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Risk perception of traffic participants

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Abstract

This article analyzes the risk perception of traffic participants by making use of *Prospect Theory*. This methodology makes a conceptual distinction between the perception of *risk* and the perception of the *outcome* of an uncertain event. In the field of transport safety such a distinction is desirable, because risks are typically very low and thus sensitive to misperception by traffic participants. Taking into account such misperception will significantly improve estimates of the valuation of transport safety. The first empirical results show that the valuation of losses is well represented by a utility function that is concave in shape. Secondly, our preliminary results show that individuals base their choice mainly on the possible outcomes and not so much on probabilities whenever there are very small probabilities (say $\leq 1/100$) and "bad outcomes" involved.

Keywords: Risk perception; Prospect theory; Traffic safety

1. Introduction

During the past decades, studies of transport safety have gained much attention among both scientists and policy makers. While the aim of the policy makers is to bring down the number of traffic accidents, the concerning budgetary decision should—from an economic point of view—depend on the valuation of transport safety by traffic participants. Recently, a number of studies have come up with estimates for the value of transport safety (e.g. see Soguel, 1995). However, a persistent shortcoming of these studies is that up until now it has always been assumed that traffic participants correctly perceive the *risks* that are involved with traveling. As such risks are typically very small, there is good reason to suspect that the individual *perception of risk* will show a certain bias with respect to the *actual risk*. Therefore, rather than imposing this assumption *a priori*, we suggest to *test it*, by making use of individual data that can be collected by handing out questionnaires.

The suitable methodology for this aim is *Prospect Theory*. Dating back to the seminal paper of Kahneman and Tversky (1979), this methodology distinguishes itself by allowing for "distorted perceptions" of the probabilities of uncertain outcomes of an event. Recently, the application of Prospect Theory has gained much interest, and indeed it is often found that individuals do have a deviant perception of small (high) probabilities (Wu and Gonzalez, 1996), while the misperception of probabilities that are close enough to 0.5 is usually small. Contrary to the field of medical decision analysis, that has richly benefited from these developments (e.g. see Bleichrodt and Pinto, 2000), it may be seen as quite remarkable that Prospect Theory has not found its place yet in the field of transport analysis. Not only can one think of assessing the risk perception of traffic accidents by its participants, but also about other topics in transport such as the risk of missing a connection of a public transport chain, the risk that one does not have a seat in a train, the risk that one cannot find a parking spot, the risk of facing congestion, etc.[1] In this paper we advocate the use of Prospect Theory for the analysis of transport safety, by exhibiting this methodology and comparing it with "classical approaches" in this field. The empirical analysis has a tentative character, but nevertheless gives some important first insights into the individual's perception of safety in transport. Also, we hope that it may serve as a guide in future analyses.

This paper is organized as follows. In Section 2 we give an overview of methodologies that have been previously applied to the case that is also studied in this paper, i.e. the monetary valuation of transport safety. As said, these approaches do not distinguish between the individual's assessment of probabilities and her valuation of possible outcomes, but adopt a unified framework of which the

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[1] Though not making use of Prospect Theory, these particular risks have been analyzed in Rietveld et al. (2001) and Peeters et al. (1998).

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expected utility framework is by far the most prominent. In Section 3 some key statistics about transport safety in The Netherlands are presented. These figures have also been used in the questionnaire that has been set up for the purpose of this paper. Section 4 exhibits the research approach that is based on Prospect Theory, and contrasts it with the "classical" methodologies of Section 2. The empirical results are discussed in Sections 5 and 6 concludes this paper.

2. Previously applied methodologies in the field of transport safety

For policy decisions it is important to have a monetary value of fatal and non-fatal road injuries. Crucial components of the valuation of a road injury are the *severity* and the *risk* of the accident. The widespread opinion among economists is that the monetary value of fatal and non-fatal road injuries should reflect preferences of individuals. Many different methods have been used for the estimation of utility functions and the determination of the monetary valuation of safety. These methods can be categorized into two groups, which have been named A and B in Table 1. This section briefly describes the methods that are listed in Table 1, with the aim to clarify how Prospect Theory can add to the existing literature and whether it can make a contribution to improve estimations of the value of a statistical life.

Table 1
Utility measurement methods

Methods used to estimate the utility (and value) of (statistical road) injuries
(A) Revealed preference methodology
(B) Stated preference methodology
Contingent valuation
Choice experiments (conjoint analysis)
Standard gamble (certainty equivalent)

2.1. Revealed preference

Revealed preference (RP) studies measure the utility of changes in the probabilities on a fatal accident and the willingness to pay (WTP) for these changes by looking at revealed behavior (e.g. Jondrow et al., 1983). In revealed preference studies it is assumed that all road users are rational and informed. This assumption implies that road users know the objective risk levels and that they act according to these. The objective probability to become involved in an accident with serious injuries is small. For example, the probability to become heavily wounded (fatally wounded) as a result of a traffic accident is 1:500 (1:7500) on a yearly basis in The Netherlands, for a car driver who drives 20,000 km per year. A problem with the valuation of a risk decline in road safety is that most market behavior decisions are not explicitly made, because safety features are often bundled with other features. For instance, one might find a certain safety feature only on the most luxurious model of a desired car, which also includes all kinds of other additional non-safety features. Even if it would be possible to disentangle the respective valuations of additional safety and non-safety features, there would still be another problem: namely that individuals take into account their perceived risk level (instead of the objective risk level) when making their decisions. If the researcher knows the risk perception of the individuals, then the RP method will improve significantly.

2.2. Contingent valuation

Contingent valuation (CV) directly asks respondents about their WTP—or willingness to accept (WTA)—for a specific risk reduction. In this methodology, it is assumed that the values elicited with CV will correspond with those that would emerge on the real market. Furthermore, it is assumed in CV road safety valuation studies that the perceived risk level equals the risk level given in the question or the risk level mentioned by the respondent. CV estimates the value of a certain decrease in the risk of a certain accident. If this is an objective risk level, the same problem occurs as with the RP method; respondents base their decisions on their perceived, instead of the real, risk level. Thus, as with the RP methodology, the estimates of the value of safety that are retrieved by the CV method would improve significantly if the researcher knows the risk perceptions of individuals.

2.3. Choice experiment

Choice Experiment is seen as an extension or variant of CV. This methodology has mostly been used for the valuation of environmental commodities (see Adamowicz et al., 1998), and has its roots in marketing science, where it is better known as *Conjoint Analysis*. Rather than asking people their WTP for a risk reduction, the respondents are asked to make repeated choices between bundles of attributes. In certainty equivalent (CE) it is assumed that a good consists of more distinguishable attributes. For the valuation of a statistical life, at least two attributes are needed: one attribute with money amounts and one with risk levels. Additionally, it is assumed that the respondents are able to gauge the given risk levels. Therefore, it also holds for CE that the estimates would improve if the researcher knows the risk perceptions of the respondents.

2.4. Standard gamble (certainty equivalent)

The standard gamble method (SG) is a certainty equivalent method. This method requires respondents to fill in a certain outcome such that the individual is indifferent between this outcome and participating in a given lottery. Preferences of the individual are then explained by expected utility theory. The standard gamble method was developed in health economics and adopted by transport economists as an alternative method to CV to estimate the economic value and utility of safety. An advantage of SG over CV is that it is possible to use higher, more comprehensible risk levels. SG assumes that a certain decline in risk *independent of the initial risk level* always results in the same WTP for road safety. If this assumption is true, valuing road safety with SG can solve the problem of misperceptions of small probabilities problem. However, it is thought that this assumption of independence of the initial risk level is rather questionable; see Persson et al. (1995) and De Blaeij et al. (2000), who show that the WTP increases with the initial risk level. Another disadvantage of the SG method is that the respondent is set in the hypothetical situation that he has experienced an accident. In other words, the situation being valued is the *ex post* situation rather than the *ex ante* situation which is being valued by RP, CV and CE. According to these reasons, we think that the SG method is not suitable for valuing the safety of traffic participants.

3. Some facts about accident probabilities in The Netherlands

The number of deaths caused by traffic accidents is low compared with the total number of deaths. Less than 1 out of 100 fatalities are due to a traffic accident. The situation is rather different for the age category between 5 and 25. In this category, 1 out of 3 deaths is due to a traffic accident, making it the most important cause of death for this age group. In the “Meerjarenplan Verkeersveiligheid” (a transport safety plan) objectives for the year 2010 have been set. In this year, the number of fatal accidents should show a decrease of 50% as compared to the base year 1986, and the amount of injuries should have decreased by 40%. The objectives are in absolute terms, which means that they are independent of the increase in mobility. If the increase in mobility is taken into account, this means that the risk on a fatal accident should decline with 5.5% and the risk on an injury with 4% per year (Koornstra et al., 1990).

Different characteristics contribute to differences in accident risk-levels that are faced by individuals. Examples are personal characteristics such as age, physical and mental health, infrastructure characteristics, transport intensity on the roads, the weather and means of transport characteristics. In the present study, we just take into account the seriousness of the accident and the transport mode. The accident probability will be defined here as the ratio between the total amount of injuries and the total amount of traveled kilometers in The Netherlands, in the year 1997. This probability can be calculated for all mobility in The Netherlands, but also for different transport segments such as cyclists, children, etc. (Koornstra et al., 1990).

We use accident probabilities at three injury levels. In Table 2 these probabilities on accidents with different injury levels are given for 1997. The probabilities are transformed into probabilities on a particular accident, per 20,000 km. The figure of 20,000 km *per annum* is also used in the questionnaire that has been used for the purpose of this paper. We chose 20,000 km because this is a typical amount of kilometers that is driven by car in The Netherlands, on a yearly basis.[2]

Table 2
Accident probabilities (Sources: CBS (1998) and SWOV (1998))

	Per 20000 km travel	Figures used in survey
Lightly wounded	1:99	1:100
Heavily wounded	1:465	1:500
Fatal/fatally wounded	1:7657	1:7500
Motorcycle	1:889	1:900
Bicycle	1:2490	1:2500
Car	1:11161	1:11000
Bus	1:625000	1:625000

4. Outline of research approach

A possibly great disadvantage of the approaches that were sketched in Section 2 is that one has to make the assumption that people correctly perceive the probabilities (*risks*) involved. In this section we propose the methodology named *Prospect Theory*, that does not make this assumption *a priori*. Instead, it will be possible to make the distinction between the perception of probabilities and the perception of outcomes.

Our procedure will consist of three steps:

1. Determination of the *certainty equivalent* in order to avoid road accidents.
2. Elicitation of the *utility function* of individual traffic participants.
3. Elicitation of the *probability weighting function* of these same individuals.

The first step will provide information on the *valuation* of the risk of certain types of accidents, while the second step will estimate a utility function that adequately represents the preferences of individuals with respect to *money losses*. Finally, the last step will assess the perception of small probabilities through estimation of the functional transformation of these probabilities. After carrying out these steps we will have obtained the following:

a. The valuation of road accidents in terms of money.
b. The valuation of money losses in terms of utility.
c. The valuation of road accidents in terms of utility.
d. The perception of small probabilities with respect to road accidents.

The focus of this paper will be on (a, c and d). Although interesting, the results in b are regarded as a by-product of this paper. We will now turn to a more detailed description of points 1–3.

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[2] This implies that for most people the situation as sketched in the questionnaire is more intuitively appealing.

1. *Determination of the willingness to pay in order to avoid road accidents*

   The aim of this part is to determine the individual's CE for the risk of a certain accident A. Note that, because an accident is an undesired event, the individual's CE will always be negative. For convenience, we will make use here of the *absolute value* of the CE. To this aim, each respondent has been confronted with a lottery of the form $L := (p,\ A;\ 1 - p,\ 0)$, with a probability p to get involved in accident A and a probability $1 - p$ to not get involved in the accident.

   One way to retrieve the individual's CE is to ask her directly about the amount of money that would leave her indifferent between the lottery L and the money. This approach has been used by Fennema and van Assen (1999). Alternatively, as has been advocated by Bostic et al. (1990), one can *provide* money values to the respondents and leave a *binary choice* up to them rather than directly asking for an amount of money.[3] If the respondents are asked to make a sequence of n choices between the lottery L and respective money values $x_1,\ x_2, \dots,\ x_n$, then one is able to approximate the individual's CE through her observed choices. In particular, with subscript notation such that $x_1 < x_2 < \cdots < x_n$, there will be a "critical value" x_i such that paying that amount is favored to being subject to the lottery, while for $x_{i+1}, x_{i+2},\ \dots, x_n$ the lottery is favored to paying the concerning amount of money. Thus, the individual's CE will be in the range (x_i, x_{i+1}), and one can for example, take the value $(x_i + x_{i+1})/2$ as an approximation.

   Clearly, the smaller the width of the interval (x_i, x_{i+1}), the more accurate the estimate of the individual's CE. One way to bring down the width of this interval is, rather than fixing the money values $x_1, x_2, \dots, x_n$ in advance, dynamically determine these according to the *bisection rule* (see Abdellaoui, 2000). This rule consists of two steps: First, a lower bound x^{L} and an upper bound x^{U} need to be found, such that the CE lies in the range between these values. Second, in each iteration the respondent is given the choice between the lottery and the money amount $x^* := (x^{\mathrm{L}} + x^{\mathrm{U}})/2$. If paying this amount is favored over the lottery, then the new lower bound for the CE will be x^*, and conversely, if the lottery is favored over paying the amount, then x^* will be the new upper bound for the CE. Thus, the width of the interval $(x^{\mathrm{L}}, x^{\mathrm{U}})$ is halved in each iteration, until it is sufficiently narrow to give a good approximation for the "true" CE. In our questionnaire, money values were adjusted according to the bisection rule, with a total of six iterations for each lottery. The questionnaire contained three different lotteries, each concerning a specific type of accident:

   - A_1 is lightly injured, e.g. broken leg, bruised limbs—one should think of first aid help in general.
   - A_2 is heavily injured, e.g. concussion of the brain, severe burn—hospital admission required.
   - A_3 is fatal or fatally injured.

   To make the questions as realistic as possible we have used the realistic probabilities that were given in Table 2.

2. *Elicitation of the utility function*

   At this stage we estimate the utility function in terms of money. It should be stressed that we only estimate the *negative part* of the utility function, so that the results only apply to *losses*. The data for the elicitation of the utility function will be obtained in the same way as in Abdellaoui (2000) and Bleichrodt and Pinto (2000). It starts by constructing a *standard sequence* of negative outcomes, which means that our questions aim at obtaining a sequence of monetary values $x_0, x_1, x_2, \dots,$ such that $U(x_1) - U(x_0) = U(x_2) - U(x_1) = \dots,$ where $U(x)$ stands for the utility of the money value x. Together with two normalizing conditions it is then possible to construct a utility function.[4]

   The first lottery takes the form $(p, 0; 1 - p, x_0) \sim (p, -10; 1 - p, x_i)$, where x_0 is provided and respondents are asked to fill in x_1. After obtaining x_1, the respondents are asked to fill in x_2 in the lottery $(p, 0; 1 - p, x_1) \sim (p, -10; 1 - p, x_2)$, etc. which yields the *standard sequence* $x_0, x_1, x_2, \dots$. Note that in this step we did not choose to obtain the x_i values through an iteration procedure such as the earlier used bisection rule. The reason for this is mainly practical, as we did not want to burden our respondents with too many questions. Secondly, we assumed that after the first part of the questionnaire, respondents would have obtained some intuition on how to correctly estimate a trade-off value, and they were actually recommended to use the bisection algorithm to gauge it. From the questionnaire, we obtained two standard sequences of length 4. The first has an initial value of −Dfl 100,000, and the second has an initial value of −Dfl 2000.[5] We decided to add a second standard sequence as a kind of insurance for the case that the first sequence does not give enough information. It could be possible for example that the first sequence is only very slowly increasing, which means that we would not have enough information about the utility of relatively small losses.

3. *Elicitation of the probability weighting function*

   This part aims at obtaining a probability weighting function $w(\cdot)$ which corresponds to the perceived probability $w(p)$ given an objective probability p. In order to do so, we designed lotteries of the form: $(p, A; 1 - p, 0) \sim (p, y; 1 - p, x)$. The monetary value

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[3] Bostic et al. (1990) find empirical evidence for stronger consistency of choice experiments than of experiments where respondents are asked to provide an amount of money themselves.

[4] Two normalizing conditions are necessary in order to assign a *location* and a *scale* to the utility function. Observed preferences are purely ordinal, and hence the mapping of these preferences onto a real-valued function requires such normalizations.

[5] One Dutch Guilder (Dfl) equals about €0.45.

Table 3
Characteristics of the WTP data

	LI	HI	F	LI[a]	HI[a]	F[a]
Associated probability	1:100	1:500	1:7500	1	1	1
Average	314	5549	10549	31356	2774647	79113971
Median	156	963	5000	15625	481250	37500000
Geometric mean	131	1690	3032	13029	844950	22740324
Harmonic mean	42	466	571	4247	232764	4282839
Standard deviation	434	7344	14658			
Variation coefficient[b]	1.383	1.323	1.390			
Skewness	2.771	1.677	1.846			

[a] Valuation of the accidents according to ‘expected utility’.
[b] The variation coefficient equals the standard deviation divided by the mean.

y is given in advance, as are the probabilities p and the accident A. Again the respondents have to fill in x directly; because of the practical reasons that we have mentioned earlier it would be too time-consuming to obtain x according to an iteration procedure.

Let x_i be respondent’s (approximated) indifference value corresponding to accident A_i. According to (cumulative) Prospect Theory,[6] this yields the equations

$$\begin{aligned} &w(p_i)U(A_i) + (1 - w(p_i))U(0) \\ &\quad = w(p_i)U(y_i) + (1 - w(p_i))U(x_i) \quad i = 1, 2, 3. \end{aligned}$$

basically stating that for the probability weighting function $w(\cdot)$ and the utility function $U(\cdot)$, one is indifferent between the lotteries (p_i, A_i; $1 - p_i$,0) and (p_i, y_i; $1 - p_i$, x_i). Now recall that in step 1 we obtained the certainty equivalent CE_i for the lotteries (p, A_i; $1 - p$, 0), so that by definition:

$$U(CE_i) = w(p_i)U(A_i) + (1 - w(p_i))U(0) \quad i = 1, 2, 3.$$

Combining these two equations now yields the following simple expression for the probability weighting function:

$$w(p_i) = \frac{[U(\mathrm{CE}_i) - U(x_i)]}{[U(y_i) - U(x_i)]}.$$

Thus, making use of the utility function that was estimated in step 2, filling in the concerning certainty equivalent CE_i that was obtained in step 1, and making use of the monetary values x_i and y_i of step 3, the value of $w(p_i)$ at the given probability p_i follows directly from this equation.

5. Estimation and results

The data were obtained by handing out questionnaires among university personnel. Many respondents found it difficult to provide answers to the posed questions, resulting in only 17 returned questionnaires (out of 33).

Note that in the following absolute values are reported; only losses are considered, so all amounts are negative. The different types of accidents are denoted as follows:

- LI: lightly injured;
- HI: heavily injured;
- F: fatally wounded/fatal.

Table 3 contains some characteristics of the outcomes of the first part of the survey. The average respondent indicated that, in order to avoid a (yearly) probability of 0.01 on an accident with light injury, she was willing to pay an amount of Dfl 314. The average WTP values for a 1/500 yearly probability on heavy injury and 1/7500 probability for fatal injury were equal to Dfl 5549 and Dfl 10,549 respectively. However, as indicated by the significant skewness to the right, the empirical distributions of the valuation showed quite some relatively high values. The table therefore also includes statistics which are less sensitive to outliners, such as the median, the geometric mean and the harmonic mean.[7] The median values are equal to Dfl 156, Dfl 963 and Dfl 5000 respectively, which in an expected utility framework would imply a (yearly) valuation of Dfl 15,625, Dfl 481,250 and Dfl 37,500,000 for avoiding light injury, heavy injury and fatal injury *with certainty*. The high standard deviations indicate that there is much variation among the respondents’ valuation of the different types of accidents. The variation coefficients show that the relative variation becomes larger as the severity of the accident increases. In other words, the differences in individual perceptions not only become larger in an absolute sense, but also in a relative sense, when more severe accidents are concerned.

For the estimation of the utility function we have chosen the Box-Cox specification. More sophisticated specifications are quite difficult to estimate as we had only a limited amount of observations. Simpler specifications, such as the linear specification, turned out to yield a likelihood which was extremely low as compared to the reported likelihoods in

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[6] See Kahneman and Tversky (1979) and Tversky and Kahneman (1992).

[7] The logarithm of the geometric mean is equal to the average of logarithms, and the inverse of the harmonic mean is equal to the average of the inverses. It can be easily shown that: harmonic mean $<$ geometric mean $<$ arithmetic mean.

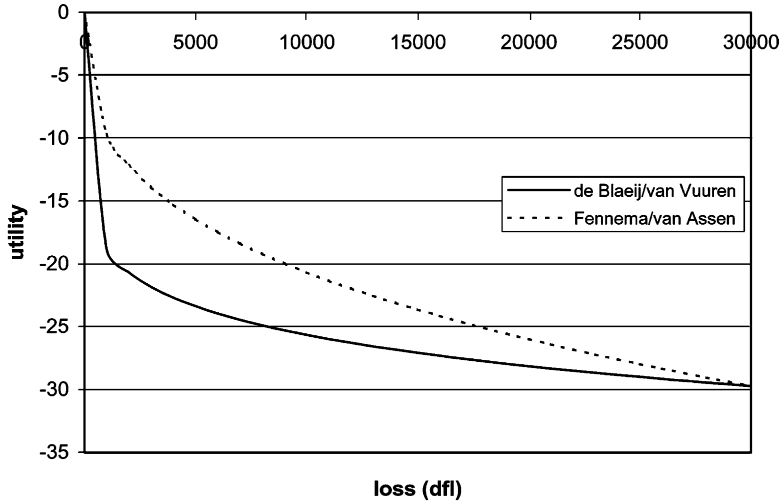

Fig. 1. Estimated utility function.

Table 4
Parameter estimates of the Box-Cox specification

Distribution ε	Normal	Logistic	Double exponential
Mean log-likelihood	−1.542	−1.775	−1.439
α	0.131	0.133	0.120
var(ε)	2.111	1.173	1.635

Table 4. Therefore, we only report the estimations of this specification, which is given by

$$U(x) = -\frac{x^{\alpha} - 1}{\alpha} + \varepsilon$$

A familiar property of this specification is that U tends to the logarithmic function as α approaches zero, and U is equal to the linear specification if α equals one. Estimation of the model points out that α lies in the range 0.12–0.13, dependent on which error distribution is chosen. This implies that the average subject exhibits a convex utility function for losses, a result that is in accordance with the findings of Fennema and van Assen (1999). These authors have estimated a power specification of the utility function,[8] and have found a parameter value which equals about 0.35. Although this estimate is not directly comparable to our estimates for the Box-Cox specification, it is clear that our results indicate a *more concave* utility function. A possible explanation for this is that Fennema and van Assen use smaller money values than we did, implying that the (conditional) utility function for small losses is *less concave* than the (conditional) utility function for large losses, as can be clearly seen in Fig. 1.[9] The likelihood scores that are reported in Table 4 indicate that the model containing a double-exponential error term suits the data best.

Note, that a possible improvement of the current model would be a stochastic α; this would allow for preference heterogeneity among different persons in a formula:

$$\alpha_i \sim N(\alpha, \tau)$$

At present we have not estimated this model. However, this remains for future research.

The result of the estimation of the probability weighting function was not a great success. Most people had a lot of difficulties with filling in the questionnaire. The results can be found in Table 5. The most remarkable property of the weighting function is that it is more or less constant, or in other words, independent of the probability itself. To illustrate this, we have drawn a graph of the probability weighting function in Fig. 2. Of course, each individual has her own weighting function, so we have taken the average values in this graph. The property that individuals are unable to tell apart small probabilities is seen to be independent from the utility specification. Not only the utility function that we have estimated above, but also the utility function of Fennema and van Assen (1999) and even the linear utility specification yield a constant probability weighting function. If we look at the absolute level of the probability weighting function, then it is seen that most people largely overestimate the probabilities involved. As is seen from the picture, this largely depends on the choice of utility function. In our specification the average level is about 0.4, while in the Fennema/van Assen and the linear specification it is about 0.3 and 0.1 respectively—still a large overestimation. The authors do not believe that the figure of 0.4 should at all be taken seriously in an absolute way, but instead it serves as an indication that the respondents are *unable* to make reasonable estimates about the risks involved. In the concluding section we will come back to this Fig. 3.

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[8] $U(x) = -x^{\alpha}$.

[9] Note that we have added the (positive) constant $U(0)$ to our utility function and have rescaled the Fennema/van Assen utility function such that the begin- and endpoints coincide. This can be done in accordance with the ordinal character of the utility function and it makes a visual comparison of the two specifications more straightforward.

Table 5
Probability weighting functions

p	de Blaeij/van Vuuren		Fennema/van Assen		Linear utility	
	$w(p)$	$w(p)/p$	$w(p)$	$w(p)/p$	$w(p)$	$w(p)/p$
1:100	0.4600	46	0.2740	27	0.193	19
1:500	0.4882	244	0.3823	191	0.2127	106
1:7500	0.4592	3444	0.2837	2128	0.1353	1015
1:625000	0.5745	359093	0.3631	226924	0.1458	91126
1:11000	0.4504	4955	0.3147	3461	0.1357	1492
1:10000	0.4366	4366	0.3259	3259	0.1693	1693
1:2500	0.4016	1004	0.2762	691	0.1172	293
1:900	0.3244	292	0.2214	199	0.1170	105

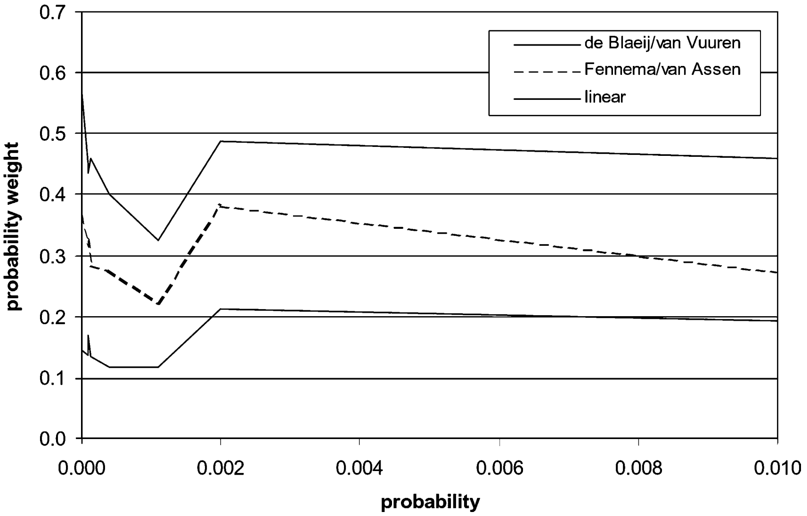

Fig. 2. Probability weighting function.

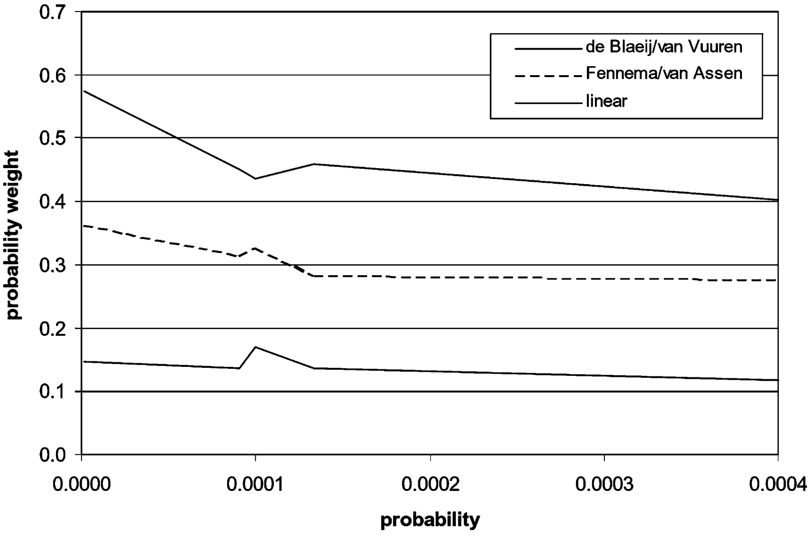

Fig. 3. Probability weighting function for fatal accidents.

6. Discussion and conclusion

In this article we have advocated the use of *Prospect Theory* for analyzing the risk perception of traffic participants. Contrasting previously applied methodologies in transport safety analyses, Prospect Theory makes a conceptual distinction between the perception of *risk* and the perception of the *outcome* of an uncertain event. In the field of transport safety such a distinction is desirable, because risks are typically very low and thus sensitive to misperception by traffic participants. In this study, the risk of an accident with various outcomes (light injury, heavy injury, fatal injury) has been analyzed, but many other applications in the field of transport, as have been mentioned in the introductory section, are obvious. The empirical results in this paper have a tentative character due to the limited number of respondents in our data set; however, we have been able to formulate some conjectures. Although, these need to be tested with a more adequate data set, the authors are convinced that the obtained results can serve as a guide in a possible future analysis.

It turned out that people have a median willingness to pay of Dfl 156 in order to avoid a yearly probability of 1/100 on an accident that results in light injury. Within *the expected utility framework* this would imply a median valuation of such an accident of Dfl 15,625. It is however found that the respondents display a lot of variation in their ‘tastes’, which even increases for more severe accidents. The median WTP for avoiding heavy injury or fatal injury is about Dfl 1000 and Dfl 5000 for yearly probabilities of 1/500 and 1/7500 respectively. Thus, expected utility theory implies a valuation of Dfl 500,000 for avoiding heavy injury and Dfl 37,500,000 for fatal injury. To compare this last value with earlier studies, the revealed preference method has generated values between Dfl 180,000 (Melinek, 1974) and Dfl 8,000,000 (Blomquist et al., 1996). Estimates obtained with the contingent valuation method are mostly higher, between Dfl 400,000 (Jones-Lee et al., 1983) and Dfl 600,000,000 (Maier et al., 1989). Comparable estimates of the valuation of a statistical injury do not exist as far as we are aware of.

The study of the *valuation of losses* has yielded a utility function that is concave in shape. We have found that this concavity is much more present than in the earlier study of Fennema and van Assen (1999), but this may well be due to the large negative amounts that were involved in our questionnaire: we suspect that most people have ‘more concave’ preferences as larger amounts of losses are involved. For example, most people would be indifferent between losing 40 million or losing 60 million, as it would imply their bankruptcy anyway.

It turned out that the last part of the questionnaire, involving the derivation of the probability weighting function, was too difficult for most respondents. On the one hand, it can be argued that the questionnaire should have been made easier. On the other hand, one may argue that the decisions that have to be made in real life are not easy either. The authors have been convinced that most people simply lack intuition to estimate very small probabilities in an ‘adequate fashion’. Secondly, it seemed that individuals base their decisions on the possible outcomes of the decision tree rather than on the probabilities involved. It looks like individuals are hardly able to distinguish between probabilities that are in the range between 0 and 1/100. It also turned out that some respondents did not fill out the questionnaire in a way that is in accordance with utility theory. Our main conjecture of this paper is therefore:

> When people have to choose to participate or not to participate in a potentially risky activity with a low probability of the “bad outcome” (say $\leq$1/100), they base their decision on the possible outcomes of the activity rather than on the probabilities involved.

As said, the most likely reason for this phenomenon is that people lack intuition for interpreting small probabilities. For probabilities, which are close enough to 0.5 it is relatively easy to think of a ‘frequency interpretation’ of the possible outcomes. For very small (or very large) probabilities this ‘frequency interpretation’ may not be applicable: For example, given the probabilities that have been used in the questionnaire, the probability that one will *ever* be involved in a bus accident (during her lifetime) equals only about 0.001.

A policy implication of this conjecture would be that governments that want to inform their citizens about the riskiness of certain activities should rather focus on the possible outcomes of those activities instead of trying to explain what exactly are the risks of those activities in terms of probabilities and/or frequencies. This policy has already been (successfully) applied for the case of smoking behavior.

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