CAPTURING PREFERENCE HETEROGENEITY OF TRUCK DRIVERS' ROUTE CHOICE BEHAVIOR WITH CONTEXT EFFECTS USING A LATENT CLASS MODEL

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ABSTRACT:

This paper aims at investigating the heterogeneous characteristics among truck drivers in route choice preferences. A latent class model incorporating membership functions is employed to examine differences between segments of drivers. A stated choice experiment designed for identifying route choice behavior of truck drivers provides the data for model estimation. The effects of road pricing and environmental bonus are examined considering context dependency. Results reveal that the latent class model outperforms the multinomial logit models in terms of goodness-of-fit and discrimination of segments. Drivers of light trucks care more about congestion than those of heavy trucks, and are highly sensitive to road pricing and slightly sensitive to a road bonus. Drivers of heavy trucks are more sensitive to road category and urban area than drivers of light trucks, and are insensitive to bonus and slightly sensitive to high pricing.

Keywords: Route choice behavior, Heterogeneity, Freight transport, Latent class model, Context effects

1. INTRODUCTION

Freight transport, which is one of the most important components of inter- and intra-city goods delivery, is increasingly concerned about environmental issues due to its increasing contribution to urban problems of congestion, environmental pollution and road accidents. Their contribution to environmental concerns is largely influenced by their route choice decisions. Different from passenger transport, goods delivery has its own features affecting route choice behavior. Drivers may in general consider the weight and/or size of truck, trip distance, sequence of addresses, etc. in their route choice decisions. Large and heavy vehicles impose extra requirements on routes in terms of accessibility of roads. The size and weight of vehicles, average transport distances, variability of client addresses, and drivers' knowledge of routes are all factors that vary largely across transport companies and drivers, and potentially have an influence on route choice behavior. Route choice may also be constrained by regulations, such as road grade, departure time period, maximum speed, pricing, and easy pick-up sites. Considering these characteristics of goods delivery and their context dependency, the route choice decisions of truck drivers need to be further investigated at both the urban and intercity scale.

Furthermore, there are environmental concerns related to drivers' choice of route. Although these concerns hold for passenger and freight transport in general, they are particularly pronounced for the latter segment given the heavier vehicles involved. Road pricing is a well-known instrument to reduce traffic congestion. In the area of passenger transport there is a large body of empirical literature on the influence of road/congestion pricing on travel behavior choice. Holguín-Vera (2008) is one of the few studies examining the impact of congestion pricing for freight transport. They found that carriers were sensitive to pricing strategies corresponding to off-hour delivery. Adelakun and Cherry (2009) found too that truck drivers are willing to pay to avoid congestion. Other recent studies provide further empirical support for this finding (Vadali et al., 2009; Zhou et al., 2009). The form of financial incentives has also received some attention. An environmental bonus has been suggested as a potentially relevant, new transport management instrument to induce drivers of trucks and vans to choose routes that, from an environmental and safety perspective, are friendlier. For example, a bonus or incentive such as tax deduction is thought to be effective in moving freight delivery traffic to off-hours. Holguín-Veras (2008) and Greenberg (2009) recently discussed the design problem of regulatory incentives by converting fixed insurance costs to per-mile charges where people pay as they drive and save as they don't. The impact of this new instrument is difficult to judge. In passenger transport, effectiveness of a bonus system to invoke drivers to avoid peak hours in their commute trips has recently been investigated in a large scale field experiment in The Netherlands (Ben Elia et al., 2009).

Previous research on freight transport rarely looks at these issues from a behavioral viewpoint in the sense that the route choice behavior of truck drivers has long been ignored. The majority of the existing literature on route choice behavior focused on passenger transport. Only few behavioral studies on route choice decision-making of truck drivers can be found. Kawamura (2002), Knorring et al. (2005) and Vadali et al. (2009) considered the trade-off behavior of truck drivers for different distances, times and/or toll costs when faced with multiple routes. To the best of author's knowledge, the study conducted by Arentze et al. (2010) is the only study tailored to route choice analysis of truck drivers. In their study, an optimal stated choice experiment specific to freight transport considering the possible effects of road pricing and bonus policies was designed and a mixed logit model was used to investigate drivers' route choice preferences and the effects of different contexts. Although the choice preferences were explicitly identified, the model adopted suffered from the inability to capture taste heterogeneity among segments of freight transport. Ignoring preference differences between respondents may lead to bias when applying the model for forecasting.

In addition to accounting for preference differences, it is important to examine situational effects within segments. People may have specific preferences in different choice situations (Swait 2002). The relation between context and choices made need to be specifically addressed in the processes of both experiment design and model development. Within the latent class framework, such context effects can be incorporated into the utility function for a particular segment under the assumption that individuals' preferences within the same segment are homogeneous. Identifying such heterogeneity would benefit the development of new navigation systems in freight transport in the sense that pre-knowledge of segment-specific preferences would support the development of a system accommodating different market requirements across drivers.

The specific purpose of this study is to investigate heterogeneous preferences among truck drivers in route choice behavior. A latent class model is used to identify the best number of segments, segment size, and the membership of different segments. We estimate the parameters based on the data from a stated choice experiment which was designed to examine the route choice behavior of truck drivers in Arentze et al. (2010).

The remainder of this paper is organized as follows: Section 2 will give a brief introduction on the latent class model with class membership specification as well as associated algorithmic issues; Section 3 represents the design of the stated choice experiment; Section 4 shows the estimation results, and the paper is concluded with an indication of future research potentials.

2. HETEROGENEITY: THE LATENT CLASS MODEL

In the field of discrete choice modeling, two models are commonly used to identify heterogeneity: the mixed logit model (ML) and latent class model (LCM). The former method assumes that the parameters of the utility function follow a particular type of distribution. The mean and variance of the parameters are both estimated and the significance of the variance indicates the existence of heterogeneous preferences. In real applications, the problem is how to specify a feasible distribution function for certain parameters, which leads to considerable testing work for different types of density functions. In contrast, the latent class model imposes an assumption that there are certain numbers of latent segments among individuals. Different from the mixed logit model in econometric approaches which estimates the random parameters by drawing randomly from some continuous joint density function, LCM uses a discrete number of segments to describe the density function of the parameters. Within each segment, the choice preferences are assumed to be homogeneous.

Assume the utility of alternative k for driver i in class s is

$$U_{ik|s} = \alpha_{k|s} + \beta_s^{'} X_{ik} + \varepsilon_{ik|s} \tag{1}$$

where $\alpha_{k|s}$ is the segment specific constant; $\beta_s^{'}$ is a vector of the utility parameters for segment *s*; X_{ik} is a vector of independent variables that are varied by route alternatives; $\varepsilon_{ik|s}$ is the error component of the utility function and is independent and identically distributed (IID). Within class *s*, the probability of driver *i* choosing alternative *k* is

$$P_{ik|s} = \frac{\exp\left(\alpha_{k|s} + \beta_s^{'} X_{ik}\right)}{\sum_{j \in J} \exp\left(\alpha_{k|s} + \beta_s^{'} X_{ik}\right)} \tag{2}$$

If the probability of being in class *s* is given by W_{is}, namely the class membership probability, the unconditional probability of choosing alternative *k* is

$$P_{ik} = \sum_{s=1}^{S} P_{ik|s} \cdot W_{is} \tag{3}$$

This means that probability P_{ik} depends on two terms of probabilities, one is the class membership probability (W_{is}) and the other is the choice probability within class ($P_{ik|s}$). The probability of individual *i* belonging to class *s*, W_{is}, can be in general represented by a standard logit formulation:

$$W_{is} = \frac{\exp\left(\theta_s^{'} Z_i\right)}{\sum_{s=1}^{S} \exp\left(\theta_s^{'} Z_i\right)} \tag{4}$$

where Z_i is a vector of segment variables of respondents related characteristics; θ_s is the vector of parameters to be estimated for segment *s*. Segment variables Z are commonly called concomitant variables of a latent class model. If no concomitant variables are specified, the delta parameters reduce to constants.

To identify the optimal number of classes, the Bayesian Information Criterion (BIC) is often used. It can be expressed as:

$$BIC = -2LL + 2K \tag{5}$$

where *LL* is the log likelihood function at convergence; *K* is the number of parameters in the model.

The advantage of BIC, compared with the single criterion of minimum log likelihood, is the incorporation of a penalty term on the number of parameters. When estimating parameters with different number of classes, the model with the least BIC value is thought to be the best.

3. STATED CHOICE EXPERIMENT

To better capture the attribute preferences intrinsic to different drivers, a stated choice experiment was designed in Arentze et al. (2010). It was implemented in the extended Eindhoven region, The Netherlands in July, 2009. The purpose of the experiment was to examine the route choice behavior of truck drivers in goods delivery. 15 freight transport companies which are active in the Eindhoven region were randomly selected and invited to participate in the experiment such that carriers and transport companies were both represented in reasonable proportions and the sample represents the existing diversity in terms of nature of freight and size of vehicles. A contact person at each company was asked to invite route planners (if any) and drivers within the company to fill out the questionnaire that included the experiment. In total, 100 drivers and a maximum of 1 planner per company constituted the sample frame for this experiment.

Questions were asked with respect to two hypothetical routes with different attribute levels and contextual variables. The factors varied in the experiment were identified by examining the relevant literature and on the basis of the results of qualitative interviews with experts. The attributes adopted to describe route alternatives consisted of congestion, road category, road pricing, road bonus, urban area, and parking/restaurant facility. Context variables included travel time difference, time of day, size of truck, distance to destination, time since rest, and time window. Because travel time is defined as an attribute of a route alternative, it is assumed that one of the two routes has the shortest travel time and only the travel time of the other route was varied. Technically, this means that travel time is a context variable, as it is defined for a choice set. The levels and the coding of attributes and context variables varied in the experiment are shown in Table 1.

Apart from main influential attributes, policy variables pricing and bonus were explicitly designed as attribute variables with the aim to measure responsiveness of truck drivers (and planners) to congestion charges and financial incentives of different forms. To avoid confusion and reduce task complexity, respondents were asked either to respond to a road-bonus or a road-pricing scenario and they were randomly assigned to one of these scenarios. In absolute terms, the same price levels were used in the bonus and price scenario, so that in effect only the label (it is an environment bonus versus it is a congestion charge) differed between the scenarios.

Due to the fact that context variables may influence subjective evaluations of the attributes, the design of the experiment should also allow the estimation of possible context effects. Context effects can be measured in conjoint choice experiments by using design strategies that allow one to vary the contextual variables independently from the attribute profiles (Oppewal and Timmermans, 1991). Therefore, a separate design was used to vary the context variables across choice sets. For each choice set, the context was determined by randomly drawing a profile from this design. Again, this was done without replacement for choice sets generated for the same respondent. In this way, context and attribute profiles varied independently of each other.

Table 1 Influential attributes and levels used in the stated choice experiment

Variables	Coding	Levels
Attributes		
Congestion	(1, 0)	No delay
	(-1, -1)	Medium delay
	(0, 1)	High delay
Road category	(1, 0)	Highway
	(-1, -1)	Main road
	(0, 1)	Local road
Bonus/Pricing	(1, 0)	None
	(-1, -1)	Medium level
	(0, 1)	High level;
Passing through urban area	(1, 0)	No
	(-1, -1)	Yes, without school
	(0, 1)	Yes, with school
Having restaurant facility	(1)	No
	(-1)	Yes
Contexts		
Normal travel time		Time difference +10%
		Time difference +25%
		Time difference +50%;
Time of day	(1,0)	Morning
	(-1,-1)	Lunch time
	(0,1)	End of day
Size of truck	(1,0)	< 3.5 ton
	(-1,-1)	3.5 - < 30 ton
	(0,1)	> 30 ton
Distance to destination	(1)	Short: 15 km
	(-1)	Long: 30 km
Time since rest	(1)	Short
	(-1)	Long
Time window	(1)	Narrow
	(-1)	Wide

On the level of attributes and contexts, the experiment involves a $3^4 \times 2^1$ and a $3^3 \times 2^3$ full factorial design for each, respectively. An orthogonal design consisting of a fraction of 27 profiles was defined for both attribute and context variables. This design allows us to estimate main effects as well as 3 two-way interaction effects. In case of attributes, it is expected that two-way interactions are particularly relevant to the road category variable. This variable may interact with the urban-area variable, in the sense that for a highway the influence of urban area (three levels) is likely negligible. Also other attributes such as facilities to rest, congestion and others may be evaluated differently depending on road category. Since the (route) choice alternatives are unlabeled, choice sets per respondent were composed by each time drawing randomly without replacement two profiles from the design.

Regarding questionnaire representation, most stated choice studies use verbal type of attribute levels, which impose an extra burden, as respondents need to construct mental representations based on textual descriptions (Arentze et al., 2003). Given the fact that the experiment includes a relatively large number of attribute variables, an effective visualization of the attributes is considered especially important in this study. Therefore, an iconic representation was used, allowing respondents to quickly capture the context variables and attribute levels describing choice alternatives. The icons adopted here are consistent with conventions of map representations drivers are generally familiar with and, at the same time, avoid too detailed visualizations (e.g., photographs) that may distract the respondent from the choice task or evoke irrelevant associations (Timmermans and Hato, 2009). A special computer program was written that generated these visualizations given the definition of the attribute profiles included in a choice set.

In addition, the questionnaire included questions intended to obtain some background information of the respondent with respect to socio-demographics (e.g., age), the company where he/she works and the job he/she has in the company. The questionnaire was implemented as a web application which supports the sampling methods described above to compile treatments (choice-set and context combinations). A link to the website was sent to each company with a request to distribute it to all truck drivers and (route) planners within the company. Each respondent received 10 choice sets, where each choice set has two alternatives. Respondents were asked to indicate 'which route they prefer for each choice set'. In total, 81 respondents joined the survey in which 4 respondents only filled in the background information by stopping before the choice experiment. Therefore, 78 valid sets of data were used for model estimation.

4. RESULTS AND DISCUSSION

4.1 Results of multinomial logit model

To evaluate the variables which were finally included in the model, a MNL model was first estimated. The model includes only the main effects of attributes to examine the significance of marginal effects leaving interaction and context effects out of consideration. Estimation results are reported in Table 2. Travel time is the only quantitative variable (here we use the log transmission because it outperforms a linear function of time with respect to the goodness-of-fit). For all other variables parameters were estimated for each level using effect coding. For variables with 3 levels, the medium level was taken as the reference. The total fit of the model is acceptable (McFadden's rho square is 0.232). Most parameters are significant at the 5% probability level and all parameters that are significant have signs as expected.

Table 2 Estimation results of MNL model

	Coefficient	t-Value
Travel time (*log*)	-3.046 **	-7.037
Congestion (no delay)	0.999 **	10.134
Congestion (heavy delay)	-0.666 **	-7.186
Road category (highway)	0.622 **	6.968
Road category (local road)	-0.518 **	-5.954
Pricing (no pricing)	0.488 **	4.166
Pricing (high pricing)	-0.511 **	-4.416
Bonus (no bonus)	-0.205 *	-1.677
Bonus (high bonus)	0.042	0.333
Urban (no)	0.356 **	4.263
Urban (yes, with residential area)	-0.513 **	-5.755
Parking/Restaurant (no)	-0.086 **	-1.432
Sample size	780	
LL(0)	-540.65	
LL(β)	-414.95	
ρ^2	0.232	

Note: ** and * are 5% and 10% significant, respectively.

Travel time appears to be the most significant attribute of all variables. In line with findings from other route-choice studies, the congestion variable also has a strongly significant impact on route choice. Drivers (and planners) avoid congestion even when it involves only a moderate delay. In addition, road category has a strong influence. Keeping everything else constant, drivers have a strong preference for highway and a strong dislike of local roads.

As it turns out, road pricing has a much bigger effect on route choice than a (environmental) bonus which is significant at the 10% level. The difference between pricing and bonus effects is consistent with prospect theory which states that for the same amount a loss (e.g., road price) has a stronger effect than a gain (e.g., bonus) (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981).

The urban-area variable also has a significant effect on route choice. Drivers have a relatively strong preference for routes that do not pass through an urbanized area and a strong dislike for routes that pass through residential areas and school zones in particular. Note that parking/restaurant is not significant and is therefore excluded from the following estimations.

4.2 Results of latent class models

To identify the membership for each segment, concomitant variables associated with individuals are generally incorporated into membership functions. A number of variables with respect to individuals' social-demographics and trip related information are available through a questionnaire administered jointly with the stated choice experiment. Several representative variables affecting drivers' route choice preferences were examined, which includes age (young or old), job position (driver or planner), actual size of truck (light or heavy), and average trip distance (short or long). Some of respondents who are both driver and planner were grouped as route planners. Descriptive statistics of the concomitant variables tested in latent class models are shown in Table 3.

Table 3 Descriptive statistics on main concomitant variables

Factors		Frequency	Percent (%)
Age	≥40 years	33	40.7
	<40 years	47	58.0
Missing		1	1.2
Total		80	100.0
Job	Driver	73	90.1
	Planner	7	8.7
Missing		1	1.2
Total		81	100.0
Actual size of truck	Heavy (≥30 ton)	32	39.5
	Light (<30 ton)	49	60.5
Total		81	100.0
Average distance	≥30 km	67	82.7
	<30 km	12	14.8
Missing		2	2.5
Total		81	100.0

Note that the variable of actual size of truck in concomitant variables indicates the real situation of drivers. It is different from what we used in the stated choice experiment which was considered as a context variable in a hypothetical environment where the variable is used to represent the choice situation in terms of different levels. In the survey background information related to individuals was provided by drivers depending on their own characteristics without context dependence. Thus, the drivers provided information about the vehicle size they commonly use. Drivers who actually have different types of vehicles may have different preferences in terms of different contexts. The same remark applies to the average trip distance variable: this is a context variable in the experiment (stated) as well as a revealed variable from the survey. In this study, we are going to examine the model with membership function (i.e., concomitant variables). Examinations for each concomitant variable indicate that only the variable of actual size of truck is significant, and consequently we included this variable into the membership function.

In order to identify the optimal number of classes, the BIC values for the base model which includes only main attribute variables were calculated. The models differ in the number of classes, ranging from 2 to 5. As shown in Table 3, BIC increases with the number of classes. The minimum value was obtained for the 2-class model, which therefore was identified as the best model and considered in further analyses. The subsequent models which incorporate context effects, interaction effects between attributes and class membership functions are estimated based on 2 classes.

Table 4 BIC values for base models with different number of classes

	2 classes	3 classes	4 classes	5 classes
BIC	1.255	1.321	1.392	1.475

Considering the degrees of freedom in model estimation and the number of observations, only a limited number of interaction and context effects can be estimated. The context and interaction variables included in the latent class model involve three components which are thought to be of high importance. More specifically, considering the estimation results in Arentze et al. (2010), the interaction variables of road category times pricing, pricing times size of truck (stated), and pricing times trip length (stated) are included.

The estimation results of a MNL^+ model and this latent class model are reported in Table 5. MNL^+ shows the estimation results by incorporating the interaction and context variables described above into the MNL model. LCM represents the results of latent class model by incorporating concomitant variables into the membership function. The goodness-of-fit of LCM (ρ^2=0.298) outperforms those of MNL (ρ^2=0.232) and MNL^+ (ρ^2=0.250) models.

Comparing with segment specific results, the parameter estimations of MNL^+ indicate the choice preferences on average. The results are consistent with that of the basic MNL model with a better goodness-of-fit and meaningful parameters signs. The context effects are significant for light trucks when facing high pricing, indicating that the effect of high price would be enhanced when the truck is in the light category. In addition, the significance of interactions between road pricing and trip length indicate that long trips are more responsive to pricing than short trips.

In case of the LCM, because there are two segments in this model with the second segment treated as the reference, positive values of membership variables relate to segment 1 while negative values relate to segment 2. Estimates of truck size in the membership function, as shown in Table 3, provides evidence that segment 1 consists of drivers using light trucks (DLT) whereas segment 2 are drivers using heavy trucks (DHT).

As expected, drivers in each of the segments are most sensitive to travel time (log) among all influential factors. The results are consistent with those of multinomial logit models. The variables related to congestion are significant for both segments, indicating that drivers/planners always prefer to avoid potential congestion. Estimations of road category variables suggest that the two segments have a similar response pattern in the sense that drivers mostly prefer highways and dislike local roads. Also, for the variables related to urban area, drivers prefer avoiding routes through urban areas or close to schools or residential neighborhoods.

In case of the strength of impacts between two segments, DLT has larger coefficients for congestion, pricing, and bonus than DHT. This means that DLT is more sensitive to traffic congestion, pricing, and bonus relative to DHT. On the other hand, DLT is less sensitive to road category and urban area. This suggests that DHT take vehicle characteristics more into account in their route choice than DLT in the sense that local roads and the route passing through urban residential areas are strongly avoided.

Regarding the differences in responding to road pricing and bonus between DLT and DHT, the DLT is very sensitive to road pricing and slightly sensitive to bonus, while DHT is insensitive to bonus and slightly sensitive to pricing. This means that DLT wishes to avoid highly-priced roads and probably can be influenced by the received bonus in their route choice decision. This might indicate that pricing and bonus policies could be designed with respect to the size of trucks. Pricing or bonus policies may get significant responses from light trucks and little from heavy trucks. In addition, DHT may be concerned more with the efficiency and convenience of goods pick-up and delivery and roads, and will probably be more sensitive to physical constraints, such as speed limit, time regulation, road space, etc. As shown, high pricing is only slightly significant for heavy trucks, which means DHT is less sensitive to pricing/bonus than DLT. This is probably due to the fact that the large freight carried by DHT outweighs the small financial differences between routes.

Because the actual size of truck is constant for each individual, while the contextual size of truck is varied in the experiment, there may have different effects from contexts on different drivers. The significance of such interaction effects depend on to what extent the drivers can imagine the hypothetic choice situations. As for the context effects on road pricing, the interactions with actual size of truck show different responses from segment specific characteristics. This indicates that respondents cannot sufficiently imagine the contexts which differ from their own perspectives, DLTs cannot sufficiently imagine the situation of driving a heavy truck, and DHTs cannot sufficiently imagine the situation of driving a light truck.

Table 5 Estimation results of MNL^+ and latent class models

	MNL^+	LCM	
		Class 1	Class 2
Travel time (*log*)	-3.114**	-2.222**	-6.806**
	(-7.041)	(-3.542)	(-8.228)
Congestion (no delay)	1.020** **	1.383**	0.716**
	(10.077)	(8.648)	(4.635)

Congestion (heavy delay)	-0.693**	**	-1.010**	-0.309**
	(-7.273)		(-7.024)	(-1.954)
Road category (highway)	0.641**	**	0.475**	1.411**
	(7.053)		(3.579)	(8.696)
Road category (local road)	-0.521**	**	-0.222*	-1.556**
	(-5.841)		(-1.677)	(-8.656)
Pricing (no pricing)	0.667**	*	1.254**	0.142
	(4.710)		(4.593)	(0.663)
Pricing (high pricing)	-0.713**		-1.242**	-0.416*
	(-4.806)		(-4.388)	(-1.775)
Bonus (no bonus)	-0.188	**	-0.468**	0.210
	(-1.515)		(-2.659)	(0.971)
Bonus (high bonus)	0.044		0.206	-0.291
	(0.347)		(1.104)	(-1.475)
Urban (no)	0.351**	**	0.347**	0.657**
	(4.090)		(2.809)	(5.079)
Urban (yes, with residential area)	-0.531**	**	-0.587**	-0.797**
	(-5.870)		(-4.347)	(-5.534)
Context effects				
Highway × Light truck	0.049		0.210	-0.386**
	(0.399)		(1.182)	(-2.014)
Local road × Light truck	0.214*		0.074	0.954**
	(1.755)		(0.416)	(4.381)
Highway × Heavy truck	-0.051	*	-0.204	0.353
	(-0.413)		(-1.167)	(1.615)
Local road × Heavy truck	-0.180		0.152	-1.168**
	(-1.446)		(0.843)	(-3.847)
No pricing × Light truck	0.273	**	0.523*	-0.006
	(1.533)		(1.847)	(-0.025)
High pricing × Light truck	-0.377**	*	-0.757**	0.206
	(-2.138)		(-2.514)	(0.826)
No pricing × Heavy truck	-0.120	**	-0.364	-0.133
	(-0.715)		(-1.459)	(-0.567)
High pricing × Heavy truck	0.250		0.677**	-0.248
	(1.555)		(2.788)	(-0.891)
No pricing × Short trip	-0.302**	*	-0.672**	-0.194
	(-2.171)		(-2.569)	(-0.898)
High pricing × Short trip	0.318**	**	0.771**	0.032
	(2.201)		(3.009)	(0.136)

Membership variables			
Constant		0.303	
		(0.911)	
Actual size of truck (large)		-0.827**	
		(-2.298)	
Segment size		61.1%	38.9%
LL(0)	-540.64	-540.65	
LL(β)	-405.57	-379.51	
ρ^2	0.250	0.298	

5. CONCLUSIONS AND DISCUSSION

Operations in the good transport sector are much aided by navigation and route planning systems that are tailored to the specific needs and requirements of trucks and good delivery. At the same time, environmental concerns and the question to what extent route choice behavior can be influenced by price policies are becoming increasingly relevant. By recognizing segment-specific characteristics and differential sensitivity to route attributes in route choice behavior, policy makers or information providers can establish effective strategies for each customer segment. In the current paper, we presented the results of analyses on differences of route choice preference between truck drivers using a latent class model. We used data of a stated choice experiment that was designed to measure quantitatively truck drivers' and route planners' preferences and their sensitivity to possible pricing policies in an earlier study. A representative sample of truck drivers and route planners in terms of diversity of types of transport in the Eindhoven region participated in the experiment.

Results of a MNL model represent the choice preferences of road attributes in average. Drivers/planners are most sensitive to travel time and try to avoid highly congested roads. Road category and urban area all have significant effects on their route choice behavior in the sense that drivers dislike local roads relative to highways, particularly, when this involves passing through residential area. Pricing has a more significant effect on route choice than road bonus. Estimate of restaurant/parking facility revealed that there is no significant effect on drivers' route choice behavior.

A MNL$^+$ model which incorporates the interaction and context variables into the MNL model was additionally estimated. Results showed consistent estimates with that of the basic MNL model but with a better goodness-of-fit. The context effects indicate that the effect of high price would be enhanced when the truck is in the light category and long trips are more responsive to pricing than short trips.

The latent class model was specified by incorporating concomitant variables into the membership function. The membership parameters identified the respondents as drivers based on actual size of truck, drivers of light trucks and drivers of heavy trucks. For the segment using light trucks, drivers are more sensitive to congestion, pricing, and bonus than drivers using heavy trucks who care specifically about road grade and whether the route passes an urban area. Regarding the pricing/bonus policies, two segments of respondents have different responses. Drivers of light trucks are highly sensitive to road pricing and slightly sensitive to road bonus, while drivers of heavy trucks are not sensitive to pricing and bonus. Context effects revealed that both segments cannot sufficiently imagine the context which differs from their own characteristics.

This study has revealed the trade-offs truck drivers/planners make in route choice and the differences in route choice preferences between segments. The quantitative estimates can readily be used to fine-tune new navigation systems for truck drivers. Several problems are worth considering in future research. Although already a range of context variables was tested in this study, it is worthwhile to repeat the experiment for a larger sample that would allow detecting smaller effects on the level of context variables and person/company variables than we presently could identify. Moreover, our focus has been on freight transport on a local scale. Whether route preferences are the same for long distance transport is another relevant question that future research could address.

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