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Capturing preference heterogeneity of truck drivers' route choice behavior with context effects using a latent class model

Tao Feng[1], Theo Arentze[2], Harry Timmermans[3]
Urban Planning Group, Department of the Built Environment, Eindhoven University of Technology, The Netherlands

This paper investigates heterogeneity in truck drivers' route choice preferences. A latent class model is estimated to identify heterogeneous 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 size of truck is a significant segmentation variable of preferences for route attributes. Drivers of light trucks care more about congestion than drivers 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 pricing.

Keywords: context effects; freight transport; heterogeneity; latent class model; route choice behavior

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. Its contribution to environmental concerns is largely influenced by 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 on 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, time access restrictions, maximum speed, pricing, and convenience for goods picking-up and putting-down (Quak and Koster, 2006). Considering these characteristics of goods delivery and their context dependency,

[1] A: PO Box 513, 5600 MB Eindhoven, The Netherlands T: +31 40247 2301 F: +31 4024 38488 E: t.feng@tue.nl
[2] A: PO Box 513, 5600 MB Eindhoven, The Netherlands T: + 31 40247 2283 F: +31 4024 38488 E: t.a.arentze@tue.nl
[3] A: PO Box 513, 5600 MB Eindhoven, The Netherlands T: + 31 40247 3315 F: +31 4024 38488
E: h.j.p.timmermans@tue.nl

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) also found too that truck drivers are willing to pay to avoid congestion. Other recent studies provide further empirical support for this finding (Runhaar et al., 2002; Viegas, 2003; 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 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 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. (2012) is the only study tailored to route choice analysis of truck drivers. In their study, a 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 choice preferences were explicitly identified, the model adopted does not allow capturing 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 needs 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 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 function 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 (Arentze et al., 2012).

The remainder of this paper is organized as follows: Section 2 will give a brief introduction to the latent class model with class membership specification as well as associated algorithmic issues; Section 3 briefly describes 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 the 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

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

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 respondent 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 theta 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 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 (Arentze et al., 2012). It was implemented in the extended Eindhoven region, The Netherlands in July, 2009. The purpose of the experiment was to examine 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 represented 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 complete 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. Here we briefly discuss the design of the experiment. For a more detailed description of the experiment readers are referred to Arentze et al. (2012).

Questions were asked with respect to two hypothetical routes with different attribute levels and contextual variables. 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. 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. 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.

The design of the experiment should also allow the estimation of possible context effects. 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 Attributes and levels used in the stated choice experiment (source: Arentze et al. 2012)

Variables	Coding	Levels	Abbr.
Attributes			
	1, 0	No delay	C1
Congestion	-1, -1	Medium delay	C2
	0, 1	High delay	C3
	1, 0	Highway	R1
Road category	-1, -1	Main road	R2
	0, 1	Local road	R3
	1, 0	None	B1/P1
Bonus/Pricing	-1, -1	Medium level	B2/P2
	0, 1	High level;	B3/P3
	1, 0	No	Ur1
Passing through urban area	-1, -1	Yes, without school	Ur2
	0, 1	Yes, with school	Ur3
Having restaurant facility	1	No	Rp1
	-1	Yes	Rp2
Contexts			
		Time difference +10%	
Normal travel time		Time difference +25%	tme
		Time difference +50%;	
	1,0	Morning	Tod1
Time of day	-1,-1	Lunch time	Tod2
	0,1	End of day	Tod3
	1,0	< 3.5 ton	Trk1
Size of truck	-1,-1	3.5 - < 30 ton	Trk2
	0,1	> 30 ton	Trk3
Distance to destination	1	Short: 15 km	Dtd1
	-1	Long: 30 km	Dtd2
Time since rest	1	Short	TsrS
	-1	Long	TsrL
Time window	1	Narrow	TwN
	-1	Wide	TwW

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 (Louviere, 1998).

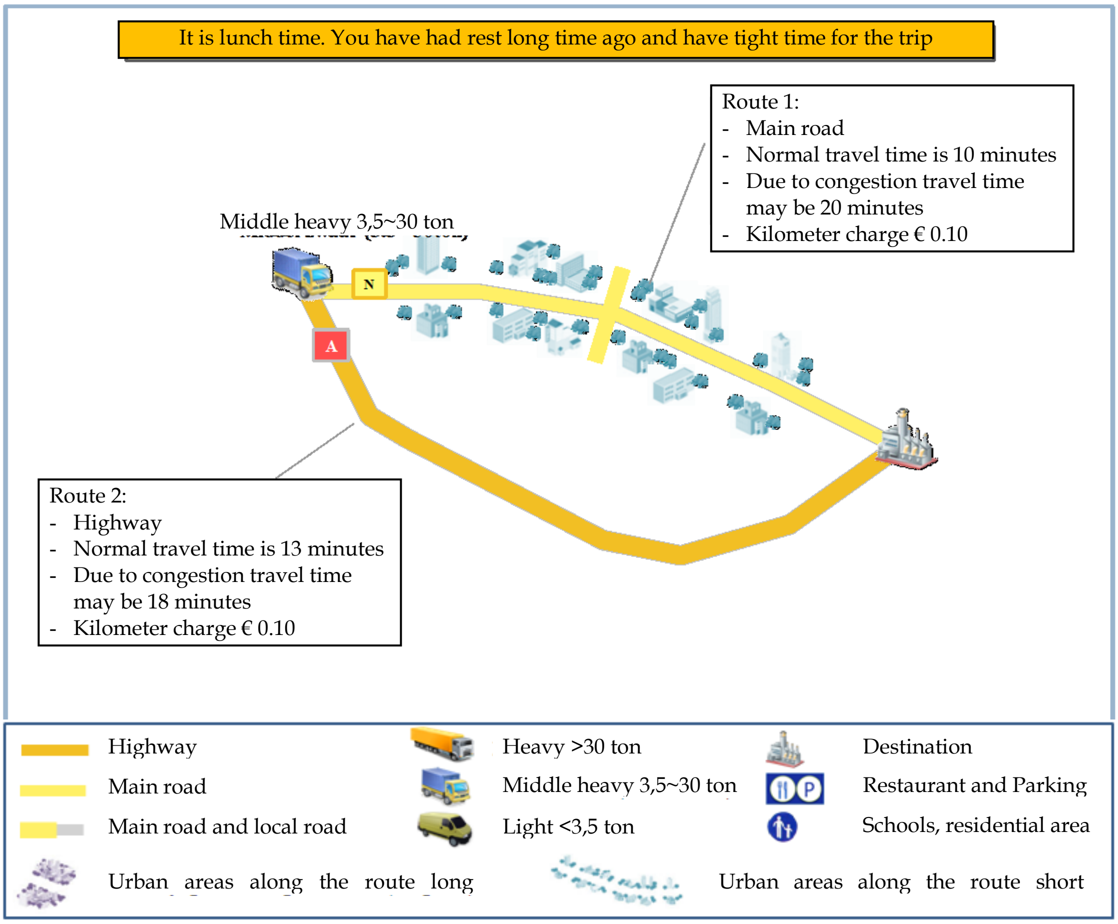

Figure 1 Example of a choice set

Given the fact that the experiment includes a relatively large number of attribute variables, an effective visualization of the attributes an iconic representation was used, allowing respondents to quickly capture the context variables and attribute levels describing choice alternatives (Figure 1). 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. Each respondent received 10 choice sets, where each choice set has two alternatives. In total, 78 respondents completed the questionnaire and, hence, 78 valid sets of data were used for model estimation.

4. Results and discussion

4.1 Sample

A number of variables with respect to individuals' socio-demographics and trip related information are available through a questionnaire administered jointly with the stated choice experiment. Several variables potentially affecting drivers' route choice preferences were examined, which include age young or old, job position driver or planner, actual size of truck light or heavy, and average trip distance short or long. In addition, respondents were asked to indicate who generally determines the route – the driver or a planner. Results showed that 58% of the drivers choose their own route freely, 12.3% need to discuss this with planners, and for others routes are fully decided by planners. We grouped respondents according to their role: planners or drivers. Respondents who are both driver and planner were grouped as planners in the subsequent discussion and analysis. Descriptive statistics of the concomitant variables tested in latent class models are shown in Table 2.

Note that the variable actual size of truck (TrkH and TrkL) differs from the similar variable we used in the stated choice experiment (Trk1, Trk2 and Trk3) as a context variable in a hypothetical environment. In the survey, background information related to individuals was used to define concomitant variables Z of membership function in the LC model. Thus, drivers who actually have different types of vehicles may have different preferences and be allocated to different clusters. The same remark applies to the average trip distance variable: this is a context variable in the experiment on trip level as well as a personal background variable obtained from the survey. First estimation results indicate that only the concomitant variable actual size of truck is significant, and consequently we included this variable in the membership function of a final model.

Table 2 Descriptive statistics on main concomitant variables

Factors		Abbr.	Frequency	Percent %
Age	≥40 years	AgO	33	40.7
	<40 years	AgY	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	TrkH	32	39.5
	Light <30 ton	TrkL	49	60.5
Total			81	100.0
Average distance	≥30 km	DistL	67	82.7
	<30 km	DistS	12	14.8
Missing			2	2.5
Total			81	100.0

4.2 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 3. Furthermore, Table 3 also shows the estimation results of an extended specification of the MNL model (referred to as MNL+) that was conducted to analyze interaction effects between the attribute variables and the truck size and trip length.

Table 3 Estimation results of MNL and MNL+ model

	MNL				MNL+			
	Coeff	Std. error	T-value	P-value	Coeff	Std. error	T-value	P-value
Travel time *log*	-3.046**	0.433	-7.037	0.000	-3.114**	0.442	-7.041	0.000
C1	0.999**	0.099	10.134	0.000	1.020**	0.101	10.077	0.000
C3	-0.666**	0.093	-7.186	0.000	-0.693**	0.095	-7.273	0.000
R1	0.622**	0.089	6.968	0.000	0.641**	0.091	7.053	0.000
R3	-0.518**	0.087	-5.954	0.000	-0.521**	0.089	-5.841	0.000
P1	0.488**	0.117	4.166	0.000	0.667**	0.142	4.710	0.000
P3	-0.511**	0.116	-4.416	0.000	-0.713**	0.148	-4.806	0.000
B1	-0.205*	0.122	-1.677	0.094	-0.188	0.124	-1.515	0.130
B3	0.042	0.126	0.333	0.739	0.044	0.128	0.347	0.729
Ur1	0.356**	0.083	4.263	0.000	0.351**	0.086	4.090	0.000
Ur3	-0.513**	0.089	-5.755	0.000	-0.531**	0.091	-5.870	0.000
Rp1	-0.086	0.060	-1.432	0.152				
R1 × Trk1					0.049	0.123	0.399	0.690
R3 × Trk1					0.214*	0.122	1.755	0.079
R1 × Trk3					-0.051	0.139	-0.413	0.680
R3 × Trk3					-0.180	0.124	-1.446	0.148
P1 × Trk1					0.273	0.178	1.533	0.125
P3 × Trk1					-0.377**	0.168	-2.138	0.475
P1 × Trk3					-0.120	0.176	-0.715	0.033
P3 × Trk3					0.250	0.161	1.555	0.120
P1 × Dtd1					-0.302**	0.139	-2.171	0.030
P3 × Dtd1					0.318**	0.144	2.201	0.028
Sample size			780		780			
*LL*0			-540.65		-540.64			
*LL*β			-414.95		-405.57			
ρ^2			0.232		0.250			
ρ^2 *adjusted*			0.220		0.227			

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

Here, travel time is the only quantitative variable. We used the log transformation because it outperforms a linear function of time in terms of goodness-of-fit. For all other variables parameters were estimated for each level using effect coding. Effect coding is considered to be superior to dummy coding (Louviere et al., 2000). Different from dummy coding, the levels of variables in effects coding are coded as -1 instead of 0. In the estimates of effect coded variables, the constant denotes the utility derived from that alternative averaged across all varied context levels (Molin and Timmermans, 2010). Here, for variables with 3 levels, the medium level was taken as the reference. The fit of the model is acceptable - McFadden's rho square is 0.232. Most parameters are significant at the 5% alpha level and all parameters that are significant have signs as expected.

As shown in Table 3, travel time appears to be the most significant attribute of all variables. The congestion variable also has a strongly significant impact on route choice. These results are identical to the findings from other route choice studies (e.g., Knorring and Kornhauser, 2005; Vadali et al., 2009). Drivers mostly intend to avoid any extent of traffic congestion. In addition, the road category attribute also plays an important role such that a stronger choice preference is to highways relative to local roads.

Moreover, road pricing has a much bigger effect on route choice than an 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 shows a significant effect on route choice. The routes that do not pass through an urbanized area are strongly preferable and routes that pass through residential areas and school zones are not preferable. Note that parking/restaurant is not significant and is therefore excluded from the following estimations.

The parameter estimations of MNL$^+$ (Table 3) indicate that significant interactions with truck size exist. 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 is 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.

4.3 Results of latent class model

In order to identify the optimal number of classes, the BIC values for base model specifications which include only main attribute variables were calculated. The models differ in the number of classes, ranging from 2 to 5. As shown in Table 4, 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 and effects of the 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. (2012), the interaction variables of road category times pricing, pricing times size of truck stated, and pricing times trip length stated are included.

The models were estimated by using the statistical software, NLOGIT 4.0 (Greene 2007). The estimation results of this latent class model are reported in Table 5. MNL$^+$ shows the estimation results after adding the interaction and context variables described above to the MNL model. LCM represents the results of the latent class model after having incorporated the concomitant variable size of truck 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.

Table 5 also shows the results of the mixed logit model, which was presented in the paper by Arentze et al. (2012). The effects of main attributes are consistent in both of the models. The log likelihood of the mixed logit model is somewhat lower than that of the latent class model. As one can see that, the ML estimation shows that there is significant unobserved heterogeneity on the valuation of congestion and price attributes. In line with this, the LCM estimation shows that different segments of truck drivers are characterized by different effects of these variables where the segments relate to the size of the truck. In other words, the LCM estimation provides insights into the nature and origin of the heterogeneity. LCM shows similar effects for main attributes and the random variables, but provides more insights in the nature of choice heterogeneity. Taking the road pricing specifically this attribute has a much bigger effect on route choice than an environmental bonus. A bonus appears to have no significant effect on route choice. The interaction of pricing with truck size indicates that drivers/planners are considerably more sensitive to road price when the truck is of the light category. In addition, the interaction between road category and size of truck confirms that the dislike of local roads is somewhat smaller when the truck is of the light category. Results of the mixed logit model do not provide insights in the nature of taste heterogeneity.

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 is β =-0.827 (p=0.388), as shown in Table 5, provides evidence that segment 1 primarily consists of drivers using light trucks DLT and segment 2 drivers using heavy trucks DHT.

As expected, drivers in each of the segments are most sensitive to travel time log among all influential factors β =-2.222 (p=0.000) for class 1 and β =-6.806 (p=0.000) for class 2. 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 (p(P1)=0.000, p(P3)=0.000) and slightly sensitive to bonus (p(B1)=0.008, p(B3)=0.291), while DHT is insensitive to bonus (p(B1)=0.454, p(B3)=0.349) and insensitive to pricing (p(P1)=0.608, p(P3)=0.145). 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 indicates 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 exists 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 size of truck show different responses from the two segments. For example, the interaction effects with light trucks are significant for the category of DLT, but not for DHT. This may indicate 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.

5. Conclusions and discussion

Operations in the goods transport sector are much aided by navigation and route planning systems that are tailored to the specific needs and requirements of trucks and goods 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 on 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 is enhanced when the truck is in the light category. Furthermore, 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 LC model revealed different clusters and estimated effects on tastes for each cluster separately. In our case, only truck size appears to be a significant explanatory variable of cluster membership. 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. This provides important indications for the design of new improved navigation systems which are able to provide route guidance tailored to a vehicle specification. For instance, the system may assign higher weights to congestion level and road price for light trucks and higher weight of road grade for heavy truck. Context effects revealed that both segments cannot sufficiently imagine the context which differs from their own characteristics.

Table 5 Estimation results of ML model and LCM

	MX				LCM							
					Class 1				Class 2			
	Coeff	Std. error	T-value	P-value	Coeff	Std. error	T-value	P-value	Coeff	Std. error	T-value	P-value
Travel time *log*	-4.579**	0.928	-4.904	0.000	-2.222**	0.642	-3.542	0.000	-6.806**	1.277	-8.228	0.000
C1	1.512**	0.334	4.524	0.000	1.383**	0.164	8.648	0.000	0.716**	0.211	4.635	0.001
C3	-0.989**	0.215	-4.596	0.000	-1.010**	0.147	-7.024	0.000	-0.309**	0.233	-1.954	0.184
R1	1.132**	0.247	4.594	0.000	0.475**	0.135	3.579	0.000	1.411**	0.252	8.696	0.000
R3	-0.799**	0.191	-4.188	0.000	-0.222*	0.136	-1.677	0.104	-1.556**	0.298	-8.656	0.000
P1	1.036**	0.331	3.132	0.002	1.254**	0.276	4.593	0.000	0.142	0.276	0.663	0.608
P3	-1.053**	0.287	-3.665	0.000	-1.242**	0.288	-4.388	0.000	-0.416*	0.286	-1.775	0.145
B1	-0.269*	0.167	-1.615	0.106	-0.468**	0.177	-2.659	0.008	0.210	0.281	0.971	0.454
B3	0.047	0.177	0.265	0.791	0.206	0.195	1.104	0.291	-0.291	0.311	-1.475	0.349
Ur1	0.450**	0.159	2.832	0.005	0.347**	0.129	2.809	0.007	0.657**	0.240	5.079	0.006
Ur3	-0.669**	0.169	-3.964	0.000	-0.587**	0.136	-4.347	0.000	-0.797**	0.201	-5.534	0.000
Rp1	-0.127	0.091	-1.403	0.161								
C1 × TsrN	0.418**	0.169	2.477	0.132								
C3 × TsrN	-0.071	0.274	-0.533	0.594								
R1 × Trk1	0.035	0.173	0.202	0.840	0.210	0.180	1.182	-0.143	-0.386**	0.274	-2.014	0.159
R3 × Trk1	0.323*	0.173	1.873	0.061	0.074	0.182	0.416	-0.282	0.954**	0.333	4.381	0.004
R1 × Trk3	-0.055	0.175	-0.314	0.753	-0.204	0.177	-1.167	-0.552	0.353	0.315	1.615	0.263
R3 × Trk3	-0.299	0.168	-1.363	0.173	0.152	0.184	0.843	-0.209	-1.168**	0.432	-3.847	0.007
R1 × AgY	0.392**	0.147	2.665	0.008								
R3 × AgY	-0.249**	0.130	-1.912	0.056								
R1 × TwS	-0.269*	0.145	-1.862	0.063								
R3 × TwS	0.071	0.134	0.533	0.594								
P1 × Trk1	0.519	0.365	1.423	0.155	0.523*	0.285	1.847	-0.036	-0.006	0.336	-0.025	0.985
P3 × Trk1	-0.526*	0.292	-1.802	0.072	-0.757**	0.252	-2.514	-0.858	0.206	0.378	0.826	0.586
P1 × Trk3	-0.256	0.338	-0.758	0.448	-0.364	0.304	-1.459	-1.354	-0.133	0.311	-0.567	0.668
P3 × Trk3	0.365	0.268	1.360	0.174	0.677**	0.245	2.788	0.197	-0.248	0.352	-0.891	0.482
P1 × Dtd1	-0.512*	0.274	-1.868	0.062	-0.672**	0.265	-2.569	-1.191	-0.194	0.261	-0.898	0.458
P3 × Dtd1	0.443*	0.233	1.855	0.064	0.771**	0.262	3.009	0.258	0.032	0.272	0.136	0.906
Ur1 × TsrS	0.288**	0.140	2.051	0.040								
Ur3 × TsrS	-0.269	0.148	-1.823	0.068								
Ur1 × Tod1	0.026	0.180	0.147	0.883								
Ur3 × Tod1	0.146	0.177	0.824	0.410								
Ur1 × Tod3	0.402**	0.171	2.351	0.019								
Ur3 × Tod3	-0.227	0.184	-1.232	0.218								
Membership variables												
Constant					0.303	0.359	0.850	0.398				
TrkH					-0.827**	0.388	-2.298	0.033				
Standard deviation of random parameters												

P1	1.566	0.686	2.284	0.022		
C1	1.120	0.530	2.114	0.035		
Segment size					61.1%	38.9%
*LL*0	-540.64				-540.64	
*LL*β	-384.55				-379.51	
ρ^2	0.289				0.298	
ρ^2 adjusted	0.254				0.279	

Estimation results suggest that an environmental bonus is less effective than pricing. A policy of using rewards rather than charging to mitigate congestion problems needs to be carefully handled. This contributes to the policy decision making where monetary incentives has been considered as important by the European Commission to reduce pollution (European Commission, 2011). On the other hand, the results suggest that drivers of light truck are more sensitive to pricing than drivers of heavy trucks. This concerns the smart pricing strategy in Europe that transport charges and taxes must be restructured in the direction of wider application of the "polluter-pays" and "user-pays" principle (European Commission, 2011). Although the main concerns of congestion management in European areas are with heavy trucks, policy makers should be aware of the fact that policy effects may differ according to the size of trucks.

This study has revealed the trade-offs truck drivers/planners make in route choice and the difference in route choice preferences between segments. However, several problems are worth considering in future research. In terms of the fact that truck drivers could not fully imagine the choice contexts, future research could further investigate real route choice behavior of truck drivers based on revealed data. It is interesting to apply more sensitive measures for pricing and bonus instead of the current three-level variables. Moreover, 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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