Federal Statistical Office, 2006).The Mikrozensus is conducted every five years. In the current version of MATSim, the agents can conduct activities (e.g. home, shopping, work, leisure, etc.) inside facilities (buildings). In the iterative solution process the agents optimize their given activity chain. The agents are not part of a household and they have no specific car type allocated to them yet. They only have an attribute that describes their car availability for the mode choice processes.

As a future development of MATSim, the agents shall be pooled in households and specific car fleets will be allocated to the households. This will not only enable analysis of energy consumption on a microscopic level, but also allow the implementation of a behavioral model to forecast the development of the car fleet and, as a result, of the energy consumption. The first step for these enhancements is a fleet ownership model.

Such a model is estimated using the MDCEV approach by Bhat (2005) on Stated Adaptation data collected in a survey conducted by Erath and Axhausen (2010). To test the performance of such a model for an application like MATSim, we applied a MDCEV model repeatedly and analyzed the residuals comparing the results to the actual choices in the experiment. Since 2004, when the MDCEV model was originally developed to analyze time use (Bhat, 2005), various researchers have used it to estimate preferences. (Sen, 2006) presented a MDCEV Model in the context of examining vehicle type, model and usage decisions of households in his dissertation Bhat and Sen (2006). The impact of demographics, built environment attributes, vehicle characteristics and gasoline prices on the same issue are analyzed in (Bhat *et al.*, 2009). Pinjari *et al.* (2009) analyzed residential self-selection effects in time-use models and Spissu *et al.* (2009) presented an analysis of weekly out-of-home activity participation. Copperman and Bhat (2007) analyzed the determinants of childrens week end activity participation. In Pinjari and Bhat (2010b), the authors introduce the nested version of the MDCEV, the multiple discrete-continuous nested extreme value (MDCNEV) model and present an application on non-worker time-use behavior. A detailed description of the MDCEV and the role of its parameters can be found in (Bhat, 2008).

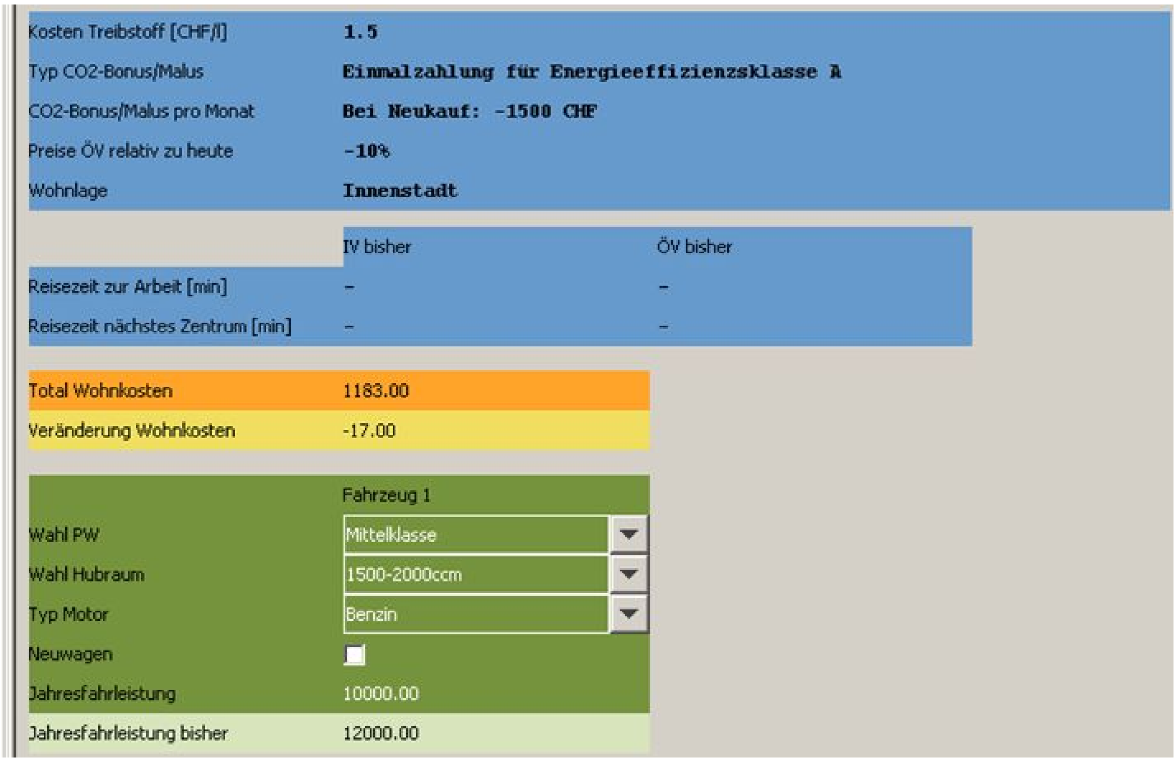
Pinjari and Bhat (2010a) presented an efficient forecasting procedure for such models. We intend to test the performance of MDCEV forecasting results with our Stated Adaption data sets about fleet choice, energy savings in household and private transport and induced demand. Unfortunately we could not find any useful literature on the topic of disaggregate validation on (multiple) discrete-continuous models. In most MNL models, validation happens on an aggregate level by comparing actual with predicted market shares, as done for MNL models since the their introduction, for example in (Train, 1978). In the case of multiple discrete-continuous models however, a disaggregate validation is more valuable because it gives more insight in the model's characteristics.

2 Data

2.1 Survey

The primary data set used here was collected within a project funded by the Swiss Federal Office of Energy and the Federal Office for the Environment on long term fuel price elasticity and the effects on mobility tool ownership and residential location choice (Erath and Axhausen, 2010). In the survey, 409 households were questioned about their long term reactions to rising fuel costs. The survey was divided in a part on socioeconomic and mobility tool related questions and a three stage stated response survey. In the first part, the respondents are presented six scenarios of fuel prices ranging from CHF 1.5/l to CHF 5.5/l for gasoline. The survey was conducted in face-to-face interviews, in which the interviewer was equipped with a computer-software that simultaneously calculated the personalized mobility costs (fixed cost separate from variable cost) based on personal information collected previously. The respondents could choose their car fleet and annual mileage for every chosen car at a high level of detail including car type,

Figure 1: Screen shot of interactive computer software used in the survey



engine size, drive-train, and if they would buy a new or a used car, while being supported by the real time calculations of the computer. Public transport season tickets, a common alternative, was always available as a choice. Figure 1 shows a screen shot of the survey.

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

2.2 Data Overview

The representativeness of the data in term of mobility tools, car ownership and socioeconomic variables is summarized in table 1. The column MZ describes the targeted share according to the Swiss national transport survey (Swiss Federal Statistical Office, 2006), the column sample the actual share in the survey. In our data, male participants are slightly over-represented, as well as the age group of 36-50 years old. We have also a significantly higher share of single person household and persons without a public transport season ticket. In terms existing fleet composition, the most frequent car types, such as upper middle class, middle class, minivan and compact, are under-represented while the more special ones like sports car and micro are over-represented. The income distribution is matched reasonably well, although there are more high income households than expected.

3 Methodology

3.1 MDCEV

The methodology used in this fleet choice model is the multiple discrete-continuous extreme value (MDCEV) approach developed by Bhat (2005). In his paper he gives a detailed description and derivation of the model. The following section is a short summary of the third chapter of the paper. The MDCEV was originally developed to estimate the influence of attributes on the decisions of allocating time (continuous) to activities (discrete) within a 24-hour budget. Because the various activities are equivalent and simultaneously chosen for each day the model considers multiple chosen alternatives. In the presented model, the discrete choices are car types, the continuous amount is annual mileage (VMT) and it is a multiple discrete model because households can own and use more than one car simultaneously.

Kim *et al.* (2002) defines the utility an individual obtains for his decisions as a sum over all j alternatives (in our case: car types):

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

In this utility structure, t_j is the continuous amount of annual mileage driven with car type j (j = 1,2,...,K), γ_j and α_j are satiation parameter to estimated within the model. The function $\psi(x_j,\varepsilon_j)$ gives the baseline utility function for the mileage driven with car type j. In section 3.1 of his paper, Bhat (2005) presents a random utility function for the baseline utility:

$$\psi(x_j, \varepsilon_j) = \exp(\beta' x_j + \varepsilon_j) \tag{2}$$

In which β' is a vector of parameters that define the influence of the observed characteristics of

Table 1: Sample Characteristics

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

the alternative x_j. ε_j captures the unobserved random utility. By combining the formulas (1) and

(2) the overall random utility function for the MDCEV model can be defined as:

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

By forming the Lagrangian and applying the Kuhn-Tucker conditions and assuming that the optimal allocation of annual mileage satisfies the budget constraint $\sum_{j=1}^{K} t_j^* = T$, the probability function can be derived. Bhat specifies a standard extreme value distribution for ε_j and assumes that it is independent from x_j as well as independently distributed across alternatives. The final result for the probability function is:

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

whereas:

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

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

3.2 Fleet Choice Model

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

For the estimation process, the Gauss code provided at Bhat's Web-page (Bhat, 2011) is used. The programm 'No Outside Good' is used and two configurations were tested. In the first the estimated satiation parameters of the model are α parameters and the γ values are constraint to be equal to one for all goods. In this case, the specific utility function is:

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

In the other configuration tested γ parameters are estimated while α values are fixed to be equal 0. In that case, the specific utility function is:

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

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

With the software application used in the interviews, the respondents could determine the type of every car choosing among nine different car types, five classes of engine size, five drive-trains(gasoline, diesel, natural gas, hybrid, electric) vehicle) and wether it would be a newly bought car or a used car (used means either to keep the currently owned car or to buy a second hand car). The options give 9·5·5·2 = 450 alternatives, which requires a classification.

The choices were classified in two different choice sets allowing to test two different model specifications. Both choice sets included 17 alternatives distinguishing between gasoline, diesel and alternative drive-trains (ATD) and between the separate car types.

The choice set of Model A, shown in table 2, also distinguished between new and used cars on the cost of grouping the car types into three groups: small, middle and large/luxurious cars. Model B neglects to discriminate between used or new cars but enables more distinction between car types, as shown in table 3. Both choice sets contain 16 car alternative and one alternative for public transport. 17 was an upper bound for alternatives due to computational reasons. The variable observations is how often this alternative was chosen as first car to give a sense of the distribution of the classification and explains why certain car types are put together.

The model used for this paper has no outside good, meaning that there was no alternative that was chosen in every observation. It is obvious that there is no car type which has to be chosen by

Table 2: Alternatives for Fleet Choice Model A

Alternative	New/Used	Drive-train	Car Types	Engine Size	Observations
A1	New	Diesel	Micro, Subcompact, Compact		160
A2	New	Diesel	Mini MPV, MiniVan Mid-Sized		89
A3	New	Diesel	Luxurious, Sports-car Full-Sized		76
A4	New	Gas, Hybrid, Electric			119
A5	New	Gasoline	Micro, Subcompact, Compact	<1500 cm^3	279
A6	New	Gasoline	Micro, Subcompact, Compact	>1500 cm^3	110
A7	New	Gasoline	Mini MPV, MiniVan Mid-Sized		155
A8	New	Gasoline	Luxurious, Sports-car Full-Sized		123
Not included					94
A10	Used	Diesel	Micro, Subcompact, Compact		170
A11	Used	Diesel	Mini MPV, MiniVan Mid-Sized		141
A12	Used	Diesel	Luxurious, Sports-car Full-Sized		49
A13	Used	Gas, Hybrid, Electric			136
A14	Used	Gasoline	Micro, Subcompact, Compact	<1500 cm^3	272
A15	Used	Gasoline	Micro, Subcompact, Compact	>1500 cm^3	135
A16	Used	Gasoline	Mini MPV, MiniVan Mid-Sized		198
A17	Used	Gasoline	Luxurious, Sports-car Full-Sized		130
A99			Public Transport		

Table 3: Alternatives for Fleet Choice Model B

Alternative	**Drive-train**	**Car Types**	**Observations**
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	

all households, as for example 'in home time' in time use models or 'housing costs' in financial allocation models.

For the estimation process, the Gauss code provided at Bhat's Web-page (Bhat, 2011) is used. The programm 'No Outside Good' is used and both configurations 'config' = 1 and 'config' = 4 were tested. 'config' = 1 means, that the estimated satiation parameters of the model are α parameters and the γ values are constraint to be equal to one for all goods. In this case, the specific utility function is:

$$U(t) = \sum_{j=1}^{K} \frac{1}{\alpha_j} \exp(\beta' x_j + \varepsilon_j) \cdot \{(t_j + 1)^{\alpha_j} - 1\} \tag{8}$$

The other configuration tested for the presented work is 'config' = 4, meaning that γ parameters are estimated while α values are fixed to be equal 0. In that case, the specific utility function is:

$$U(t) = \sum_{j=1}^{K} \gamma_j \cdot \exp(\beta' x_j + \varepsilon_j) \cdot \ln\left(\frac{x_j}{\gamma_j} + 1\right) \tag{9}$$

The models estimated assumed satiation parameters that differ across individuals. The γ parameters are estimated as a function of household income, fuel price and a constant. We did not reach convergence for models using α parameters differing across individuals in the given time frame. Because of this, and because of the slightly better model fit, only results using γ satiation parameters are presented in this paper.

3.3 Forecasting procedure

The forecasting procedure as well as the Gauss code used for this paper were developed and introduced by Pinjari and Bhat (2010a). In chapter four of his paper, two algorithms are presented, one for estimations with γ_j as satiation parameters and a fixed α, and one for estimations with α_j as satiation parameters. The algorithms presented in the paper are both for models with outside goods. On the Web-page of Bhat (2011), the Gauss code of the forecasting procedure can be downloaded.

In the first step of the algorithm, the baseline utilities $\exp(\beta' x_j + \varepsilon_j)$ of all alternatives are calculated out of the model parameters β , the input data and the Gumbel distributed unobserved utility ε. In the code developed by Pinjari and Bhat (2010a), the random numbers used are from a Halton-Sequence, after Halton (1960). In the current work, random numbers were drawn on the fly with the random function of the Gauss programm.

The 17 alternatives are then sorted in decreasing baseline utility and it is assumed that the first alternative is chosen. To check if a second alternative (with the second highest baseline utility) is chosen, an estimate of the overall budget is calculated. If the estimated budget is smaller than the actual budget, the next alternative in line is considered, until the budget is exhausted. If the estimated budget is higher than the actual, an iterative procedure, described in detail in (Pinjari and Bhat, 2010a), is used to find an adjusted baseline utility for the last alternative to meet the actual budget within a tolerance band.

After the exact number of chosen alternatives is determined, the mileage allocated to every of the chosen alternatives is calculated using the adjusted baseline utility of the previous steps and the satiation parameters γ.

The above algorithm calculates the consumption data (mileage) for one observation. It can be repeated multiple times to achieve more robust results. In the current work simulations with 10 repetitions and 50 repetitions are calculated, presented and compared.

4 Results

4.1 Estimation Results

Table 4 and table 5 show the estimated β -parameters for the two Models. Please note that **boldly** written numbers are significant at a 95% level and numbers written in *italic* are significant at a 90% level. The Alternatives are labeled according to table 2 and table 3. For an easier and quicker reading of the table, an indication is given in the column "Alternative", where the car type (-group) is indicated. In Model A, A1 to A8 are new cars, A9 to A17 are used cars. In Model B, D means diesel and B means gasoline.

The satiation parameters presented are θ-parameters. To model γ parameters that differ across individuals, they are parameterized in the following form, dependent of monthly household income and given fuel price:

$$\gamma_j = \exp(\theta_C + \theta_I \cdot Income + \theta_F \cdot Fuelprice) \tag{10}$$

The variable Const is the alternative specific constant. One can see that new gasoline cars, which are the majority of cars available on the market, have no significant negative value, in contrast to other car types. The strongest negative constants have luxurious car types in both Models, as they are the also the most expensive ones. Public Transport has a strong constant in both Models.

Income is gross household income in 1'000 CHF per month. The significant effect of this variable is, that high income households are more likely to buy luxurious and middle class cars. Interestingly, car types with alternative drive-trains (ADT) – A4, A13, Other – are negatively influenced by income, although they are more expensive. This indicates that early adopters are not necessarily high income people. In general the effect of income is not as strong as expected but has a stronger influence on the satiation parameters.

Fuel is the fuel price, varying in the experiment from 1.5 CHF/l to 5.5 CHF/l, Fuel^2 is the square of the fuel price. The higher the fuel price, the most alternatives are less likely to be chosen, except for ADT alternatives and diesel types with a quadratic fuel price function. In the case of

Table 4: Estimated β Parameters of Fleet Choice Model A, mean log likelihood: -3.41

Alternative	Const	Income	Fuel	Fuel2	DistW	Male	Urban	Inertia	Ac.1	Ac.2	GA	HT	SC	θ_C	θ_I	θ_F
A1 (small)														**2.60**	**-0.14**	0.18
A2 (middle)	-7.81	0.02	1.03	**-0.18**	0.52	-0.25	-0.07	1.15						*18.19*	-0.08	*-3.29*
A3 (lux)	-7.43	0.02	*0.75*	**-0.14**	0.24	**0.52**	0.34	2.76						1.02	0.09	-0.11
A4 (hybrid)	-1.02	-0.03	*0.13*		0.42	**-1.41**	0.23	-6.06	0.01	-0.01				0.64	2.61	1.69
A5 (small)	*0.93*	**-0.06**	**-0.17**		0.44	**-0.40**	0.04	**1.43**						**1.42**	**-0.13**	0.04
A6 (small)	0.31	0.02	**-0.40**		0.57	0.04	0.18	**1.57**						**1.44**	**-0.08**	-0.02
A7 (middle)	0.34	0.01	**-0.38**		0.29	-0.15	*0.29*	**2.20**						**2.74**	**-0.15**	-0.08
A8 (lux)	-0.34	0.00	**-0.53**		*0.63*	**-0.43**	*-0.31*	**5.20**						**1.46**	-0.04	**-0.24**
A10 (small)	-0.33	*-0.05*	**-0.23**		*0.67*	**0.49**	-0.22	**2.10**						**5.28**	**-0.35**	0.04
A11 (middle)	-7.32	**0.14**	0.18	*-0.08*	**1.28**	0.10	*0.31*	**2.58**						**2.00**	*-0.08*	-0.01
A12 (lux)	**-2.67**	**0.17**	**-0.29**		**1.58**	**1.17**	**0.70**	**3.30**						1.07	-0.01	0.16
A13 (hybrid)	0.62	-0.03	0.10		**1.01**	**-0.77**	0.28	**3.51**	0.01	-0.01				0.38	1.95	1.43
A14 (small)	0.00	-0.02	**-0.34**		**1.31**	**-0.48**	0.24	**3.13**						**1.69**	**-0.11**	-0.05
A15 (small)	-0.56	0.02	**-0.32**		**1.57**	0.30	0.10	**2.30**						**5.06**	**-0.28**	-0.19
A16 (middle)	0.55	**0.07**	**-0.57**		**1.23**	-0.13	**0.72**	**3.27**						0.89	2.42	1.76
A17 (lux)	*-1.96*	**0.09**	**-0.63**		**1.04**	**0.65**	**-0.65**	**6.78**						**2.19**	**-0.19**	*0.19*
A99 (PT)	**4.40**	**-0.06**	**-0.29**		**1.02**	**-0.33**	**0.36**		0.01	-0.01	**2.24**	**1.06**	**1.42**	**-4.14**	**0.09**	**0.06**

Table 5: Estimated β Parameters of Fleet Choice Model B, mean log likelihood: -2.70

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

rising fuel prices people with less efficient gasoline cars would switch to diesel until a certain fuel price is reached before adjusting the annual milage or buying a hybrid or electric car.

Dist. is the respondent's distance between home and workplace in 100 km. All alternatives have a high parameter for commuting distance. That means that people with longer distance to the workplace tend to own more cars, because the utility of making the discrete choice for every car type increases in Model B. Distinguishing between new and used cars as in Model A, we see that long commuters prefer used cars.

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

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

Urban is a dummy which is equal one for people living in inner city or urban areas and zero for people in suburbs and rural areas. Resident location has not a big influence on fleet choice, except that public transport and ADT are preferred in urban areas, which is plausible.

Inertia is a dummy to capture inertia effects. It is one if the chosen car type is one of the actual cars types the household already owns. This has the expected significant and substantial influence, because it can be considered as capturing a substantial part of unobserved influence that led to the decision for the specific car type. The higher this parameter, the more likely the car type is chosen because it is already known. To lower this parameter, the more this alternative is considered to be a car type to change to. The parameter is smaller for all diesel alternatives, indicating that households switch from gasoline to diesel. The smaller the car type, the more likely it is to be switched to.

Acc.1 and Acc.2 are two variables for accessability, coming from a factor analysis of private transport accessability and public transport accessability, based on a national aggregate transport model (**?**). Acc.1 stands for general accessability of the respondent's home municipality and Acc.2 for any differences in public transport accessability. Effects are only found in Model B. ADT are more often chosen in areas with higher accessability in comparison to gasoline and diesel cars, and the effect is even greater for the public transport accessability.

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

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

4.2 Forecasting Results

4.2.1 Stated Adaption MDCEV Models for Comparison

In this section two further models that also use Stated Adaption data sets for MDCEV modeling are briefly presented. The models differ in terms of context, survey methodology, sample size and, most importantly, number of available alternatives. This allows us to draw a broader picture of different possible outcomes of forecasting MDCEV models and their assessment. It is important to note that the assessment presented in the following sections is an assessment of the specific models and to some extent also of MDCEV models based on stated response data rather than an assessment of the MDCEV methodology per se.

The first model used for comparison is the Priority Evaluator (PE) model. The data set was collected in a survey of homeowners about investment in energy efficiency in housing and mobility, described in (Jäggi and Axhausen, 2010). The participants of this survey were presented with their annual energy consumption in an internet tool using the Priority Evaluator method by Hoinville (1977). The detailed energy consumption of every household was previously recorded in a paper and pen survey. The participants were asked to reduce the energy consumption of the household by selecting among different measures such as insulating the facade, replacing the windows, installing a heat pump, buy a more efficient car or fly less. Although the potential energy savings of every measures were pre-specified for each participant, it is assumed that the participants could determine the pattern of energy reduction well, thanks to the interactive nature of the internet tool. The continuous amount is the energy saved and the budget the total reduction. In this special form of MDCEV model, persons do not maximize utility by buying goods, but minimize damage by allocating bads. The number of alternatives in the model is 12, the number of observations is 197.

The second model used for comparison is the Induced Demand (ID) model. The data set was collected in a survey about th reactions of travelers to changing travel times. The survey was is described in Weis *et al.* (2010). The participants in this survey were confronted with significant changes in travel time (between -30 and + 90minutes) to a previously reported, typical schedule. The survey was conducted using face-to-face interviews supported by computer software, so that the participants could adjust their activity schedules interactively. The adjustments are categorized in three alternatives: change of departure time, change of activity time and change of travel time. The continuous amount is time and the budget the total compensation of travel time stated by the respondents. The number of alternatives in the model is 3, the number of observations is 612.

4.2.2 Disaggregate Simulation Results

In this section, the results of the forecasting procedure for the above mentioned models are presented, compared and analyzed. The simulation results of the fleet choice model are eventually to be used to allocate car types to households and agents in the MATSim environment and thus are part of a wider transport modeling framework. In this context it is of importance to know about the accuracy of the predictions and to have indicators to evaluate and compare the models. The tools in this paper are hit ratio and the absolute and relative residuals, calculated as the differences between the forecast and the data used for the estimation. The predictions are also tested for their stability by comparing the results of forecasts with 10 or 50 repetitions.

The hit ratio gives the percentage of chosen alternatives in observed data, that are matched in the forecast (discrete choice only). The hit ratio is calculated for every repetition separately, and then the mean is taken. For example, if in the observed data mileage is allocated to alternatives A1, A2 and A3, and in the forecast to alternatives A3 and A4, then the hit ratio is 33.33% because one third of the observed choices are matched.

$$HR = \frac{N_{match}}{N_{data}} \tag{11}$$

To calculate the residuals, the mean of the predicted mileage for every alternative is taken over all repetitions. The residuals are calculated with the formula

$$R_{abs} = \sum_{j=1}^{K} \frac{|t_j - \hat{t}_j|}{2} \tag{12}$$

while $\hat{t}_j$ is the predicted amount of mileage and t_j the observed value. The differences are divided by 2 because otherwise the mileage would show up twice in the residual, one time in the alternative it is falsely allocated an one time in the alternative it should have been allocated but was not.

Because the mileage budget differs among observations, in contrast to e.g. time-use models, only residuals relative to the total amount of annual mileage of the observation can be used for comparison, as shown in equation (13).

$$R_{rel} = \frac{R_{abs}}{\sum_{j=1}^{K} t_j} \tag{13}$$

This also allows a standardized comparison between different models with different budgets, as done the next section. Table 6 shows the hit ratio and the residuals for the forecasts of the two fleet choice models with different repetitions per observation as well as for different satiation parameters. The reference model of the last row of table 6 is derived from a forecast with all parameters set to zero. The same values are also calculated for the two comparison models, PE and ID. It is important to consider that these values should not be compared across models, but instead the improvement between reference and actual model.

Table 6 allows us to analyze the influence of several factors on simulation performance comparing the different specifications. At first we see that the number of simulation draws has only small influence on the quality of the results, as with 10 draws for each observation the same residuals are achieved as with 50.

The second thing we see is that the model specifications lead to substantial improvement in performance compared to the random model. The models using α-satiation performed worse than the ones with γ-satiation. The exclusion of the public transport alternative let to higher hit ratios and lower residuals (better performance) using α-satiation the reverse effect with γ-satiation. The best specification of the Model A choice set was achieved using γ-satiation and including the public transport alternative, as shown in table 4. Compared to the worst specification of Model A it could allocate an additional 6.5% of the overall budget correctly. Nevertheless with this models, still only about 35% of the overall budget was allocated correctly.

Table 6: Model Simulation Overview

				Hit Ratio [%]			R_{rel} [%]		
Model	Alt.	Sat.	Rep	**Mean**	< 5%	> 50%	1. Quartile	**Mean**	3. Quart
Ref. Model			50	**8.7**	14.3	0.0	85.4	**88.9**	92.9
Model A, no PT	16	α	10	**39.6**	40.0	35.8	45.1	**70.7**	100.0
Model A, no PT	16	α	50	**39.6**	39.0	37.8	43.4	**70.5**	100.0
Model A	17	α	10	**25.3**	11.1	1.2	57.6	**71.9**	90.0
Model A	17	α	50	**25.3**	8.3	1.4	57.6	**71.3**	87.6
Model A, no PT	16	γ	50	**36.8**	41.1	34.2	43.1	**69.3**	100.0
Model A	17	γ	50	**55.3**	12.9	47.3	42.6	**65.4**	90.9
Model B	17	γ	50	**66.5**	12.3	56.6	10.7	**48.7**	90.0
MNL Model	17	-	-	**25.4**	51.6	5.6	16.7	**76.2**	95.5
PE Ref. Model			50	**51.7**	0.0	69.0	59.2	**67.1**	75.4
PE Model	12	γ	50	**78.7**	5.1	93.3	40.0	**52.8**	66.8
ID Ref. Model			50	**58.7**	10.5	54.7	31.9	**65.9**	100.0
ID Model	3	γ	50	**59.5**	4.2	68.0	0.0	**56.7**	100.0

The more detailed distinction between car types of Model B leads to better performance. The model, showed in table 5 is able to allocated more than half of the overall budget correctly (R_{Rel} = 48.7%), and manages to reproduce almost two third of unobserved choices (HR = 66.5%). Thus we can identify this Model specification as the best one for this data set so far. For comparison reasons a simple MNL Model was estimated and simulated, using the choice set and variable specifications of Model B. For the estimation of the MNL Model only one alternative is chosen, the one with the highest VMT. For the enumeration, the overall budget was allocated entirely to this single chosen alternative, so that the simulation results are perfectly comparable. The performance is substantially worse in every regard, confirming the assumption that more sophisticated modeling frameworks like MDCEVs enable substantially better models.

The hit ratios of the two comparison models are significantly higher, because less alternatives are involved. In the ID model with only three alternatives, even the reference model has a high hit ratio. This is also true for the PE model, where usually about three to 7 out of 12 alternatives are chosen. A overview over all models about the number of alternatives chosen and the percentage of corner solution is given in table 7. We can also see that for some of the fleet choice model specifications, about 40% of all cases have a hit ratio of <5% and can be considered as a total failure.

On the other side, the relative residual is not determined by the number of alternatives and thus a better measures for comparisons. The best fleet choice model could achieve a reduction of 40.2% of mean relative residual compared to reference model. The PE model achieved a reduction of 14.3% and the ID model one of 9.2%. Whether this numbers can be considered as especially low or acceptable cannot be determined yet. But they give a first set for an assessment of further models.

Looking at the distribution of residuals supports the findings of the hit ratio. Figure 2 shows the distributions for the reference model and Model A, both excluding and including the public transport alternative. All of them were calculated using 50 repetitions.

The shapes of the distributions differ among the three models. The bars in the figure shows in each case how many predictions are made within a 2% range, e.g., in the reference model, in about 13% of the cases, the R_{rel} value is between 0.9 and 0.92. In this, totally random model, all of the forecasts are between 65% and 100% wrong, with the expected shape of a gumbel distribution. The estimated models have a totally different shape: Except the almost 40% completely wrong cases excluding PT (see hit ratio numbers) and the 16% of the model including PT, the relative residuals are fairly equally distributed. The big improvement of the PT model is the much smaller portion of completely false predictions Nevertheless, a share of 16% wrongly predicted observations is still high.

Figure 3 shows the residual distribution of Model B and the MNL model. The residuals have again a different shape, with a substantial number of both correct and wrong allocations. The MNL model has a high share of completely false allocations due to the model characteristic of only one chosen alternative: if the wrong alternative is chosen R_{rel} is one. Model B however has a significant share of relatively good predictions.

The shapes of the residual distributions of the two comparison models, the PE and ID model, differ significantly from the ones of the fleet choice models, as shown in figures 4 and **??**. While the PE residuals are approximately normally distributed, in both random and specified cases, ID residuals have a step like shape with a large part of completely false forecasts (30%), a large part of completely correct forecasts (30%) and a equal distribution in between. On what these different characteristics depend on is difficult to say. Our results strongly indicate that it is less a matter of specification but of data set.

One hypothesis is that the share of wrong forecasts depends on the percentage of non-chosen alternatives or corner solutions. Table 7 gives an overview of this relationship for the presented models:

Figure 2: Distribution of Residuals: Fleet Choice Model A

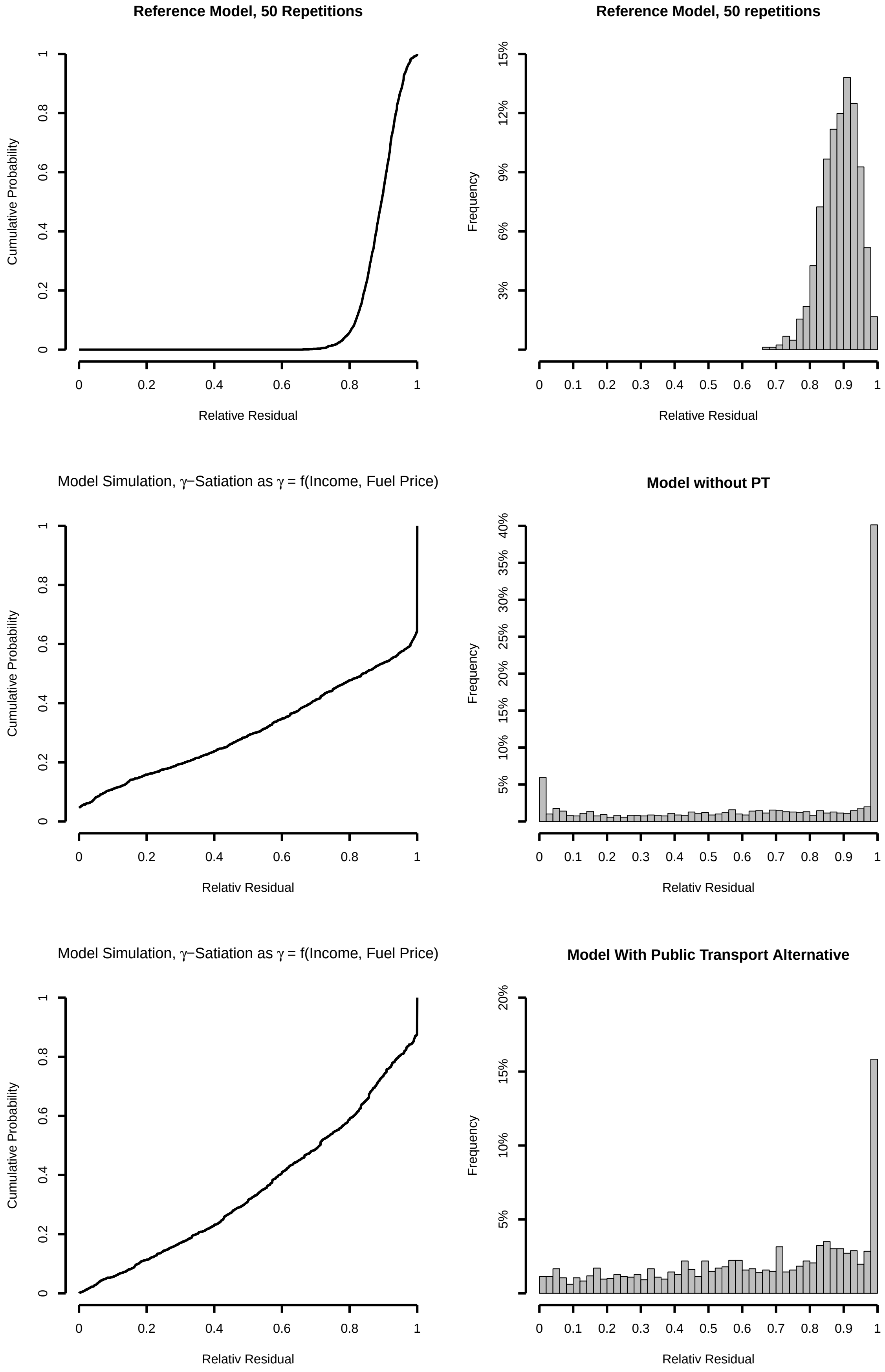
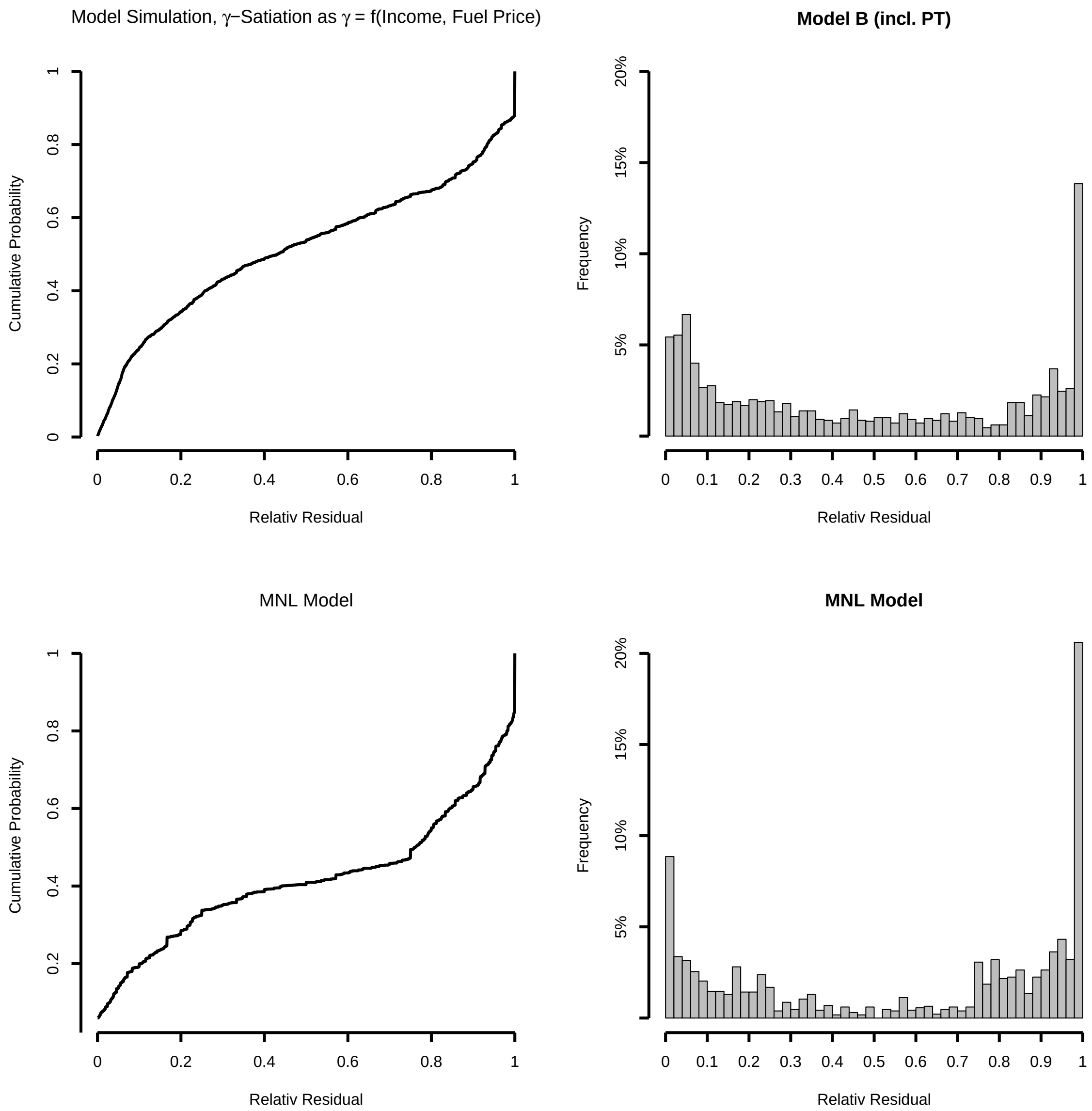
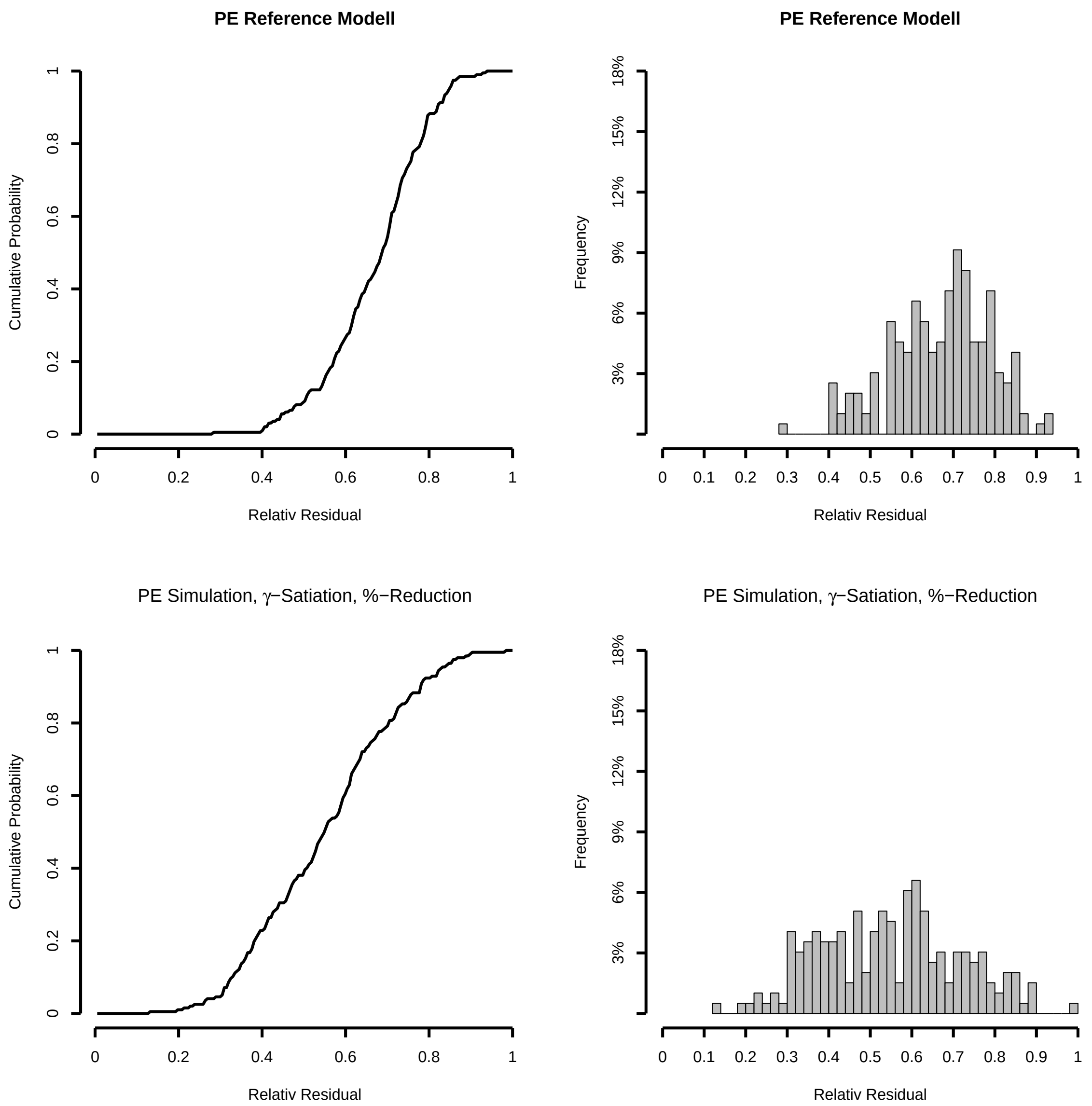


Figure 3: Distribution of Residuals: Fleet Choice Model B and MNL Model



More corner solutions mean higher share of completely false predictions for the fleet choice model and the PE model. That indicates that some kind of relationship exists. However, the ID model has a high share of wrong predictions despite a modest number of corner solutions. The hypothesis must therefore be rejected. Another hypothesis is that the presence of a strong alternative that is predominantly chosen as the only one is responsible for a high share of false predictions, due to the fact that inn the ID model over 67% of the observations have chosen the same (single) alternative (changing departure time). But that does not explain the high share in the fleet choice Model without public transport, where the strongest alternative, PT, was left out and all other alternative are relatively equal.

Figure 4: Distribution of Residuals: Priority Evaluator Model



The strongest correlation with share of false prediction was found with the absolute number of chosen alternatives in a model. Figure 6 shows the plot including the linear regression. The relationship is very clear but there are only very few data sets compared. Although the log-linear relationship might look different considering more models, it proofs nevertheless that a relationship exists. Since the share of predictions cannot be negative, the line can also be steeper, because we do not know where the threshold of zero false prediction lies, we only know the upper boundary of 4.4 chosen alternatives in average.

Figure 5: Distribution of Residuals: Induced Demand Model

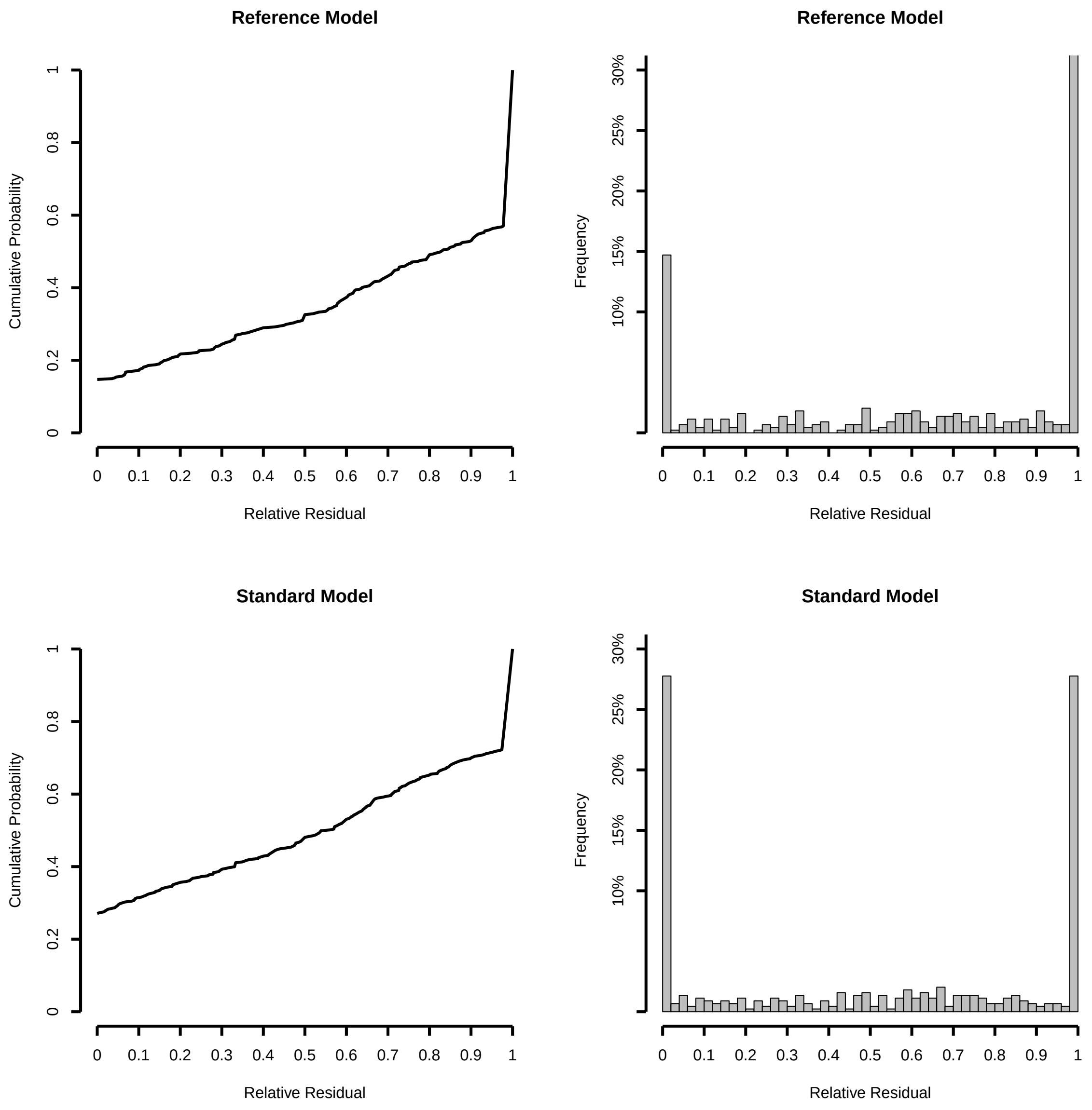
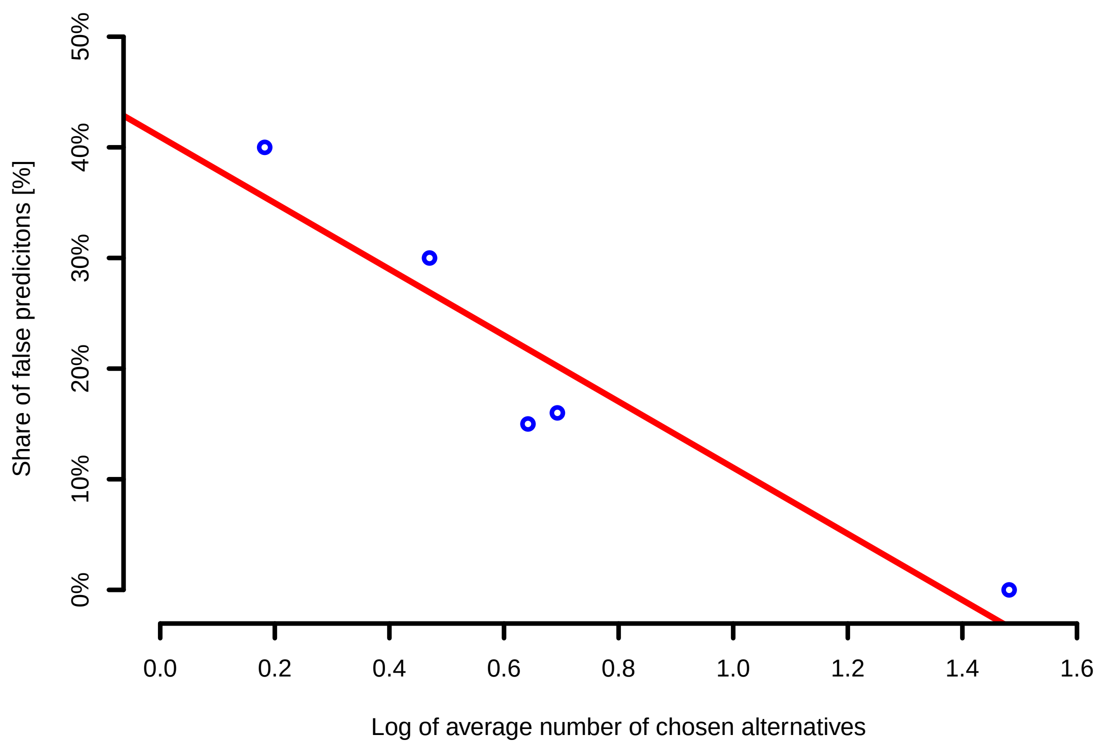


Table 7: Relationship Corner Solutions - Forecast Accuracy

	Alt.	Alt. Chosen		Corner Solutions [%]		Completely False [%]
Model		**Mean**	**Range**	**Data**	**Simulation**	**Simulation**
FC Model A, no PT	16	1.2	1 to 4	92.3	90.8	40.0
FC Model A	17	2.0	1 to 5	88.5	86.6	16.0
FC Model B	17	1.9	1 to 5	88.8	87.8	15.0
FC MNL	17	1.0	1	88.8	94.1	20.9
Induced Demand	3	1.6	1 to 3	48.4	56.0	30.0
Priority Evaluator	12	4.4	1 to 10	63.0	38.0	0.0

Figure 6: Influence of Data Characteristics on Residuals



4.3 Aggregate Simulation Results

This section contains a brief consideration of aggregate "market shares" of the car types from the fleet choice model. Figure 7 shows the market shares for the observed data, for the simulation and also for only the completely wrongly predicted cases. It is obvious, that alternatives with medium sized market shares are are fairly well predicted, while alternatives with a high market share are over and alternatives with a low market share are under predicted. The high amount of completely false predictions stem to a good part from the highly over predicted alternatives. The MNL model that has only one chosen alternative and 20.9% false predictions does not fit well into this model, but it was left out because the methodological framework is different. But it does not contradict it fully either.

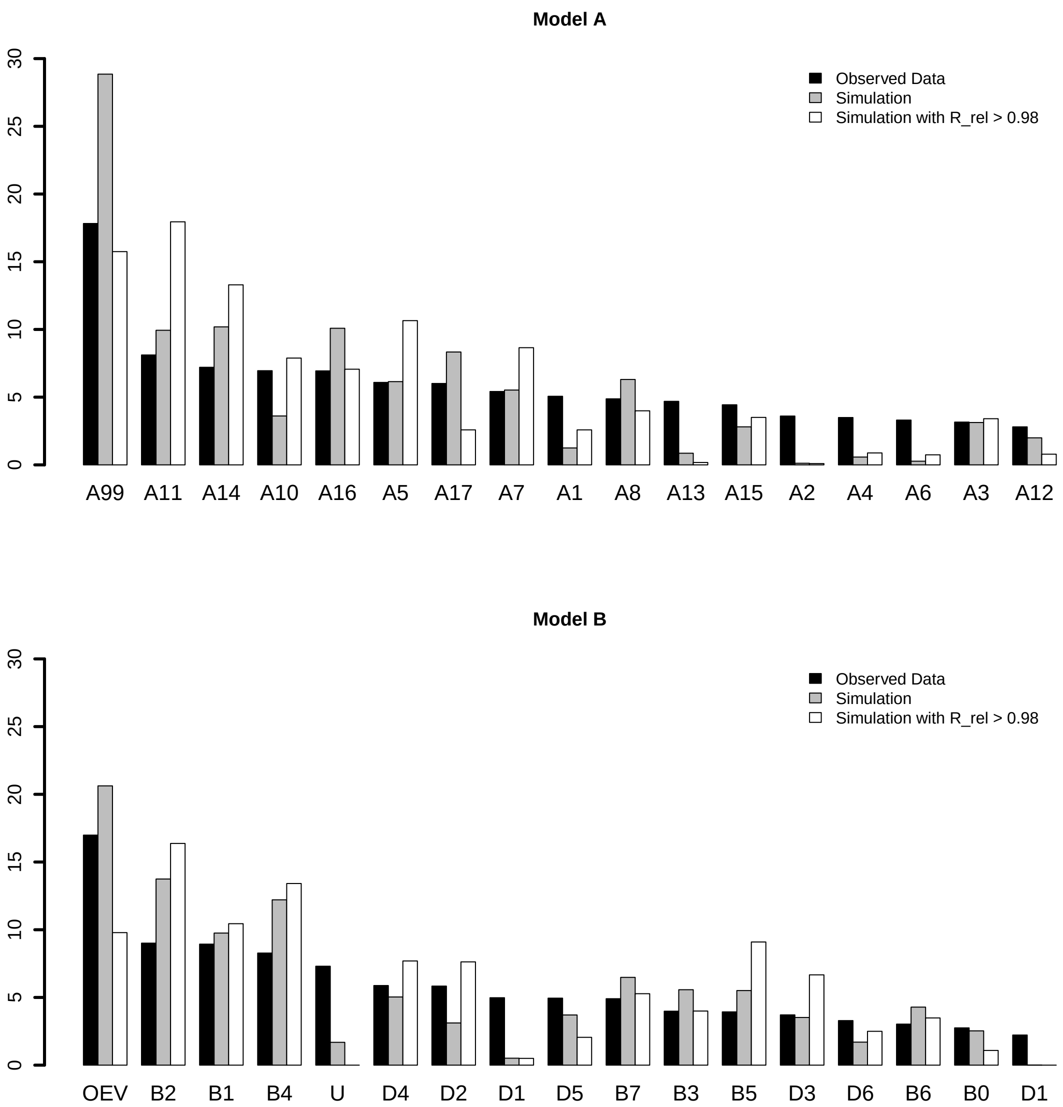
5 Conclusion and Outlook

The results shown in this paper are very interesting yet fairly hard to judge because of the lack of comparable work in the literature. This is the first time that discrete continuous models of sophisticated stated adaption data are assessed in a disaggregate way and compared. It shows how models, established to predict changes in behavior in the case of high fuel prices, drastic energy laws or dramatic travel time changes, perform when implemented. It also shows how different model specifications and models from different data sets perform and what the differences are.

The models and the forecasting procedure used for this paper are relatively new developments. However, the methodology is relatively easy to understand and well documented and the needed software is freely available and we consider it as a very useful and promising technique in choice modeling. Because of the fact that the results of such model estimations are not particularly easy to interpret and an evaluation of the model fit as well as the suitability for implementation are not obvious, an indicator set to analyze the residuals and compare different models is very useful.

As this paper shows, the outcome of a forecast is on no account trivial or useless. The extreme differences in the distribution of the residuals and the, in several cases unsatisfying, overall accuracy show that such an analysis is needed not only to assess the specific models, but also to improve them in an iterative process. The analysis of residuals give much more insight to the usefulness of the models then the model fit parameters from the estimation. Therefore the presented simulation assessments are related to the presented models and can not be assigned to the methodology per se.

Figure 7: Aggregate Shares of the Fleet Choice Models



To give a concise assessment of the forecasting quality of stated preference models or even the MDCEV methodology, this analysis can be considered a first step: Four models from three data sets were analyzed and compared. The differences of the distributions of the residuals are most interesting. We assume that the shapes are strongly linked to the share of false predictions ($R_{Rel} \geq 0.98$). The correlation we found between the number of chosen alternatives and the distribution of the residuals indicates that the MDCEV framework in combination with the applied simulation algorithm performs better the more multiple choices are observed. The evidence is still vague, but it will hopefully become more stringent when the presented analysis is expended on additional models and data sets.

It would be also helpful to have models based on revealed preference data to asses in the same, disaggregate way and have more experience in judging the prediction quality. From an absolute view, we think that the presented models are significantly better than randomness, but not as accurate as one could expect looking only at the estimation parameters and their significance. The models presented in this paper are all based on very complex, difficult and relatively new survey methods that require the participants to imagine very unfamiliar choice situations and thus have a much lower consistency than revealed preference data. Nevertheless, with a accurate assessment of the estimated models, they can give useful insights.

6 Acknowledgement

This work was carried out within the THELMA project (www.thelma-emobility.net) and funded by a range of stakeholders led by the Competence Center for Energy & Mobility and SwissElectric Research.

7 References

Balmer, M. (2007) Travel demand modeling for multi-agent traffic simulations: Algorithms and systems, Ph.D. Thesis, ETH Zurich, Zurich, May 2007.

Balmer, M., K. Meister, M. Rieser, K. Nagel and K. W. Axhausen (2008) Agent-based simulation of travel demand: Structure and computational performance of MATSim-T, paper presented at the *Innovations in Travel Modeling (ITM'08)*, Portland, June 2008.

Beckx, C., T. A. Arentze, L. Int Panis, D. Janssens, J. Vankerkorn and G. Wets (2009) An integrated activity-based modelling framework to assess vehicle emissions: Approach and application, *Environment and Planning B*, **36** (6) 1086–1102.

Bhat, C. R. (2005) A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions, *Transportation Research Part B: Methodological*, **39** (8) 679–707.

Bhat, C. R. (2008) The multiple discrete-continuous extreme value (mdcev) model: Role of utility function parameters, identification considerations, and model extensions, *Transportation Research Part B: Methodological*, **42** (3) 274–303.

Bhat, C. R. (2011) Chandra bhat's web-page, webpage, February 2011, `http://www.ce.utexas.edu/prof/bhat/fULL_PAPERS.htm`.

Bhat, C. R. and S. Sen (2006) Household vehicle type holdings and usage: An application of multiple discrete-continuous extreme value model, *Transportation Research Part B: Methodological*, **40** (1) 35–53.

Bhat, C. R., S. Sen and N. Eluru (2009) The impact of demographics, built environment attributes, vehicle characteistics, and gasoline prices on household vehicle holdings and use, *Transportation Research Part B: Methodological*, **43** (1) 1–18.

Bradley, M. A., J. L. Bowman and B. Griesenbeck (2010) SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution, *Journal of Choice Modelling*, **3** (1) 5–31.

Copperman, R. B. and C. R. Bhat (2007) An analysis of the determinants of children's weekend physical activity participation, *Transportation*, **34** (1) 67–87.

Erath, A. and K. W. Axhausen (2010) Long term fuel price elasticity: Effects on mobility tool ownership and residential location choice, *Technical Report*, Swiss Federal Office of Energy (SFOE), Federal Office for the Environment (FOEN), IVT, ETH Zurich, Berne.

Halton, J. H. (1960) On the efficiency of certain quasi-random sequences of points in evaluating multi-dimensional integrals, *Numerische Mathematik*, **2** (1) 84–90.

Hoinville, G. (1977) The priority evaluator method, *Working Paper*, **3**, Social & Community Planning Research, London, September 1977.

Jäggi, B. and K. W. Axhausen (2010) Surveying energy efficiency in housing and transport using a priority evaluator, *Working Paper*, **636**, IVT, ETH Zurich, Zurich.

Kim, J., G. M. Allenby and P. E. Rossi (2002) Modeling consumer demand for variety, *Marketing Science*, **21** (3) 229–250.

Meister, K., M. Rieser, F. Ciari, A. Horni, M. Balmer and K. W. Axhausen (2009) Anwendung eines agentenbasierten Modells der Verkehrsnachfrage auf die Schweiz, *Straßenverkehrstechnik*, **53** (5) 269–280.

Pinjari, A. R. and C. R. Bhat (2010a) An efficient forecasting procedure for kuhn-tucker consumer demand model systems: Application to residential energy consumption analysis, *Technical Report*, University of South Florida, July 2010.

Pinjari, A. R. and C. R. Bhat (2010b) A multiple discrete-continuous nested extreme value (mdcnev) moddel: Formulation and application to non-worker activity time-se and timing behavior on weekdays, *Transportation Research Part B: Methodological*, **44** (4) 562–583.

Pinjari, A. R., C. R. Bhat and D. A. Hensher (2009) Residential self-selection effects in an activity time-use behavior model, *Transportation Research Part B: Methodological*, **43** (7) 729–748.

Salvini, P. A. and E. J. Miller (2005) ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems, *Networks and Spatial Economics*, **5** (2) 217–234.

Sen, S. (2006) A joint multiple discrete continuous extreme value (mdcev) model and multinomial logit model (mnl) for examining vehicle type/vintage, make/model and usage decisions of the household, Ph.D. Thesis, University of Texas, Austin, August 2006.

Simma, A. and K. W. Axhausen (2001a) Commitments and modal usage: An analysis of german and dutch panels, *Working Paper*, **98**, IVT, ETH Zurich, Zurich.

Simma, A. and K. W. Axhausen (2001b) Successive days, related travel behaviour?, *Working Paper*, **62**, IVT, ETH Zurich, Zurich.

Simma, A. and K. W. Axhausen (2003) Commitments and modal usage: Analysis of german and dutch panels, *Transportation Research Record*, **1854**, 22–31.

Simma, A., R. Schlich and K. W. Axhausen (2002) Destination choice modelling for different leisure activities, *Working Paper*, **99**, IVT, ETH Zurich, Zurich.

Spissu, E., A. R. Pinjari, C. R. Bhat, R. M. Pendyala and K. W. Axhausen (2009) An analysis of weekly out-of-home discretionary activity participation and time use behaviour, *Transportation*, **36** (5) 483–510.

Swiss Federal Statistical Office (2006) *Ergebnisse des Mikrozensus 2005 zum Verkehrsverhalten*, Swiss Federal Statistical Office, Neuchatel.

Train, K. E. (1978) A validation test of a disaggregate mode choice model, *Transportation Research*, **12** (3) 167–174.

Weis, C., C. Dobler and K. W. Axhausen (2010) An interactive stated adaptation survey of activity scheduling decisions, *Working Paper*, **637**, IVT, ETH Zurich, Zurich.