Is car drivers' response to congestion charging schemes based on the correct perception of price signals?

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Abstract

This paper deals with the question how the capability of car drivers to estimate travel distance, travel time, fuel costs and other motoring costs as well as the cost of a new hypothetical congestion charge influences their decision to change their travel behaviour. The analysis makes use of an integrated choice and latent variable model (ICLV) which merges classic choice models with the structural equation approach (SEM) for latent variables. The integrated choice and latent variable model improves the explanatory power considerably compared with a conventional choice model. The paper provides evidence that charge complexity decreases the resistance in considering behavioural changes, a finding which can be explained by the ambiguity avoidance.

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JEL codes: R41, R48, C43

1.0 Introduction

Over the last decade research has made considerable progress in developing, testing and applying methods to estimate the social marginal costs of road use (see for example Nash et al., 2010 and INFRAS et al, 2007 for an overview on estimation methods). At the same time, both technically and practically feasible electronic road pricing systems have become available which are capable to charge road users by taking into account several dimensions of pricing such as time of day, type of road, road section, type of vehicle etc. Meanwhile there are also practical examples for dynamic road pricing schemes which involve a considerable amount of complexity in charging structures such as the I-15 and SR91 HOT lane projects as well as the Singapore ERP scheme. However, while first-best pricing appears to move from a theoretical concept towards a both technically and practically feasible concept, the question remains whether a theoretically optimal, fully dynamic and highly differentiated charging regime will be too complex for car drivers to understand and to generate the desired rational changes in travel behaviour. Against this background it becomes increasingly important to analyse whether and to what extent car drives are able to predict such highly differentiated charges correctly, and to respond rationally to these price signals.

This paper deals with the question how the capability of car drivers to estimate travel distance, travel time, fuel costs and other motoring costs as well as the cost of a new hypothetical congestion charge influences their decision to change their travel behaviour. It attempts to answer the following research questions: (1) Are car drivers able to predict highly differentiated charges and to adjust their travel behaviour accordingly? (2) How can this prediction capability of drivers be incorporated into discrete choice models for predicting behavioural response to complex road user charges? (3) What are the consequences for charging policy if road users' responses do not fully reflect the expected rational response to complex charges, either due to a lack of capability to predict charges correctly, or because car drivers disengage from the process of attempting to do so?

The paper is an extension of initial research carried out in the EU funded project GRACE (http://www.grace-eu.org) which dealt with the design of charging schemes aimed at reflecting the complex nature of marginal cost estimates.

2.0 Methodology

2.1 Definition of complexity

The research on complex road user charges presented in this paper starts from the following definition of charge complexity based on Bonsall et al. 2007:

A road user charge can be regarded as complex if (1) a large number of charging dimensions does exist (e.g. time, location, type of road, level of congestion, type of vehicle), (2) the number of charge levels in each dimension is high, (3) the calculations required for estimating the charge to be paid for a specific journey are difficult and time-consuming (e.g. is the charge fixed or is it a function of one or more variables, is the function linear or more complicated etc.) (4) the amount of information needed to be collected for calculating the charge is high, (5) the number of discounts and exemptions is high.

Apparently, there exists an *objective* complexity which can be defined through the factors described above, and a *perceived* complexity which finally influences peoples' behavioral responses and which is the subject of interest in this paper. Perceived complexity refers to the degree of difficulty which an individual faces when estimating the charge to be paid for a specific journey. Apart from the objective factors listed in the definition above, it is influenced by a number of not directly observable factors such as

- Individuals' general attitudes to travel cost and cost saving strategies,
- Individuals' capability to deal with incomplete information and to supplement missing information by own search and collection on the one hand,
- Individuals' capability to deal with various and complex information on the other hand,
- Individuals' capability to perform the necessary calculations if many charge dimensions and charge levels have to be considered,
- Individuals' capability to deal with uncertainty over prices and their attitudes towards risk,
- Individuals' coping strategies used when a full evaluation of available travel options is not possible or considered to be not justified,
- The degree of individuals' familiarity and experience with making complex decisions in general and in dealing with complex prices in particular.

Out of these issues, this paper seeks to identify how the prediction ability of individuals in combination with their attitudes to travel costs influences their behavioral response on a complex road charge. Bonsall et al., 2004 provide an excellent overview on case study evidence from different branches and on the relevant literature from psychology and human decision making. Out of this review the following major issues have guided the design of the study presented in this paper.

A first issue refers to the fact that people face problems in estimating travel distance correctly (see Bonsall 2004). Travel distance is often estimated via travel time whereby there is evidence that journey times tend to be over-estimated for interurban journeys and under-estimated for urban journeys (see Kang et al. 2003). A second issue is the capability of humans to process information and to perform (complicated) calculations. Psychology has established the seven-items rule according to which people can deal with no more than seven (plus/minus two) items of numeric or abstract data at a time (see Miller 1956). Furthermore, the capability to process complex information is apparently influenced by socio-demographic factors such as age, education level and income, by familiarity and experience with the choice situation and by mental ability as well as mental and emotional state (see for example Altman et al. 2001, FDS 2001 and OFGEM 2001). Ellsberg 1961 shows that out of several alternatives people choose the one they understand while not choosing those they do not understand, e.g. their choices are based on understanding of an alternative rather than its utility. This leads to the issue of peoples' attitudes to cost and to risk. Ellsberg 1961 and Kahnemann and Tversky 1984 suggest that people are risk averse. Consumers prefer to know the price of a service before they decide to purchase the service, and there is evidence from sectors such as telecommunication (Telephone, TV, internet) and energy that consumers prefer fixed tariffs over variable ones. There is also evidence that, while people in general are so-called cognitive misers (e.g. they economize their decision process by avoiding efforts on working out precisely decisions which involve trivial sums of money, see for example Gabriano and Edell, 1997, Swait and Adamovicz, 2001, Bettmann et al., 1998), different people show different attitudes to costs – there are people seeking for the best deal, others even show game-playing behavior and again others prefer not to spend any effort in seeking for a good deal.

These issues were considered in the design of the survey used for this study, tested in an initial analysis of the survey data (section 3) and used for the development of the following propositions to be tested in modeling of the survey responses.

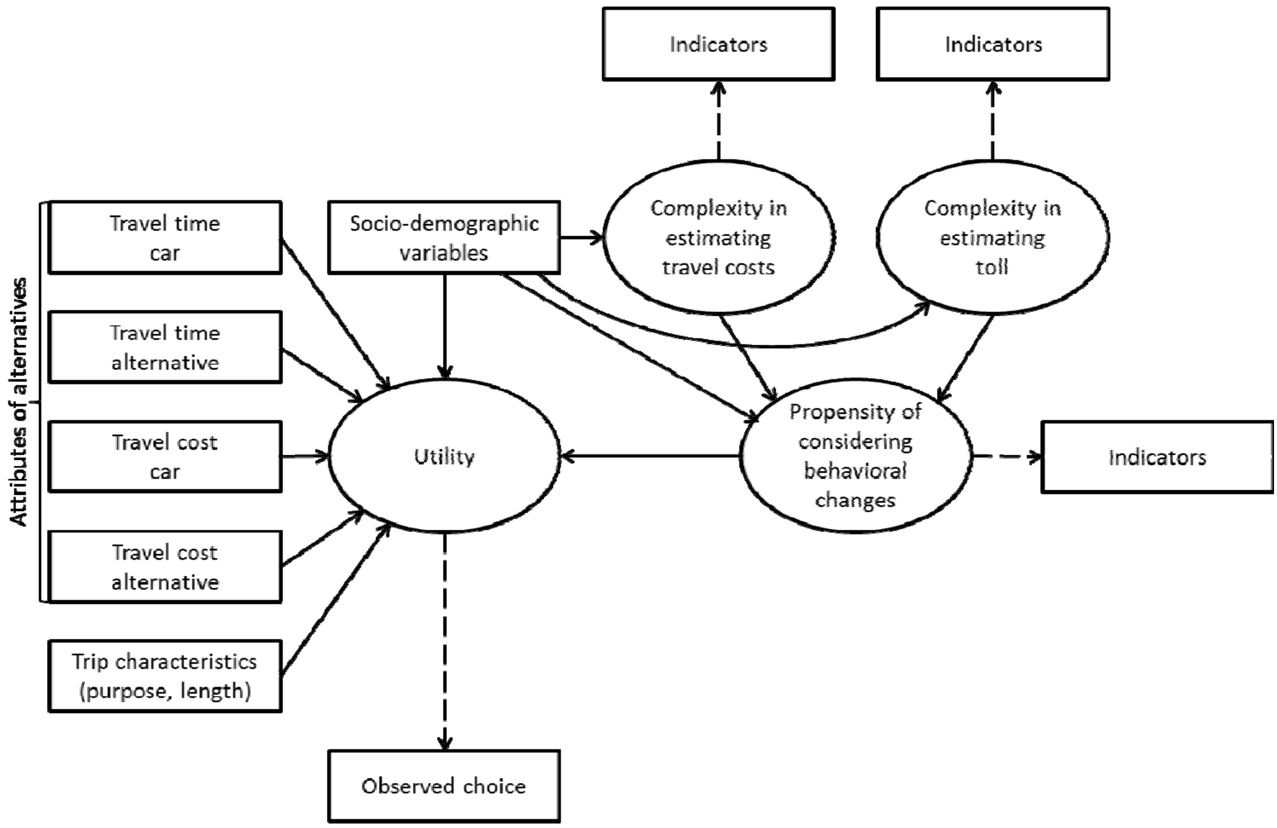
(1) Individuals' precision in estimating travel distance, fuel costs and other costs of car driving influences the propensity of considering behavioral changes.
(2) Individuals' precision in estimating the charge to be paid influences the propensity of considering behavioral changes.
(3) Individuals' attitudes to costs in general and travel cost in particular influence the propensity of considering behavioral changes.
(4) Both socio-economic factors (age, gender, education level, income) and trip characteristics (travel purpose, mandatory versus discretionary trip, trip frequency etc.) influence the estimation precision for both the charge and the other parameters mentioned above.
(5) Socio-economic factors and trip characteristics influence the propensity of considering behavioral changes.
(6) The propensity of considering behavioral changes influences the final behavioral response on the introduction of a road charges, together with the common explanatory variables such as the attributes of the available alternatives, the characteristics of the journey and the socio-economic characteristics of the car drivers.

There is no clear literature evidence whether complexity in prices increases or decreases the propensity of people to change behavior. Swait and Adamovicz 2001 suggest that increasing complexity makes people more likely to stick with the status-quo. However, introducing a congestion charge does not provide people with a new or changed option in terms of a different product, and an unpredictable road charge might people make fearing that the charge will be too high for them. Due to these mixed arguments, there is no a-priori hypothesis on the direction into which charge complexity impacts the propensity of behavioral changes.

2.2 Modelling

Traditional modelling of car drivers' behavioural responses on a price increase as it were be caused by introducing a congestion charge is based on directly observed attributes (mainly time and cost) of the alternatives (the choice set) and on the observed characteristics of the decision maker. The decision maker's internal process of preference formulation and the role of not directly observable factors such as attitudes, lifestyles etc. remain unexplained forming a so-called black box in conventional discrete choice analysis. This holds even more for modelling responses on a hypothetical congestion charge when a high degree of complexity regarding the number of charging dimensions and the number of charge levels within each dimension involves a great deal of uncertainty in the prediction of charges and, consequently in the decision for a certain behavioural response. Apparently, there exist different approaches to incorporate the effects of uncertainty on charges to be paid, and of problems in predicting charge levels on behavioural responses into discrete choice models. Potential approaches include for example i) to quantify a transaction cost for processing the information needed to understand and predict complex charges, ii) to consider a "penalty" on the charge level depending on the degree of complexity, iii) to incorporate the individuals' process of predicting the complex charge and deciding on a response into the traditional discrete choice modelling framework.

Figure 1: Structure of the integrated choice and latent variable model for incorporating charge complexity (based on the general framework in Ben-Akiva et al. 1999)



The research presented in this paper provides a first attempt to follow the last option, e.g. to incorporate the issues surrounding the individuals' understanding and prediction of complex charges into discrete choice analysis. The analysis makes use of an integrated choice and latent variable model (ICLV) which merges classic choice models with the structural equation approach (SEM) for latent variables. Based on the propositions suggested in section 2.1 and supported by an initial analysis of the survey data used, the model applied in this paper consists of a traditional choice part and a hierarchical latent variable part as shown in figure 1.

Let a decision maker q (q=1,.., N) be faced with a set C_i of mutually exclusive alternatives I (with i=1, .., M). X_{iq} describes the vector of observed explanatory variables forming the systematic part of the utility U_{iq}. L_{iq} represents a vector of latent variables (either latent characteristics of the decision maker or latent attributes of the alternatives) and ε_{iq} represents the stochastic utility component. The utility is then

$$U_{iq} = V(X_{iq}, L_{iq}; \theta, \beta) + \varepsilon_{iq} \tag{1}$$

where θ and β are the coefficient vectors for the observed explanatory and for the unobserved latent variables. As it is common practice, the systematic (representative) utility is taken as linear function

$$V_{iq} = \sum_k \theta_{ik} X_{ikq} + \sum_l \beta_{il} L_{ilq} \text{ , } k = 1,.., K \tag{2}$$

where the index k refers to an explanatory variable and the index l to a latent variable.
Assuming that ε_{iq} is independently, identically distributed (i.i.d.) extreme value the binary choice model

$$P(y_{iq} \middle| X_{iq}, L_{iq}; \theta, \beta) = \frac{e^{V(X_{iq}, L_{iq}; \theta, \beta)}}{\sum_{j \in C_M} e^{V(X_{jq}, L_{jq}, \theta, \beta)}} \tag{3}$$

is obtained where the observed choice indicator y_i for alternative i is

$$y_i = \begin{cases} 1, \, if \;\, U_i = \max_j \{U_j\} \\ 0, \, otherwise \end{cases} \tag{4}$$

For the treatment of the latent variables a MIMIC (Multiple Indicator Multiple Cause) model has to be estimated where L_{iq} is explained by characteristics of the decision makers and of the alternatives through structural equations. The formulation used in this paper is based on Ashok et al. 2002. It allows for interrelationships between latent variables as well as for the influence of observed explanatory variables X_{iq} on the latent variables

$$L_{ilq} = \sum_{l} \varphi_{ilq} L_{ilq} + \sum_{r} \alpha_{ilr} X_{irq} + v_{ilq} , \tag{5}$$

The unobservable latent variables L_{ilq} are operationalised by a set of indicators I by means of a linear factor model through the measurement equation

$$I_{ipq} = \sum_{l} \gamma_{ilp} L_{ilq} + \zeta_{ipq} \tag{6}$$

In equations (5) - (6) the index r refers to an explanatory variable, the index p refers to an indicator. φ, α and γ are parameters to be estimated, where γ indicates which share of variance of the indicator I is explained by the latent variable L. ν as well as ς are error terms with zero mean and standard deviation to be estimated.

The simplest approach to include latent variables in a discrete choice model is to perform a sequential estimation procedure which involves in a first step the estimation of the latent variable part (5) - (6) and the computation of the factor scores. In a second step the choice model is estimated by using the factor scores obtained to replace the latent variables as additional exogenous variables. While this approach is straightforward allowing to use standard software for discrete choice (such as NLOGIT, or STATA) and SEM (such as AMOS), the caveat is that it does not guarantee unbiased estimators for the parameters involved, and tends to underestimate standard errors (see for example Walker and Ben-Akiva, 2002, Morikawa et al. 2002). Furthermore, a sequential estimation does not allow for latent variables impacting on each other. For these reasons, in this paper the choice model and the latent variables model are estimated simultaneously. Simultaneous estimation requires maximising the likelihood function for the joint choice probability

$$P(y_{iq}, L_{ilq} \left| \cdot \right.) = \int_{L_{ilq}} P(y_i = 1 \left| X_{ikq}, L_{ilq}; \theta_{ik}, \beta_{il} \right.) \cdot f_I \left(I_{ipq} \left| L_{ilq}, \gamma \right. \right) \cdot f_L \left(L_{ilq} \left| X_{iqr}; \alpha_{ilr}, \varphi_{ilq} \right. \right) \tag{7}$$

where $f_L \left(L_{ilq} \left| X_{irq}; \alpha_{ilr}, \varphi_{ilq} \right. \right)$ is the probability density function of the indicators for the latent variables. Joint estimation of choice and latent variable models is computationally demanding and has so far required researchers to develop own estimation routines or to use specifically designed software such as BIOGEME. The model presented in this paper was estimated by using the SEM software package Mplus (see Muthen and Muthen, 2007). For the joint estimation of the choice and latent variable model, the MLR estimator and for integration Monte Carlo simulation was used.

3.0 Data

The research presented in this paper uses data obtained within a two-stage CATI-survey with regular car drivers in two German cities (Cologne and Frankfurt). Both cities share common topographic and infrastructure characteristics (crossed by a river, surrounded by a motorway ring, possessing a highly developed public transport network) and both frequently face congestion problems. The questionnaires used in these surveys were aimed at exploring drivers' attitudes towards complex charging schemes, their ability to predict charges as well as the general costs of car driving, and their potential behavioural responses.

The questionnaire was originally developed within the GRACE project and applied to the cities of Newcastle, Oxford, Cologne and Thessaloniki (conducted in 2006, see Bonsall et al. 2007 for more details). The basic concept was that the questionnaire would ask respondents to indicate their understanding of, and likely response to, a complex charging scheme which they had had time to study. The questionnaire was designed to be conducted in two stages. The first interview was used to screen suitable respondents, to gain an insight into the type and characteristics of a regular journey they were making, to obtain data on personal characteristics and attitudes (age, sex, attitude to complex prices), and to establish their willingness to take part in a further telephone interview. The questionnaire, (accessible in Link et al., 2007), contained the following elements:

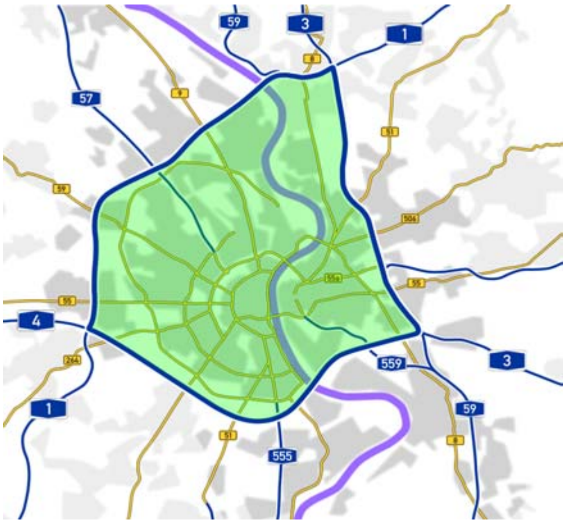
1. Screening questions (identifying whether the interviewee was a car user, making a regular journey of more than 5 km distance through the charging zone and paying for that journey);
2. A description of the journey (origin, destination, frequency, purpose, approximate length and duration etc.);
3. Details of the arrangements they would make for their regular journey if their car was not available;
4. Personal characteristics and attitudes (gender, age, education, household characteristics including income and car ownership, effort expended in getting value for money in non-transport contexts, value of time)

Figure 2: Example of a charging scheme presented to respondents in Cologne

Charge B: Road charge for the motorway ring around Cologne and for all roads inside the motorway ring

For all roads inside the motorway ring (see map: green area), including the motorway ring around Cologne itself (see map: bold blue), the charges described in the table below would have to be paid.

Tariff periods	Charge level per km for ...	
	all roads inside the motorway ring	the motorway ring around Cologne
Weekdays		
0:00 – 7:00	no charge	
7:00 – 9:00	**0.20 €**	**0.10 €**
9:00 – 10:00	**0.10 €**	no charge
10:00 – 16:00	no charge	
16:00 – 17:00	**0.10 €**	
17:00 – 18:00	**0.20 €**	
18:00 – 24:00	no charge	
Saturdays		
0:00 – 9:00	no charge	no charge
9:00 – 18:00		**0.10 €**
18:00 – 24:00		no charge
Sundays		
0:00 – 24:00	no charge	



Map: Charging zones for Cologne

The information gathered in this first interview was used to determine which of several alternative charging regimes should be allocated to each willing respondent. In total five different schemes were developed for both Cologne and Frankfurt. Each of them followed the same charging principles for both cities (for example charging a ring road around the city and the innercity area at different prices, charging the crossing of the river Rhine and the river Main respectively and so on). The schemes varied in terms of the area covered and the structure of the charges (e.g. time periods, whether per kilometre or at a cordon, etc), but all were deliberately complex. An example of such a charging scheme is given in figure 2, Link et al. 2007 contains the full set of schemes for Cologne which were then adapted for Frankfurt in a separate survey. The allocation of schemes to respondents was intended to ensure that respondents received a scheme that was relevant to their regular journey and presented them with some degree of complexity.

Table 1: Socio-demographic characteristics of the sample in (%)

	Cologne (N=210)	Frankfurt (N=200)
Gender		
Male	46	54
Female	54	46
Age		
18-25	6	4
26-35	12	16
36-50	49	38
51-60	15	19
>60	18	23
Average age	46	49
Household size		
Single	17	16
2 persons	35	38
3 persons	20	22
4 persons	17	20
> 4 persons	11	4
Education		
Graduating after 9 or 10 years[1]	23	24
Completed apprenticeship, graduating after 12 or 13 years[2]	43	40
University degree[3]	34	36
Employment situation		
Self-employed	13	14
Employed	60	55
Retired	14	19
Looking for family/home	5	5
Student	4	2
Unemployed	3	1
Other	1	4
Income*		
Up to 2000 €	23	20
2001-3000 €	31	34
>3000 €	31	36
No response	15	10

* Disposable household income per month.- [1] Haupt-/Volks-,Realschulabschluss oder gleich-wertiger Abschluss (German equivalents of CSE and GCSE). – Fachhochschul-reife (vocational baccalaureat diploma), allgemeine/fachgebundene Hochschulreife (diploma from German secondary school qualifying for university admission or matriculation), Berufsausbildungs-abschluss (apprenticeship). – [3] Fach-/Hochschulstudium ,universitärer Studienabschluss.

The second interview was conducted a few days later, after giving the respondents time to study the charging scheme and to consider their possible responses to it. It sought more detail about the respondent's regular journey, tested their understanding of the charging scheme and asked them to indicate their likely response to it. The major elements of the interview were:

1. Perceived characteristics of current travel arrangements (estimates of current cost, distance, and duration; estimates of fixed costs of car use. Stated accuracy of these estimates given for pre-defined ranges of uncertainty).
2. Perception of the congestion charge (estimate of the congestion charge to be paid for making the journey identified in the first interview (a) assuming no change in travel arrangements and (b) assuming various specified changes in travel arrangements, e.g. travelling at a different time, by a different route etc. Stated accuracy of these estimates given for pre-defined ranges of uncertainty).
3. Likelihood of each of a series of behavioural responses (no change, change route, change time, change mode, reduced frequency, car sharing, etc) whereby multiple responses were allowed[1].
4. Exploration of the effect of complexity (assessment of complexity of the charges, effect of less complex charges, willingness to pay to avoid complexity).

An initial analysis of the survey was performed in order to provide more details on the propositions derived in section 2.1 and to add eventually further information for model development. The major findings of this analysis can be summarised as follows:

1. In contrast to literature evidence, respondents over-estimate trip duration (by 13% and 18% in Cologne and Frankfurt respectively) but estimate trip length rather precisely (2% of Cologne respondents and 4% of the Frankfurt respondents under-estimate this parameter). A reason for the rather correct estimation of distance which contradicts available literature evidence might be that more than half of the journeys are work journeys and German taxpayers can deduct a per-km rate from their taxable income, e.g. have knowledge about the distance to their workplace. Fuel costs are over-estimated while the congestion charge to be paid is under-estimated by the Cologne respondents and slightly over-estimated by the Frankfurt respondents. There is

[1] Multiple answers on potential behavioural responses were allowed in order to provide respondents realistic opportunities for response (for example respondents could choose a new route and a new time).

considerable variation in the estimation accuracy between the charging schemes and as to be expected accuracy is lower in particular for those charging schemes with a higher degree of complexity.

2. A self-evaluation of respondents' capability for correct estimation of these trip parameters and the related costs (asked in pre-defined bands of uncertainty in km and Euro cents respectively) which was requested in the interview has proven as too optimistic.
3. Respondents believe that their estimates for the hypothetical charge to be paid as well as for potential savings by changing behaviour (other route, other departure time) are more precise than for example trip distance which is a wrong belief as a comparison between estimated and objective values has shown .
4. More than one third of the respondents believe that the charge to be paid for their regular journey is below the threshold above which they would seriously consider changes in travel behaviour. However, this is a wrong belief for the majority of respondents due to failure of estimating the congestion charge correctly.
5. The majority of respondents (53% of the Cologne respondents and 60% of those in Frankfurt) are risk avers and prefer a fixed, known tariff over a variable unknown tariff even though the variable tariff could lie below the fixed tariff.
6. More than half of the respondents stated that in response to the introduction of a congestion charge they would continue travelling by car as now, 39% and 10% would shift to public transport and cycling respectively, 21% would share a car, and 19% and 28% would travel a new route and at a new time respectively (see table 3).

These results support the idea that traditional modelling of responses by using objective values for the congestion charge will probably not properly reflect the influence of uncertainty about the absolute amount of charges to be paid by motorists in their decision on changing travel behaviour or not. Rather, modelling likely responses on complex congestion charges should consider the capability of respondents to estimate the most important parameters of their journey as well as the congestion charge to be paid, within the context of general attitudes to travel costs and by explicitly considering the effect of complex versus easier charging schemes.

Table 2: Characteristics of the most frequent regular trip with more than 5 km distance

Journey purpose (%)**	**Cologne (N=210)**	**Frankfurt (N=200)**
Work	54	52
Education	2	3
Shopping	25	22
Leisure	26	24
bringing/picking up children	9	12
Other	10	16
Journey frequency (trip per week (%)		
Once	23	22
Twice	18	23
three times	12	12
four times	8	11
five times	33	26
six times	3	2
seven times	1	2
more than seven times	2	2
Trip chains (%)		
one purpose	80	78
more than 1 purpose	20	22
Number of passengers (%)		
Alone	69	71
1 passenger	20	17
2 passengers	9	6
> 2 passengers	2	6
Average trip length in km (mean)	21	19
Average trip duration in min. (mean)	42	38
** Multiple responses.		

4. Estimation results

In the following, both results from a conventional choice model and from an integrated choice and latent variable models are presented, in order to assess to what extent the inclusion of the latent variable model provides additional explanatory power compared with a classic choice model. In model formulation, two problems had to be solved. First, as indicated in section 3, respondents were asked to state the likelihood of each response on a hypothetical road charge based on an ordinal scale ranging from “very” likely”, “fairly likely”, “neither likely nor unlikely”, “unlikely” or “very unlikely”. Second, the sum of the stated likelihoods on each response was not constrained to one, e.g. respondents were allowed to state that two or more types of responses were equally likely. The first problem can be solved i) by allocating an arbitrary probability to each specified likelihood category and recoding the data, e.g.

transforming the ordinal variable into a continuous one, or ii) by transforming the ordinal variable into a binary one by defining one of the likelihood categories (for example "very likely") as 1 and all others as 0. For the second problem, there are again two possible approaches: i) to factor the probabilities such that they sum to one, or (ii) to calibrate separate models on the unconstrained choices. As Bonsall et al. 2007, this paper uses a binary logit model formulation as it offers the advantage of closed form for choice formulation and is readily interpretable. The problem of ordinal responses for the likelihood of behavioural changes was treated by coding all responses stating "very likely" and "fairly likely" as 1, all others as 0.

Table 3: Behavioral responses on the introduction of a road user charge

Response* (in %)	Cologne	Frankfurt	Joint sample
Car as now	53.8	52.0	52.9
New route	19.0	16.0	18.6
New time	22.4	33.5	27.8
Reduced frequency	13.3	8.0	10.7
Public transport	41.4	36.5	39.0
Bicycle	3.3	17.0	10.0
Car share	24.3	18.0	21.2
Stop journey	17.1	11.0	14.1

*) Multiple answers allowed. Responses coded as 1/0 variables where 1 was allocated when respondents stated that the response was "Very likely" or "Fairly likely".

The following discussion focuses on the model for the response "use of public transport versus continue car driving". It was indicated by 39% of the sample as the most likely response to the introduction of a congestion charge and represents the second-largest group probability (see table 3). This response is of high relevance for transport policy since a modal shift from car to public transport will eventually require capacity expansion (more and/or longer trains/buses, upgrade/new lines etc.).

The conventional binary logit model for the response "use of public transport" is

$$U_{iq} = V(X_{iq}, \theta) + \varepsilon_{iq} = \sum_{k=1}^{K} \theta_{ik} X_{ikq} + \varepsilon_{iq} \tag{8}$$

where X is the vector of explanatory variables (see table 3). As usual, X contains the directly observed variables such as the attributes (time and cost) of the alternatives and the decision makers. In addition, a binary variable is included which indicates whether respondents of the survey thought that the charge to be paid by them would be below a threshold from which on respondents would think about behavioural changes.

Table 3: List of indicators, latent variables and explanatory variables

	Explanatory variables X		Indicators I		Latent variables L
X_1	Gender (b)	I_1	Accuracy in estimating travel distance[5)] (c)	L_1	Complexity in estimating general travel costs (c)
X_2	Age (C)	I_2	Accuracy in estimating travel cost[5)] (c)	L_2	Complexity in estimating the charge to be paid (c)
X_3	Work (b)	I_3	Accuracy in estimating road charge[5)] (c)	L_3	Resistance in considering behavioural changes (c)
X_4	School (b)	I_4	Accuracy in estimating simplified road charge[5)] (c)		
X_5	Shopping (b)	I_5	Effort taken to work out best deal for purchasing services[6)] (o)		
X_6	Children (b)	I_6	Frequency of thinking about reducing travel costs[7)] (o)		
X_7	Leisure (b)	I_7	Thinking about behavioural changes after introduction of road charge[8)] (o)		
X_8	Personality type 1[1)] (b)	I_8	Likelihood of considering travel alternatives after introduction of road charge if charge were easier to estimate[9)] (o)		
X_9	Personality type 2[2)] (b)				
X_{10}	Captive[3)] (b)				
X_{11}	Complicatedness[4)] (b)				
X_{12}	Belief that charge is below threshold of considering behavioural changes[5)] (b)				

(b) = binary variable. (c) = cardinal variable. (o) = ordinal variable.
1) Variable takes the value of 1 if respondent stated that “he cannot be bothered to think carefully about trivial sums of money”. – 2) Variable takes the value of 1 if respondent stated that “he cannot work things out that precisely”- 3) Variable takes the value of 1 if respondent stated that “he has no choice about making the journey”.- 4) Variable takes the value of 1 if respondent stated that the charging scheme was very difficult or fairly difficult to understand. – 5) Calculated as ratio between range of uncertainty and absolute estimate. -6) Coded as 1= a lot of effort, 2= usually some effort, 3= sometimes an effort, 4= rarely much effort, 5= no effort.- 7) Coded as 1=several times a week, 2= several times a month, 3= only in case of important decisions, 4= never.-– 8) Coded as 1= a lot of thoughts, 2= some thoughts, 3= not much thoughts, 4= no thoughts.- 9) Coded as 1= very likely, 2= fairly likely, 3= fairly unlikely, 4= very unlikely.

The R^2 (defined as explained variance divided by total variance) of this conventional model is 16.6% (see table 4). All parameters are significant and have the intuitive sign, except the one for the time difference between car and public transport which – though having the intuitive sign - fails to be significant. Furthermore, it should be noted that in this model the cost of public transport and not – in parallel to the time attribute – the difference between car cost (excluding the charge to be paid) and public transport cost was used due to the fact that the cost difference failed to be significant.

The results from this simple model indicate that as a response on the introduction of a hypothetical congestion charge the probability to use public transport instead of continuing to drive car is as higher

- as higher the estimated road charge is,
- as lower the cost of public transport is,
- as higher the time difference between car and public transport is (though not significant),
- if the decision maker is not captive in making the journey by car,
- if the trip is a shopping trip (while all other trip purposes proven to have no significant effect),
- if the car driver believes that the charge is above the threshold from which on he would seriously consider to change behaviour.

Table 4: ML parameter estimates for the conventional binary Logit model and for the integrated choice and latent variable model

	Conventional choice model		Integrated choice and latent variables models	
	coefficient	t-value	coefficient	t-value
Time difference car – public transport	0.279	0.856	0.235	0.648
Cost public transport[1)]	-0.362	-2.862**	0.195	2.044**
Estimated charge to be paid	0.117	2.049**	0.144	2.213**
Shopping	0.775	2.631**	1.011	3.021**
Captive	-0.559	-2.294**	-0.601	-2.181**
Charge below threshold	-0.801	-2.829**	-	-
Resistance of considering behavioural changes			-1.090	-4.589**
Constant	-0.308	-1.652*	0.685	1.753**
R^2	0.166		0.334	

1) In the integrated choice and latent variable model the variable “difference between car cost excl. Toll and public transport cost” was used.
* Significant at 10% level.- ** Significant at 5% level.

The integrated choice and latent variable model is

$$U_{iq} = V(X_{iq}, L_{iq}; \theta, \beta) + \varepsilon_{iq}$$
$$V_{iq} = \sum_{k=1}^{K} \theta_{ik} X_{ikq} + \sum_{l=1}^{L} \beta_{il} L_{ilq} + \varepsilon_{iq} \tag{9}$$

with the structural equations for L=3 latent variables (see table 3)

$$L_{lq} = \sum_{l=1, l \neq 1}^{L} \varphi_{lq} L_{lq} + \sum_{r=1}^{R} \alpha_{lrq} X_{rq} + v_{lq}, \quad l = 1,..,L, L = 3 \tag{10}$$

and the measurement equations for the L=3 latent variables with P=8 indicators (see table 3)

$$I_{pq} = \sum_{l=1}^{L} \gamma_{plq} L_{lq} + \varsigma_{pq}, \quad p = 1,..,P, P = 8. \tag{11}$$

In equations (10) and (11) the index i is skipped because the latent variables and indicators do not refer to alternatives but describe the effects of complexity and uncertainty in estimating car costs – in contrast to available studies on mode choice where latent variables are used to describe the not directly observable attributes such as comfort, safety etc. for each of the alternatives.

The integrated choice and latent variable model (right-hand columns of table 4) provides with an R^2 of 33.4% a considerably higher explanatory power than the conventional choice model. In contrast to the conventional choice model, the integrated model includes a significant effect of the difference between car cost (excluding the toll) and public transport costs while the time difference between car and public transport is still not significant. The variable *Below threshold* is now captured in the latent variable part (see table 5) and vanishes from the choice part. The latent variable *Resistance of considering behavioural changes* impacts negatively on the probability of using public transport after the introduction of the road charge.

Table 5: ML parameter estimates for the impact of complexity and socio-demographic variables on the resistance of considering behavioural changes

	Resistance of considering behavioural changes		Complexity of general travel cost		Charge complexity	
Explanatory variable	coefficient	t-value	coefficient	t-value	coefficient	t-value
Complexity of general travel cost	-0.144	-1.092	-	-	-	
Charge complexity	-0.118	-1.725*	-	-	-	-
Gender	-0.362	-2.618**	-	-	-	-
Age	-	-	-0.035	-2.276**	0.013	3.303**
Work	-0.419	-2.534**	-0.928	-2.166**	-	-
School	-0.753	-2.745**	-	-	-	-
Below threshold	0.662	5.384**	-	-	-	-
Personality type 1	0.454	2.728**	-	-	-	-
Personality type 2	-	-	-	-	0.327	1.467
Perceived complicatedness	-	-	-	-	0.248	2.325**
* Significant at 10% level.- ** Significant at 5% level.						

The parameter estimates for the latent variable part are shown in table 5. The latent variable C*omplexity of general travel costs* which reflects the estimation accuracy for trip distance and motoring costs other than the road charge appears to has no significant impact on the resistance to consider changes in travel behaviour. The latent variable *Charge complexity* indicating the estimation accuracy in estimating the charge to be paid has a significant negative effect on the variable R*esistance*, e.g. the results indicate that higher complexity of the charging scheme which is reflected in greater uncertainty on the estimate for the charge decreases the resistance in considering behavioural changes. As discussed in section 2.1 there is no pre-defined knowledge on the direction into which complexity of charges will influence behaviour. The results obtained in this paper might be explained by the fact that people seek to have certainty on prices to be paid and that, if there is uncertainty (as it is obviously the case if estimating the charge level is not precisely possible) people tend to avoid a behaviour where the price is not known beforehand – an explanation which is supported by available literature (see section 2.1). Further research is necessary for a final conclusion and interpretation of this issue.

Further results indicate that

- age plays a role in estimating both general travel cost and the road charge precisely, however with opposite signs (while higher age reduces the estimation complexity for general travel cost – which could be an expression of experience and familiarity with the trip - it increase it for the charge to be paid);

- the travel purposes work and school have a significant impact on the estimation accuracy (both are purposes which indicate familiarity with the journey);
- the belief of car drives that the charge will be below the threshold of considering behavioural changes increases the resistance of considering behavioural changes;
- car drivers stating that they do not spent effort on working out trivial sums of money, and those stating that they are not capable to work out things that precisely have a higher resistance in considering behavioural changes;
- perceived complicatedness of the charging scheme increases the latent variable C*harge complexity*.

The modelling results provide no support for proposition P1 while proposition P2 is supported. Furthermore, the results also support propositions P3 – P4 are supported by the modelling results.

5.0 Conclusions

In response to the question raised in the title of this paper, the research presented has shown that complex price signals are not correctly perceived by motorists. The results indicate that whilst car drivers (at least in the two survey cities) are relatively capable to estimate travel distance precisely, they are not so in estimating duration, fuel and other motoring costs and in particular the hypothetical road charge. The results further suggest that this capability is influenced by socio-demographic characteristics (age) and – via the travel purposes work and education - by familiarity and experience with the journey. The paper provides evidence that charge complexity decreases the resistance in considering behavioural changes, a finding which can be explained by ambiguity avoidance. However, further research is necessary to test this finding, given that there is also some literature evidence suggesting that people tend to stick with the status-quo if a decision situation becomes too complex.

The research presented in this paper has included the impacts of estimation precision for a complex congestion charge on the propensity of considering behavioural changes, together with the attitudes to travel costs, into a discrete choice model. The explanatory power of the integrated choice and latent variable model has improved considerably compared with a conventional choice model indicating that the process of understanding congestion charges and its impact on the considerations of changing behaviour are important issues to be taken into account. The model contributes to a better explanation of responses which apparently cannot be fully explained by pure utility maximisation but also by problems incurred in (too) complex charging policies. It should be noted that the latent variable part of the integrated model – as all models of this type - cannot be applied for forecasting the effects of a specific, new complex charging scheme. This is due to the fact that the parameters within the latent variable part are individual- and survey-specific and would require repeated surveys in order to obtain the indicator values needed for the measurement equations.

The research presented in this paper cannot give an advice on how many dimensions and charge levels a congestion charging scheme should have in order to be perceived correctly and to induce the desired behavioural responses. However, given the result that the perceived complexity of the hypothetical congestion charging policy is influenced by experience and familiarity with the choice situation, transport politicians should spent efforts for well-designed information campaigns including the provision of web-and telephone based support when the introduction of congestion charging is intended.

References

Altmann, J., Rupp, B., Varaiya, P. 2001. Effects of pricing on internet user behavior.

Ashok, K., Dillon, W. R., Yuan, S. 2002. Extending discrete choice models to incorporate attitudinal and other latent variables. Journal of Marketing Research, 39 (1), pp. 31-46.

Bettmann, J.R., Luce, M.F., Payne, J.W. 1998. Constructive consumer choice processes. Journal of Consumer Research, 25, 3, pp. 187-217.

Bonsall, P. 2004. Targeted Marketing to reduce non-users' misperceptions. Final report to EPSRC.

Bonsall, P., Shires, J., Matthews, B., Maule, J., Beale, J. 2005. Road user charging – pricing structures. Final Report prepared for the Department of Transport, PPAD 09/159/002, Leeds.

Bonsall, P., Shires, J., Maule, J., Matthews, B. 2005. Can people respond to complex price signals?

Bonsall, P., Shires, J., Ngoduy, D., Link, H., Becker, A., Papaiopannou, P., Xanthopoulos, P. 2007. Optimal Complexity of Prices for Transport Infrastructure. Deliverable 6 of the GRACE project funded by Sixth Framework Programme, ITS, University of Leeds.

FDS International Ltd. 2001. Transparency on mobile phone tariff information report. Report for the DTI, Consumer Affairs Directorate.

Garbarino, E.C., Edell, J.A. 1997. Cognitive effort, affect and choice. Journal of Consumer Research 24, pp. 147-158.

INFRAS, CE, ISI and University of Gdansk (2007). Handbook on estimation of external cost in the transport sector. Produced within the study Internalisation Measures and Policies for All external Cost of Transport (IMPACT). Delft.

Kahnemann , D., Tversky, A. 1984. Choices, values and frames. American Psychologist, vol 39 (4), pp. 341-350.

Kang, Y.S., Herr, P.M., Page, C.M. 2003. Time and distance: Asymmetries in consumer trip knowledge and judgements. Journal of Consumer Research, 30, pp. 420-429.

Link, H., Becker, A. 2007. Responses to road user charges varying in their level of complexity – Survey report Germany. Annex 1 to Deliverable D6 of the GRACE project funded by Sixth Framework Programme, ITS, University of Leeds.

Miller, G.A. 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63, pp. 81-97

Morikawa, T., Ben-Akiva, M., McFadden, D.L. 2002. Discrete choice models incorporating revealed preferences and psychometric data, in: Philip H. Franses and Alan L.Montgomery (eds.): Econometric Models in Marketing, Elsevier, Amsterdam, 29–55.

Muthen,L., Muthen, B. 2007. Mplus User's Guide. 5th ed., Muthén & Muthén: Los Angeles.

Nash, C., Shires, J., Link, H. 2010. Measuring the marginal social costs of road transport: what are the most important elements? Universities of Leeds, Sheffield and York, http://eprints.whiterose.ac.uk/

OFGEM 2001. Attitudes to price information: Qualitative and quantitative research. Study commissioned by the OFGEM.

Swait, J., Adamovicz, W. 2001. The influence of task complexity on consumer choice: A latent class model of decision strategy. Journal of Consumer Research, 28, pp. 135-148.

Walker J. L. (2001) PhD Thesis: Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables, Massachusetts Institute of Technology.

Walker, J., Ben-Akiva, M. 2002. Generalised random utility model. Mathematical Social Sciences, 43, pp. 303-343.