Identification of Parameters for Prospect Theory Model for Travel Choice Analysis

Erel Avineri *
Centre for Transport & Society
Faculty of the Built Environment
University of the West of England, Bristol
Frenchay Campus, Coldharbour Lane
Bristol BS16 1QY, UK
Tel. +44(0)117 32 831997
Fax: +44(0)117 32 83002
E-mail: Erel.Avineri@uwe.ac.uk

Piet H.L. Bovy
Department of Transport & Planning
Faculty of Civil Engineering and Geosciences
Delft University of Technology, P.O. Box 5048
2600 GA Delft, the Netherlands
Tel. +31(0)15 27 84981
Fax: +31(0)15 27 83179
E-mail: P.H.L.Bovy@tudelft.nl

*—Corresponding Author

Paper length:
Abstract, body, and references 6267 words
1 table 250
4 figures 1000
Total 7497

Revised Version – September 2008
Accepted for Publication in Transportation Research Record
(Paper Number 08-1281)
Abstract
Travelers’ responses to risk and uncertainty involved in their travel choices have been argued to be a research area that can be better addressed by a descriptive approach rather than a normative one. Prospect theory, a descriptive model of decision making under risk and uncertainty, has been recently incorporated to travel behavior modeling. This paper describes some of the major challenges modelers are faced with when applying prospect theory to risky travel behavior contexts. In particular we discuss options in determining the values of crucial parameters of prospect theoretical travel choice models such as the reference point and the loss aversion factor. Prospect theory has been originally proposed in order to capture observed choices between alternatives framed as lotteries and gambles, and has been applied fruitfully to some settings in economics. However, due to some unique characteristics of travel journeys and the environment of decision making, application of prospect theory to a travel choice context is not trivial. Modeling challenges due to lack of in-consensus reference point value and other difficulties in setting values to other parameters are described in this paper, and several methodological approaches to set the parameter values of prospect theory are suggested and illustrated.
Studies on travel behavior have found that travelers consider journey time variability and other reliability measures of transport systems to be important factors that influence their travel choices (1). Route choices, mode choices and time scheduling of journeys are made by travelers in response to information on the transport system reliability, may this information be gained by their own experience (being familiar with the system reliabilities) or provided by external sources of information. Much of the recent interest researchers and practitioners have on travelers’ behavior under risk and uncertainty is motivated by emerging developments of Advanced Traveler Information Systems (ATIS). Information about variability of travel times and other uncertainties is provided by some commercial ATIS, such as in-car navigation systems and web-based journey planners.

1 INTRODUCTION: A NORMATIVE APPROACH TO MODEL TRAVELERS’ CHOICES UNDER RISK AND UNCERTAINTY

Much of literature about travelers’ responses to risk and uncertainty takes a rather normative approach, i.e. it is concerned with the question “How should rational travelers behave in response to network uncertainties?” Behavioral assumptions of transport models can generally be traced back to economics and statistics, assuming individual travelers behave as ‘homo economicus’, rational economic human beings who try to do their best in maximizing their utilities and minimizing the risk/uncertainties involved in their choices. However, recent studies provide evidence that the behavior of travelers is typified by limited cognitive resources and bounded rationality (‘homo psychologicus’). Therefore, normative models provide only limited explanation to travelers’ behavior. Moreover, recent evidences show that even when travelers are provided with explicit information on the uncertainty involved with travel choices, they turn out to interpret and value this information in a way that systematically violates the assumptions of rational behavior (2,3). A more descriptive approach to model travel behavior, inspired by works of cognitive psychologists and experimental economics is concerned with the question “How do travelers behave in response to network uncertainties?” However, in travel-choice modeling a clear distinction is not always made between normative and descriptive models of travel behavior. Often, the behavioral assumptions on travelers’ perception of reliability, and travelers’ responses to risk and uncertainty are made without reference to existing theories in the behavioral sciences. It may be required to relax some of the assumptions of rationality and produce a series of different prescriptions or predictions about travel behavior.

It is common to measure the performance of a transport system by a trade off between travel time and its variability (or standard deviation) (4,5,6). Travel time variability is commonly considered as a negative utility to the traveler, who is mainly interested in making short and reliable journeys, seeking to trade off travel time and travel time variance. Statistical functions related to reliability have been incorporated into travel behavior models in order to represent this trade off in travel choices. Lam & Small suggested representing reliability by the difference between 90th percentile and the median value of travel time (7). Recently, additional measures of travel time reliability, based on the width and shape of the travel time distribution, have been suggested (8,9,10,11).

Noland & Polak reviewed the empirical results of studies that estimated coefficients of various measures of variability (6). They have made an observation that the estimated measures of reliability have not been found to be statistically significant, or that they are statistically significant but with a counter-intuitive “wrong” sign. One of their conclusions is...
that only very little is known about how travelers perceive reliability, and about the ways travelers interpret, process and use information on reliability. Descriptive research on travel behavior has found a wealth of empirical evidence concerning travelers’ bounded rationality, cognitive errors and heuristic decision-making mechanisms. However, many of these aspects are commonly written out of the formal travel demand models, and assumptions on travelers’ responses to risk and uncertainty are usually made without reference to the existing theories and findings in behavioral sciences. Experiments in behavioral studies often find systematic deviations from the predictions of classical Expected Utility Theory (EUT). Kahneman & Tversky (12) showed that changing the ways in which options are framed could generate predictable and dramatic shifts in preference. Similar EUT violations were found in a travel behavior context by Avineri & Prashker (2). Kahneman & Tversky’s prospect theory (PT) offers a descriptive alternative to EUT (12).

Decision making, with an emphasis on understanding the goals that underlie individuals’ choice processes has been a major field of interest for cognitive psychologists and behavioral economists. PT and other theories of choice making have been fruitfully applied to some settings in economics and consumers’ behavior (13,14).

2 PROSPECT THEORY AND ITS APPLICATIONS IN MODELING TRAVELERS’ CHOICES

PT is based on observations of people’s stated choices between risky alternatives, originally framed as lotteries, but has been extended since then to handle general risky situations. PT assumes that lottery outcomes are mapped as gains or losses relative to some reference point. Such a reference point may be the current asset position, but may be influenced by the presentation of the lottery or expectations of the decision-maker. In the evaluation phase the decision-maker utilizes a value function \( v(\cdot) \) and a probability weighting function \( \pi(\cdot) \).

Consider a lottery with a set \( X \) of \( n \) probabilistic outcomes. An outcome \( x_i \) has a probability of \( p_i \). The prospect-theoretic value of each lottery, \( f \), is given by:

\[
f = \sum_{i=1}^{n} \pi(p_i) v(x_i)
\]

Note that the argument of the value function is the lottery payoff, which is the change in wealth, and not the level of it. In PT, the carriers of utility are gains and losses measured against some implicit reference point.

The value function is assumed to be concave in gains and convex in losses, a pattern which is consistent with the experimental evidence on domain-sensitive risk preferences. A strong intuition about preferences in risky environments is that people treat gains and losses differently. This observed risk-taking behavior, called loss aversion, refers to the fact that people tend to be more sensitive to decreases in their wealth than to increases. To capture loss aversion, the value function is assumed to be steeper for losses than for gains. This value function is described in Figure 1.
Kahneman & Tversky’s experimental results imply a reversed-S-shaped probability weighting function. Diminishing marginal sensitivity occurs in this function with respect to the benchmark case of certainty. As probabilities move further away from the 0 and 1 endpoints, the probability weighting function flattens out. Experimental results reveal that this curve tends to lie disproportionately below the 45 degrees line, as shown in Figure 2.

Two important implications of the probability weighting function should be noted. First, the overweighting of small probabilities implies that decision-makers will make risk-seeking choices when offered low probability high-reward lotteries. At the same time the behavior of people exhibit underweighting of high probabilities. Empirical studies on
probability weighting have generally confirmed that small probabilities are overweighted and large probabilities are underweighted (15,16,17).

Tversky & Kahneman developed a version of PT that employs cumulative rather than separable decision weights (16). This version, called Cumulative Prospect Theory (CPT) applies the cumulative functional separately to gains and to losses. The following functional form for the value function fits the CPT assumptions:

\[
v(x) = \begin{cases} 
  x^\alpha & \text{if } x \geq 0 \\
  -\lambda(-x)^\beta & \text{if } x < 0 
\end{cases}
\]

The parameter \( \lambda (\lambda \geq 1) \) describes the degree of loss aversion while parameters \( \alpha \) and \( \beta (\alpha \leq 1, \beta \leq 1) \) measure the degree of diminishing sensitivity. Tversky & Kahneman estimated \( \alpha = \beta = 0.88 \) and \( \lambda = 2.25 \). While this parameter value has been confirmed in some works (14), others suggested higher values (18,19).

The weighting functions proposed by Tversky & Kahneman (16) for gains and losses are, respectively:

\[
\pi^+(p) = p^\gamma / ([p^\gamma + (1-p)^\gamma]^{1/\gamma}) \\
\pi^-(p) = p^\delta / ([p^\delta + (1-p)^\delta]^{1/\delta})
\]

where \( \delta > 0 \) measures the elevation of the weighting function and \( \gamma > 0 \) measures its degree of curvature.

The values which fit best Tversky & Kahneman’s experimental results are \( \gamma = 0.61 \) and \( \delta = 0.69 \). In recent empirical studies on the probability weighting function (20,21,22), the parameter estimates are reasonably close to those of Tversky & Kahneman.

A comprehensive explanation of PT, and its later version, CPT can be found in (23). Travel behavior researchers have recently studied the application of PT and CPT to route choice modeling (2,23,24,25), departure time modeling (3) and passengers’ choice of public transport service (26,27). Travelers’ preferences as revealed in field studies and laboratory studies reported in the above studies support the findings of PT. A robust finding in many of the above studies is the emergence of risk aversion when travel choices are framed as gains (relative to a reference point), and risk seeking when travel choices are framed as losses. Not all of the above studies fully integrated the PT features. An element missing from some of these works is the weighting function. In others, the empirical analyses are based on small scale stated preferences surveys, limited to provide validated results. Only little attempt has been done to estimate the parameter values. The next sections describe some of the major challenges in estimating these parameters in the travel context, and discuss possible methodologies to set their values.

### 3 SETTING A VALUE TO THE REFERENCE POINT

Travelers, aware of the reliabilities of transport systems, make their route, mode or timing choices in situations which are different from the decision making scenarios studied by experimental economics and economic psychologists, commonly framed as monetary-based gambling problems. The main difference is that in a travel choice context there is no consensus about the reference point, while when dealing with monetary gains and losses, $0
may be the common reference point (as demonstrated in Eq. 3 above). Within the context of travel behavior modeling, a reference point may represent a threshold value that distinguishes between ‘gains’ and ‘losses’ of the journey, as perceived by the traveler. While we do not have an adequate model to predict (or measure) the value of the reference point, it was found in many studies that humans' adoption of a reference point is influenced by implicit information, explicit information, or even irrelevant information. A-priori perception of travel time, influencing travelers’ value of the reference point, may have an indirect influence on travelers’ choices.

Although empirical results provide some evidence to the robustness of PT findings without having a pre-defined and homogeneous reference point among travelers (2), the sensitivity to the value of reference point and to other parameter values have not been tested in large scale and complex situations.

Since the reference point value plays an important role in the studies of PT, travel choices (and their effects on the system performance) are sensitive to the value of the reference point, as demonstrated in (2) and (24).

In order to describe different methodologies in setting a value to the reference point (denoted as \( r_p \)), a simple decision problem is illustrated. A traveler is faced with a choice between two alternative journey options, A and B, each having a different travel time distribution. Option A has a fixed journey time of 30 minutes. Choosing option B, the traveler has a 15% chance to experience 25 minutes travel time, 70% chance to experience 30 minutes travel time, and 15% chance to experience a 35 minutes travel time. Viewed as a probabilistic prospect, \( f \) (as defined in EQ. 1) yields the payoffs \((r_p-25, r_p-30, r_p-35)\), with the probabilities \((0.15, 0.7, 0.15)\), respectively. The predictions of a CPT-based model are sensitive to the value of the reference point. Assuming the functional forms and the parameter estimates in Kahneman & Tversky, the cumulative weighted prospect values of both choices \((CWV_A, CWV_B)\) can be easily calculated for values of reference points between 20 and 40 minutes, as presented in Figure 3. While for values of the reference point above 28 minutes a prospect maximizer prefers the fixed-time alternative A over the risky one \((CWV_A>CWV_B)\), for values less than 28 minutes the risky alternative B is preferred.

![Figure 3: Sensitivity of the CPT prediction to the value of the reference point.](image-url)
Three approaches to set a value to the reference point are suggested: (i) setting a value to the reference point based on mean/median travel time; (ii) a direct way to set a value to the reference point; (iii) deriving the parameter value from stated/revealed preferences. A basic assumption of all these approaches is that travelers generally behave as prospect maximizers, relative to a reference point.

*Setting a Value to the Reference Point Based on Average, Mode or Median Travel Time*

In the absence of a methodology to evaluate the value of the reference point, one may assume that it may be related to the actual travel time experienced on average in the population of the target traveler group, such as typically an average of about 30 minutes one-way commuting time in many countries. This approach has been suggested in (23). Alternatively, the value of the reference point may be based on the median value rather than the average. Values on the mean or median travel time for particular travel purposes, modes, user groups or spatial contexts can be derived from national (or regional) travel surveys. In some special cases, observations may be made in order to estimate the value of the reference point as part of the modeling process.

Using the CPT parameters estimated in (16), and setting the value of 30 minutes to the reference point, the cumulative weighted value of choice A’s prospect in the above example is 0 and the cumulative weighted value of choice B’s prospect (CWV₈) is –1.07. A negative prospect value reflects a loss for the traveler. Since CPT aims in prospect maximization, a prospect traveler would avoid choosing B and prefer a choice A which has higher prospect value.

The main strengths of this approach are its simplicity and providing a clear rational underlying its choice. It may be argued that the approach is too much depended on the travel context. While 30 minutes may represent a common journey time for car commuters, different values of reference point may be associated with journeys made for other purposes or by other modes of transport. Modelers, straggling to estimate travelers’ Value of Travel Time (VOTT) for different trip purposes and modes, might find that associating trips purposes and modes with unique reference point values might face them with an additional challenge. As an alternative to the use of mean travel time as a reference point value, others parameters of the travel time distribution, such as the median value or the mode, can be used.

*A Direct Way to Set a Value of the Reference Point*

While commuters may have gathered experiences with the transport system, its attributes and the un reliabilities associated with them, they may not necessarily consider their actual experience as the reference point. One may argue that their perception of travel time (or other journey attributes) as ‘gains’ and ‘losses’, although may influenced by their actual experience, cannot be captured only by this element. As an alternative, travelers may be asked in a direct way about their reference point value – and what values of travel time may be considered by them as ‘gains’ and ‘losses’. While this approach has not been empirically explored in this context, to illustrate it findings on the ‘Ideal Commuting Time’ reported in (28) are revisited. The participants of a survey, representing 1300 households in the San Francisco Bay, have been asked about their actual commute time and about their desired commute time. Redmond & Mokhtarian (28) found that most people have a non-zero optimum commute time. Based on the analysis of their sample, ideal on-way commute time often fell into the 15-19 minutes category, with an average of 15.8 minutes, where only 1.2% of the sample reported an ideal
commuting time of zero. As Redmond & Mokhtarian comment: “in answering a question about her ideal commute time, the respondent may partly be considering what she thinks is realistic for her circumstances, which will again bias the ideal upwards. In particular, “zero” (or a very small number) may not be considered a “realistic ideal”. (28, page 182).

The distribution of the ‘Ideal Commuting Time’ among respondents, and the distribution of actual commute time by the same commuters, are presented in Figure 4. Assuming traveler’s reference point of travel time may be represented by her ‘desired’ commute time, the cumulative prospect value of the choices travelers face in the hypothetical example may be easily calculated. Most (89%) of the travelers, having a desired commute time of over 30 minutes, should find alternative B more attractive than alternative A: both alternatives generate outcomes of about 30 minutes, thus travelers find themselves in the ‘loss’ side, and following the original findings of prospect theory will seek for the more risky alternative (B).

The above approach to estimate reference point values can be easily tested in a laboratory environment. Surveys can be designed to capture both the ‘desired’ travel time and the stated preferences of individual travelers facing risky choices (but a knowledge of the distributions of ideal and actual times of a group of travelers may suffice to calculate shares for the group). However, the trustworthiness of travelers’ responses to questions about ‘desired travel time’, as well as their ability to represent the value of the reference point remain unanswered questions.

Deriving the Parameter Value from Stated/Revealed Preferences
The value of the reference point can be derived from respondents’ preferences in Stated Preferences surveys and laboratory experiments. Based on the SP database, and setting values to other PT parameters (see the next section), the PT predictions can be tested for different
values of the reference point. The reference point can be set to the value that provides the best prediction value (likelihood ratio or other statistical methods can be used, see for examples 2,26). The major deficits of this approach are its dependence on the parameter values that have to be estimated as well, and the lack of systematic search approach that guarantees a fast convergence to the optimum. There are practical problems in using Revealed Preferences methods to derive a value to the reference point – mainly due to the lack of real choice situations with sufficient information on uncertainty provided to the travelers.

Use of a Mixed Approach
So far, due to the very limited empirical research, it is difficult to judge which of the above described approaches provides a better estimation of the value of the reference point, and which of them (if any) produce valid predictions of travel choices. From a practical perspective, a mixed approach that incorporates elements of more than one approach may be the most effective one.

Dealing with traveler’s experienced travel time, the framing of the resulting travel time as a gain or a loss related to an individual reference point may be based on the traveler’s past experiences and expectations. Such a reference point may differ from one traveler to another, and may also differ from situation to situation, and may be changed over time due to changes in preferences. This may call to a dynamic estimation of the reference point values that may require updating from time to time.

4 SETTING VALUES TO THE LOSS AVERSION PARAMETER AND OTHER CPT PARAMETERS
At the current state of the art, and in the absence of empirical findings in a travel choice context, one may consider using the functional forms and the parameter values estimated by Tversky & Kahneman. Although similar estimates were found in data sets from different decision-making tasks, it is not trivial to assume that these estimates may be transferable to decision problems in the travel behavior domain, although predictions based on them will provide better approximations than the predictions produced by the classical models. After all, the original parameter values have been derived from choices framed as lottery gambles (in a laboratory setting) that incorporated money outcomes and any attempt to draw conclusions related to travel-choice based on these values should be questioned. Moreover, sensitivity analysis (mainly, those based on $\gamma$ and $\delta$ parameter values) indicate a need for some caution in drawing conclusions based on a particular set of parameter values that have not been confirmed and validated through an empirical study on travelers’ behavior (23). Therefore, we should still be cautious against over-interpreting these estimates as robust, and large-scale empirical studies need to be undertaken to test whether they are transferable to applied settings of travel choice.

A robust behavior described by prospect theory is loss aversion, captured by the shape of the value function and by a value of $\lambda$, the loss aversion parameter, larger than 1. In a travel-choice context, one may argue that the consequences of undesired variable outcomes may have an extreme effect on scheduled activities or on travelers’ ability to use transport modes or services linked with the unreliable service. Thus, in some situations outcomes may be associated by travelers with a more extreme negative impact, and a higher value of $\lambda$ might be more appropriate in such a context.
Recent literature directly investigated the presence of loss aversion in travel choice preferences \((2,3,23,29)\). Based on two large-scale stated preferences surveys held in the Netherlands to assess VOTT, Van de Kaa \((29)\) found that setting a value of \(\lambda = 2.0\) provides an explanation of over 55\% of the responses.

One approach to estimate the parameter value of the loss aversion parameter \(\lambda\) is to have it derived from the ratio between the VOTT associated with travel times considered by the traveler as losses, and the VOTT associated with travel times considered as gains. These VOTT estimates may be derived from the travelers’ stated or revealed preferences, and their willingness to pay to reduce travel time in different situations. For example, \(\lambda\) may be calculated as follows:

Based on the shape of the value function (Eq. 3):

\[
\frac{VOTT_{\text{late}}}{VOTT_{\text{early}}} = -\frac{\lambda(-x)^{\beta}}{x^a}
\]

and, for \(x = 1\):

\[
-\frac{\lambda(-x)^{\beta}}{x^a} = \lambda
\]

where \(VOTT_{\text{late}}\) is the VOTT estimate of late arrivals at the destination, and \(VOTT_{\text{early}}\) is the VOTT estimate of on time or early arrival at the destination where the first parameter may be associated with a loss and the second one with a gain.

Tilahun & Levinson \((30)\) analyzed the VOTTs of travelers on the I-394 MnPASS High Occupancy/Toll lane project in the Minneapolis/St. Paul region. Their findings, presented in the first two rows of Table 1, are used to illustrate the above approach.

<table>
<thead>
<tr>
<th>(VOTT_{\text{early}})</th>
<th>Morning</th>
<th>Afternoon</th>
</tr>
</thead>
<tbody>
<tr>
<td>11.63</td>
<td>13.09</td>
<td>13.08</td>
</tr>
<tr>
<td>14.86</td>
<td>9.90</td>
<td>21.22</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>1.28</td>
<td>0.76</td>
</tr>
</tbody>
</table>

The loss aversion factor estimates vary depending on the context, but in general is lower than the value provided in Tversky & Kahnemann. One possible explanation is that a traveler experiencing an early arrival to destination may not necessarily associate it with gaining, since some penalty for being too early might be generated. This may explain the \(\lambda < 1\) for morning travelers: many of the them are commuters, having strict working hours, and their penalty for being early might be larger than the penalty of being late (compared with the afternoon travelers, who may not experience much penalty in getting early to their destination – usually home). This presents the modeler with two challenges: not only that the value of \(\lambda\) may vary based on the journey destination or purpose, the disutilities of being early or late at arrival to destination are additional “gains” and “looses” that are not addressed by value function of travel time. The schedule delay, defined by Small \((31)\) as the difference between the chosen time of arrival and the official (or desired) arrival time carries additional cost to the traveler. This element may be handled as well by prospect theory, assuming travelers may value schedule delay against an implicit reference point. However, the generalization of
prospect theory models to handle more than one utility (value) at the same time (travel time and schedule delay) have not been studied yet in the literature and more theoretical and empirical research should be done before it can be applied to a travel choice context.

Since the value function has different curvature for ‘gains’ and ‘losses’ (represented by the parameters $\alpha$ and $\beta$, accordingly – see Eq. 3), the estimations of these parameter values are dependent on the estimated parameter value of the reference point. Another challenge is the estimation of the weighting functions parameters. Separate weighting functions are proposed for ‘gains’ and ‘losses’ that are measured from a reference point ($\gamma$ and $\delta$, accordingly - see Eqs. 4-5). Again, the estimations of these parameter values are dependent on reference point estimated value.

One might ask: should we consider using travel-choice models based on PT and its extensions rather than models based on the utility maximization assumption? One would be very careful with such a conclusion, and be aware of the specific challenges modelers may face when applying a CPT framework to model travel behavior. Moreover, even in the context of experimental psychology, PT and its extensions should not be considered as a full-fledged theory in order to describe single-choice decision-making under risk. One of the problems is that parameterizations based on experimental results tend to be too extreme in their implications. Recently, researchers argued for further research, both in formalization and parameterization, before making PT applicable to choice modeling (32).

It has been shown that CPT predictions may be sensitive to its parameter values. Thus, one of the major disadvantages of using CPT is the requirement to conduct empirical estimation of parameter values in different travel behavior contexts. Unlike the reference point, other CPT parameters can not be directly estimated by simply questioning a sample of travelers about their values, since travelers are not aware of such bounded-rationality mechanisms in their decision making process (and may reject the CPT assumptions as a description of their choice behavior). In general, estimation of the parameter values is not a territory that has been much explored, neither in travel choice nor in economics context. Even when estimated, one can not ensure that parameter values may be used in a different context or applied settings, and whether generalizable assumptions on their values can be made. If a generalized parameterization is not plausible, a calibration of a CPT-based choice model might suffer from the need to estimate the coefficients of the travel attributes’ values/utilities, and simultaneously estimate the CPT model parameters.

A major difficulty in setting values to CPT parameters is caused by the individual differences between travelers; due to different tastes, different experiences they had through traveling, their cognitive abilities, and the social context in which the journey is made, the parameters that define the individual traveler’s preferences towards risky travel prospects may be much different between travelers. Even choices made by the same traveler may have a different context every time a travel choice is made. The purpose of the journey (commuting, business travel, or social visit) may also have some effect on the traveler’s attitudes towards the risks and uncertainties involved in the travel choice. The above may result in heterogeneous parameter values and a rather diffused and complex distribution of parameter values over population, time and other dimensions of travel.

In the context of travel choices, being different from choices between risky monetary prospects, an alternative model for the editing of prospects may be suggested, where travel choice gains and losses are not defined over a single reference point but over two points – one for travel gains and the other for travel losses, where traveler preferences to values in the
region between these two reference points are assumed to be indifferent. In the context of travel choices, where a traveler does not necessarily have a crisp and sharp definition of a reference point in mind, a sound assumption may be that the perception of the reference point in the mind of a traveler is vague or fuzzy rather than crisp. Empirical research on travelers’ reference points may support or reject the fuzzy reference point hypothesis (33). Extension into fuzzy CPT models might make the theory more complicated although not necessarily providing much better predictive value.

Another issue that deserves some attention before applying PT to model travel choice behavior is the dynamic nature of data acquisition. Most empirical studies measured travelers’ responses to risky choices based on single-choice stated-preference methods. However, many travel choices may be considered to be a routine and can be described as a repeated choice situation, where feedback (resulted travel time) is involved. There is a relation between the travel utilities that occurred in past time periods and travelers’ current travel-choices (2). The travel time distribution is not likely to be completely known to travelers, and their perception of travel time may be dynamically updated, based on recent experience. Another important question is how the reference point is updated through time as a function of the outcomes in past decisions (34). PT was originally proposed in order to capture description-based decisions in one-shot tasks. Recently Avineri & Prashker (23) showed that CPT fails to predict route-choice feedback-based decisions (although a dynamic generalization of the CPT static model may provide valid predictions of travel choices).

5 SUMMARY AND CONCLUSIONS
Modeling travelers’ choices under risk and uncertainty has been argued to be a research area that can be better addressed by a descriptive approach rather than a normative one. There is much evidence that travelers do not behave as rational decision makers in response to risk and uncertainty, and that their choices generally violate the predictions of normative models such as EUT. PT, a model of decision making under risk and uncertainty, has been recently proposed to travel behavior modeling. This paper described some of the major challenges modelers are faced with when applying PT to travel behavior context. PT is not a full-fledged theory of decision making, and there is an on-going debate about its applicability in an economics context. In addition to the general complexities in estimating CPT parameter values, transport researchers are faced with additional difficulties and challenges. Due to the different contexts travel journeys are made in, different modes and trip purposes, it is difficult to estimate a set of parameter values that represent the common decision maker. Moreover, due to the lack of definite and in-consensus reference points in travel contexts, modelers may have difficulties in understanding and modeling possible outcomes as ‘gains’ and ‘losses’, as observed and framed by the travelers. In addition, some open questions remain about the suitability of PT, originally designed to describe static situations of choice making, to the more dynamic environment of travel choice.

Taking into consideration the modeling difficulties discussed in this paper, it may be concluded that the main challenge modelers are facing is not a mathematical one. Before developing deeper the theoretical aspects of such models, more literature from behavioral science should be used in order to design experiments and interpret the travelers’ responses to reliability in the traffic network. More empirical studies should be conducted, and travelers’
responses to risk and uncertainty should be explored in order to further explore usability and suitability of PT in the modeling of travel choices. Further research may look at the development of SP experiments specifically designed to facilitate the independent estimation of CPT parameters and explore their role in travel choices.

Although this paper mainly addresses researchers and developers of travel behavior models, it carries a strong message to practitioners as well: applying PT, assuming the same functional forms and parameter values that were estimated by psychologists and economists in non-transport contexts is not likely to provide better predictive values. Researchers and practitioners should be aware of possible solutions, some of them demonstrated in this paper, and to the level of complexity in the application. However, the intention of this paper is not to discourage the use of PT among transport researchers and practitioners. Despite the need for further development of theoretical and empirical concepts (mainly the estimation of parameter values), the insights obtained from the early work on PT provides qualitative predictions of travelers’ choices under risk and uncertainty. PT can be useful for understanding and, furthermore, finding opportunities to influence travel behavior.

ACKNOWLEDGMENTS
We are grateful for the valuable comments and suggestions received from anonymous reviewers. These contributed highly to the improvement of this paper.
This work was partly supported by TU-Delft, The Netherlands and the University of the West of England, Bristol, UK. It is part of the TU-Delft Scientific Research Program “Towards Reliable Mobility”, integrated in TRAIL (Netherlands Research School for Transport, Infrastructure and Logistics) R&D Program.

REFERENCES


