ABSTRACT

Automobile drivers were recently found to be risk averse when choosing among routes that had an average travel time shorter than the certain travel time of a route considered as a reference. Conversely, drivers were found to be risk seeking when choosing among routes that had an average travel time longer than the certain travel time of the reference route. In a driving simulation study in which the reference route had a range of travel times, this pattern was replicated when the reference range was smaller than the ranges of the available routes. However, the pattern was reversed when the reference range was larger than the ranges of the available routes. We recently proposed a simple heuristic model that fit the relatively complex data quite well. Actual or potential applications of this research include the design of variable message signs and of route choice support systems.

INTRODUCTION

A significant amount of effort has been put into developing models of automobile drivers route choice for both theoretical and practical purposes (for reviews, see Ben-Akiva & Lerman, 1997; Bovy & Stern, 1990). A central concern of route choice models is to describe drivers’ attitudes toward travel time variability. In the language of the psychology of choice, models should predict for which route choice scenarios drivers are risk averse and for which route choice scenarios drivers are risk seeking.

The terms risk averse and risk seeking have more than one interpretation (e.g., Cohen, Jaffray, & Said, 1987; Lopes, 1984). However, at the behavioral level, most interpretations refer to the pattern of choices that a participant makes when presented with an option having one certain outcome and an option or options having an equal (or almost equal) expected value but more than one possible outcome. Usually, a decision maker who chooses the certain option more often is termed risk averse, and a decision maker is risk seeking if he or she chooses the certain option less often.

Here we term a driver as risk averse if, among travel time distributions that have equal expectations, he or she more often chooses the route with the smaller variability. Conversely, a driver is termed risk seeking if, among travel time distributions that have equal expectations, he or she more often chooses the route with the larger variability. We refer to risk aversion and risk seekingness as risk attitudes.

The goal of this work is to investigate in more depth the complex influence of range of travel time on risk attitude and to investigate whether a relatively simple model can account for this influence. We build on a recent study by the present authors (Katsikopoulos, Duse-Anthony, Fisher, & Duffy, 2000).

Risk Attitude

Katsikopoulos et al. (2000) found that risk attitude in route choice is influenced by whether the route choice scenario is classified as belonging to the domain of gains or to the domain of losses.

A route choice scenario included a route that was considered as a reference route. That is, participants were either asked to imagine that they are driving on that route or were put in a simulated environment and were asked to drive on that route.
Interstate 93 was the reference route. The route choice scenario also included an alternative to the reference route. Participants had to choose whether to stay on Interstate 93 or to divert to Route 28 so as to minimize their travel time to downtown Boston. These particular routes were used in order to make the scenarios more plausible, as all participants lived in Massachusetts.

Participants were instructed to base their decisions solely on the travel time information given on each scenario. Despite this instruction, it is possible that participants brought prior experiences they might have had with Interstate 93 and Route 28 into the experiment. This is a problematic possibility for many reasons. For example, it is known that there is an interaction between drivers' experience and information that might contradict driver's expectations (Kantowitz, Hanowski, & Kantowitz, 1997). In order to reduce the extent of prior experience with these routes, the participants were based in western Massachusetts and thus had limited or no actual driving experience on Interstate 93 and Route 28. Then it was found that route choices were significantly affected by the characteristics of each scenario. This is consistent with the participants relying mostly on the travel time information given for each scenario rather on prior experience.

Travel time information consisted of a certain travel time (c) for the reference route and of a range of travel times for the alternative routes. In the scenario of Table 1, Interstate 93 took c min, with c = 100, and Route 28 could take from 80 to 110 min.

The range of travel times is symbolized with r; in the scenario of Table 1, r = 110 - 80 = 30. It is natural to assume that r provides an index of variability. The midpoint of this range is naturally equated with the drivers' perception of expected travel time and is symbolized by e; in the scenario of Table 1, e = (110 + 80)/2 = 95.

Route choice scenarios in which the alternative route has an expected travel time smaller than that of the reference route are classified as belonging to the domain of gains. The scenario of Table 1 belongs to the domain of gains. Conversely, scenarios in which the alternative route has an expected travel time larger than that of the reference route are classified as belonging to the domain of losses. In Table 1, if the range of travel times for the alternative route were changed to 90 to 120 min, the scenario would belong to the domain of losses.

Overall, drivers were risk averse for gains and risk seeking for losses. Diversion frequency among alternative routes with fixed expectation e smaller than the reference travel time c was decreasing in the range of the alternative router r. Also, diversion frequency was increasing in r when e was larger than the reference travel time c.

This finding is consistent with risk attitude reversals for other choices (Tversky & Kahneman, 1981). It is an important finding as it contradicts previous research, on the basis of which it appeared that drivers are always risk averse (Abdel-Aty, Kitamura, & Jovanis, 1997; Jackson & Jucker, 1981).

Here we investigate the robustness of this finding. Of most importance is that we extend the investigation of drivers' risk attitudes to route choice scenarios in which the reference route has a range of travel times, as opposed to a certain travel time. Clearly, a risky reference route is much more realistic. Of particular interest is the case in which the range of travel times for the reference route is larger than the ranges of travel times for the alternative routes. Intuitively, this may additionally influence risk attitude because the reference route is more risky than alternative routes in the sense of having a larger range.

Modeling

Katsikopoulos et al. (2000) proposed a simple model that described risk attitude reversals quite well. This model represents a break from the tradition of choice models
that assume humans have the capacity for complex transformations of all probabilities and values involved (e.g., Tversky & Kahneman, 1981, 1992).

Instead, drivers are assumed here to exhibit bounded rationality (Simon, 1957). That is, a simple heuristic is used to process probabilistic travel time information (see also Gigerenzer & Goldstein, 1996). Specifically, a driver is assumed to heuristically estimate a probabilistic travel time as simply a point inside the given range.

This estimate may vary across route choice scenarios. Formally, for a route with expectation $e$ and range $r$, the estimated travel time, $ETT$, equals

$$ETT = e + \lambda r; \lambda \sim N(\mu, \sigma^2), -1/2 \leq \lambda \leq 1/2. \hspace{1cm} (1)$$

In Equation 1, the distribution of $\lambda$ is bounded between $-1/2$ and $1/2$ to ensure that $ETT$ falls within the given range of travel times. Also, $\lambda$ can be thought of as varying across drivers.

Finally, for a reference route with certain travel time $c$, $ETT = c$. The model proposes that drivers choose the route with the smallest $ETT$. For the alternative route, $ETT$ is a random variable, so diversion occurs with some probability, which equals

$$P(div) = P[e + \lambda r < c] = P[\lambda < (c - e)/r]. \hspace{1cm} (2)$$

From Equation 2, the model predicts that $P(div)$ is decreasing in $r$ when $c > e$ (i.e., in the domain of gains) and that $P(div)$ is increasing in $r$ when $c < e$ (i.e., in the domain of losses).

Now consider scenarios with risky reference routes. For example, in Table 2, the reference has $e_R = 100$ and $r_R = 60$, and the alternative has again $e_A = 95$ and $r_A = 30$.

Generally, as with Equation 2, it is a matter of simple algebra to show that

$$P(div) = P[\lambda < (e_R - e_A)/(r_A - r_R)]; r_A > r_R. \hspace{1cm} (3)$$

$$P(div) = P[\lambda > (e_R - e_A)/(r_A - r_R)]; r_A < r_R. \hspace{1cm} (4)$$

When the reference route has a range of travel times, $P(div)$ is decreasing in $r_A$ for $(e_R - e_A)/(r_A - r_R) > 0$. Thus drivers are predicted to be risk averse in the domain of gains (i.e., for $e_R > e_A$) when the reference route is less risky than the alternative routes (i.e., when $r_A > r_R$). Note that this was observed for $r_R = 0$. Additionally, drivers are again predicted to be risk averse in the domain of losses (i.e., for $e_R < e_A$) when the reference route is more risky than the alternatives (i.e., when $r_A < r_R$).

Similarly, $P(div)$ is increasing in $r_A$ for $(e_R - e_A)/(r_A - r_R) < 0$. Drivers are predicted to be risk seeking in the domain of losses (i.e., for $e_R < e_A$) when the reference route is less risky than the alternative routes (i.e., when $r_A > r_R$). This was observed for $r_R = 0$. Additionally, drivers are predicted to be risk-seeking in the domain of gains (i.e., for $e_R > e_A$) when the reference route is more risky than the alternatives (i.e., when $r_A < r_R$).

Thus, interestingly enough, the model predicts the opposite risk attitude reversal when the reference range is larger than the alternative ranges (see Figure 1). This expresses the intuitive argument that reference risk influences risk attitude.

EXPERIMENT

This experiment had two goals: (a) to replicate the risk attitude reversal found for route choice scenarios in which the range of the reference route is smaller than the range of the alternative routes; and (b) to test whether the opposite risk attitude reversal is observed when the range of the reference route is larger than the range of the alternatives.

Method

Thirty college students (15 women, 15 men) up to 30 years of age ($M = 23.7$, SD = 3.5) who had valid driving licenses were recruited from the University of Massachusetts and the local area. Each participant attended an hour-long session. No
participant appeared to have problems comprehending and performing the task. The equipment and procedure used were identical to the ones used in the second experiment of Katsikopoulos et al. (2000). The most important aspects are as follows.

The University of Massachusetts driving simulator, consisting of an actual car connected to three computers and a projector that displays a virtual traffic database, was used (for details see Holton & Fisher, 1998). We used it because reviews of comparisons between driving simulator and field data indicate that such simulators provide route choice data of high external validity (e.g., Kaptein, Theeuwes, & van der Horst, 1995). Furthermore, in Katsikopoulos et al. (2000), it was found that this specific driving simulation environment induced a more realistic amount of cognitive load than does a more traditional paper-and-pencil environment. Overall it is thus reasonable to assume that use of this simulator is sufficient and necessary for the collection of data representative of real route choices.

The participants’ task was to drive in the right lane of the virtual world, follow a lead vehicle, and make route choices. The lead vehicle was programmed to move at a constant speed of 40 km/h. This was done in order to mitigate simulator discomfort for any participants and because not controlling for participants’ speed may have altered the amount of exposure to route information and/or route choices.

Each scenario involved two routes that participants were to assume would lead them to their workplace in downtown Boston. Participants were asked to imagine that most of the time they used Interstate 93 to get to work and that they currently were actually driving on that route; thus they were led to regard Interstate 93 as their reference route. The alternative route was Route 28. As said, it was made clear to participants that they should not be influenced by any prior experiences they might have had with those routes. Information was displayed on a variable message sign (VMS) by the right side of the road (see Tables 1 and 2). Participants spoke aloud their route choice, and the experimenter recorded it.

All participants were presented with the same route choice scenarios. In all scenarios, $e_R = 100$ min (see Katsikopoulos et al., 2000, for discussion of this setting). The two levels of $e_A$ (95, 105), three levels of $r_R$ (0, 30, 60), and six levels of $r_A$ (0, 20, 30, 40, 50, 60) were crossed to produce 36 scenarios. Thus in this design there were scenarios with reference ranges smaller and larger than the alternative range and scenarios for gains and losses. There were six virtual traffic databases, each containing six VMSs with each one of the levels of $e_A$, $r_R$, $r_A$ appearing an equal number of times in each database (thrice, twice, and once, respectively). Except for the different VMSs, all databases were identical. The order of presentation of databases was randomized across participants.

Data

For clarity, we present the data in three figures. In Figure 2, which depicts observed frequency of diversion to the alternative route, $N(\text{div})$ as a function of $r_A$ is given for scenarios with $e_A = 95$ and $r_R = 0$ or 60. In Figure 3, the same graph is given for $e_A = 105$. Two solid lines, one for each level or $r_R$, connect the six observations for the six levels or $r_A$.

In Figure 4, observed $N(\text{div})$ as a function of $r_A$ is given for scenarios with $r_R = 30$. Two solid lines, one for each level of $e_A$ (95 and 105), connect the six observations for the six levels of $r_A$.

Allowing $\mu$ and $\sigma$ to vary freely, the predictions that minimize the total square of errors for all scenarios based on Equations 3 and 4 are given by the dotted lines in Figures 2 through 4. The error was 369.41 for $\mu = 0.03$ and $\sigma = 0.37$. For these $\mu$ and $\sigma$ values, $R^2 = .84$. 
The data were analyzed using a 2 (e_A) × 3 (r_R) × 6 (r_A) repeated-measures analysis of variance (see Myers, DiCecco, White, & Borden, 1982, for discussion of use of the F test to analyze dichotomous data). For effects involving factors with more than two levels, the degrees of freedom reflect the Huynh-Feldt (Huynh & Feldt, 1970, 1976) adjustment.

Consistent with Katsikopoulouse et al. (2000), drivers diverted significantly less often as the alternative expectation e_A increased, F(1, 29) = 223.10, MSE = 74.68, p < .001. The effect of alternative range, r_A, which was also significant, F(5, 145) = 3.79, MSE = 0.75, p < .003, depended on the level of the alternative expectation e_A. This is indicated by a significant interaction between alternative range r_A and alternative expectation e_A, F(5, 145) = 2.34, MSE = 0.30, p < .04.

Of most importance for the hypothesis of different risk attitude reversals for different relative positions of the two ranges, the interaction between alternative range r_A and alternative expectation e_A depended on the level of the reference range r_R. The three-way interaction was significant, F(10, 290) = 10.60, MSE = 1.43, p < .001.

The overall trends in Figure 2 are as follows. When e_A = 95 (i.e., for gains), drivers were risk averse for r_R = 0 < r_A but risk seeking for r_R = 60 > r_A. In terms of overall trends in Figure 3, when e_A = 105 (i.e., for losses), drivers are risk seeking for r_R = 0 < r_A but risk averse for r_R = 60 > r_A.

Based on these trends, when r_R = 30 and e_A = 95, one may expect the N(div) curve to be decreasing when r_A > 30. Conversely, one may expect the N(div) curve to be increasing when r_A < 30. When r_R = 30 and e_A = 105, one may expect the N(div) curve to be increasing when r_A > 30 and to be decreasing when r_A < 30. In other words, when r_R = 30, the N(div) curve for e_A = 95 may be concave and the N(div) curve for e_A = 105 may be convex.

Overall, such concave and convex trends can be seen in Figure 4. A test proposed by Neyman (1949) was used to assess their significance. Briefly, the best-fitting polynomial of each curve is identified — that is, the one that produces a significantly better X^2 statistic value from all polynomials of the immediate lower order and a not significantly poorer X^2 value from all polynomials of the immediate higher order. Then it is determined whether it is concave or convex. In Figure 4 the long-dashed lines represent the best-fitting polynomials. The polynomial for the curve for e_A = 95 is concave. The polynomial for the curve for e_A = 105 is very slightly convex. However, the drop in N(divd) from r_A = 40 to r_A = 50 contributes greatly to this.

The interaction between alternative range r_A and reference range r_R approached but did not reach significance, F(10, 290) = 1.53, MSE = 0.20, p = .128. However, the interaction is evident by inspection of Figures 2 and through 4. Presumably, the mirror-image data patterns for e_A = 95 and 105 masked the interaction for the full data set. Separate analyses for the 12 combinations of alternative range r_A and alternative expectation e_A, it was found that the reference range r_R effect was significant for 8 of these combinations.

Certain mirror-image data patterns are responsible for the absence of this effect. For example, in Figure 2 for e_A = 95, N(div) is a decreasing function for r_R = 0 that starts at N(div) = 27 for r_A = 0. Additionally, N(div) is an increasing function for r_R = 60 that starts at N(div) = 10 for r_A = 0, and the two curves intersect at N(div) = 26 for r_A = 40.

Consistent with this, reference range r_R and alternative expectation e_A interact. The interaction was significant with F(2, 58) = 3.61, MSE = 0.56, p < .04.
Discussion

The data replicate those of Katsikopoulos et al. (2000) for risk aversion for gains and risk seekingness for losses when the reference range is smaller than the alternative range. In fact, no floor or ceiling effects are present in these data, as was the case in Katsikopoulos et al. Of most importance is that the data are consistent with the hypothesis of risk seekingness for gains and risk aversion for losses when the reference range is larger than the alternative range. A simple heuristic model proposed recently by the authors fit the data quite well.

SUMMARY

In this study, information on travel time ranges was presented on a VMS by the right side of a road in a simulated driving environment, so as to aid drivers’ route choice. Our study offers two main contributions. The first is the empirical demonstration of the complex influence of the range of travel times on drivers’ risk attitude. The second contribution is the development of a simple route choice model that proposes that drivers heuristically estimate their travel time as a point inside the range given and that fits the relatively complex data quite well.

IMPLICATIONS FOR DESIGN AND PRACTICE

The contributions of this study can be translated into practical benefits. Note that VMSs that display travel time information in the form of ranges are currently in operation in highways in metropolitan areas around the United States (e.g., Atlanta, Georgia, and Saint Louis, Missouri). There are at least two ways in which the results of this study can be useful in such situations.

First, the efficiency of the transportation network can be improved. This can be done by the optimal programming of the VMS. Specifically, given a pair of travel time ranges along two routes to a common destination, the model developed here can be used to determine the percentage of drivers who would stay on one route and of those who would divert to the other. Then the VMS can be turned on and off for such amounts of time that would lead to the rerouting of a desired percentage of traffic flow.

Second, driver decision making can be supported. This can be done by an in-vehicle system that estimates, from past route choices, the driver’s $\mu$ and $\sigma$ parameters. These estimates can be used, for a given pair of travel time ranges, to suggest to the driver the route that the driver would have chosen with the higher probability according to the model.

ADDED MATERIAL

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 Susan A. Duffy's coauthors sadly report that she passed away on February 14, 2002.

 TABLE 1: Route Choice Scenario in which Reference Route Has a Certain Travel Time

<table>
<thead>
<tr>
<th>Estimated Travel Time to Downtown Boston</th>
<th>Route</th>
</tr>
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<tbody>
<tr>
<td>100 min</td>
<td>1-93</td>
</tr>
<tr>
<td>80-110 min</td>
<td>Route 28</td>
</tr>
</tbody>
</table>

 TABLE 2: Route Choice Scenario in which Reference Route Has a Range of Travel Times

<table>
<thead>
<tr>
<th>Estimated Travel Time to Downtown Boston</th>
<th>Route</th>
</tr>
</thead>
<tbody>
<tr>
<td>70-130 min</td>
<td>1-93</td>
</tr>
<tr>
<td>80-110 min</td>
<td>Route 28</td>
</tr>
</tbody>
</table>

 Figure 1. Model predictions for the dependence of the probability of diversion, $P(\text{div})$, on alternative range, $r_A$. Solid lines represent predictions for route choice scenarios with $r_R < r_A$, and dotted lines represent predictions for scenarios with $r_R > r_A$.

 Figure 2. Number of participants $N(\text{div})$ diverting to the alternative route, as a function of the range of travel time of the alternative route $r_A$, expected travel time of the alternative route $e_A = 95$, and range of travel time of the reference route $r_R = 0$ (squares) or 60 (triangles). Observations are connected by solid lines and predictions by dotted lines.

 Figure 3. Number of participants $N(\text{div})$ diverting to the alternative route, as a function of the range of travel time of the alternative route $r_A$, expected travel time for the alternative route $e_A = 105$, and range of travel time of the reference route $r_R = 0$ (squares) or 60 (triangles). Observations are connected by solid lines and predictions by dotted lines.

 Figure 4. Number of participants $N(\text{div})$ diverting to the alternative route, as a function of the range of travel time of the alternative route $r_A$, expected travel time of the alternative route $e_A = 95$ (squares) or 105 (triangles), and range of travel time of the reference route $r_R = 30$. Observations are connected by solid lines and predictions by dotted lines. Best-fitting polynomials of observed curves are depicted as long-dashed lines not connecting any points.

 REFERENCES


