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A comparison of bus passengers' and car drivers' valuation of casualty risk reductions in their routes

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Abstract

Introduction
The economic value of safety represents an important guide to transport policy, and more studies on individuals' valuation of road safety are called for. This paper presents a stated preference study of the value of preventing fatal and serious injuries involving bus passengers and car drivers in road accidents.
Objectives
Former valuation studies based on travel behaviour and route choice have involved primarily car drivers. Our study also included bus passengers, thus providing a comparison of two types of transport mode users. Moreover, the comparison was based on two different valuation methods.
Methodology
About 600 bus passengers and nearly 2300 car users from different areas of Norway reported a recent trip, described by its distance and travel cost. Then they answered stated choice tasks that took a reference in the reported trip and involved trade-offs among travel time, fatal and seriously injured victims and travel costs. Afterwards, they faced a simple trade-off between travel costs, and fatal and seriously injured victims.
Findings
Pooling the data from the two stated preference formats, we derived values of a statistical life and of a statistical seriously injured victim. Regarding the value of statistical life, our point estimates were NOK 45.5 million and NOK 58.3 million for bus users and car users respectively.
Discussion
The point estimates for bus passengers and car users were not statistically different given their confidence intervals. Thus, we recommend the use of a single value, identical for both modes of transport, for the prevention of a statistical fatality as well as for a statistical injury

Keywords: choice experiment, contingent valuation, fatality, injury, insecurity, time saving

1. Introduction

Estimates of the economic value of safety, primarily based on individuals' valuation of casualty risk reduction, can guide policy (Wijnen and Stipdonk, 2016). Approximately 15 years ago, the hypothetical route choice approach to the valuation of statistical lives and limbs was introduced (Ortúzar and Rizzi, 2001; Rizzi and Ortúzar, 2003). Since then, discrete choice experiments (DCE) for car drivers, involving travel alternatives differing in time, cost and other travel attributes, have been carried out in Chile (Iragüen and Ortúzar, 2004; Hojman et al., 2005; Rizzi and Ortúzar, 2006), the Netherlands (de Blaeij et al., 2002), Belgium (de Brabander, 2006), Australia (Hensher et al., 2009), Norway (Tofte, 2006; Veisten et al. 2013) and Spain (González et al., 2016). Flügel et al. (2015) reported an application of DCE to cycling; and Hensher et al. (2011) to walking. Wijnen and Stipdonk (2016) call for more studies on individuals' valuation of road safety.

This paper extends the above-referred research, by including bus passengers' valuation of statistical lives and limbs. We compare bus passengers' valuation against car drivers' in a common stated preference (SP). To our knowledge this has not been reported in the literature. Samples of bus passengers and car drivers described a recent trip (i.e. trip length, travel time and cost) which was used as reference in the experimental design. Then, the trip lengths together with traffic volumes on the reported roads, were used to establish reference levels for the casualty risk (presented as the annual number of killed and seriously injured bus passengers, or car drivers, in the given route length). After responding to a series of choice situations (DCE) involving the above attributes, both bus passengers and car drivers faced a contingent valuation question about their willingness to pay (WTP) a set of money amounts for specific casualty reductions; a so-called multiple bounded (MB). Thus, we were able to obtain value estimates from two different SP methods.

The remainder of the paper is arranged as follows: The next section provides the theoretical and methodological basis for the valuation of statistical lives (VSL) and serious injuries (VSSI), for the two SP methodologies used; this also includes hypotheses about value estimates from bus passengers compared to car drivers. In the third section the internet-based survey material used is described. The fourth section provides model results with attribute estimates and the implicit VSL and VSSI. Finally, our main findings are discussed in the concluding section.

2. Theoretical and methodological approaches

2.1. Theoretical and empirical expectations related to valuation of statistical lives and injuries, for bus passengers vs. car drivers

At least in Europe, there are two casualty risk differences between travelling by bus and by car:

- The risk of fatality or serious injury is lower for bus transport than for car transport in countries within the Organization for Economic Cooperation and Development – OECD (Elvik et al., 2009).
- The risk of fatality or serious injury is (perceived) as less controllable in bus transport compared to car transport (Slovic et al., 1979; Carlsson et al., 2004).

The standard model of mortality risk valuation formulates expected utility as a weighted average of utilities associated with wealth given survival or death, with weights expressed by the survival and death probabilities; as it can be assumed *a priori* that increased safety (reduced risk) is a desired economic good, individuals' WTP for a risk reduction should be non-negative (Drèze, 1962; Schelling, 1968; Mishan, 1971; Jones-Lee, 1974; Pratt and Zeckhauser, 1996). One implication of this model is that VSL should increase with baseline risk (Jones-Lee, 1974; Weinstein et al., 1980). However, even if fatality risks for car drivers are higher than for bus passengers, transport risk constitutes one out of several risks; and for most individuals, these other risks determine the overall risk of death or health impairment (Elvik et al., 2009). Given the fact that background risks are at least an order of magnitude larger than transport risks in OECD countries, the effect of the comparatively small difference in risk between bus passengers and car drivers on WTP and VSL might be very limited – or negligible (Hammitt and Graham, 1999; Eeckhoudt and Hammitt, 2001). The effect of initial risk on VSSI is expected to be similar for VSL, transport injury risks contribute relatively more to overall injury risks than to overall fatality risks (Elvik et al., 2009). Viscusi and Evans (1990) found a positive effect of baseline risk on WTP to reduce injury risk.

Public transport involves other risks than going by car; for example, the security risks related to sharing a mode with other individuals. The statistical risk of attacks/violence on public transport or at station/bus stop is small in Norway (Backer-Grøndahl et al., 2009). Notwithstanding, subjective risk has an emotional component, in addition to the cognitive element (Sjöberg, 1998, 1999); and the emotional discomfort might be different, and possibly more important, for personal security risk compared to accident risk (Teigen et al., 1988; Brun, 1992; Moen and Rundmo, 2006). In a survey of Norwegians, Backer-Grøndahl et al. (2009) found that security risk was considered more important than accident risk for the attractiveness of a transport mode. Another survey of Norwegians, indicated that the cognitive component of risk (accident probability) was more pronounced for private transport modes, while the emotional component of risk (accident fear or fear of other unpleasant/dangerous incidents) was more pronounced for public transport modes (Moen and Rundmo, 2006; Rundmo et al., 2011).

Emotional dread might still be important for accident risk in public transport; although small, when accidents happen they will normally imply several casualties. Moreover, accident risk when riding a bus will be perceived as less controllable than accident risk when sitting behind the wheel of one's automobile; and this relative lack of control may affect the emotional component of risk (Slovic et al., 1979). In fact, Chilton et al. (2006) found a large dread effect in the valuation of rail accident death risk relative to automobile accident death risk. Thus, there are potentially opposite effects on the WTP for accident risk reductions in public transport compared to the WTP for accident risk reductions in car travel.

2.2. An operational model for the valuation of safety in discrete choice experiments (DCE)

Assume the utility of each available alternative *j* for person *i* is given by:

$$V_{ij} = \alpha \cdot \mathrm{CAS}_{ij} + \beta \cdot c_{ij} + \gamma \cdot t_{ij} \tag{1}$$

where CAS refers to casualties, c to costs, and t to time use. This is a simplified specification where all attributes enter utility additively. V_{ij} represents the deterministic part of a random utility function, U_{ij}, also including an error term ε_{ij} reflecting non-observability of part of what drives the choices (McFadden, 1974). We also include another error term to account for the correlation among choices/responses, l, from the same individual, τ_{ij}, yielding a mixed logit (ML) model (Train, 2009):

$$U_{ijl} = V_{ijl} + \tau_{ij} + \varepsilon_{ijl} \tag{2}$$

It is assumed that each alternative has a probability of being chosen given by the probability that U_{ijl} is the highest random utility for each individual i. The monetised marginal utility of an attribute in an alternative is given by the marginal rate of substitution between that attribute and the cost attribute; and with a simple linear specification of V_{ijl} this equals the ratio of the casualty coefficient and the cost coefficient:

$$\mathrm{WTP}_{\mathrm{CAS}} = \frac{\partial V_i / \partial \mathrm{CAS}}{\partial V_i / \partial c}\Bigg|_{V=\bar{V}} = \frac{\alpha}{\beta} \tag{3}$$

This expression for the WTP of a marginal reduction of casualties can be termed the "subjective value of a casualty reduction" (Hojman et al., 2005; Veisten et al., 2013). The casualties will contain a share of fatalities (Δ_f) and a share of serious injuries (Δ_{si}). Similarly, γ/β yields a subjective value of travel time savings (Gaudry et al., 1989; Hensher et al., 2005; Sillano and Ortúzar, 2005).

We will assume that τ is an iid Normal error term and ε is the traditional iid Gumbel error term (i.e. Extreme Value Type I) of logit models. The likelihood of the observed sequence of choices for individual i (suppressing this subscript for notational convenience), is given as:

$$\int \prod_l \prod_j \left(\frac{\exp\left(\alpha \cdot \mathrm{CAS}_{jl} + \beta \cdot c_{jl} + \gamma \cdot t_{jl} + \tau_j\right)}{\sum_j \exp\left(\alpha \cdot \mathrm{CAS}_{jl} + \beta \cdot c_{jl} + \gamma \cdot t_{jl} + \tau_j\right)} \right)^{g_j} \prod_j f\left(\tau_j\right) d\left(\tau_j\right) \tag{4}$$

where $f(\tau_j)$ is the Normal density function with zero mean and variance (σ) to be estimated, and g_{jl} is a dummy variable that takes the value of one if alternative j is chosen in choice scenario l and zero otherwise. If τ_j is zero in equation (4) the ML model collapses to the simple multinomial logit model (Ortúzar and Willumsen, 2011).

In the choice situations presented to respondents, both the left-hand and right-hand alternatives could have the lower number of casualties (and/or travel time and cost). We can thus apply a generic choice model. However, another way of modelling the choices is to re-arrange the alternatives in the data such that Alternative 1 (the re-arranged left-hand alternative) can be labelled the "safer route", always having the lower casualty number. Then the alternative-specific constant (ASC) can be interpreted as a preference for safety *per se* when travelling. For the ML model (4), there are then four or five coefficients to be estimated: the coefficients for casualties, time, and cost, a coefficient for the value of the standard deviation of the iid Normal error added to every alternative across all choices from the same individual (the pseudo panel effect), plus an ASC for the "safer route" alternative when modelling with labelled choices.

The valuation of a statistical casualty (VSC) can be derived from the estimated WTP for a marginal reduction of casualties (3), based on the ML model (4). Dividing the WTP measure by the (individual) risk change (δr_{CAS}) yields an estimate of the VSC equal to $\mathrm{WTP}_{\mathrm{CAS}}/\delta r_{\mathrm{CAS}}$. VSC can also be calculated as the sum of individual valuations for an aggregate risk change equal to one casualty reduction per year (Veisten et al., 2013). An individual driver's casualty risk per trip on a route of a given length is given by the number of casualties on that route per reference period (say a year) divided by the ratio of the average number of daily vehicle km (on the route) and the route length, or average annual daily traffic (*AADT*), times 365; that is: $r_{\mathrm{CAS}} = \mathrm{casualties}_{\mathrm{yr}}/(AADT \cdot 365)$. The risk change equivalent to *one* casualty reduction is then:

$$\delta r_{\mathrm{CAS}} = \frac{\mathrm{casualties}_{\mathrm{yr}}^{\mathrm{before}} - \mathrm{casualties}_{\mathrm{yr}}^{\mathrm{after}}}{AADT \cdot 365} = \frac{1}{AADT \cdot 365} \tag{5}$$

Then the VSC is given as:

$$\mathrm{VSC} = \frac{\mathrm{WTP}_{\mathrm{CAS}}}{\delta r_{\mathrm{CAS}}} = \frac{\mathrm{WTP}_{\mathrm{CAS}}}{1 / AADT \cdot 365} = \mathrm{WTP}_{\mathrm{CAS}} \cdot \left(AADT \cdot 365 \right) \qquad (6)$$

Note that compared to equations (11) and (12) in Hensher et al. (2009, p. 696), we do not divide by the number of casualties over the trip length, since the valuation from the choice experiment is given for *one* casualty change.

We will calculate VSC based on sample average $\mathrm{WTP}_{\mathrm{CAS}}$, sample average risk change (δr_{CAS}) and sample average *AADT*, respectively, for bus passengers and car drivers.

To derive VSL and VSSI from VSC, based on $\mathrm{WTP}_{\mathrm{CAS}}$ for combined reductions of fatalities and serious injuries, we employ the so-called *death-risk equivalent*, which equals to the relative value of preventing a serious injury with respect to preventing a fatality: DRE_{si} = VSSI/VSL (Jones-Lee et al., 1995). Given a DRE_{si} estimate and actual shares of serious injuries, p_{si}, and fatalities $(1–p)_f$ in bus or car accidents, VSL may be obtained from the following formula (Hultkrantz et al., 2006):

$$\mathrm{VSL} = \frac{\mathrm{VSC}}{\mathrm{DRE}_{si} \cdot p_{si} + (1 - p)_f} \qquad (7)$$

As the SP experiments presented in this paper cannot be applied to estimate a DRE we used a value of 0.2 following Veisten et al. (2013). Note also that Swedish studies from the last decade have estimated DRE_{si} between 0.15 and 0.2, the former being the official Swedish value (Svensson 2009). Jones-Lee et al. (1995) estimated values of DRE_{si} between 0.1 and 0.15. Hultkrantz et al. (2006) and Svensson (2009) wrote the VSL formula with $\mathrm{WTP}_{\mathrm{CAS}}$ instead of VSC. Then, the denominator would include the relative risk changes for serious injuries and fatalities, and each share should be multiplied by the risk change, Δr_{CAS} =1/(AADT·365).

2.3. Multiple-bounded (MB) format of contingent valuation

Contingent valuation used to be the predominant SP method for valuation of risk changes and estimating VSL in the previous century. Traditionally, one would specify a road safety project for the respondents without any link to travel behaviour and apply a standard risk measure, such as a change in the number of casualties in a population of, e.g., one million (Jones-Lee et al., 1985, 1995; Beattie et al., 1998; Carthy et al., 1999; Corso et al., 2001; Persson et al., 2001; Krupnick et al., 2002; Alberini et al., 2004; Andersson, 2007). But, also applying contingent valuation formats, one may present risk changes in terms of numbers of fatalities and seriously injured persons (Hultkrantz et al., 2006; Svensson, 2009), instead of tiny probabilities. In the MB format, the respondent is offered a specific improvement (in our case, a specific reduction in casualty numbers) and asked if he/she would be willing to pay a set of different money amounts. For each amount, respondents can express their level of uncertainty by including a semantic scale with levels: “definitely no”, “probably no”, “uncertain”, “probably yes”, and “definitely yes” (Welsh and Poe, 1998; Broberg and Brännlund, 2008). For an illustration of a MB-format please refer to Figure 2 below.

One way of modelling the MB responses, similar to a DCE, is to consider the answer to each proposed amount as a single choice that does not involve other attributes than casualties and costs (omitting travel time). Thus, the answers to the various amounts are stacked into a series of single-bounded discrete choices. Then, for example, answering “probably yes” or “definitely yes”, can be considered as choosing “Alternative 1”, the “safer route”, which will always have the lower casualty number (and higher costs). Answering “probably no” or “definitely no” can be considered as an implicit choice of the “riskier route”, while “uncertain” can be considered as an “opt-out” (or interpreted as either a “yes” or a “no”). This facilitates a pooled modelling of the two SP methodologies; WTP_{CAS} will equal α/β also when using the MB data. The ML modelling of the MB answers should be close to the random effects probit model applied by Alberini et al. (2003).

Related to the valuation of risk changes, we only know of open-ended contingent valuation formats being compared with DCE; for example, Magat et al. (1988) and Ortúzar et al. (2000) found that DCE yielded the higher estimates, respectively, for morbidity risk reduction and reduced health risk from air pollution.

2.4. Models including covariates

The utility specification, $V_{ij}= \alpha \cdot CAS_{jl}+\beta \cdot c_{jl}+\gamma \cdot t_{jl}$, can be extended to include covariates. One way of doing this is to interact these with the casualty, time, and/or cost attributes (Beggs et al., 1981), the so-called level of service (LOS) variables. This yields models with systematic taste variations, customising the marginal utilities (with respect to cost, casualties and time) according to the demographic profile of each respondent *i*. Schematically, the indirect utility is now written as (Ortúzar and Willumsen, 2011, p 279):

$$V_{ij} = \left(\alpha + \sum_d \alpha_d X_{di}\right)\mathrm{CAS}_j + \left(\gamma + \sum_d \gamma_d X_{di}\right)t_j + \left(\beta + \sum_d \beta_d X_{di}\right)c_j \qquad (8)$$

The new coefficients to be estimated are α_d, β_d, γ_d, where d indicates covariates, X (either binary or continuous demographic variables). The subscript i accompanying each covariate means that the values of these variables depend only on the respondents' characteristics and as such they are the same across all alternatives and choice scenarios for every respondent (Beggs et al., 1981). With this formulation, the marginal utility for casualties, $MU_{\mathrm{CAS}} = \alpha + \sum_d \alpha_d X_{di}$, depends on the individual characteristics and, as such, it may differ across respondents. This also affects WTP:

$$\mathrm{WTP}_{\mathrm{CAS}} = \frac{\alpha + \sum_d \alpha_d X_{di}}{\beta + \sum_d \beta_d X_{di}} \qquad (9)$$

$\mathrm{WTP}_{\mathrm{CAS}}$ now has to be estimated with respect to average or median values of the individual characteristics. One also ought to verify that marginal utilities are negative for every respondent and this is a useful extra test for model quality.

2.5. Hypotheses

Based on the exposition above, we will apply our survey data to test null hypotheses of equality between WTP for casualty risk reductions between bus passengers and car drivers. As different methodical approaches are likely to impact on estimation results and, therefore, may alter the conclusion of hypothesis testing, we investigate equality under different hypotheses.

H1 is based on a comparison of discrete choice experiments and is formally given as:

H1) $\mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{DCE,bus}} = \mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{DCE,car}}$

H2 is based on the multiple bound contingent valuation approach:

H2) $\mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{MB,bus}} = \mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{MB,car}}$

In order to increase robustness, we also test for equality based on a joint estimation model using the pooled data from both types of SP-approaches:

H3) $\mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{Pooled\,DCE\text{-}MB,bus}} = \mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{Pooled\,DCE\text{-}MB,car}}$

Moreover, we will test whether or not the results are sensitive to the fact that some respondents might have regarded the assigned baseline casualty levels as “too high”. For this reason, we ran additional models with a reduced sample excluding the disbelievers (i.e. “belief”):

H4) $\mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{Pooled\,DCE\text{-}MB,bus,\,belief}} = \mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{Pooled\,DCE\text{-}MB,car,\,belief}}$

As AADT might differ between bus passengers and car drivers, the VSL might also differ between these two samples even if their $\mathrm{WTP}_{\mathrm{CAS}}$ were equal. For this reason, we also re-tested the three first hypotheses above with VSL (and, implicitly, VSSI).

H1*) $\mathrm{VSL}^{\mathrm{DCE,bus}} = \mathrm{VSL}^{\mathrm{DCE,car}}$

H2*) $\mathrm{VSL}^{\mathrm{MB,\,bus}} = \mathrm{VSL}^{\mathrm{MB,\,car}}$

H3*) $\mathrm{VSL}^{\mathrm{Pooled\,DCE\text{-}MB,\,bus}} = \mathrm{VSL}^{\mathrm{Pooled\,DCE\text{-}MB,\,car}}$

3. Material

3.1. Survey development

The SP survey was based on an underlying requirement of a fully flexible design; implying that respondents from any part of Norway would describe a recent trip, whether by bus or by car, and assess changes in casualty numbers, travel time, and costs. While the respondents reported the travel time and the cost, the casualty numbers had to be calculated in a flexible way that had to be applicable to any type of reported trip, or road section (see Table 1). Thus, the casualty attribute was tested first in focus group sessions, before a quantitative test in a small pilot. In the pilot study, the casualty attribute levels with respect to the base levels were: –50%, –25%, 0, 25%, 50%. The utility balance was relatively good for both time and cost, but regarding the casualty attribute almost 80% of the chosen trip alternatives were those with the lowest casualty number, suggesting that the levels of cost or time increase could not balance the gain in safety. For this reason, the range of the casualty attribute was reduced to: –30%, –15%, 0, 15%, 30% (see Table 1).

The internet survey was carried out in two waves via e-mail recruiting from the national internet panel of *Synovate Norway* (now part of *Ipsos MMI* (http://ipsos-mmi.no)). In the first wave (April 2010), 9,489 respondents answered a questionnaire related with the valuation of travel time, reliability, and comfort (Ramjerdi et al., 2010). From this sample 832 bus passengers and 3,109 car drivers were asked to participate in the second-wave survey, about two weeks later. 74.64% of the bus passengers and 75.33% of the car drivers completed it (i.e. 621 and 2,342 individuals respectively). The response rate in the first wave was 21.87%, such that the effective response rates for the second wave survey were 21.87%×74.64%=16.32% and 21.87%×75.33=16.47%, respectively, for bus passengers and car drivers.

The final questionnaire of the second wave part of the survey was structured as follows:

- Introduction to the issue of fatality/injury risk and casualty numbers.
- Scenario for change in casualty numbers and choices/valuations.
- Questions on reasoning for choices/valuations.
- Respondent's income.
- Questions on fatality/injury risk beliefs, accident experience.

3.2.Designing scenario and choice questions

The safety attribute was presented in the survey as the annual expected number of casualties (fatalities and serious injuries), on a road trip of a certain length with a certain travel density (Hojman et al., 2005), depending on the calculated length and traffic density (AADT) of each respondents' reported trip. A trip of a given duration, in minutes, was converted to length in kilometres by assuming an average speed of 35 km/hour for bus transport and 45 km/hour for car transport (Denstadli et al., 2006).

Once the length in kilometres of each trip was known, official accident statistics for Norway from 1998 to 2005 were used to estimate accident rates per kilometre driven. Account was taken of the fact that the rates depend on traffic volume. The rate of serious injuries was adjusted for underreporting; that is, the number of serious injuries was multiplied by 1/0.7 (Elvik and Borger Mysen, 1999; Veisten et al., 2013). Regarding traffic volume (Hensher et al., 2009), initial *AADT* levels were based on the urbanization level at the respondents' place of residence, simplifying it to just three levels: 12,000 for cities, 6,000 for other densely populated areas, and 2,000 for rural areas. Further, the initial *AADT* level could be adjusted to one level upwards or downwards, if the respondents' own assessment of traffic volume on the reported trip differed from the initially calculated *AADT*. The different routes that respondents reported to have gone by bus or car, all around Norway, were grouped into 10×3 route classes, applying trip length (min) and *AADT* (see Table 1).

Table 1: Base levels of safety attributes (fatalities and serious injuries) in the DCE, derived from actual trip lengths (min) reported by bus passengers and car drivers

		Mean annual expected number of casualties*							
		Bus passengers				Car drivers			
Base time (min)	Mean time (min)	Km	AADT 12,000	AADT 6,000	AADT 2,000	Km	AADT 12,000	AADT 6,000	AADT 2,000
10 – 19	15	8.75	3	2	2	11.25	4	3	2
20 – 44	32	18.67	6	4	2	24	8	6	5
45 – 74	60	35	11	8	4	45	14	11	6
75 – 119	90	52.5	16	12	7	67.5	21	16	8
120 – 179	150	87.5	27	21	11	112.5	35	26	14
180 – 239	210	122.5	38	29	15	157.5	49	37	20
240 – 359	300	175	55	41	22	225	70	53	28
360 – 539	450	262.5	82	62	33	337.5	106	79	42
540 – 1439	990	577.5	181	136	72	742.5	232	174	93
1440 +	1500	875	274	205	110	1125	352	264	141

* Casualties refer to the sum of fatalities and serious injuries.

However, while the base levels for car drivers are somewhat on the higher side, the base levels for bus passengers ended up being far above their actual levels. There was a trade-off in the scenario design, between a more realistic one involving complicated minuscule casualty figures and a less realistic one with simple integer figures. To assess the perceived realism of the casualty figures, we asked respondents if the presented base level of casualties on their reported road section “seemed to be correct”, “seemed to be too low”, or “seemed to be too high”.

The casualty attribute range and levels, were based on the three-attribute design for pair-wise choices from De Jong et al. (2007), with two lower levels than the base (–30%, –15%) and two higher levels than the base (15%, 30%), in Table 1, rounded to integer. The exception was for the 10-19 min base level, plus the 20-44 min base level for bus transport (for *AADT* level of 2,000), where absolute rather than relative changes were applied, since the base levels were too small to yield any differentiation between attribute levels based on the 15 and 30% changes. That is, increases were set to, respectively, 1 and 2 casualties, and reductions set to -1 and -2 casualties, compared to the base levels.

The full-factorial design for a choice experiment with three attributes with five attribute levels would yield 5^3=125 choice pairs. This was reduced to 96 choice pairs by means of two adjustments: (i) the choice pairs with dominant alternatives were removed; and (ii) not all combinations of the time level increases/decreases were included with the cost and casualty variables. The 96 choice pairs were then blocked into six choices per respondent (De Jong et al., 2007). The three attributes were related with trip alternatives in the pair-wise choice structure, plus an opt-out option, as depicted in Figure 1.

Everything else equal, would you choose travel alternative 1 or travel alternative 2?		
Alternative 1	**Alternative 2**	**Alternative 3**
Average travel time per trip: X min (approximately X·K·52/60 hours per year) Cost per trip: Y NOK (approximately Y·K·52 NOK per year)	Average travel time per trip: R min (approximately R·K·52/60 hours per year) Cost per trip: S NOK (approximately S·K·52 NOK per year)	do not know

Seriously/severely injured and fatalities per year: Z	Seriously/severely injured and fatalities per year: T	
○	○	○

Figure 1: Illustration of choice experiment situation, for bus passengers and car drivers; K is a variable based on the respondents' answer to a survey question on how often they use bus or car per week.

Before answering the DCE, respondents were informed about the implications of serious injuries, with descriptions of pain and duration in hospital and pain/discomfort after leaving hospital, based on Beattie et al. (1998).

After the DCE, both bus passengers and car drivers faced the MB question about their willingness to accept increases in, respectively, ticket and toll prices for casualty reductions. This would imply reductions in casualties and increases in costs related to the same reference level as for the DCE.

The particular MB format question used is shown in Figure 2. A typical (and expected) pattern in answering is "diagonal" as illustrated there, i.e. "definitely yes" for the lowest amount and "definitely no" for the highest amount.

What is the maximum amount you are willing to pay in increased ticket cost per trip?					
Increased cost per trip:	*Definitely yes*	*Probably yes*	*Unsure*	*Probably no*	*Definitely no*
½ (cost level 1 – base cost)	◉	○	○	○	○
cost level 1 – base cost	○	◉	○	○	○
½ (cost level 1 – base cost + cost level 2 – base cost)	○	○	◉	○	○
cost level 2 – base cost	○	○	◉	○	○
2 (cost level 2 – base cost)	○	○	○	◉	○
5 (cost level 2 – base cost)	○	○	○	○	◉

Figure 2: Illustration of multiple bounded question for bus passengers (with similar structure and wording for car drivers, with road toll as payment vehicle); typical response pattern.

4. Results

4.1. Descriptive statistics

Table 2 lists the means and ranges of the demographic variables considered for modelling.

Table 2: Descriptive statistics for demographic variables

	Bus passengers (*n* = 609)			Car drivers (*n* = 2,290)		
	Mean	Minimum	Maximum	Mean	Minimum	Maximum
Age	44.71	18	81	49.89	17	84
Children (below 18 years) in household	0.21	0	1	0.36	0	1
University degree	0.67	0	1	0.62	0	1
Income (personal monthly net income, NOK)*	7,380	0	55,000	12,860	0	55,000
Income missing	0.09	0	1	0.05	0	1
Gender (1 for males)	0.36	0	1	0.65	0	1
Live in urban area	0.72	0	1	0.45	0	1
Live in semi-urban area	0.17	0	1	0.33	0	1
Live in rural area	0.11	0	1	0.22	0	1
Daily travel distance by mode (km)	4.90	1	200	19.78	1	600
Relative/friend seriously injured/killed in road accident	0.23	0	1	0.25	0	1

* Income average was calculated by taking midpoints from income intervals setting the maximum to NOK 55,000; the averages in the table are downward biased, since the 54 bus passengers and 138 car drivers that did not provide income information were set to zero. If missing values are excluded, the averages become NOK 17,324 (n=555) for bus passengers and NOK 24,000 (n=2,205) for car drivers.

The sample of bus passengers had slightly lower average age, a considerably higher share of females, lower average income, were more urban, and reported shorter travel distances, compared to car drivers.

More than 80% of the bus passengers and more than 70% of the car drivers considered that the route they had driven had fairly high or very high density, exemplified in the questionnaire as *AADT* 5-10,000 and *AADT* >10,000, respectively. If respondents had been pre-registered with, for example, low traffic density on their reported trip (i.e. *AADT* < 5,000), based on the urbanised degree of their municipality, but considered that there was “very high density” on the route, their *AADT* was adjusted to 6,000. Conversely, respondents pre-registered as driving on routes with high traffic density (*AADT* = 12,000) but who considered their route as having low density, had their *AADT* adjusted to 6,000.

Regarding the respondents’ assessment of their assigned annual casualty base levels (being above their actual levels, particularly for bus transport), 58% of the bus passengers and 52% of the car drivers considered the casualty numbers “too high”. 24% of the bus passengers and 35% of the car drivers considered the casualty numbers for the trip they had reported as “correct” (just about 3%, in both samples, considered the numbers “too low”, and the remaining answered “don’t know”). We carried out split tests of car-bus WTP differences, one with those believing in the casualty levels and another with those thinking that the levels were “too high”.

4.2. Model results with level-of-service attributes

For both samples (bus passengers and car drivers), we estimated two different ML models, one generic and one including an ASC (for the “safer route”), to account for a potential preference for safety *per se* (Table 3). The opt-out alternatives were treated as in Veisten et al. (2013), that is, they were excluded as a third alternative. However, if a respondent answered in the follow-up questions that “route A and B were almost alike”, her observations were entered twice, once as choosing the safer route and once as choosing the more dangerous route. We excluded respondents who always chose the opt-out alternative (11 bus passengers and 52 car drivers), as they did not provide any information about the relative importance of the attributes. Regarding potential lexicographic (i.e. non-compensatory) answers, 41% of bus passengers and 37% of car drivers always chose the alternative with the lowest number of casualties; 2.9% and 1.8% respectively, always chose the alternative with the lowest travel time, and 3.5% and 4.9% respectively, always chose the alternative with the lowest cost. A relatively high share of potentially lexicographic answers for the safety attribute had also been observed in former DCE studies (Hojman et al., 2003; Iragüen and Ortúzar, 2004).

Table 3: ML of DCE with level-of-service attributes*

Parameters	Generic model				Alternative-specific model			
	Bus passengers		Car drivers		Bus passengers		Car drivers	
	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value
ASC_safer_route	-	-	-	-	2.18 (0.163)	0.00	1.65 (0.0767)	0.00
Cost	-0.0183 (0.00275)	0.00	-0.0181 (0.00216)	0.00	-0.0184 (0.00308)	0.00	-0.0162 (0.0021)	0.00
Casualty	-0.230 (0.0370)	0.00	-0.385 (0.325)	0.00	-0.0956 (0.0255)	0.00	-0.157 (0.0238)	0.00
Time	-0.0459 (0.00589)	0.00	-0.0554 (0.00497)	0.00	-0.0406 (0.00545)	0.00	-0.0493 (0.00489)	0.00
Sigma	1.44 (0.0911)	0.00	1.24 (0.0359)	0.00	1.41 (0.109)	0.00	1.23 (0.0425)	0.00
Halton draws	500		500		500		500	
Number of observations	3,612		13,602		3,612		13,602	
Number of individuals	608		2,290		608		2,290	
Null log-likelihood	-2,503.648		-9,428.188		-2,503.648		-9,428.188	
Constant log-likelihood	-1,874.121		-7,651.628		-1,874.121		-7,651.628	
Final-log-likelihood	-1,770.892		-7,090.715		-1,587.423		-6,644.355	
ρ^2(Null)	0.293		0.2479		0.366		0.2953	
ρ^2(Cte)	0.055		0.0733		0.153		0.1316	
$\bar{\rho}^2$ (Null)	0.291		0.2475		0.364		0.2947	
Derived values (St. error)								
Value of travel time saving (NOK/hour)	150.49		183.65		132.39		182.59	
WTP_{CAS} (NOK/casualty)	12.57 (2.10**)		21.27 (1.83**)		5.20 (1.18**)		9.69 (1.22**)	
$\mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{DCE,car}} - \mathrm{WTP}_{\mathrm{CAS}}^{\mathrm{DCE,bus}}$	8.70 (2.78)				4.50 (1.70)			
95% confidence interval	3.25–14.04				1.16–7.76			
Hypothesis test	Reject H1				Reject H1			

* All models were estimated using BIOGEME (Bierlaire, 2003). Robust standard error and p-values were computed taking into account the repeated observations nature of the data. Opt-out options were removed from estimation.

** Applying the 'delta method' (Hole et al., 2007), that takes into account the correlation between the cost and casualty coefficients.

In the ML model with LOS attributes, the coefficients for casualties, time, and cost have the expected negative signs for both transport groups. The term accounting for the correlated nature of choices among individuals (Sigma) has a relatively high magnitude and is highly significant. Thus, addressing correlation among observations from the same individual reveals a significant amount of heterogeneity among individuals. An (unobserved) heterogeneity among individuals has been consistently found in ML models based on SP-data and is simply a natural result of individuals having different preferences and / or restrictions unobservable to the modeler .

We tested hypothesis H1 by looking at the difference in the WTP for car drivers and bus passengers. If the difference is not statistically significant from zero (with significance level of 0.05) we cannot reject H1. The generic model WTP difference was estimated at NOK 8.70 with a standard error of 2.78. As the 95% confidence interval for the differences is then [3.25-14.04], the difference is significantly different from zero and we can reject H1. The same result is found for the alternative specific model.

A similar modelling procedure was carried out for the MB responses, where the time attribute was not available (Table 4). As done with the opt-out alternative in the DCE, we excluded "unsure" MB responses. Responses "definitely yes" and "probably yes" were coded as choosing the safer alternative (implying that a policy instrument reducing casualties was set in place), while responses "probably no" and "definitely no" were coded as choosing the more dangerous alternative (the *status quo* without the policy instrument).

Table 4: ML for MB format data with level-of-service attributes*

Parameters	Generic model				Alternative-specific model			
	Bus passengers		Car drivers		Bus passengers		Car drivers	
	Value (rob.std. err)	Rob. P-value	Value (rob.std . err)	Rob. P-value	Value (rob.std. err)	Rob. P-valu e	Value (rob.std. err)	Rob. P-value
ASC_safer_route	-	-	-	-	2.42 (3.15)	0.44	0.608 (0.177)	0.00
Cost	-0.0333 (0.0056)	0.00	-0.0403 (0.011)	0.00	-0.0444 (0.0388)	0.25	-0.040 (0.0107	0.00

Casualty	-0.289 (0.0639)	0.00	-0.379 (0.091)	0.00	-0.214 (0.134)	0.11	-0.294 (0.0827)	0.00
Sigma	1.43 (0.158)	0.00	1.60 (0.147)	0.00	1.89 (2.37)	0.42	1.46 (0.125)	0.00
Halton draws	500		500		500		500	
Number of observations	3,114		12,125		3,114		12,125	
Number of individuals	606		2,289		606		2,289	
Null log-likelihood	-2,158.460		-8,404.410		-2,158.460		-8,404.410	
Constant log-likelihood	-1,966.505		-8,341.609		-1,966.505		-8,341.609	
Final-log-likelihood	-1561.511		-5,844.149		-1,494.218		-5,817.166	
ρ^2(Null)	0.277		0.305		0.308		0.308	
ρ^2(Cte)	0.206		0.300		0.240		0.303	
$\bar{\rho}^2$ (Null)	0.275		0.304		0.306		0.307	
Derived values (St. error)								
WTP_{CAS} (NOK/casualty)	8.68 (1.35**)		9.40 (1.18**)		4.82 (1.67**)		7.35 (1.30**)	
$WTP_{CAS}^{MB,car} - WTP_{CAS}^{MB,bus}$	0.73 (1.79)				2.53 (2.12)			
95% confidence interval	-2.78–4.16				-1.63–6.60			
Hypothesis test	Retain H2				Retain H2			

* All models were estimated using BIOGEME (Bierlaire, 2003). Robust standard error and p-values were computed taking into account the repeated observations nature of the data. In this case the level-of-service attributes were only casualties and cost. The number of respondents is slightly higher than in the DCE, since we excluded a few respondents that always chose the opt-out alternative in the DCE.

** Applying the 'delta method' (Hole et al., 2007), that takes into account the correlation between the cost and casualty coefficient.

The coefficients of casualties and cost have the expected negative signs for both the bus transport group and the automobile transport group. The robust correlation coefficient between the coefficients of cost and risk is 0.946 (while in the other models it was found to be around 0.5). That is why the lower bound of the ratio is non-negative, even though both confidence intervals for the single parameters have a negative lower bound. Again, the term accounting for the correlated nature of choices among individuals (Sigma) has a relatively high magnitude and is highly significant. However, in this case, based on the comparison of WTP differences that are not significantly different from zero, we cannot reject H2.

We also analysed the MB data as interval data, following the approach proposed by Bromberg and Brännlund (2008). The intervals applied were defined between the highest "definite yes" bid and the lowest "probably no" bid. If no bid was accepted with "definitely yes" (no bid rejected with "probably no") the interval was open below (above). The WTP was calculated for a reduction in one casualty (as the offered risk reduction was individual-specific). The result regarding hypothesis H2 was the same as when using the binary model format for MB, in Table 4; that is, H2 could not be rejected because the estimated WTP_{CAS} for bus passengers was not significantly different from the WTP_{CAS} for car drivers.

Finally, we estimated joint models for the DCE and MB data. That is, we merged the datasets, including 6+6=12 choices per respondents (again, opt-out alternatives in DCE and "unsure" responses in MB were excluded). Technically, the person specific error term, τ_j, had to be divided into one error component associated with the DCE data ($\tau_{j,DCE}$) and one for the MB data ($\tau_{j,MB}$), as the random terms cannot be assigned two different scale parameters. Thus, the estimation programme reported a higher number of "individuals" due to the separate panel structure applied to DCE and MB. We also split the alternative specific constant between the two SP formats and introduced a scale parameter for the MB data (i.e. normalised to one for the DCE data), allowing for different error variance in the two SP formats (Table 5).

Table 5: ML for combined DCE-MB data with level-of-service attributes*

Parameters	Generic model				Alternative-specific model			
	Bus passengers		Car drivers		Bus passengers		Car drivers	
	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value
ASC_safer_route_DCE	-	-	-	-	1.86 (0.147)	0.00	1.53 (0.0897)	0.00
ASC_safer_route_MB	-	-	-	-	1.32 (0.178)	0.00	0.279 (0.116)	0.02
Cost	-0.0262 (0.00249)	0.00	-0.0247 (0.00248)	0.00	-0.0243 (0.0026)	0.00	-0.0219 (0.00218)	0.00
Casualty	-0.246 (0.0292)	0.00	-0.329 (0.0265)	0.00	-0.128 (0.0213)	0.00	-0.180 (0.0235)	0.00
Time	-0.0491 (0.00536)	0.00	-0.0542 (0.00507)	0.00	-0.0433 (0.00491)	0.00	-0.0542 (0.00489)	0.00

Sigma	1.39 (0.107)	0.00	1.23 (0.0620)	0.00	1.12 (0.109)	0.00	1.06 (0.0807)	0.00
Lambda MB (scale parameter)	1.07 (0.116)	0.55***	1.31 (0.190)	0.11***	1.18 (0.177)	0.31***	1.52 (0.274)	0.06***
Halton draws	500		500		500		500	
Number of observations	6,726		25,727		6,726		25,727	
Number of individuals	606 (1214)		2,290 (4,579)		606 (1214)		2,290 (4,579)	
Null log-likelihood	-4,662.108		-17,832.598		-4,662.108		-17,832.598	
Constant log-likelihood	-3,894.833		-16,558.560		-3,894.833		-16,558.560	
Final-log-likelihood	-3,344.233		-13,120.861		-3,115.929		-12,558.700	
ρ^2(Null)	0.283		0.264		0.332		0.296	
ρ^2(Cte)	0.141		0.208		0.200		0.242	
$\bar{\rho}^2$ (Null)	0.282		0.264		0.330		0.295	
Derived values (St. error)								
Value of travel time saving (NOK/hour)	112.44		131.66		106.91		148.49	
WTP_{CAS} (NOK/casualty)	9.39 (0.92**)		13.32 (1.27**)		5.27 (0.79**)		8.22 (0.87*’)	
$WTP_{CAS}^{DCE\text{-}MB,car} - WTP_{CAS}^{DCE\text{-}MB,bus}$	3.93 (1.57)				2.95 (1.17)			
95% confidence interval	0.86–6.94				0.65–5.21			
Hypothesis test	Reject H3				Reject H3			

* All models were estimated using BIOGEME (Bierlaire, 2003). Robust standard error and p-values were computed taking into account the repeated observations nature of the data. The number of individuals in parentheses represents the sum of DCE and MB responses; although the same respondents answered the DCE and MB (“within-subject”), the model handles the DCE and MB choices with separate panel structures.

** Applying the ‘delta method’ (Hole et al., 2007), that takes into account the correlation between the cost and casualty coefficients.

*** Robust p-value against 1.

The results from the combined DCE-MB model are consistent with the results from the separate models in terms of coefficient signs and preference heterogeneity (Sigma). The scale parameter for the MB sample is higher than unity, suggesting a lower error variance in the “MB choices” (accept or reject the costs). The effect is, however, not statistically significant. The ASC coefficient is relatively higher for the DCE data, for both bus passengers and car drivers, but especially for the latter. Based on the joint ML model, the WTP-differences between car drivers and bus passengers are significantly different from zero, so we can reject H3.

Considering the joint DCE-MB as the best available data source, we conclude that car drivers have a higher WTP for casualty risk reduction than bus passengers (rejecting

H3). However, the two SP formats provide different results (rejecting H1 of equality between bus and car using DCE but retaining H2 of equality using MB).

4.3. Model results when excluding those considering the casualty levels as "too high"

It is typically assumed that respondents not finding a survey realistic might answer it without intent (Ortuzar and Willumsen, 2011). For this reason, we decided to check our results considering only those that had considered the casualty levels as reasonably or low, rather than too high. Table 6 displays the modelling results for the joint DCE-MB model, when excluding respondents considering the presented casualty levels as "too high".

Table 6: ML alternative-specific model for combined DCE-MB data with level-of-service attributes, considering scenario belief*

Parameters	Casualty number "seemed correct"			
	Bus passengers		Car drivers	
	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value
ASC_safer_route_DCE	2.07 (0.290)	0.00	1.55 (0.154)	0.00
ASC_safer_route_MB	1.90 (0.443)	0.00	0.404 (1.73)	0.02
Cost	-0.0273 (0.00608)	0.00	-0.0170 (0.00303)	0.00
Casualty	-0.0963 (0.0326)	0.00	-0.175 (0.0322)	0.00
Time	-0.0444 (0.00920)	0.00	-0.0472 (0.00718)	0.00
Sigma	1.25 (0.228)	0.00	1.05 (0.149)	0.00
Lambda MB (scale parameter)	1.55 (2.05)	0.79***	1.31 (0.393)	0.49***
Halton draws	500		500	
Number of observations	1649		9051	
Number of individuals	295		1614	
Null log-likelihood	-1143.000		-6273.675	
Constant log-likelihood	-934.633		-5753.435	
Final-log-likelihood	-724.076		-4464.390	
r^2(Null)	0.367		0.288	
r^2(Cte)	0.225		0.224	
$\bar{\rho}^2$ (Null)	0.360		0.287	

Derived values (St. error)

Value of travel time saving (NOK/hour)	97.6	166.6
WTP_{CAS} (NOK/casualty)	3.527 (1.055)	10.294 (1.351)
$WTP_{CAS}^{DCE\text{-}MB,car} - WTP_{CAS}^{DCE\text{-}MB,bus}$	6.77 (1.71)	
95% confidence interval	3.41–10.13	
Hypothesis test	reject H4	

* All models were estimated using BIOGEME (Bierlaire, 2003). Robust t-tests were computed taking into account the repeated observations nature of the data. The number of individuals in parentheses represents the sum of DCE and MB responses; although the same respondents answered the DCE and MB surveys ("within-subject"), the model handles the DCE and MB choices with separate panel structures.

** Applying the 'delta method' (Hole et al., 2007), that takes into account the correlation between the cost and casualty coefficient.

*** Robust p-value against 1.

Interestingly, after excluding the "disbelievers" the estimate value for WTP_{cas} is reduced for bus (from NOK 5.27 to NOK 3.52) but increased for car (from NOK 8.22 to NOK 10.29). Thus, the gap has increased, and we can reject – as for the whole sample – the hypothesis of equal WTP for bus and car users.

4.4. Model results including individual characteristics

Table 7 displays the modelling results for the joint DCE-MB model when allowing for systematic taste variations among individuals.

Table 7: Mixed logit model with covariates

Parameters	Bus passengers				Car drivers			
	Generic model		Alternative-specific model		Generic model		Alternative-specific model	
	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value	Value (rob.std. err)	Rob. P-value
ASC_safer_route_DCE	-	-	2.22 (0.245)	0.00	-	-	1.48 (0.0879)	0.00
ASC_safer_route_MB	-	-	1.70 (0.187)	0.00	-	-	0.213 (0.119)	0.07
Casualty	-0.247 (0.0714)	0.00	-0.0721 (0.0692)	0.30	-0.250 (0.0650)	0.00	-0.138 (0.0510)	0.01
Casualty-age	-0.00188 (0.00132)	0.15	-0.00129 (0.00097	0.18	-0.00351 (0.00118)	0.00	-0.00254 (0.000839)	0.00
Casualty-children in household	-0.164 (0.0632)	0.01	-0.0628 (0.0912)	0.49	-0.108 (0.0349)	0.00	-0.0547 (0.0277)	0.05

Casualty-male	0.157 (0.0467)	0.00	0.0688 (0.0299)	0.02	0.152 (0.0344)	0.00	0.105 (0.0245)	0.00
Time	-0.0543 (0.0160)	0.00	-0.0466 (0.0137	0.00	-0.0679 (0.0225)	0.00	-0.0682 (0.0217)	0.00
Time-age	0.00045 (0.00030)	0.14	0.00037 (0.00023)	0.11	0.00112 (0.000341)	0.00	0.00107 (0.000332)	0.00
Time-children in household	-0.0241 (0.0155)	0.12	-0.0176 (0.0165)	0.29	-0.0146 (0.0101)	0.15	-0.0113 (0.0101)	0.26
Time-university degree	0.00764 (0.0119)	0.52	0.00604 (0.0074)	0.41	-0.0126 (0.00878)	0.15	-0.0100 (0.00845)	0.24
Time-log (daily travel distance by bus/car)	-0.00658 (0.00349)	0.06	-0.00793 (0.00339)	0.02	-0.00576 (0.00276)	0.04	-0.00598 (0.00265)	0.02
Time-live in semi-urban area	-0.0142 (0.0121)	0.22	-0.0106 (0.00968)	0.27	-0.0190 (0.0123)	0.12	-0.0192 (0.0122)	0.12
Time-live in urban area	-0.0176 (0.0121)	0.15	-0.00829 (0.00934)	0.37	-0.0206 (0.0103)	0.04	-0.0209 (0.0102)	0.04
Cost	-0.0611 (0.0323)	0.06	-0.0269 (0.0414)	0.52	-0.0735 (0.0434)	0.09	-0.0612 (0.0384)	0.11
Cost-log(Income)	0.00409 (0.00329)	0.21	0.00126 (0.00463)	0.79	0.00544 (0.00413)	0.19	0.00446 (0.00365)	0.22
Cost-income missing	0.0363 (0.0333)	0.28	0.0141 (0.0560)	0.80	0.0576 (0.0436)	0.19	0.0466 (0.0389)	0.23
Cost-log (daily travel distance by bus/car)	-0.0102 (0.00261)	0.00	-0.00883 (0.00368)	0.02	-0.00236 (0.00075)	0.00	-0.00218 (0.000769)	0.00
Sigma	1.31 (0.102)	0.00	1.42 (0.23)	0.00	1.22 (0.0598)	0.00	1.05 (0.0802)	0.00
Lambda CV (scale parameter)	1.15 (0.144)	0.30**	4.59 (5.12)	0.48**	1.31 (0.192)	0.10**	1.53 (0.281)	0.06**
Halton draws	500		500		500		500	
Number of observations	6,726		6,726		25,727		25,727	
Number of individuals	606 (1214)		606 (1214)		2,290 (4,579)		2,290 (4,579)	
Null log-likelihood	-4,662.108		-4,662.108		-17,832.598		-17,832.598	
Constant log-likelihood	-3,894.833		-3,894.833		-16,558.560		-16,558.560	
Final-log-likelihood	-3,236.015		-2954.368		-12,958.401		-12,436.554	
ρ^2(Null)	0.306		0.366		0.273		0.303	
ρ^2(Cte)	0.169		0.241		0.217		0.249	
$\bar{\rho}^2$ (Null)	0.302		0.362		0.272		0.302	

* All models were estimated using BIOGEME (Bierlaire, 2003). Robust standard error and p-values were computed taking into account the repeated observations nature of the data. 1. For the demographic variables 'children in household', 'university degree', 'income missing', 'male', 'live in semi-urban area', 'live in urban area', and 'relative/friend seriously injured/killed in road accident', the interaction is the product of a LOS variable times a dummy taking the value of one if the individual possesses the demographic characteristic. For 'age', 'income' and 'daily travel distance by car', the interaction multiplies the LOS variable by the demographic variable (i.e. considering it a continuous variable).

** Robust p-value against 1.

Table 7 shows similar parameter estimates between the bus passenger sample and the car driver sample. From the interaction variables, it appears that the marginal disutility of risk increases with age (but the result is not statistically significant for the bus sample). There is an indication of male respondents having lower marginal disutility from casualty risk than women. Finally, the marginal disutility of risk appears to be higher for respondents from a household with children.

Based on the parameters estimated and the specified utility function, we calculated individual values for all three marginal utilities, and from these we computed individual-specific WTP. Figure 3 depicts the cumulative distribution function (CDF) of WTP_{CAS} for bus passengers and car drivers.

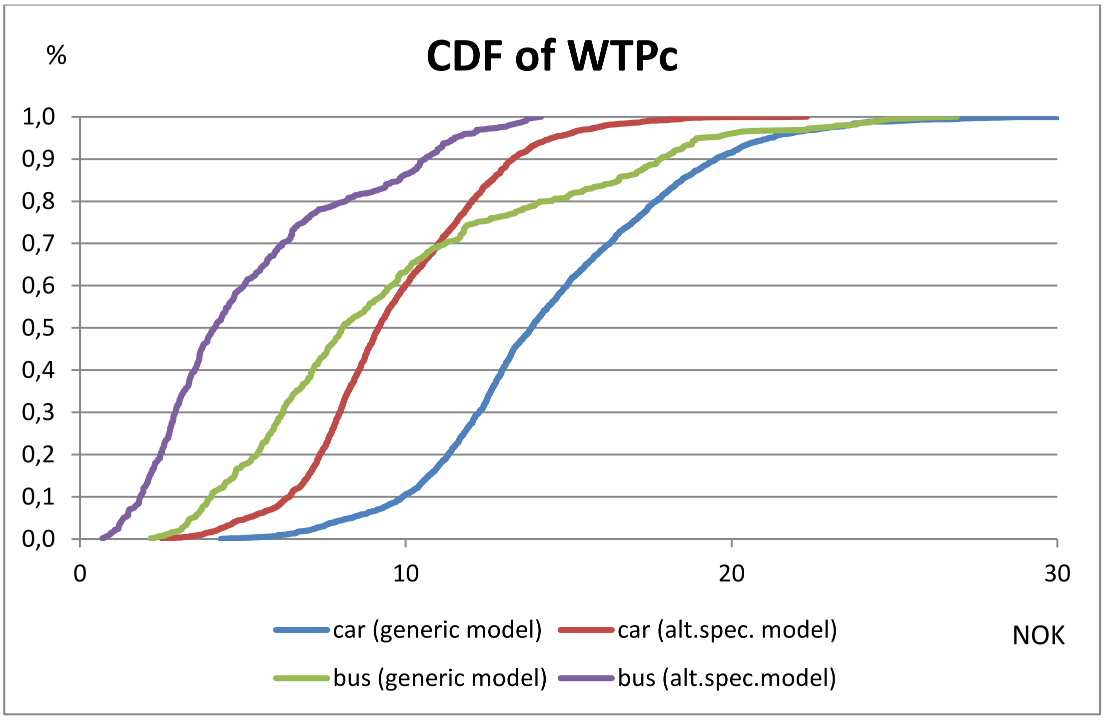

Figure 3: Estimated CDF of WTP_{CAS}

Figure 3 shows that all individual-based WTP_{CAS} estimates are positive. Considering first the generic model, for bus passengers, the mean WTP_{CAS} was calculated at NOK 9.68 (the median value was NOK 8.06). As a measure of dispersion, the 10^{th} and 90^{th} percentiles of the distribution of point estimates were respectively NOK 4.02 and NOK

17.80. For car drivers, the mean WTP_{CAS} was calculated at NOK 14.39 (the median value was NOK 13.85). The 10th and 90th percentiles were, respectively, NOK 9.90 and NOK 19.52.

The corresponding values for the alternative-specific models are as follows: (i) for bus passengers, the mean WTP_{CAS} was calculated at NOK 5.20 (median 4.12). The 10th and 90th percentiles of the distribution of point estimates were respectively NOK 1.85 and NOK 10.62, (ii) for car drivers, the mean WTP_{CAS} was calculated at NOK 9.61 (median 9.17). The 10th and 90th percentiles were, respectively, NOK 6.41 and NOK 13.29.

4.5.Comparing VSL/VSSI between modes and SP methods

This sub-section presents the derived VSL and VSSI for bus passengers and car drivers, based on the three ML models with only LOS attributes (DCE, MB, and combined DCE-MB) and the combined ML model for the DCE-MB data including individual characteristics.

From equation (6) we have that VSC equals $WTP_{CAS} \cdot AADT \cdot 365$. We estimated $AADT$ as our sample average (i.e. of the adjusted distribution between 2,000, 6,000 and 12,000), yielding 8,641 (rounded to 8,500) for bus passengers and 7,038 (rounded to 7,000) for car drivers. Using equation (7) we can estimate VSL given the actual shares of serious injuries, p_{si}, and fatalities $(1–p)_f$, in bus and car accidents respectively; we used the values p_{si} = 0.8 and $(1–p)_f$ = 0.2, for both bus and car accidents. These are the approximate proportions that follow from Norwegian official figures, from 1998 to 2005, when serious injuries were upward adjusted due to underreporting. As indicated above, we estimated DRE_{si} = 0.2 (Veisten et al., 2013), and therefore VSSI = 0.2·VSL. Table 8 lists the estimates.

Table 8: Values of statistical life and limb (NOK million), based on alternative specific models*

Value (confidence interval)	**Bus passengers**	**Car drivers**	**Differences (car minus bus)**	**Hypothesis Test**
From DCE only				
VSL	44.8 (24.8 – 64.8)	68.8 (51.8. – 85.8)	24.0 (-2.2 – 49.7)	Retain H1*

VSSI	9.0 (5.0 – 13.0)	13.8 (10.4 – 17.2)	4.8 (-0.4 – 9.9)	
From MB only				
VSL	41.5 (13.3 – 69.8)	52.2 (34.0 – 70.3)	10.6 (-23.0 – 43.5)	Retain H2*
VSSI	8.3 (2.7 – 14.0)	10.4 (6.8 – 14.1)	2.1 (-4.6 – 8.7)	
From joint DCE-MB				
VSL	45.5 (32.0 – 58.8)	58.3 (46.3 – 70.4)	12.9 (-5.1 – 30.6)	Retain H3*
VSSI	9.1 (6.4 – 11.8)	11.7 (9.3 – 14.1)	2.6 (-1.0 – 6.1)	
From joint DCE-MB with covariates				
VSL	44.8 [15.9 – 91.5]	68.2 [45.5– 94.2]	Not applicable	
VSSI	9.0 [3.2 – 18.3]	13.6 [9.1 – 18.7]		

* The confidence intervals in the separate DCE and MB models, for bus passengers and car drivers, represent 95% confidence intervals estimated according to the 'delta method' described by Hole et al. (2007). For the above calculation, we assumed that AADT was given (i.e. not a random variable). For the model with covariates, VSL and VSSI were calculated using the median of the individual point estimates of WTP_{CAS}, and their variation was illustrated by the 10^{th} and 90^{th} percentiles of the distribution of their individual WTP_{CAS} point estimates.

Regarding the VSL and VSSI point estimates, the valuations are lower for bus passengers than for car drivers. However, the effect is not statistically significant at the 5% level (i.e. the 95% confidence intervals of the VSL difference include zero). Therefore, H1*, H2*, and H3* cannot be rejected, implying that the VSL for car drivers and bus passengers may be considered as alike. Note that the results for H1* (and H3*) do not confirm our results for H1 (and H3) regarding the WTPc. The apparent reason for this is the difference in baseline risk (here measured by AADT) between bus and car users. Note also that the VSL and VSSI estimates are sensitive to the assumed *AADT* and DRE_{si} values. Veisten et al. (2013) show how much the discrete choice experiment estimates for car drivers vary for *AADT* values of 4,000, 7,000 and 10,000 and for DRE_{si} values of 0.1, 0.2 and 0.3. The applied average sample *AADT* could be considered a random variable (with a distribution), such that the "real" confidence intervals of VSL and VSSI may even be larger.

5. Discussion

In the valuation literature, there is an increasing discussion about whether the value of a statistical life, or of statistical injuries, should be differentiated, and, if so, according to what criteria. In that context, it is of interest to examine whether different groups of road users value road safety differently.

We obtained VSL estimates, for bus passengers and car drivers in the interval of EUR 1.5 – 12 million, with point estimates (mean values) between EUR 5 and 8.5 million, using a conversion rate of NOK/EUR = 7.8972 (for May 2010, http://www.norges-bank.no/en/Statistics/exchange_rates/currency/EUR). The VSSI is assumed to constitute one fifth of VSL, that is, between EUR 1-1.7 million. These figures are relatively high compared to official figures and the international transport literature (Veisten et al., 2013). However, these values are in accord with those reported by Lindhjem et al. (2011) in their meta-analysis of the VSL studies in the areas of transport, health and air pollution studies. They obtain a mean estimate for the VSL in their meta-analysis of EUR 7 million.

To the best of our knowledge, our paper provides a first comparison of accident risk valuation between samples of bus passengers and car drivers. Both samples faced similar scenarios, with similar casualty base levels and changes, and similar cost figures, although the payment vehicle differed (ticket prices versus toll prices). Both samples also faced two different SP methods. For both methods, a reference level of casualty numbers was related to the respondents' reported trip length, together with a rather crude estimate of traffic density.

When comparing estimated WTP for one annual casualty change, we found no difference between both samples when the estimates were based on the MB format. However, based on the DCE and the joint DCE-MB data, the estimated WTP from the car drivers' sample was significantly larger than the estimated WTP from the bus passengers' sample. Thus, there seems to be a difference in accident risk valuation between these two transport mode users.

The casualty risk is actually lower for bus transport than for automobile transport in Norway, and for bus transport other risks related to personal security might be considered more pertinent (Moen and Rundmo, 2006; Backer-Grøndahl et al., 2007; Rundmo et al., 2011). Thus, we might assume that the risk related to accidents is a more inclusive risk for car drivers than for bus passengers. At least, our data indicates a similar pattern as observed by Foster and Mourato (2003) and Goldberg and Roosen (2007), although our type of good/attribute was different. VSL and VSSI can differ between population groups, if these groups differ in terms of income or other attributes. However, our combined DCE-MB model with covariates did not indicate that differences in individual characteristics brought about differences in valuations.

The presented annual number of casualties (killed and seriously injured bus passengers or car drivers/passengers) for the reported trip length, in the survey scenario, were higher than the actual levels, particularly for bus transport. Thus, respondents were asked if the calculated annual casualty number presented to them in the experiment seemed correct or was too high, or too low. For both transport modes, several respondents found the levels too high, but their exclusion from the modelling exercise did not change the hypothesis testing (H4 and H3 were rejected in either case).

In all models presented, the coefficients of casualties, time, and cost had the expected negative signs, for bus passengers as well as for car drivers, fulfilling a basic requirement of theoretical validity. The estimated value of travel time savings, from the DCE, was close to former estimates for Norway (Ramjerdi et al., 2010), fulfilling a requirement of external validity.

6. Conclusion

Our empirical evidence based on stated preference data suggests that bus passengers have a lower WTP to reduce the number of causalities on their route compared to car drivers. The hypothesis of equal WTP was rejected with 4 of 6 modelling approaches based on statistical tests. However, the VSL and VSSI mean estimates, taking into account different baseline risk of bus and car users, were found not statistically significant. We therefore do not recommend using different values of safety for bus passengers and car drivers in projects appraisal.

Although the casualty numbers in our SP scenario were somewhat crudely established, and also a bit exaggerated for the sake of the experimental design, particularly for bus passengers, our approach appeared to work sufficiently well to provide theoretically valid results, for both transport mode users. Our scenario design was driven by the need of a generalised structure that could be applicable to all bus and car trips of minimum ten minutes length all around Norway. However, further improvement and SP scenario developments in new studies are encouraged.

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